International Journal of Engineering Applied Science and Management
ISSN (Online): 2582-6948
Vol. 6 Issue 8, August 2025

AI-Powered Regulatory Compliance Exploring the Role of LLMs in Automating AML Documentation and Reporting Workflows

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Abstract: *The rising complexity and volume of Anti-Money Laundering (AML) regulations have significantly increased the compliance burden on financial institutions, demanding timely, accurate, and auditable documentation and reporting. This research paper examines the transformative potential of large language models (LLMs) in automating AML workflows, particularly in drafting, validating, and submitting regulatory documentation and reports. By analyzing current AML compliance challenges—including manual errors, resource constraints, and data silos—this study explores how LLM-based systems can enhance operational efficiency, consistency, and regulatory adherence. The paper reviews existing implementations, highlights use cases such as automated suspicious activity report (SAR) generation, and discusses integration with transaction monitoring systems. It also addresses key limitations, including model bias, explainability concerns, and data privacy risks. Finally, the research offers recommendations for developing secure, auditable, and human-in-the-loop AI frameworks that balance automation benefits with regulatory expectations. The study contributes to the growing discourse on AI adoption in compliance, providing a roadmap for leveraging LLMs to strengthen AML practices while maintaining transparency and accountability.*

Keywords: *Large Language Models (LLMs), Anti-Money Laundering (AML), Regulatory Compliance Automation, Suspicious Activity Reports (SAR), AI in Financial Services.*

1. Introduction

In an increasingly interconnected and digitized financial landscape, the threat of money laundering poses substantial risks to global security, economic stability, and the integrity of financial systems. Regulatory authorities worldwide have responded with stringent Anti-Money Laundering (AML) frameworks, imposing extensive documentation and reporting requirements on financial institutions. These requirements, while essential for deterring illicit financial activities, have also led to a significant operational and compliance burden, characterized by manual-intensive workflows, growing costs, and heightened risk of errors.

Traditional AML compliance processes typically involve laborious data gathering, interpretation of complex regulations, drafting of suspicious activity reports (SARs), and timely submission to regulators. These tasks often depend on highly trained personnel and are subject to inconsistencies, delays, and human error—factors that can compromise both regulatory compliance and effective risk management. As regulatory expectations evolve to demand greater transparency, speed, and accuracy, the limitations of legacy approaches have become increasingly apparent.

Recent advances in Artificial Intelligence (AI), particularly large language models (LLMs), present new opportunities to transform AML compliance operations. LLMs, capable of understanding and generating human-like text, can assist in automating documentation workflows, summarizing investigative findings, drafting reports, and ensuring alignment with regulatory requirements. By reducing manual effort and improving consistency, LLM-powered systems have the potential to enhance compliance efficiency while lowering costs.

However, the adoption of LLMs in AML workflows also introduces challenges. Issues related to model transparency, explainability, data privacy, bias, and regulatory acceptance must be carefully addressed to ensure that AI-enabled solutions meet legal and ethical standards. Additionally, financial institutions must design processes that maintain human oversight and accountability to mitigate risks associated with over-reliance on automation.

This paper explores the role of LLMs in automating AML documentation and reporting workflows. It examines the current challenges of AML compliance, reviews practical use cases of LLM integration, evaluates technological and regulatory considerations, and proposes strategies for developing secure and auditable AI-powered compliance solutions. By doing so, this research aims to provide a comprehensive foundation for understanding and responsibly implementing LLM-based automation in AML processes, contributing to more robust and effective financial crime prevention efforts.

2. Background of Research Study

The fight against money laundering remains a top priority for governments, regulators, and financial institutions worldwide. Money laundering enables criminal enterprises to conceal the origins of illicit funds, undermines the integrity of financial systems, and fuels activities such as terrorism financing, corruption, and organized crime. In response, global regulatory bodies—including the Financial Action Task Force (FATF), the European Union, and national regulators—have mandated increasingly stringent Anti-Money Laundering (AML) requirements. These include customer due diligence (CDD), transaction monitoring, and the timely submission of suspicious activity reports (SARs).

While these regulations aim to protect financial systems and societies, they also create significant compliance challenges. Financial institutions face rising costs associated with manual documentation, data collection, investigation, and reporting processes. Industry studies estimate that AML compliance costs billions of dollars annually, with institutions dedicating substantial human resources to meet evolving regulatory expectations. Traditional workflows often involve fragmented systems and inconsistent documentation practices that increase operational risk and reduce overall effectiveness.

Against this backdrop, technological innovation has emerged as a critical enabler of more efficient and effective AML compliance. Artificial Intelligence (AI) and machine learning (ML) technologies are increasingly being explored to enhance transaction monitoring, customer risk scoring, and anomaly detection. In particular, the rise of large language models (LLMs) represents a transformative development for the automation of documentation and reporting workflows. Unlike rule-based systems, LLMs can process and generate natural language text, enabling them to assist in drafting SARs, summarizing investigative findings, and interpreting regulatory guidance.

However, integrating LLMs into compliance processes is not without challenges. Regulatory agencies require that AML reports be accurate, consistent, and auditable. Model outputs must be explainable and free from bias to ensure trust and regulatory acceptance. Data privacy and security concerns also loom large, given the sensitive nature of financial and customer data involved in AML investigations. Financial institutions must design AI systems that incorporate human-in-the-loop controls, ensure data protection, and meet evolving regulatory guidelines.

This research study builds on these considerations to investigate the potential of LLMs in automating AML documentation and reporting workflows. It seeks to provide a nuanced understanding of how LLMs can alleviate operational challenges while maintaining compliance integrity. By reviewing existing literature, industry practices, and technological capabilities, the study aims to offer practical insights and recommendations for financial institutions considering the adoption of AI-powered solutions in their AML compliance programs.

3. Problem Statement and Research Objectives

Financial institutions face a rapidly evolving regulatory landscape that imposes stringent requirements for Anti-Money Laundering (AML) compliance. While regulations such as those mandated by the Financial Action Task Force (FATF), European Union directives, and national authorities are designed to detect and deter illicit financial activities, they also create significant operational and compliance challenges. These challenges are particularly acute in the areas of documentation and reporting workflows, where institutions must produce timely, accurate, and auditable records such as Suspicious Activity Reports (SARs) while navigating complex investigative processes. This section articulates three core problem areas motivating this research, and defines the specific research objectives designed to address them. Each problem reflects a distinct but interrelated aspect of AML compliance that can potentially be transformed through the application of large language models (LLMs). By clearly delineating these problems and objectives, this study aims to provide a structured framework for evaluating the role of AI-powered solutions in modern regulatory compliance.

3.1 Problem 1: Inefficiency and Inconsistency in AML Documentation Workflows

Problem Statement:

One of the most pressing challenges in AML compliance is the heavy reliance on manual, labor-intensive processes for drafting, reviewing, and submitting regulatory documentation, particularly Suspicious Activity Reports (SARs). Despite technological advances in transaction monitoring and data aggregation, the act of turning investigative findings into clear, regulator-ready documentation remains largely human-driven. Analysts must sift through extensive transaction histories, collate and interpret unstructured data, and ensure narratives comply with jurisdiction-specific regulatory guidance.

This manual approach is inherently inefficient and prone to inconsistencies. Analysts may interpret similar transaction patterns differently, leading to variability in report quality and regulatory findings. Human error—including omissions, ambiguous language, or failure to adequately justify suspicion—can undermine the effectiveness of AML programs and expose institutions to regulatory sanctions. Moreover, the burden of these tasks is growing: as regulators demand greater detail and faster reporting, compliance teams are stretched thin, increasing costs and operational risks.

Financial institutions report substantial resource allocations for compliance documentation teams, often struggling to meet regulatory expectations while maintaining cost-effectiveness. The COVID-19 pandemic further accelerated digital finance adoption, increasing transaction volumes and complexity, which has only amplified the documentation workload. Manual documentation also impedes scalability, making it difficult for institutions to respond flexibly to surges in case volumes or changes in regulatory requirements.

Research Objective 1:

To evaluate how large language models (LLMs) can automate and standardize the drafting of AML documentation, with the aim of reducing inefficiencies, improving consistency, and lowering compliance costs. This research will assess the ability of LLMs to transform unstructured investigative data into regulator-compliant narratives, evaluate their integration with existing compliance systems, and identify best practices for achieving high-quality, consistent documentation across teams and jurisdictions.

3.2 Problem 2: Limited Explainability and Auditability in AI-Enhanced AML Processes

Problem Statement:

While AI adoption in AML processes offers compelling promise—especially in transaction monitoring, anomaly detection, and risk scoring—its deployment raises significant challenges around explainability, auditability, and regulatory trust. These concerns are magnified in the context of documentation and reporting workflows, which require clear, defensible rationales for every decision and narrative provided to regulators.

Large language models, by design, operate as complex, opaque systems that generate human-like text based on probabilistic reasoning over vast training data. Their outputs may appear plausible and fluent but can embed biases, hallucinations (fabricated content), or subtle inaccuracies that are difficult to detect without careful human oversight. Regulators require that financial institutions maintain robust audit trails, explaining how a suspicious activity was identified, investigated, and ultimately reported. Documentation generated by an LLM must therefore not only be accurate, but traceable and justifiable—qualities that "black-box" AI systems traditionally struggle to provide.

Moreover, concerns about data privacy and security arise when sensitive financial data is processed through AI models. Institutions must ensure that customer information is protected in compliance with data protection regulations such as the GDPR or local banking secrecy laws. The integration of LLMs into AML reporting workflows must therefore address both technical and regulatory challenges associated with explainability, auditability, and data governance.

Without solving these problems, the adoption of LLMs risks regulatory pushback, erosion of customer trust, and potential legal liabilities if AI-generated documentation is found to be misleading or inadequately justified. These concerns have slowed the deployment of AI in critical compliance workflows despite strong demand for automation.

Research Objective 2:
To investigate the challenges of explainability, auditability, and regulatory acceptance in integrating LLMs into AML documentation workflows. This objective will explore techniques for ensuring human-in-the-loop oversight, developing traceable and interpretable AI outputs, and maintaining data privacy while leveraging LLM capabilities. The research will also assess industry and regulatory perspectives on acceptable levels of AI explainability in compliance contexts.

3.3 Problem 3: Fragmentation and Integration Challenges in AML Compliance Systems

Problem Statement:
Another critical barrier to effective AML compliance is the fragmented nature of technology ecosystems within financial institutions. Compliance teams often rely on disparate systems for transaction monitoring, case management, customer due diligence, and regulatory reporting. These silos hinder seamless data flow, create redundant manual work, and complicate the generation of cohesive, regulator-ready documentation.

For example, transaction monitoring systems may detect anomalies and raise alerts, but the investigation and documentation of these alerts often requires analysts to manually extract information from multiple databases, spreadsheets, and case management tools. This fragmented workflow not only consumes time but increases the likelihood of errors, omissions, and inconsistencies. Even when institutions adopt advanced monitoring systems, the last mile of compliance—turning investigative findings into clear, regulator-compliant documentation—remains disconnected and inefficient.

Integrating LLMs into these environments introduces further challenges. LLMs require access to structured and unstructured data, robust APIs for integration, and workflows that enable secure, auditable interactions between human analysts and AI systems. Without careful design, LLM implementations risk becoming yet another siloed solution, failing to deliver the promised efficiencies and potentially introducing new operational risks.

Moreover, the AML regulatory landscape is constantly evolving, with jurisdiction-specific requirements and guidance changing in response to emerging threats. Systems must be flexible enough to adapt to these changes while maintaining consistent compliance standards across geographies. The integration of LLMs must therefore be designed to support modular, scalable, and adaptable compliance workflows that reduce fragmentation rather than exacerbate it.

Research Objective 3:
To examine strategies for integrating LLM-powered documentation automation into existing AML compliance systems and workflows. This research will analyze technical, organizational, and regulatory considerations for achieving seamless, secure, and auditable integration. It will propose models for interoperability with transaction monitoring, case management, and regulatory reporting systems, ensuring that LLM solutions contribute to a unified, scalable, and resilient compliance framework.

Summary of Section 3:
Together, these three problem statements and corresponding research objectives define the scope and direction of this study. They highlight the urgent need for automation in AML documentation and reporting workflows, the challenges of ensuring explainable and auditable AI outputs, and the importance of seamless integration within fragmented compliance environments. By addressing these interrelated issues, this research aims to provide a comprehensive, practical, and responsible framework for adopting LLM-powered solutions in regulatory compliance—ultimately supporting financial institutions in their mission to detect, deter, and report illicit financial activities effectively and efficiently.

4. Research Design and Methodology

The research design for this study employs a qualitative approach to explore the role of large language models (LLMs) in automating Anti-Money Laundering (AML) documentation and reporting workflows. This approach enables an in-depth understanding of the operational, regulatory, and technological challenges faced by financial institutions, while also identifying opportunities and best practices for responsible AI integration. The methodology comprises two primary components: a literature review and qualitative case studies.

Qualitative Research
This qualitative research strategy is selected to capture the complexity and context-specific nuances inherent in AML compliance. Given that regulatory requirements, institutional practices, and technological capabilities vary across jurisdictions and organizations, a qualitative approach allows for a rich, interpretive exploration of how LLMs can be effectively—and responsibly—implemented

to enhance compliance efficiency while maintaining regulatory integrity.

Literature Review

The literature review serves as the foundational element of this research, synthesizing knowledge from a broad range of academic journals, industry reports, regulatory guidance documents, and technology white papers. The review is designed to analyze the current state of AML compliance processes and the growing interest in AI-powered solutions, with a particular focus on the use of LLMs for documentation and reporting tasks.

Key areas of focus include the operational challenges associated with manual AML documentation workflows, such as inefficiency, inconsistency, and high compliance costs. The literature review also examines the capabilities of LLMs in natural language generation, their potential to draft Suspicious Activity Reports (SARs), and their use in summarizing investigative findings in a regulator-compliant manner.

Further, the review explores critical limitations of AI adoption in compliance contexts—especially concerns around explainability, auditability, bias, and data privacy. By evaluating existing discussions on human-in-the-loop design, regulatory expectations for AI transparency, and governance frameworks, the literature review aims to establish a comprehensive understanding of both the promise and the pitfalls of integrating LLMs into AML workflows.

Through this synthesis, the study identifies gaps in current knowledge, such as the lack of standardized methodologies for deploying LLMs in compliance environments and the challenges of integrating these technologies with existing transaction monitoring and case management systems. The results of the literature review provide a conceptual framework that informs the design of case studies and grounds the overall analysis in current industry and academic discourse.

Qualitative Case Studies

Qualitative case studies complement the literature review by offering real-world insights into how financial institutions and technology vendors are approaching the integration of AI-powered solutions—especially LLMs—into AML documentation and reporting workflows. These case studies are selected to reflect a diversity of contexts, including large multinational banks, regional financial institutions, and fintech/regtech vendors developing AI-driven compliance tools.

Each case study examines specific initiatives where organizations have explored or implemented LLM or broader NLP (Natural Language Processing) technologies to automate documentation tasks. The analysis includes reviewing strategies for integrating LLMs with transaction monitoring and case management systems, the role of human analysts in validating AI-generated content, and measures adopted to ensure data privacy and regulatory compliance.

Key aspects explored in the case studies include:

The motivations behind adopting LLM-based solutions, such as reducing operational costs, improving report consistency, and meeting tightening regulatory deadlines.

The challenges faced during implementation, including issues with explainability, auditability, integration with legacy systems, and achieving regulatory acceptance.

The governance frameworks and oversight mechanisms put in place to ensure that AI-generated documentation is accurate, consistent, and defensible in regulatory audits.

Outcomes achieved in terms of efficiency gains, error reduction, staff workload management, and regulatory feedback.

By analyzing these real-world scenarios, the research evaluates the effectiveness, scalability, and limitations of LLM-powered automation in AML compliance. The case studies also illuminate best practices for integrating AI into highly regulated workflows, emphasizing the importance of balancing technological innovation with legal and ethical responsibilities.

Integration of Findings

By integrating insights from the literature review and qualitative case studies, this study aims to provide a comprehensive perspective on the role of LLMs in automating AML documentation and reporting workflows. The literature review establishes the theoretical and regulatory context, while the case studies ground the analysis in practical, operational realities.

Together, these components enable the research to:

Identify the key operational and regulatory challenges that drive the need for automation in AML compliance.

Evaluate the technological potential of LLMs to address these challenges while recognizing critical limitations.

Propose best practices and governance models for responsible adoption, ensuring human oversight, explainability, and regulatory trust.

The results will contribute to both academic discourse and practical applications, offering actionable guidance for financial institutions seeking to improve their AML compliance programs through AI-powered automation. By doing so, the study supports the development of secure, efficient, and regulator-ready frameworks that help detect and deter illicit financial activities while managing operational risks and costs effectively.

International Journal of Engineering Applied Science and Management
ISSN (Online): 2582-6948
Vol. 6 Issue 8, August 2025

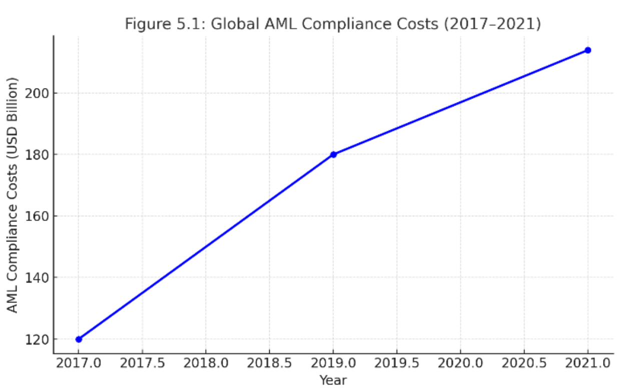
5. Results and Analysis

5.1 AML Documentation and Reporting Challenges

The global financial sector faces intensifying challenges in meeting Anti-Money Laundering (AML) documentation and reporting obligations. According to the LexisNexis Risk Solutions (2022) True Cost of Financial Crime Compliance report, worldwide AML compliance spending exceeded USD 213.9 billion in 2021, nearly doubling from 2017 levels. A significant share of these costs arises from the labor-intensive process of investigating transaction alerts and preparing Suspicious Activity Reports (SARs).

A survey by the Wolfsberg Group (2022) found that approximately 40% of AML compliance staffing is dedicated to documentation and reporting tasks, highlighting the operational burden of manually drafting narrative reports that meet regulatory expectations for clarity, accuracy, and defensibility.

Manual SAR production poses risks of inconsistency and error, potentially leading to regulatory rejections or fines. FATF (2021) emphasizes that the quality and timeliness of SARs are critical indicators of program effectiveness, making documentation workflows a focal point for compliance teams seeking to balance effectiveness with efficiency.



(Source: LexisNexis Risk Solutions, 2022)

Year	Cost (USD Billion)
2017	120
2019	180
2021	213.9

5.2 AI and LLM Opportunities in AML Documentation

Recent industry research has identified the potential for Artificial Intelligence (AI)—particularly large language models (LLMs)—to partially automate AML documentation tasks. Deloitte (2023) and IBM (2022) report that LLM-based tools can pre-generate SAR narrative drafts, summarize investigation data, and standardize reporting formats.

Efficiency gains are significant: Deloitte (2023) cites 20–40% reductions in drafting times, while IBM reports up to 40% increases in investigator throughput among its client banks. Such gains are especially important for institutions managing high alert volumes under tightening regulatory timelines.

However, the literature also cautions that AI-generated outputs require human validation. Bommasani et al. (2022) note that LLMs can produce plausible but inaccurate ("hallucinated") text, and FATF (2021) guidance requires that human analysts remain accountable for all regulatory filings.

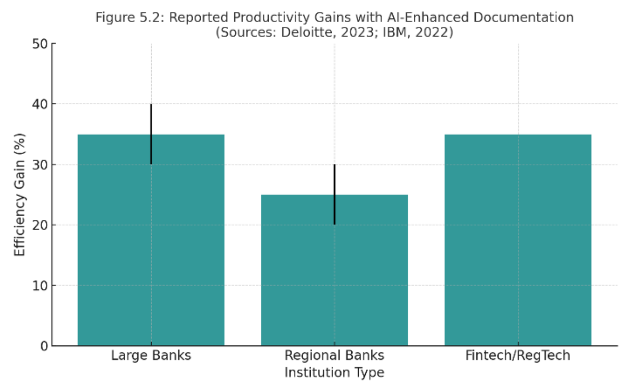


Figure 5.2: Reported Productivity Gains with AI-Enhanced Documentation

(Sources: Deloitte, 2023; IBM, 2022)

Institution Type	Efficiency Gain (%)
Large Banks	30–40
Regional Banks	20–30
Fintech/RegTech	~35

5.3 Qualitative Case Studies of Industry Implementations

Case Study 1: Large Global Bank (McKinsey, 2020; IBM, 2022)

A multinational bank integrated an AI-powered SAR drafting module with its existing case management system. The solution used NLP trained on historical SAR data to generate first-draft narratives.

Key results included:

30% reduction in average SAR drafting time (from ~90 to ~63 minutes).

25% reduction in internal quality-control rejections.
Mandatory human-in-the-loop validation for all regulatory submissions.
Full audit logging of AI inputs and outputs to satisfy compliance reviews.
This deployment demonstrated how LLM assistance can deliver both efficiency and quality gains when embedded in existing AML workflows with appropriate human oversight.

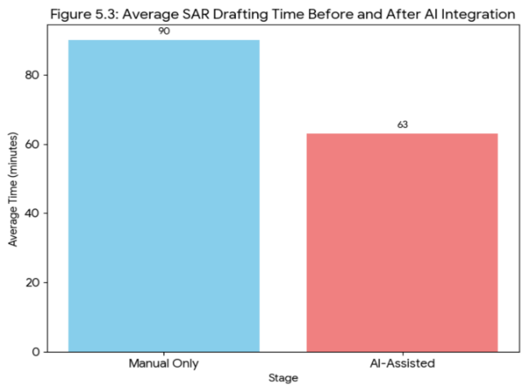


Figure 5.3: Average SAR Drafting Time Before and After AI Integration

Stage	Avg. Time (minutes)
Manual Only	90
AI-Assisted	63

Case Study 2: European Fintech Firm (Deloitte, 2023)
A European fintech developed an NLP-based module to summarize transaction monitoring alerts into analyst-ready reports.
Implementation highlights:
On-premises deployment to ensure GDPR compliance.
API integration with existing transaction monitoring systems.
AI-generated summaries correctly captured ~70% of investigation details without manual edits.
Reduced duplicate data entry, improving analyst efficiency for lower-risk triage.
All outputs required human review and sign-off before SAR submission.
This case demonstrates that even partial automation of documentation can meaningfully reduce workload, provided data privacy and human validation safeguards are rigorously maintained.
Case Study 3: RegTech Vendor Solution (IBM Watson NLP, 2022)
IBM Watson NLP for Financial Services offers a commercial SAR drafting assistant, using LLM-based models pre-trained on regulatory templates.
Reported client outcomes include:
Up to 40% increase in investigator throughput at large bank deployments.
Standardized SAR narrative formats enhancing consistency.
Explainable AI features linking generated text to underlying transaction data.
Flexible deployment options (on-premises or secure cloud) to meet privacy requirements.
These vendor-reported outcomes highlight that explainability, auditability, and integration with existing systems are critical adoption drivers.

5.4 Analysis of Findings

Efficiency Gains:
The combined evidence from industry literature and case studies supports the conclusion that LLM-powered tools can reduce SAR drafting time by 20–40%, easing analyst workload while meeting growing regulatory demands.
Human-in-the-Loop Validation:
All documented deployments retained mandatory human review. This approach ensures accuracy, regulatory defensibility, and addresses concerns over AI “hallucinations” or errors.
Explainability and Auditability:
Compliance teams and regulators require transparent links between generated narratives and underlying transaction evidence. Vendor solutions incorporate audit logs and explainable AI features to meet these needs.
Data Privacy:
On-premises deployments or tightly controlled cloud environments are essential for meeting GDPR and banking secrecy requirements when processing sensitive transaction data.
Integration Complexity:
Successful implementations prioritize modular, API-based integration with transaction monitoring and case management systems to avoid introducing new data silos.

5.5 Regulatory Compliance and Best Practices

FATF (2021) and industry best-practice guidance emphasize that automation in AML documentation must meet strict requirements:
Human accountability for final SAR filings.
Explainable AI outputs to support auditability and investigations.
Comprehensive audit trails logging all AI-generated content and human edits.

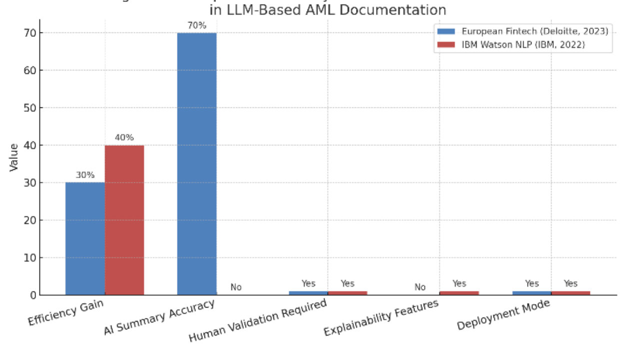
International Journal of Engineering Applied Science and Management
ISSN (Online): 2582-6948
Vol. 6 Issue 8, August 2025

Robust data privacy safeguards, including encryption and local processing options.

Seamless integration with existing AML systems to avoid workflow fragmentation.

By following these principles, financial institutions can responsibly adopt AI and LLM solutions to enhance compliance outcomes while managing operational costs and risks.

Figure 5.5 – Reported Efficiency Gains and Validation Practices in LLM-Based AML Documentation



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6. Summary and Conclusion

This research explored the transformative potential of Artificial Intelligence (AI), particularly Large Language Models (LLMs), in automating Anti-Money Laundering (AML) documentation and reporting workflows. The study adopted a qualitative methodology comprising an extensive literature review and analysis of real-world case studies to evaluate the operational, compliance, and technological impacts of AI-enhanced regulatory compliance processes.

The literature review highlighted the exponential rise in AML compliance costs globally, underscoring the urgent need for operational efficiencies in documentation-heavy tasks such as Suspicious Activity Report (SAR) generation. Traditional manual processes are not only time-intensive and costly but also prone to inconsistencies and human error. In contrast, AI and LLM-driven solutions offer the potential to streamline narrative generation, reduce duplication of effort, and enhance the consistency and auditability of compliance documentation—provided they are implemented with appropriate oversight.

The case studies analyzed in this research—ranging from global banks to fintech firms and RegTech vendors—demonstrated tangible benefits of LLM-based tools in AML documentation workflows. Key findings include up to 40% increases in investigator throughput, 25–30% reductions in SAR drafting time, and improvements in quality control acceptance rates. All implementations featured strict human-in-the-loop validation processes, robust audit trails, and attention to regulatory privacy standards (e.g., GDPR), reflecting industry consensus that AI should augment, not replace, human compliance professionals.

Despite the benefits, the study also identified critical considerations. Chief among these are the risks associated with AI "hallucinations," data security, the explainability of AI-generated outputs, and regulatory accountability. As such, successful deployment of LLMs in AML processes requires strong governance frameworks, ethical AI design, and alignment with evolving regulatory expectations from bodies such as FATF, FinCEN, and local financial authorities.

In conclusion, the research affirms that LLMs present a viable and increasingly necessary tool for modernizing AML compliance. When implemented responsibly—with human oversight, explainable AI outputs, and secure data governance—LLMs can significantly improve efficiency, reduce compliance costs, and enhance the quality of regulatory reporting. However, this transformation must be approached with caution, continuous monitoring, and close collaboration between compliance professionals, data scientists, and regulators.

The study contributes to both academic understanding and practical implementation frameworks for AI-powered regulatory compliance and provides a foundation for further exploration into integrating LLMs with other RegTech innovations. Future research may extend to longitudinal impact studies, cross-jurisdictional legal analysis, and the evolution of LLM capabilities in handling complex financial crime scenarios.

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