



ASSOCIAÇÃO DE POLITÉCNICOS DO NORTE (APNOR)

INSTITUTO POLITÉCNICO DE BRAGANÇA

**AI for Anti-Money Laundering:
The Rise of LLMs and Agentic AI**

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To obtain the Master Degree in Management, Specialisation in Business
Management

Supervisors:

Luis Carlos Magalhaes Pires

Vakhtang Chkareuli

Bragança, December, 2025.



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Abstract

The increasing intricacy of international finance systems has heightened the demand for effective and smart anti-money laundering (AML) solutions. Conventional AML architectures, relying essentially on rule-driven alerts and manual analysis, are under increased strain given growing volumes, non-native-language documents, and complex chains of transactions. Recent developments in AI, especially LLMs and agentic AI systems, have unleashed a new paradigm that could assist-not replace-AML officers' decisions on transaction analysis, onboarding reviews, and document interpretation. This study explores whether AML professionals supported by AI perform better compared to their non-AI counterparts through an experiment conducted within the Reference banking institution in Georgia.

Fifty-two employees of AML are randomly assigned to either the AI-enhanced tool group using LLMs combined with secure chatbot user interfaces or the purely traditional method group. Participants perform five common AML tasks: multilingual contract analysis, company due diligence, ownership tracing, person-of-interest profiling and onboarding risk assessment.

Each task is assessed by four performance measures: time efficiency, task accuracy, user satisfaction, and confidence level. After completing the tasks, both groups are required to take a survey to assess subjective workload also we are measuring their time and correction of the tasks, perceived effectiveness of the tools at hand, and openness to integrating AI into their work.

The central hypothesis is that the AI-supported group will outperform the control group across key dimensions, with striking advantages for both time-sensitive and language-dependent tasks. In addition, the study investigates whether AI use increases AML professionals' confidence in their decisions and reduces cognitive load. This is a hybrid research approach: by empirical data and participant feedback, it offers insights useful in practice for financial institutions considering implementing AI as a decision-support layer in compliance departments. It also adds to an emerging literature calling for human-centered design of AI in high-stakes financial environments.

Keywords: artificial intelligence, anti-money laundering, large language models, financial compliance, cognitive workload, AI collaboration, AML efficiency

Resumo

A crescente complexidade dos sistemas financeiros internacionais aumentou a necessidade de soluções eficazes e inteligentes para a prevenção da lavagem de dinheiro (AML). As arquiteturas tradicionais de AML, baseadas principalmente em alertas por regras fixas e análises manuais, enfrentam crescente pressão devido ao aumento do volume de transações, documentos em múltiplos idiomas e cadeias complexas de propriedade. Os avanços recentes em inteligência artificial (IA) especialmente os grandes modelos de linguagem (LLMs) e os sistemas de IA agêntica introduzem um novo paradigma que pode *auxiliar*, e não substituir, os analistas de AML em tarefas como análise de transações, revisões de onboarding e interpretação de documentos.

Este estudo investiga se profissionais de AML apoiados por IA apresentam melhor desempenho do que seus colegas que utilizam métodos tradicionais, por meio de um experimento conduzido em uma Instituição Bancária de Referência na Geórgia (RBIG). Cinquenta e dois colaboradores da área de AML foram aleatoriamente divididos em dois grupos: um utilizando uma ferramenta de IA baseada em LLM com interface segura de chatbot e outro utilizando apenas métodos convencionais. Os participantes executaram cinco tarefas típicas de AML: análise multilíngue de contratos, due diligence de empresas, rastreamento de propriedade, perfilamento de pessoas de interesse e avaliação de risco de novos clientes.

Cada tarefa foi avaliada segundo quatro dimensões de desempenho: eficiência temporal, precisão, satisfação do usuário e nível de confiança. Após a conclusão das tarefas, ambos os grupos responderam a um questionário sobre carga de trabalho percebida, número de correções realizadas, eficácia percebida das ferramentas e abertura para integrar IA em suas atividades futuras.

A hipótese central propõe que o grupo assistido por IA superará o grupo de controle em todas as principais dimensões, com vantagens marcantes em tarefas sensíveis ao tempo e dependentes de idioma. Além disso, o estudo investiga se o uso da IA aumenta a confiança dos profissionais de AML em suas decisões e reduz a carga cognitiva. Adotando uma abordagem híbrida, baseada em dados empíricos e no feedback dos participantes, esta pesquisa oferece percepções práticas para instituições financeiras que consideram implementar a IA como uma camada de apoio à decisão nos departamentos de conformidade, além de contribuir para a literatura emergente sobre o design centrado no ser humano de sistemas de IA em ambientes financeiros de alto risco.

Palavras-chave: inteligência artificial, prevenção à lavagem de dinheiro, grandes modelos de linguagem, conformidade financeira, carga cognitiva, colaboração homem-IA, eficiência em AML.

აბსტრაქტი

საერთაშორისო ფინანსური სისტემების განვითარება ზრდის მოთხოვნას ეფექტურ და ინტელექტუალურ ფულის გათვრების წინააღმდეგ საბრძოლველ (AML) სისტემებზე. ტრადიციული AML არქიტექტურები, რომლებიც ძირითადად ემყარება წესებზე დაფუძნებულ (rule-based) სისტემებს და მექანიკურ ანალიზს, ზრდის თანამშრომლებზე დატვირთვას, რადგან მატულობს ტრანზაქციების მოცულობა, ჩნდება უცხოენოვანი დოკუმენტები და რთული ტრანზაქციული ჯაჭვები. ხელოვნური ინტელექტის (AI) უახლესმა მიღწევებმა განსაკუთრებით დიდი ენობრივი მოდელების (LLM) და აგენტური AI სისტემების განვითარებამ წარმოშვა ახალი შეხედულება, რომელიც AML სპეციალისტების გადაწყვეტილების მიღების პროცესს ეხმარება, მაგრამ არ ანაცვლებს მას.

კვლევა სწავლობს, უკეთესად ასრულებენ თუ არა ამოცანებს ის AML სპეციალისტები, რომლებიც AI-ის იყენებენ, ვიდრე ისინი, ვინც მხოლოდ ტრადიციული მეთოდებით მუშაობენ. ექსპერიმენტი ჩატარდა საქართველოში მოქმედ მითითებულ საბანკო ინსტიტუტში (RBIG), სადაც 52 AML თანამშრომელი შემთხვევითად გაიყო ორ ჯგუფად: ერთმა გამოიყენა LLM-ზე დაფუძნებული AI ინსტრუმენტი უსაფრთხო ჩატბოტის ინტერფეისით, ხოლო მეორემ მხოლოდ ტრადიციული მეთოდები. მონაწილეებმა შეასრულეს AML-ის ოთხი ტიპური ამოცანა: მრავალენოვანი კონტრაქტის ანალიზი, კომპანიის დუ დილიჯენსი, მფლობელობის ჯაჭვის იდენტიფიცირება, და ახალ კლიენტთა რისკის შეფასება.

თითოეული ამოცანა შეფასდა ოთხი კრიტერიუმით: დროის ეფექტიანობა, სიზუსტე, მომხმარებლის კმაყოფილება და თავდაჯერებულობის დონე. დავალების დასრულების შემდეგ ორივე ჯგუფმა შეავსო გამოკითხვა, რომელიც აფასებდა სამუშაო დატვირთვას, დავალების შესწორებათა რაოდენობას, ინსტრუმენტების ეფექტურობის აღქმას და AI-ის მომავალში ინტეგრაციისადმი დამოკიდებულებას.

კვლევის ცენტრალური ჰიპოთეზაა, რომ AI-ის მხარდაჭერილი ჯგუფი აჩვენებს უკეთეს შედეგებს ყველა ძირითად პარამეტრში, განსაკუთრებით დროის მიმართ სენსიტიურ და ენასთან დაკავშირებულ ამოცანებში. დამატებით, კვლევა სწავლობს, თუ რამდენად ზრდის AI-ს გამოყენება AML სპეციალისტთა თავდაჯერებულობასა და ამცირებს კოგნიტურ დატვირთვას. კვლევა წარმოადგენს შერეულ მეთოდოლოგიურ მიდგომას, რომელიც ემყარება როგორც

ემპირიულ მონაცემებს, ისე მონაწილეთა უკუკავშირს და სთავაზობს პრაქტიკულ რეკომენდაციებს ფინანსურ ინსტიტუტებს AI-ის დანერგვასთან დაკავშირებით, როგორც გადაწყვეტილების მხარდაჭერის მექანიზმს. იგი ასევე ამდიდრებს მიმდინარე აკადემიურ დისკურსს, რომელიც მიმართულია მაღალი რისკის ფინანსურ სფეროებში ადამიანზე ორიენტირებული AI სისტემების შექმნისკენ.

საკვანძო სიტყვები: ხელოვნური ინტელექტი, ფულის გათეთრების წინააღმდეგ ბრძოლა, დიდი ენობრივი მოდელები, ფინანსური შესაბამისობა, კოგნიტური დატვირთვა, AI თანამშრომლობა, AML ეფექტიანობა.

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Abbreviations and Acronyms

AI	Artificial Intelligence
AML	Anti-Money Laundering
API	Application Programming Interface
BTU	Business and Technology University (Georgia)
CPU	Central Processing Unit
EBA	European Banking Authority
EU	European Union
FATF	Financial Action Task Force
GDPR	General Data Protection Regulation
IMF	International Monetary Fund
IPB	Instituto Politécnico de Bragança
KYC	Know Your Customer
LLM	Large Language Model
ML	Machine Learning
NLP	Natural Language Processing
OECD	Organisation for Economic Co-operation and Development
RBIG	Reference Banking Institution in Georgia
XAI	Explainable Artificial Intelligence

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Introduction

Money laundering continues to be among the most pervasive and challenging financial crimes influencing political integrity, institutional trust, and worldwide economic stability. The means of hiding the source of illicitly acquired cash keeps changing in size and complexity, therefore financial organizations have to improve their systems of monitoring and compliance. Strict anti-money laundering (AML) systems are required by regulatory organizations like the Financial Action Task Force (FATF), European Banking Authority (EBA), and national central banks; financial institutions to put in place strong mechanisms for customer due diligence, transaction monitoring, and suspicious activity reporting. Traditional AML techniques mostly dependent on rule-based engines and hand analysis, however, find it difficult to match the pace, complexity, and multilingual capacity of current financial transactions. These systems frequently provide an abundance of false positives, cause inefficiencies in investigative processes, and put heavy cognitive strain on compliance personnel.

Artificial intelligence (AI) has developed into a possibly transformative answer for the AML industry against this background. Particularly, large language models (LLMs) and agentic artificial intelligence instruments provide a fresh frontier in natural language processing, data synthesis, and decision improvement. These systems can interact with human users in real time, grasp context, and extract meaning from unformatted documents unlike traditional automation tools. Few have investigated the whole potential of artificial intelligence as an assistive interface for AML officials even though many financial companies have used it in backend detection engines. Most modern deployments are opaque, under-explained, and divorced from human workflows so restricting user confidence, auditability, and more general acceptance.

In mid-2025, the Reference banking institution in Georgia (RBIG) started a local LLM-driven chatbot pilot accessible to staff in sensitive sections, including AML, via internally hosted AI integration. Designed not as a substitute for human analysts but rather as a decision-support tool meant to help with media screening, multilingual document review, Know-Your-Customer profile creation and ownership tracing. This test matched the introduction of fresh organizational positions such as the "AI and AML Specialist" and "AI Ambassador" to direct adoption, offer training, and gather input. Still unknown beyond anecdotal accounts, the real effect of these tools on employee satisfaction, task performance, and accuracy remained.

This study addresses this gap by employing a well-designed experimental approach. Two equally-sized groups of fifty-two Georgia AML professionals were randomly allocated to either use artificial intelligence solutions or work without them manually. Every team did five regular AML activities meant to mimic daily

operations. The jobs included sophisticated cognitive processes such as international contract analysis, entity profiling, and risk evaluation. Time to completion, task correctness, and participant satisfaction were all assessed. It was recorded, and then a post-task questionnaire was completed to assess confidence, weariness, and faith in the technologies utilized. This research will answer the following questions by comparing AI-assisted and non-AI groups: Does AI actually improve AML work? If so, how does it affect the speed, accuracy, and contentment of people who are performing it?

This research seeks to make both academic and practical contributions. In principle, it contributes to the restricted empirical evidence on human-AI cooperation in regulatory financial institutions. Practically, it provides insights for financial organizations looking to deploy LLMs and agentic AI solutions responsibly, focusing on augmentation rather than substitution, transparency rather than automation, and trust as a key design objective. As financial crime gets more difficult and regulation stricter, the ability to incorporate sophisticated, understandable, and helpful AI into the compliance function may provide a competitive advantage. The next major step in the fight against money laundering.

Introduction to AML and Compliance Challenges

One of the most pressing and constant dangers to the integrity of the world financial system is money laundering. It is often described as the means by which people or corporations hide the illicit sources of their money, hence including it into the honest economy (Levi & Reuter, 2006). Beyond its technical definition, money laundering distorts financial markets, feeds corruption, and subverts government. Furthermore facilitating other major crimes including tax evasion, political corruption, terrorism funding, and drug trafficking (Chaikin & Sharman, 2009).

As shown on Figure 1, the Financial Action Task Force (2018) describes the process as a three-stage cycle placement, layering, and integration.



Figure 1. Three stages of professional money laundering (from the Financial Action Task Force, FATF).

Source: FATF. (2018). Professional Money Laundering (Figure 1, page 20).

Financial services internationalization together with technical innovation and globalized markets has made money laundering increasingly difficult both in implementation and detection. Fighting financial crime has therefore turned into a major support for contemporary banking compliance and economic policy.

Leading mostly by the Financial Action Task Force (FATF), created in 1989 by the G7 countries, the worldwide policy reaction to this phenomena has developed throughout many decades. Forty suggestions FATF presented have become the basis of counter-financing of terrorism (CFT) and global Anti-Money Laundering (AML) systems. Through regional and national laws, including the European Union's numerous AML Directives and comparable national laws spanning major financial hubs (Ferwerda, 2012), these suggestions were subsequently approved and localized. These systems aim not just to detect questionable transactions but also to develop a culture of compliance inside financial organizations by means of Ferwerda (2012). Know Your Customer (KYC) regulations, more thorough

due diligence, and regular surveillance. These systems are still quite resource-intensive and often reactive, highlighting compliance over proactive risk management despite their widespread use.

Research in academia reveals a persistent issue with the efficiency with which anti-money laundering (AML) initiatives react to financial crimes. Money laundering affects all areas of the economy, from modest fraud in individual transactions to more serious problems in trade, investments, and capital mobility, according to Unger and Busuioc (2007). Their study examining data from several nations revealed that even the most conservative predictions placed the amount of money being laundered at about 5% of the entire GDP. This sum far surpasses what national agencies can find and recover, therefore drawing attention to the flaws of compliance systems relying on fixed criteria and manual inspections. Banks and financial institutions really have to scan millions of transactions every day with automated systems, many of which lack contextual understanding and result in an exorbitant number of false alarms.

Among the most serious operating inefficiencies in AML systems is the false positives issue alerts incorrectly marked as suspicious. Rule-based systems are necessarily inflexible, depending on set thresholds that fall short of catching the subtlety of actual behavior, as Malhotra and Malhotra (2019) stress. Many times, these systems give sensitivity over accuracy, which produces false positive rates of more than 90% in some banks. The results are great: because of alert fatigue, compliance officers spend considerable parts of their working hours examining non-suspicious cases while real threats may go undiscovered. Moreover, this inefficiency results in significant financial expenditures as organizations must recruit more personnel to fulfill regulatory requirements without necessarily enhancing detection precision.

Apart from operational inefficiency, data fragmentation and multilingual complexity hamper AML compliance. Chaikin and Sharman (2009) explain how cross-border financial flows layered through shell businesses and offshore accounts make it challenging for national authorities to identify ownership structures. Even if data is easily accessible, they sometimes appear in unformatted or non-standardized forms, contracts, transaction logs or legal disclosures drafted in several languages. Unger and Busuioc (2007) similarly point out that the absence of interoperability between national systems obstructs efficient information exchange, therefore enabling launderers to use jurisdictional loopholes. These facts place significant cognitive and administrative burdens on AML professionals, who have to interpret enormous amounts of diverse data within tight deadlines.

AML rule's effectiveness is still debatable despite decades of international cooperation and technical advancements. Although the objective of AML legislation is great, Ferwerda (2012) argues that there is not enough empirical evidence to establish that it has helped to lower crime. While the measurable deterrent effect is minimal, compliance costs continue to increase especially for smaller institutions. This brings up queries about how suitable current AML strategies are in relation to their objectives. Likewise, Levi and Reuter (2006) say that AML enforcement often serves symbolic ends, therefore satisfying political and reputational obligations rather than really impeding illicit finances. Their criticism

emphasizes the need for creativity in both policy and technology, with a concentration on solutions that improve contextual thinking, linguistic understanding, and analytical precision.

Malhotra and Malhotra (2019) hold that artificial intelligence especially: By sorting out extraneous information, giving high-risk events priority, and translating international documents correctly, natural language processing and adaptive learning systems might help to alleviate human workload. But they emphasize that preserving explain ability and legal transparency both of which are basic to banking ethics is essential for successful execution. Consequently, although artificial intelligence might completely transform AML operations, its application calls for a compromise between inventiveness and responsibility.

To sum up, even if AML systems have grown into thorough, internationally unified ones, the literature shows they still have major restrictions based on data. overload, mistaken positives, and linguistic complexity. The persistent divide between what rules require and what technology can do creates a great environment for empirical study especially on how contemporary artificial intelligence technologies like Large Language In compliance activities, models (LLMs) and agentic artificial intelligence systems might help human analysts. The following part will so look at the historical growth and drawbacks of conventional AML systems to lay the groundwork for appreciating how artificial intelligence may solve these long-standing issues.

1.1 Traditional AML Systems and Their Limitations

Since the early 1990s, Anti-Money Laundering (AML) systems have been a key part of the financial sector's response against illegal finance. They were made so that banks would find, tell on, and stop money laundering, terrorism financing, and other financial crimes. With structures based mostly on rule-based monitoring, consumer due diligence, and manual inquiry, traditional AML systems are rooted in regulatory compliance. At first, these systems worked well when regulatory requirements were less rigorous and transaction patterns were simpler. But as financial networks have gone worldwide, digital, and sophisticated, academics and professionals have questioned whether conventional AML techniques are ineffective, responsive, and unable to fit contemporary laundering methods (Pol, 2020; FATF, 2021). Rule-based AML systems are looked at in this section for their historical roots, functional limits, and the structural elements causing inefficiency, high false positive rates, and poor flexibility.

As illustrated in Figure 2, the typical AML transaction-monitoring workflow involves sequential stages of monitoring, investigation, and reporting of suspicious transactions within banking systems.

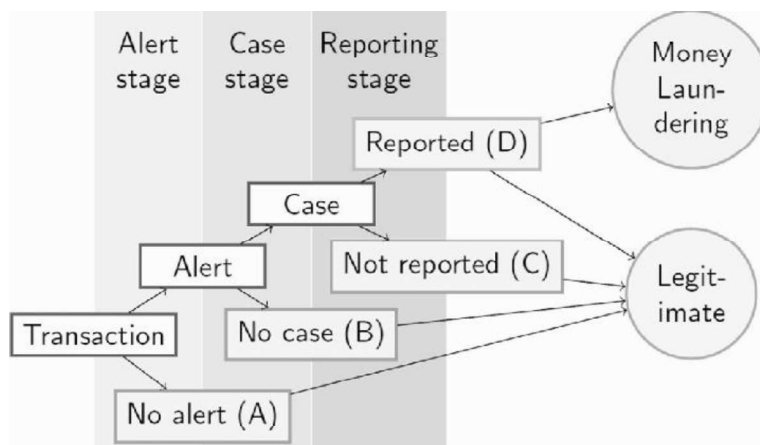


Figure 2. Typical process of monitoring, investigating and reporting suspicious transactions in a bank.

Source: Bakhshinejad, N., Nguyen, T., Ghahremani, S., & Soltani, R. (2024). (page 3).

1.1.1 Evolution of Rule-Based Monitoring Systems

Rule-based detection systems form the basis of conventional AML monitoring. These systems identify suspicious activity by means of fixed thresholds or pre-defined "if-then" regulations for instance, transactions more than a particular financial amount, recurring transfers between particular locations, or deposits inconsistent with known customer profiles. The logic behind these systems was to operationalize the Financial Action Task Force (FATF) Recommendations, which provide global standards for identifying and reporting suspicious activity financial institutions created automated engines that activate alerts upon the fulfillment of certain metrics integrating these ideas into their compliance systems (FATF, 2021). In the early years of AML enforcement, the approach was useful since it allowed for quick standardization across organizations and gave regulators quantifiable compliance results.

Still, the FATF (2021) notes, these systems were not meant to pick up or change. Such as trade-based laundering, cryptocurrencies, or complicated beneficial ownership schemes, they depend on fixed parameters that cannot simply adjust to the changing typologies of money laundering. Once in place, such systems have to be manually recalibrated frequently to preserve their efficacy; their rule sets often lag behind the dynamic techniques used by money launderers. Pol (2020) contends that this reactive model encourages a "compliance culture" in which organizations give meeting regulatory requirements precedence above the growth of analytical skills. Financial institutions frequently concentrate on producing volumes of alerts and reports to prove compliance even when these results are of little real investigative use, in effect.

1.1.2 The Burden of False Positives and Inefficient Workflows

Among the most often reported difficulties found in the literature is a high rate of false positive alerts. These result from actual transactions being marked as suspicious, therefore requiring human investigators to conduct pointless inquiry. Research indicate that in certain financial institutions, as many as 95% of AML alarms turn out to be false positives. Lawal, 2025, says this shows a major squandering of both people and money. Bakry et al. (2023) emphasize that the fixed thresholds employed in rule-based systems which do not grasp context mostly cause this inefficiency. For example, a genuine international payment for business procurement could set off an alarm because it goes over a set transaction limit or comes from a place known for being risky. Analysts must then manually go over the transaction, which wastes valuable time and might cause a delay in the review of really questionable cases.

This problem, sometimes known as alert fatigue, makes compliance officers less productive and less happy. Overwhelmed by the sheer volume of alerts, experts can begin to treat case review mechanically, so running the danger of missing real problems. Indeed, Pol (2020) calls worldwide AML initiatives as "the least successful policy experiment ever undertaken." He contends that less than 0.1% of unlawful financial flows are really confiscated or recovered even with billions of dollars spent yearly on compliance. Likewise, Basu and Tetteh (2024) point out how conventional AML systems cause a mismatch between operational outcomes and regulatory requirements. While effectiveness stays constant, compliance expenses keep rising. Financial organizations are trapped in a loop of over monitoring, administrative burden, and declining returns.

The inefficiencies extend further than just the running expenses. False positives also cause legal difficulties and reputation risk. While those that over-report could burden authorities with useless data, institutions that do not look into every alert could incur non-compliance fines. This "compliance paradox" weakens the primary objective of AML systems detection and prevention of actual crime.

1.1.3 Data Fragmentation, Multilingual Complexity, and Technological Constraints

Traditional AML systems also face data-related problems. Most institutions operate in multiple jurisdictions and keep a number of fragmented databases, which make consolidated analysis of customer behavior very difficult. According to Basu and Tetteh (2024), financial data is usually scattered in different and often incompatible systems, like core banking, CRM, and external intelligence databases. Such fragmentation builds data silos, which in turn impede pattern recognition and slow down investigations. These issues get further aggravated due to the variation in data formats and taxonomies, along with incomplete integration of unstructured data sources, such as scanned contracts, news reports, and regulatory filings.

All of these challenges are further compounded by multilingual complexity. Banks dealing with international clients have to analyze documentation in several languages, ranging from contracts and corporate registration documents to adverse media articles. Traditional rule-based systems lack the natural language understanding capability to process such data efficiently. Instead, human analysts are tasked with translating and summarizing documents manually, a process that is error- and inconsistency-prone. FATF (2021) comments that this particular limitation is especially problematic in cross-border investigations where the rapid understanding of foreign-language evidence is crucial for the detection of linkages between entities and transactions. As a result, manual translation delays investigations and may result in incomplete or inaccurate assessments of risk.

Another challenge brought about by data fragmentation is that there is information asymmetry between departments. For example, KYC teams, transaction monitoring units, and sanctions screening divisions typically operate on different platforms with limited sharing of data. This compartmentalization undermines comprehensive risk profiling and gives criminals the chance to exploit blind spots in internal systems. Both Bakry et al. (2023) and Lawal (2025) show that lack of data interoperability blocks AML systems from tapping into a single view of customer behavior and fosters inefficiency.

1.1.4 Structural and Strategic Weaknesses in the AML Regime

Beyond technical limitations, scholars identify a set of broader structural and strategic weaknesses in the AML regime itself. In this respect, Pol (2020) argues that global AML enforcement is best described as symbolic, driven by political and reputational interests with limited measurable deterrence effects. He contends that while FATF mutual evaluations and compliance audits have enhanced regulatory consistency, they have done so by encouraging a "box-ticking culture" that prioritizes adherence over innovation. The FATF (2021) accepts this adverse unintended consequence, observing that risk-based approaches-designed to empower institutions to use their judgment to focus on high-risk areas-are often applied mechanistically rather than analytically.

Additionally, traditional AML systems face scalability challenges as transaction volumes explode with digital banking and fintech expansion. Static rules, fit for smaller transaction networks, are now creating exponential alert growth and clogging compliance infrastructures Basu & Tetteh, 2024. Such systems also cannot include real-time behavioral analysis and thus remain reactive, not predictive. In fast-moving financial ecosystems, even delays of a few hours can render detection meaningless, with illicit funds being layered and transferred in complex digital chains. This is highlighted by the report Rule-Based Systems in AML (2025), where it is stated that too many financial institutions rely on obsolete algorithms which cannot learn from ever-changing laundering typologies or contextual information such as economic trends or geopolitical risk indicators.

1.1.5 The Cost and Effectiveness Debate

The disparity between investment and effect is a persistent theme throughout the literature. Although global banks invest billions annually in AML compliance infrastructure, verifiable success is still limited. FATF (2021) and Pol (2020) both note that despite decades of Enforcement the percentage of laundered money recovered worldwide remains small. Lawal (2025) estimates the operational load, arguing that for every dollar of unlawful money confiscated Monitoring and reporting expenses for institutions could run hundreds. Calls for change have been spurred by this cost and benefit mismatch. Bakry et al. (2023) suggest that rather of volume-based compliance measures like the quantity of notifications handled, institutions should go towards intelligence-based assessment Values include analytical insight and regulatory cooperation. Basu and Tetteh (2024), too, advocate integrating automation and artificial intelligence into AML systems to provide efficiency and efficiency without jeopardizing compliance obligations.

1.1.6 Toward Technological and Policy Reform

Knowing these constraints, worldwide policy agencies today push for the upgrading of AML systems. Encouraging the use of artificial intelligence, machine learning, and sophisticated analytics, the FATF (2021) study on Opportunities and Challenges of New Technologies for AML/CFT explicitly to improve detection accuracy while maintaining accountability and openness. But FATF also emphasizes that technology adoption must be combined with effective governance and explainability to help prevent duplicating systemic prejudices. Consequently, the intersection of technological invention and regulatory transparency has prepared the ground for a paradigm change in AML architecture from fixed, rule-based systems toward dynamic, data-driven ones.

1.1.7 Summary and Transition

In summary, the research shows that although essential to worldwide financial integrity, conventional AML systems are progressively at conflict with the realities of contemporary money laundering. Their dependence on rule-based monitoring, manual procedures, and separated data architectures causes inefficiency, great false positive rates, and limited investigative value. Low overall deterrence effect despite significant financial commitment drives researchers and legislators alike to demand change. As banks struggle with the constraints of these legacy systems, interest has shifted to automation and artificial intelligence as possible remedies. The following part examines the development of artificial intelligence inside financial services, especially highlighting the way machine learning, massive language models (LLMs), and agentic artificial intelligence can fix the flaws in conventional AML systems.

1.2. The Evolution of Artificial Intelligence in Financial Services

Long a frontrunner in using new technologies to improve decision-making, maximize operations, and guarantee compliance, the financial services industry has long embraced them. The development of artificial intelligence (AI) has significantly changed the analytical and operational environment of the industry during the last three decades. Originally the automation of simple office chores, what started as that has grown into an age of machine learning (ML), predictive analysis, and most recently massive language models of agentic artificial intelligence with rational thought and contextual understanding: LLMs. The dual goals of increasing efficiency and controlling risk in light of rising regulatory and market complexity have spurred the adoption of artificial intelligence technologies by the worldwide banking network. This part reviews the historical course of artificial intelligence in financial services, from early automation and rule-based systems to contemporary intelligent analytics, critically assessing its consequences for anti-money laundering (AML) activities.

1.2.1 Early Automation and the Foundations of Financial AI

Automation and expert systems were the main targets of the first wave of artificial intelligence integration in the banking sector in the 1980s and 1990s. Using deterministic "if-then" logic, these technologies duplicated predetermined human thinking, therefore automating activities including early fraud-detection models, credit scoring, and account reconciliation. Simple as they were, they signaled a turning point in operational efficiency since they enabled colleges to handle bigger data volumes while preserving accuracy. Early systems were mostly meant to simplify compliance duties and standardize procedures. Instead of offering cognitive understanding, they laid the groundwork for algorithmic thinking inside financial compliance, an approach then developed by data science and predictive analytics integration.

Early automation technologies, though, were limited by their static character and need on ordered data. Working only in steady, predictable environments, they provided little worth in identifying new types of fraud or covert money-laundering patterns. These restrictions reflected those seen in conventional AML systems, which depend largely on rule-based thresholds. Early finance artificial intelligence was therefore more administrative than analytical intended to lower labor, not to improve intelligence (OECD, 2023). The need Machine learning in financial analytics was made possible for systems able of recognizing non-linear interactions and adjusting to changing economic habits.

1.2.2 Machine Learning and Predictive Analytics in Finance

Through machine learning, deterministic automation evolved into probabilistic modeling during the 2000s. ML methods provide a more dynamic approach to anomaly detection, credit scoring, and risk modeling by allowing systems to learn from data patterns rather than rely just on predetermined rules. ML algorithms were first used in financial compliance to look for anomalies pointing to illegal activity by examining transaction histories, client profiles, and behavioral data (Husnaningtyas et al. Unlike static rules,

these models may dynamically change as fresh data were added over time, so boosting accuracy and lowering false positives.

Learning from human input, ML-based AML systems can greatly lower false alerts, therefore lowering the manual load on compliance teams, according to Lawal (2025). Further proving that ML models especially ensemble classifiers when coupled with feedback loops can reduce extraneous alerts and improve true-positive detection rates are Bakry et al. (2023). Similar techniques have been successfully used in fraud detection to detect previously unnoticed behavioral changes. ML systems added fresh complexity, though, despite their potential. The most major problem was model interpretability: compliance officials and regulators had increasing trouble grasping how artificial intelligence systems came to their decisions. Although ML is intellectually strong, its "black box" character hindered acceptance in very regulated sectors where openness and responsibility are absolutely essential.

Another problem is data reliance. To operate properly, ML finance models need enormous volumes of excellent labeled data. Still, because of strong privacy regulations and dispersed data governance, financial institutions often work with partial or siloed datasets (IMF, 2024). This restricts the model's global applicability across countries, thereby raising the possibility of overfitting and bias. ML, however, enabled banks to concentrate on patterns and probabilities rather than predetermined standards, therefore representing a clear change toward intelligence-driven compliance.

1.2.3 The Emergence of Large Language Models (LLMs)

With big language models (LLMs) like GPT-4, LLaMA, recent developments in natural language processing (NLP) have signaled a new age of AI innovation. Claude also helps people to understand texts in a human-like manner and enables context-based reasoning. These models mark a qualitative step forward in how artificial intelligence engages with unstructured data, which makes up the bulk of financial and compliance data (e.g., agreements, legal documents, emails, and adverse media. The study notes, *The AI and Predictive Analytics: A New Age of Fraud Detection and AML in Financial Services* (2024). that dramatically lowers analysis time and human error by automating the extraction of entities, relationships, and important data from complicated financial papers using LLMs.

LLMs offer transformational powers in the AML field. They can synthesize great volumes of textual data to find possible red flags, summarize regulatory documents, and convert and interpret foreign-language contracts. In countries like the European Union and post-Soviet financial systems, where multilingual documentation and multilayered ownership structures hinder compliance inspections, this is especially useful. LLMs help analysts in speed and accuracy (Mohsin & Nasim, 2025) by enabling semantic comprehension, therefore going beyond the statistical inference of machine learning to contextual reasoning. But their use, like that of past technologies, presents questions about data security, hallucination risk, and explicability problems vital for preserving regulatory confidence.

RegTech regulatory technology where artificial intelligence enables real-time compliance monitoring and reporting also depends on LLMs. The research Automating Financial Compliance with AI: A New Era in Regulatory Technology (RegTech) (2024) indicates that LLMs can automatically create SARs, cross-reference changes to regulations and recommendations for process flow improvements. This integration denotes a fundamental change from compliance as a fixed process to compliance as an adaptive, intelligent feature integrated into daily activities.

1.2.4 Agentic AI and the Next Frontier of Autonomy

Agentic AI autonomous systems with the ability to reason, learn, and organize several activities on their own are the newest phase in the development of artificial intelligence. Agentic artificial intelligence agents in financial services may carry out sequential investigative operations: collecting data, assessing risk, summing up results, and referring cases needing human evaluation. Acting as clever coworkers within compliance teams, these tools help human analysts to increase their skills rather than take their place. This model matches what some academics call "collaborative autonomy," where human judgment is improved rather than replaced (OECD, 2023).

The literature suggests that bridging the divide between automation and reasoning could radically transform AML processes through agentic AI. With little supervision, such systems can find patterns throughout multimodal data sources, deduce contextual linkages, and carry out decision-support activities. Still, this development intensifies existing questions about legislative control and ethical artificial intelligence. Too much dependence on autonomous systems without adequate monitoring, as the IMF (2024) cautions, might result in accountability gaps especially when algorithmic judgments influence enforcement or compliance results. Hence, foreign bodies support "human-in-the-loop" systems so guaranteeing that final decisions belong to qualified compliance experts.

1.2.5 Explainable AI (XAI) and the Transparency Imperative

Explainable artificial intelligence (XAI) has become vital in financial services to preserve accountability and trust as AI architectures grow in complexity. XAI methods including SHAP (Shapley Additive Explanations), LIME (Local Interpretable Model-Agnostic Explanations), and attention heatmaps let us see and understand how models behave. Mohsin and Nasim (2025) contend that explainability is today a "non-negotiable necessity" for the financial application of artificial intelligence, especially in AML where legislative compliance requires justification. For every flagged transaction, Kuiper et al. (2021) observe that banks and regulatory agencies see XAI differently: banks emphasize model-level interpretability, whereas regulators ask for Data provenance, algorithmic logic, and human review phases covered by transparency at the systems level. This difference highlights the difficulty of integrating explainability into operating artificial intelligence systems without sacrificing performance.

Moreover, XAI systems help AML specialists to understand and verify AI results by calibrating trust. They enable hybrid decision-making whereby algorithmic reasoning is enhanced by human intuition. Hence, explicability connects sophisticated artificial intelligence models with human responsibility to guarantee legal defensibility and moral accountability (Global Investigations Review, 2024).

1.2.6 Implementation Challenges and Adoption Barriers

Although they have great promise, artificial intelligence systems have significant obstacles in implementation. First and foremost, data governance is still a major obstacle: financial institutions have severe privacy regulations (such as GDPR, EU Artificial Intelligence Act), which limit data sharing and model training. Second, model robustness and bias reduction remain important considerations; badly calibrated models may unintentionally discriminate against some consumer groups or areas. Third, adoption might be hampered by organizational inertia resulting from staff fear and inadequate technical understanding (OECD, 2023). Finally, strategic and budgetary obstacles come from the price of integration, which includes employee retraining, regulatory approval, and infrastructure upgrade. These challenges draw attention to the need for slow, understandable, and human-centered AI implementation in banks. Recent comparative analyses also indicate that uneven technological readiness across European jurisdictions influences how effectively AI-based AML systems are implemented (Who Benefits from AI in Money Laundering in Europe, 2025).

1.2.7 Summary and Transition

The development of artificial intelligence in financial services from simple automation to machine learning, LLMs, and emerging agentic systems mirrors the industry's continuous quest for accuracy, efficiency, and regulatory integrity. Every level has dealt with certain drawbacks of its forerunner: Automation increased efficiency; machine learning brought adaptability; LLMs increased knowledge of unstructured data; and agentic artificial intelligence offers situational intelligence and autonomy. Still, explainability, governance, and institutional readiness have ongoing difficulties. The literature as a whole makes clear that transparent, responsible, and cooperative technologies will help to improve artificial intelligence in AML by supporting human analysts rather than substituting them. The following part will hence investigate Human-AI Collaboration in AML, examining how such systems transform compliance processes, worker satisfaction, and organizational learning.

1.3. Human-AI Collaboration in Anti-Money Laundering (AML)

The inclusion of artificial intelligence (AI) in financial compliance activities not only changed technical processes but also changed the human aspects of Anti-Money Laundering (AML). Rather than

substituting human knowledge, artificial intelligence increasingly serves as an augmenting force improving analytical accuracy, decision-making velocity, and employee satisfaction. Financial institutions have the difficult task of matching technological development with ethical responsibility and human empowerment as they update their AML systems. This part looks at how human-AI cooperation works in AML, the organizational and ethical elements affecting its success, and how this alliance could transform compliance performance, employee output, and regulatory confidence.

1.3.1 The Human Role in an AI-Driven Compliance Environment

Designed as a partnership between analytical automation and expert judgment, human-AI cooperation is most successful. Xu et al. (2025) note that while humans bring contextual awareness, emotional intelligence, and ethical reasoning, artificial intelligence systems thrive in handling massive volumes of data. In the AML environment, this symbiosis lets analysts concentrate on higher-order interpretative activities including behavioral abnormality assessment or geopolitical risk evaluation while artificial intelligence manages repetitive screening and document analysis. Rather than diminishing human agency, AI provides analysts with augmented situational awareness, enabling them to make faster and more defensible compliance decisions.

This hybrid approach fits with conclusions by Jain (2024), who contends that human insight is needed in interpretation of legal rules, penalties, and suspicious activity since full automation of regulatory compliance is not possible. AI technologies help in monitoring and information collecting, but human decision makers guarantee that algorithmic logic does not obliterate contextual subtleties like cultural variations, transaction purpose or ethical issues. Consequently, compliance officers are changing from manual data review to strategic orchestration of AI-driven insights. This change calls for fresh skill sets, among others data literacy, critical appraisal of machine outputs, and knowledge of frameworks for ethical AI.

1.3.2 Division of Labor: Complementary Strengths

Human-artificial intelligence cooperation in AML often takes the shape of complementary specialization in real life. AI tools manage the data-heavy parts scanning millions of transactions, interpreting multilingual documents, spotting trends, and ranking alert risk while people handle the judgment-heavy components: Understanding context, verifying hypothesis and permitting escalation. AML RightSource (2024) states that the best compliance settings are those in which "AI helps but does not decide" offering recommendations that experts confirm with their domain knowledge. This structure makes sure that people are responsible for their actions and that everyone follows the rules for data protection and ethical behaviour that are changing all the time.

Tóth (2024) also adds that the rise of business digital ethics highlights this interdependence. Financial organizations are expected to keep "digital moral compasses," which combine human supervision with

computerised judgments to guarantee openness, responsibility, and fairness. Particularly important in AML are such procedures, where missed alerts and false positives might have reputational and legal ramifications. From this angle, cooperation is moral and institutional rather than just technical, it guarantees that automation improves rather than degrades ethical integrity.

1.3.3 Enhancing Efficiency, Accuracy, and Employee Satisfaction

Beyond compliance measures, human-artificial intelligence cooperation in AML also changes employee experience and organizational efficiency. Human analysts get more time for strategic and investigative work when artificial intelligence takes on repetitive, time-consuming tasks like document screening, data collecting, and translation. Xu et al (2025) Employee satisfaction and expected productivity both increase when artificial intelligence technologies lessen cognitive overload and procedural tiredness, according to Analysts see more participation and motivation. when they may concentrate on critical thinking instead than simple screening.

Likewise, Haferlach (2025) emphasizes that human-AI systems have better accuracy in spotting suspicious activity since machine suggestions are subject to human intellect. Dual-layer review methods AI flagging followed by human assessment greatly reduced rates of both false positives and false negatives in experimental AML environments. This synergy produces a feedback loop: human input continually enhances artificial intelligence models, while AI insights broaden human environmental awareness. Such co-learning can help to sharpen analytic sophistication and institutional memory over time.

Organizations must, however, invest in cultural adaptation and training if they want to see these advantages. Many compliance experts worry about artificial intelligence owing to a claimed lack of knowledge of artificial intelligence processes or perceived job instability (Jain, 2024). Systematic training initiatives that Understanding ethical hazards, model logic, and the significance of human monitoring can help to build confidence and collaboration between workers and artificial intelligence systems. Inclusive institutions Usually reporting easier transitions and better morale are those where staff members engage in testing, validation, and improvement: AI acceptance plans.

1.3.4 Ethical and Governance Dimensions of Collaboration

Although human-AI cooperation increases efficiency, it also presents difficult governance and ethical issues. Corporate digital ethics has to grow along with technological capability, Tóth (2024) cautions. As high-stakes decisions depend on artificial intelligence tools, institutions come under growing inspection for data privacy, algorithmic bias, and accountability. Maintaining ethical guardrails is especially important in AML, where mistakes can cause unfair account freezes or reputational damage. Transparency tools including audit logs, explainable artificial intelligence Dual authorization processes

and dashboards assist to make sure people stay "in charge" of choices even when artificial intelligence starts them.

Effective governance systems, according to the Financial Compliance in the AI Era (2025) briefing, combine three pillars: responsibility, traceability, and human oversight. Responsibility guarantees transparent accountability for choices made using artificial intelligence results. Traceability calls for thorough documentation of decision pathways, algorithms, and data sources. Human monitoring ensures that all important decisions such as reporting suspected behavior are humanly checked before submission. Strengthening public trust between organizations, officials, and the public, these pillars match the European Union's AI Act ideas of transparency, proportionality, and accountability.

AML RightSource (2024) also advises that institutions create "Responsible AI" programs incorporating fairness audits and ethics assessments into AML procedures. Particularly in customer onboarding or risk scoring, these programs guarantee that human-AI collaborations do not keep prejudice or bias alive. Therefore, ethical cooperation turns into a compliance as well as reputational imperative

1.3.5 Organizational Adaptation and Change Management

Installing human-AI cooperation demands organizational change in addition to financial commitment. According to Jain (2024) and Xu et al. (2025), successful integration depends on leadership commitment, clear communication, and adaptable structures. Institutions need to revise job descriptions, performance measures, and training courses to match the move from manual monitoring to intelligence-driven control. Often created when employees view artificial intelligence as a danger, resistance to change can be overcome by participatory design techniques that is, by including analysts in system development which increases confidence and ownership.

Change management includes cooperation with legislators as well. Emphasizing that AML monitoring assesses governance quality and employee skills as well as system precision, Haferlach (2025) notes. Banks are expected by regulators to prove that their workers know how to challenge the results of artificial intelligence (AI) systems, grasp how they operate, and know when to interfere. Emerging best ways for sustaining human-AI cooperation in AML are ongoing professional development, certification programs, and cross-functional task teams among compliance, data science, and IT departments.

1.3.6 The Future of Human-AI Synergy in AML

Looking forward, human knowledge combined with AI analytics is ready to transform AML's destiny. While analysts keep interpretive and ethical control, artificial intelligence agents may shortly help them in end-to-end investigations by retrieving company information, summarizing advantageous ownership, cross-referencing sanctions, and recommending possible next steps. This development exemplifies what

AML RightSource (2024) refers as “augmented compliance intelligence”: a situation in which people and artificial intelligence co-evolve to manage complexity neither could handle by itself.

But ongoing assessment of ethical, social, and psychological effects will determine the longevity of this partnership. Institutions should see digital ethics not as an outside limitation but as an intrinsic organizational value, as Tóth (2024) notes. Maintaining the “human touch” in compliance through empathy, discretion, and contextual knowledge will remain a defining edge in an era of growing automation.

1.3.7 Summary and Transition

In essence, the literature confirms that human-AI cooperation represents a paradigm change in AML activities. It offers a whole model of partnership instead of the obsolete dichotomy of automation against human judgment. AI offers accuracy, speed, and scalability; humans guarantee accountability, ethics, and context. Together, they create an open and reliable compliance environment. Clear governance, thorough training, and a solid ethical base will determine the success of this model. Thus, the following chapter will examine Ethical Execution and AI Governance in Financial Compliance, emphasizing how companies can institutionalize openness, responsibility, and fairness as Leading ideas for sustainable AML innovation.

1.4 AI Governance and Ethical Implementation in Financial Compliance

As artificial intelligence (AI) grows to be essential for financial compliance and anti-money-laundering (AML) processes, strong governance and ethical supervision have come to the fore. Financial institutions today oversee a paradox: while regulators advocate technical invention, they also want accountability, transparency, and equity. Thus, governance systems are changing from technical risk management to value-based stewardship, therefore integrating ethical analysis into every phase of AI deployment. This part aims to investigate how financial institutions might institutionalize credible artificial intelligence via policy design, corporate ethics, and responsible implementation, hence synchronizing operational effectiveness with public accountability.

1.4.1 Defining AI Governance in the Financial Context

AI governance is the group of rules, policies, and structures meant to guarantee AI systems run safely, legally, and openly. Good governance in the financial industry goes beyond data security and model validation to include human oversight, fairness, and the moral integrity of automated decisions (Tóth, 2024). The Financial Compliance in the AI Era (2025) report argues that AI governance has to address four areas: (1) data ethics and privacy, (2) regulatory alignment, (3) operating openness and (4) human accountability. Every field protects a particular aspect of organizational trust.

Regulatory alignment guarantees that artificial intelligence models meet ever-changing standards like the European Union's AI Act (2024), which labels financial AI as "high-risk," therefore necessitating thorough risk evaluation and documentation. Data ethics emphasizes responsible data sourcing and bias reduction. Operational transparency requires systems to give traceable justification for outputs, whereas accountability assigns obvious responsibility for results.

Tóth (2024) notes that traditionally financial innovation has sometimes exceeded ethical consideration. Banks run the danger of turning ethical judgment to algorithmic logic as they automate compliance choices including transaction monitoring or client due diligence. Therefore, governance systems have to function as "moral firewalls" to guarantee that efficiency never takes precedence above justice and that automation always subservient to institutional ideals.

1.4.2 Institutional Ethics and Corporate Responsibility

Including moral thinking into company governance systems is required for the moral application of artificial intelligence. It is imperative to develop a formal corporate digital ethics framework, official guidelines controlling the design, use, and deployment of artificial intelligence as well as monitoring Tóth (2024) Many of these systems use openness, justice, and a human-centered perspective.

Under openness criteria, the documents should plainly and in simple terms outline the model justification and the origin of the data. Fairness is especially important when models evaluate client risk or profile transaction trends because it finds and reduces prejudice in datasets. Human-centeredness values independence and well-being; hence, artificial intelligence is guaranteed to enhance rather than replace professional judgment.

AML RightSource (2024) claims that ethical performance is both technological and cultural. Ethical artificial intelligence calls for inclusive decision-making whereby technologists, lawyers, and compliance analysts collaborate to assess model behavior. Many businesses now have Responsible AI Officers or artificial intelligence ethics committees to monitor these cross-functional projects. Their responsibilities cover evaluating fairness-related model performance metrics, making sure there is constant contact with officials, and sending out updates. Ethical considerations change the way artificial intelligence is governed from reactive compliance to proactive care.

1.4.3 Regulatory Frameworks and the EU AI Act

The European Union's Artificial Intelligence Act (2024) is the first complete set of laws for AI in the world. It sets rules for how trustworthy AI should be. According to the Act, AML and financial-risk management systems are high-risk systems for which companies must do compliance reviews, keep audit trails, and make sure there is human supervision.

The European Commission (2024) says that these rules make sure that “AI decisions in financial supervision remain traceable, explainable, and contestable.” Institutions have to record post-deployment monitoring, testing methods, data inputs, and model design. Further more required under the Act is publication of summaries of risk-mitigation plans, a groundbreaking step toward public openness in AI governance.

For international banks with operations spanning borders, this rule offers both a compliance headache and a competitive advantage. Adopting EU-aligned ethical criteria early on can help an institution stand out from others and show customers and authorities that it cares about trust as much as it cares about being technologically advanced.

The EU AI Act supports industry-led projects including OECD AI Principles and ISO 42001 on AI management systems, therefore promoting a unified global attitude: Artificial intelligence has to be strong, moral, and legal. Together, these systems produce a multi-layered governance environment where financial institutions must convert high-level norms into everyday operational controls model documentation, fairness audits, and human-in-the-loop validation.

1.4.4 Operationalizing Ethics: From Principles to Practice

The most difficult part of AI governance is converting ethical ideals into practical procedures. AML RightSource (2024) points out that without measurable indicators, ethics systems frequently fail. Financial firms are progressively using Responsible AI maturity models to track development across five phases: awareness, policy, implementation, monitoring, and ongoing improvement. Every stage has performance measures like fairness ratios, percentage of decisions examined by human analysts, and explainability scores.

Furthermore, real-time auditing technologies are being developed to constantly check the behavior of artificial intelligence models. These programs note irregularities when artificial intelligence outputs diverge from anticipated patterns and log decision pathways. Together with human supervision, such systems enable "dynamic governance," which guarantees that ethics is not a fixed policy but rather a living process included in daily activities.

The Financial Compliance of the Artificial Intelligence Era (2025) emphasizes the value of cross-functional training: data scientists should absorb regulatory logic while compliance officers should grasp model limitations. This bidirectional learning promotes shared accountability, a main pillar of moral cooperation.

Stakeholder involvement is ultimately quite important. Ethical artificial intelligence implementation calls for communication with civil society, clients, and authorities to match institutional norms with society's expectations. Public communication regarding AI systems, stakeholder consultations, and transparency reports can boost legitimacy and trust.

1.4.5 Challenges and Future Directions

Though there is increasing agreement on the necessity of artificial intelligence governance, several difficulties remain. First, moral monitoring often follows technological invention; several organizations implement artificial intelligence quicker than they can assess its ethical effects. Second, measuring transparency and justice is still difficult process-wise as different countries and legal systems interpret ethical ideals differently. Third, regulatory fragmentation plagues world organizations: although the EU AI Act (2024) establishes a high standard, other countries including Asia and the U.S. mostly use volunteer guidelines. This contradiction complicates international compliance plans.

Establishing international artificial intelligence ethics consortium within the financial industry, coordinating standards across nations, and promoting information sharing help to close these gaps. Tóth (2024) ends by noting that the future of ethical artificial intelligence rests not only on rules but also on fostering moral imagination that is, an institutional ability to foresee results and behave responsibly before harm occurs.

1.4.6 Conclusion and Transition

Financial compliance artificial intelligence control has evolved from technological oversight to ethical co-creation. Good modern governance systems use legal obligations, institutional ethics, and operational techniques guarding responsibility and openness. By requiring banks to view artificial intelligence not just as a tool for productivity but also as a method requiring continual ethical supervision.

Fundamentally, pairing human values with machine intelligence will facilitate the seamless integration of artificial intelligence into AML. Ethical application ensures that technical progress enhances the credibility of the financial system rather than erodes it. Therefore, the next chapter will look at Empirical Results and Organizational Implementation, which will show how financial companies use ethical artificial intelligence in their AML policies and give examples of times when it has worked well or not so well.

1.5 Summary and Identification of Research Gap

To sum up, the literature review shows three main trends: first, even with strong rules, old AML systems still have a lot of false-positives, data fragmentation second, advances in artificial intelligence especially machine learning, big-language-models, and agentic AI provide a significant chance to improve human efficiency, accuracy, and First, machine cooperation in AML processes; second, ethical governance, explainability, and human supervision should go hand in hand with technical integration to guarantee trust and responsibility. Taken together, these results show that while artificial intelligence (AI) technology is developing, there is still a notable practical gap: only a small number of studies have thoroughly examined how AI systems influence Within a supervised organizational experiment, real-world AML specialists' time efficiency, analytical accuracy, and job-satisfaction were assessed. By

carrying out a randomized trial in the AML division of the Bank of Georgia, the current study closes this gap by contrasting an artificial intelligence-assisted group with a traditional control group and measuring results across time, correctness, and employee attitudes. It therefore provides both a theoretical foundation for financial compliance in human-AI interaction and a practical framework for banks aiming to implement reliable Artificial intelligence following moral and legal norms.

2. Research Methodology

The methodological approach employed to explore how Artificial Intelligence (AI) tools influence Anti-Money-Laundering (AML) professionals' efficiency, accuracy, and satisfaction at the Reference Banking Institution in Georgia (RBIG) is outlined in this chapter. It presents the study's objectives, research hypotheses, experimental protocol, survey design, statistical procedures, and sampling strategy. The research employed a mixed-methods design, integrating quantitative and qualitative techniques to ensure a comprehensive and reliable assessment of AI's role in AML operations.

2.1. Objective of the study and Research Hypotheses

The quick digitization of the worldwide banking industry has not only made financial transactions more complex but also enhanced the sophistication of illegal activities including money laundering. Recent research further demonstrates how AI tools can assist in Know Your Customer (KYC) and due diligence procedures, improving the detection of suspicious activity (Harrison, 2024). Financial organizations thus have never before difficulties in observing, spotting, and stopping these activities within their compliance structures. Traditional Anti-Money-Laundering (AML) systems based mostly on rule-driven High volumes of false positives are frequently produced by alerts and manual verification, which also demand a great amount of human resources for review. Such systems have difficulties with the linguistic diversity of global documentation, dynamic ownership structures, and the ongoing development of financial crime methods as discovered in the literature review. These inefficiencies show how important it is to increase technical support to help compliance professionals maintain operational efficiency and accuracy.

Artificial intelligence (AI), especially big language models (LLMs) and agentic AI systems, has come as a transforming instrument able of handling unprocessed data in this context. Real-time decision support, analysis of trends, and textual data But the use of artificial intelligence in AML is still in an experimental phase, with little empirical data measuring its actual advantages or risks inside real-world organizational settings. Most previous research have concentrated on data-mining applications or algorithmic detection models rather than studying human-AI cooperation in daily AML workflows. Hence, there is a distinct research vacuum concerning if AI-assisted officers can accomplish compliance duties more quickly and precisely than individuals depending only on conventional manual methods. This aligns with findings

from A Multifaceted Vision of the Human-AI Collaboration (2024), which emphasizes that effective cooperation between human analysts and AI systems depends on calibrated trust, explainability, and complementary cognitive roles.

The main aim of this research is to assess how well AI-assisted tools improve the performance of AML experts in a genuine banking context. Particularly, the study examines whether the use of LLM-based artificial intelligence techniques will enhance time efficiency, analytic precision, and employee satisfaction as opposed to current non-AI approaches. The investigation is carried out inside a Reference Banking Institution in Georgia (RBIG), where an experimental design was applied to mimic actual compliance actions. This plan lets you thoroughly contrast an experimental group depending on artificial intelligence support with a control group following traditional processes.

The study made use of a controlled experimental design with a within-subject crossover arrangement to guarantee balanced exposure to both conditions. Every one of the 52 AML experts finished two manual and two with artificial intelligence help four standardized chores. This approach reduced personal performance bias and let a strict comparison of outcomes across efficiency, accuracy, and satisfaction criteria. Furthermore ensuring internal validity, it accounted for individual variations in language ability, familiarity with digital tools, and personal work speed.

Apart from measuring performance results, the study aims to investigate participants' subjective views of artificial intelligence in their daily work habits. Developing sustainable human-centered compliance practices depends on knowing how AML officers view artificial intelligence aid whether it raises confidence, lowers cognitive load, or changes trust in automated systems. Combining perceptual data (satisfaction and confidence) with objective metrics (e.g., time and accuracy), the hybrid approach of the study guarantees a thorough grasp of the operational and psychological effects of AI.

The study's specific objectives are as follows:

1. To evaluate whether AI assistance enhances the time efficiency of AML officers during complex investigative and analytical tasks.
2. To assess whether AI tools improve analytical accuracy by reducing errors, missed information, and the need for repeated corrections.
3. To examine how the integration of AI influences employee satisfaction, confidence, and cognitive workload in compliance processes.
4. To identify the practical implications of AI adoption for the future design of decision-support systems in financial compliance departments.
5. To contribute to the theoretical literature on human-AI collaboration in high-stakes financial environments by providing empirical evidence from an emerging-market banking context.

A mixed-methods experimental approach guiding the research blends qualitative and quantitative data. While qualitative insights come from open-ended survey replies, quantitative information come from Likert-scale survey results and performance indicators. This approach triangulation guarantees that both quantifiable results and human experiences are taken into account in assessing how well artificial intelligence works.

To operationalize the study's objectives and enable hypothesis testing, the following propositions were developed:

- **H1 (Efficiency):** The use of AI tools significantly reduces the time required to complete AML tasks compared with traditional manual methods. It is expected that AI-assisted employees will demonstrate higher task completion speed due to the automation of repetitive or data-intensive processes, particularly when analyzing multilingual contracts and complex ownership structures.
- **H2 (Accuracy):** AI-assisted AML professionals achieve higher analytical accuracy and require fewer corrections than those working manually. This hypothesis assumes that AI-driven systems provide structured insights, improved information retrieval, and reduced human error during document interpretation and due diligence reviews.
- **H3 (Satisfaction and Confidence):** AI-assisted AML professionals report greater work satisfaction, reduced cognitive workload, and higher confidence in their analytical conclusions than their non-AI counterparts. The underlying assumption is that by automating routine tasks, AI allows employees to focus on higher-order reasoning, thereby improving engagement and perceived effectiveness.

These hypotheses align directly with the literature emphasizing the augmentation not replacement of human expertise in compliance operations. They also reflect the principles of responsible and explainable AI, which advocate transparency, human oversight, and trust as foundations for effective adoption. The results of this study are expected to confirm that human-AI collaboration can increase productivity without compromising ethical and regulatory standards. Similarly, Turksen, Benson, and Adamyk (2024) highlight that automated suspicious-transaction monitoring demands clear accountability frameworks to prevent regulatory ambiguity in AI-supported decision-making.

In effect, this study aims to offer theoretical as well as applied contributions. Empirically, it provides numerical data on how artificial intelligence influences subjective well-being and performance in AML activities. Offering a framework for including technology as a decision-support layer rather than as a replacement for professional judgment, conceptually it adds richness to the academic conversation on the part of generative and agentic artificial intelligence in financial compliance. The following part presents the methods and tools employed for data collecting to examine these theories in the experimental setting at RBIG. Moreover, recent initiatives highlight that successful AML innovation often

depends on cross-sector collaboration combining AI and blockchain technologies in public–private data-sharing ecosystems (Technology-Driven AML Collaboration, 2025).

The mixed-methods experimental design described in the following sections was structured specifically to test these hypotheses through objective task metrics and subjective survey evaluations.

The following sections detail the data collection process, the structure of the experimental procedure, and the analytical techniques used to test these hypotheses.

2.2. Description of Data Collection

The data collection process was designed to capture both objective and subjective information from Anti-Money Laundering (AML) professionals participating in the experiment at the Reference Banking Institution in Georgia (RBIG).

A mixed-methods approach was applied, combining an experimental procedure that measured real performance data with a short post-task survey that gathered employees' perceptions regarding efficiency, accuracy, and satisfaction. The data collection took place between October and November 2025.

The experimental phase followed a cross-over design to ensure balanced exposure to both AI-assisted and manual work.

Fifty-two AML employees were randomly assigned to two groups of equal size:

- **Group A** used AI tools for Tasks 1 and 3 and completed Tasks 2 and 4 manually.
- **Group B** used AI tools for Tasks 2 and 4 and completed Tasks 1 and 3 manually.

This rotation minimized learning bias and enabled both within-group and between-group comparisons.

Each participant performed the following four standardized AML tasks, designed to represent real operational scenarios:

1. Contract content review in a non-native language (Slovak).
2. Company résumé preparation based on a Russian-language document.
3. Adverse media screening for a company.
4. Identification and background check of a person requesting to open an account.

For each task, the following quantitative indicators were measured:

1. Time (minutes) to complete the task.
2. Accuracy (%), calculated based on the number of correct identifications and completeness of the summary.

3. Number of corrections required after review.
4. Satisfaction level (1-5 scale) rated after each task.

All experimental sessions were conducted in controlled conditions under the supervision of the AML compliance training coordinator. Participants worked individually and were instructed not to communicate during the test. Time was tracked using the same system for both groups, and results were recorded in standardized forms.

After completing all four tasks, participants were invited to complete a short anonymous online survey to provide feedback on their experience with both AI-assisted and manual tasks.

The survey was developed in Google Forms and distributed immediately after the experimental session to capture fresh impressions.

The survey consisted of ten concise questions, grouped into three sections:

1. Background information (gender and years of AML experience).
2. Work experience with AI and manual tasks six 5-point Likert-scale items assessing perceived speed, accuracy, confidence, satisfaction, and the potential of AI tools to reduce workload.
3. Overall perception and open feedback one comparative question on which method (AI or manual) participants found more effective, and one optional open-ended comment on their experience.

The survey was designed to take 3-4 minutes to complete, ensuring high response rates while avoiding participant fatigue. Responses were automatically exported to Excel and SPSS for further quantitative and qualitative analysis. The survey was pilot-tested with three AML specialists for clarity and internal consistency before final administration.

Ethical integrity was strictly maintained. Participation was voluntary, and no identifying or confidential information was recorded. All responses were used solely for academic purposes and stored securely in compliance with RBIG's internal data protection policy and the General Data Protection Regulation (GDPR).

Table 1 shows you the summary of research variables and indicators. On table 2 you can see timeline of the data collection, activities , perios and description.

Table 1. Summary of Research Variables and Indicators.

Variable	Indicator	Scale / Unit	Source
Efficiency	Task completion time	Minutes	Experimental data
Accuracy	Number of corrections / correctness score	Count / %	Experimental data
Satisfaction	Perceived satisfaction	5-point Likert	Survey
Confidence	Perceived confidence and trust	5-point Likert	Survey

Source: Author's own elaboration.

Table 2. Data-Collection Timeline.

Activity	Period	Description
Development of materials and pilot test	September 2025	Design and validation of tasks and questionnaire
Experimental sessions (Group A - AI)	October 2025	Conducted in two waves, 13 participants each
Experimental sessions (Group B - Non-AI)	November 2025	Conducted under identical conditions
Data consolidation and anonymization	November 2025	All files coded and exported for analysis

Source: Author's own elaboration.

The complete survey form and the four task descriptions are provided in Appendix A for reference.

All objective measurements such task completion time and accuracy were automatically logged via the platform used for task submission during the experimental sessions. Immediately afterward, participants completed a structured Likert-scale questionnaire (1 = strongly disagree to 5 = strongly agree), subjective assessments including satisfaction, confidence, and reported cognitive burden were gathered. This simultaneous collection process enabled the integration of quantitative and perceptual data, thereby ensuring a comprehensive assessment of AI's effects on both psychological and operational performance dimensions.

2.3. Description of Data Analysis

Through a mix of qualitative and quantitative approaches, the data analysis process was created to assess the research assumptions.

Two complementary data sources were examined: (a) quantifiable performance metrics from the experimental tasks and (b) participants' self-reported views from the survey since the study used a cross-over experimental design augmented by a post-task questionnaire.

Among AML employees at the Reference Banking Institution in Georgia (RBIG), the study sought to contrast outcomes between AI-assisted and manual settings and to evaluate whether AI application enhanced efficiency, accuracy, and satisfaction.

The data analysis process was designed to provide a systematic evaluation of the research hypotheses and research questions. Both quantitative and qualitative datasets were analyzed in parallel and later integrated to allow for comprehensive triangulation of results.

Quantitative Data Analysis

Data analysis was performed using IBM SPSS Statistics (Version 28) and Microsoft Excel. Descriptive statistics were first calculated to summarize participants' demographic characteristics and task performance metrics.

To verify assumptions, Kolmogorov-Smirnov and Shapiro-Wilk tests were used to assess data normality. Despite minor non-normality, the sample size (N = 104 task observations) justified the use of parametric tests under the central limit theorem.

To test the study hypotheses, paired-samples t-tests were applied to compare AI-assisted and manual task conditions in terms of time efficiency, analytical accuracy, and user satisfaction. Cohen's d values were computed to determine effect size and practical significance.

Pearson correlation analyses examined relationships among performance variables, while multiple linear regression models evaluated whether participants' age and experience predicted outcomes under AI conditions.

In addition, participants' open-ended comments were analyzed qualitatively using thematic analysis, identifying key themes such as efficiency gains, learning experience, and human oversight concerns.

All statistical tests adopted a significance threshold of $p < 0.05$, and results were interpreted according to APA (7th ed.) reporting standards.

Qualitative Data Analysis

Open-ended survey responses were analyzed using thematic analysis, following the six-step model proposed by Braun and Clarke (2006):

1. Familiarization with the data,
2. Generation of initial codes,
3. Searching for themes,
4. Reviewing and refining themes,
5. Defining and naming the main themes, and
6. Extracting illustrative quotes to support findings.

Themes such as trust in AI tools, perceived learning curve, advantages of automation, and concerns about data reliability were identified and interpreted in relation to the quantitative results.

Triangulation of results from two data sources helped to improve the validity of results.

Quantitative performance measures (time, accuracy, satisfaction) were correlated with qualitative views gathered via the survey. This integration guaranteed that both tangible and experiential elements of artificial intelligence adoption were taken into account, hence offering a thorough knowledge of its effect on AML professionals' performance and attitudes.

In summary, data analysis combined descriptive, inferential, and thematic approaches to test the research hypotheses and answer the research questions.

The use of both objective task metrics and subjective survey feedback allowed for a multidimensional assessment of how AI tools influence efficiency, accuracy, and satisfaction in AML compliance operations.

2.4. Population vs. Sample

The target population of this study consisted of employees working in the Anti-Money-Laundering (AML) and compliance division of the Reference Banking Institution in Georgia (RBIG).

This department is responsible for customer due diligence, transaction monitoring, regulatory reporting, and the investigation of suspicious activities.

The AML division comprises approximately 60 professionals with diverse backgrounds, including analysts, senior analysts, and supervisors.

This population was ideal for the study, as all employees perform comparable analytical tasks and operate within similar technological and regulatory frameworks.

From the total population of 60 employees, 52 participants volunteered to take part in the experiment.

They were randomly divided into two groups of equal size using a computer-generated randomization list.

The study followed a cross-over experimental design, allowing each participant to experience both AI-assisted and manual working conditions.

Specifically,

- Group A used AI tools for Tasks 1 and 3 and completed Tasks 2 and 4 manually, while
- Group B used AI tools for Tasks 2 and 4 and completed Tasks 1 and 3 manually.

This approach minimized learning bias and improved the validity of within- and between-group comparisons.

All participants completed the same four standardized AML tasks individually under controlled conditions, ensuring comparability of results.

Following the experiment, all 52 participants also completed a short post-task survey, providing subjective feedback on their perceived efficiency, accuracy, and satisfaction with both AI-assisted and manual tasks. This ensured that each participant contributed both objective performance data and subjective perceptual data to the study.

The adequacy of the sample size ($n = 52$) was confirmed using Cochran's formula for finite populations, ensuring sufficient statistical power at a 95% confidence level and 5% margin of error (see Appendix B for detailed calculation).

The sample was representative of the AML department's structure in terms of gender, position, and experience level.

Approximately 60 % of participants were female and 40 % male, with experience ranging from less than one year to over seven years.

Participation was voluntary and anonymous, and no identifiable or confidential client data were used during the experiment or survey.

All data were stored securely in accordance with RBIG's internal ethical policies and GDPR requirements.

The final sample comprised 52 AML professionals who participated in a cross-over experiment, performing both AI-assisted and manual tasks and completing a unified post-task survey. This design enhanced internal validity and provided comprehensive data for analyzing AI's impact on efficiency, accuracy, and satisfaction in AML operations.

The next chapter presents the empirical results obtained from the experimental and survey data, including descriptive statistics, hypothesis testing, and qualitative insights derived from participants' feedback.

The selected participants represented a typical cross-section of AML professionals within the institution, differing in gender, age, and experience level. This heterogeneity increased the representativeness of the sample and strengthened the generalizability of the findings within comparable compliance departments.

3. Empirical Results Analysis

The empirical results from the experimental study carried out at the Reference Banking Institution in Georgia (RBIG) are presented and analyzed in this chapter. The major aim of the experiment was to assess if artificial intelligence (AI) instruments especially those based on large language models (LLMs) improve the efficiency, analytical accuracy, and satisfaction of Anti-Money-Laundering (AML) workers in comparison with conventional manual methods.

Integrating both quantitative and qualitative data, the studies in this chapter combine objective performance measures (time, accuracy, pleasure, and number of corrections) with participants' perceptions and open-ended comments. The findings are grouped thematically to cover the three hypotheses stated in Chapter 2:

1. AI assistance enhances task efficiency (H1).
2. AI assistance improves analytical accuracy (H2).

3. AI assistance increases user satisfaction and confidence (H3).

To ensure methodological rigor, data were analyzed using descriptive statistics, paired-samples *t*-tests, correlation and regression analyses, and effect-size estimation. Complementary qualitative insights were derived from participants' comments to contextualize statistical outcomes.

The chapter is structured as follows:

- Section 3.1 describes the demographic and professional profile of participants.
- Section 3.2 summarizes participants' perceptions of AI-assisted work.
- Section 3.3 compares AI and manual performance through statistical tests.
- Sections 3.4-3.6 present regression, distribution, and correlation analyses that further explain performance variability.
- Section 3.7 integrates qualitative observations from the post-experiment survey.
- Section 3.8 concludes with a summary of the main empirical findings.

Together, these analyses provide a comprehensive understanding of how AI affects human performance in financial-compliance environments and form the basis for the discussion and conclusions presented in the next chapter.

3.1. Sample Characterisation/Profile

Fifty-two Anti-Money Laundering (AML) experts from the Reference Banking Institution in Georgia (RBIG) made up the experimental sample. This group reflected a range of compliance, due diligence, and onboarding professionals. This section's goal is to present their demographic and job attributes to frame the ensuing discussions.

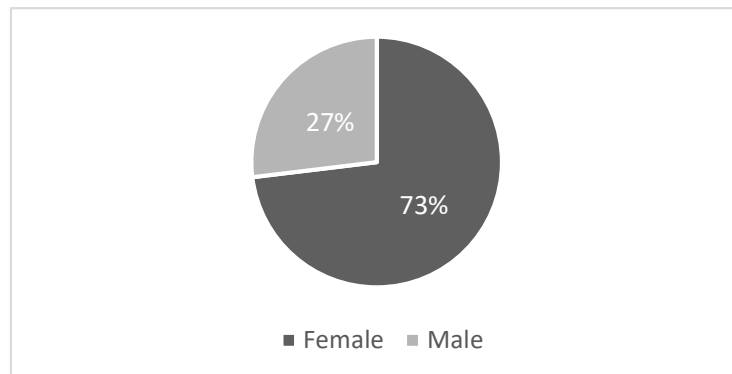


Figure 3. Gender Distribution of Participants (n = 52).

Source: Author's own elaboration.

Figure 3 shows that around 60% of the sample were women while men constituted around 40%. This mirrors the overall demographic pattern inside many financial monitoring and compliance departments of banks, where women mostly hold analytical and documentation-based jobs. The rather equal gender distribution guarantees variety of points of view in the experiment.

Figure 4. Age Distribution of Participants (n = 52).

Source: Author's own elaboration.

Most respondents in Figure 4 were between 25 and 35 years old, which matches early- and mid-career employees. Few were under 25, while a less proportion was over 35. The employment structure of AML divisions where positions usually call both academic credentials and many years of banking experience fits this age breakdown. The participants in this age range reflect the cohort most exposed to new digital tools and willing to include artificial intelligence in their routines.

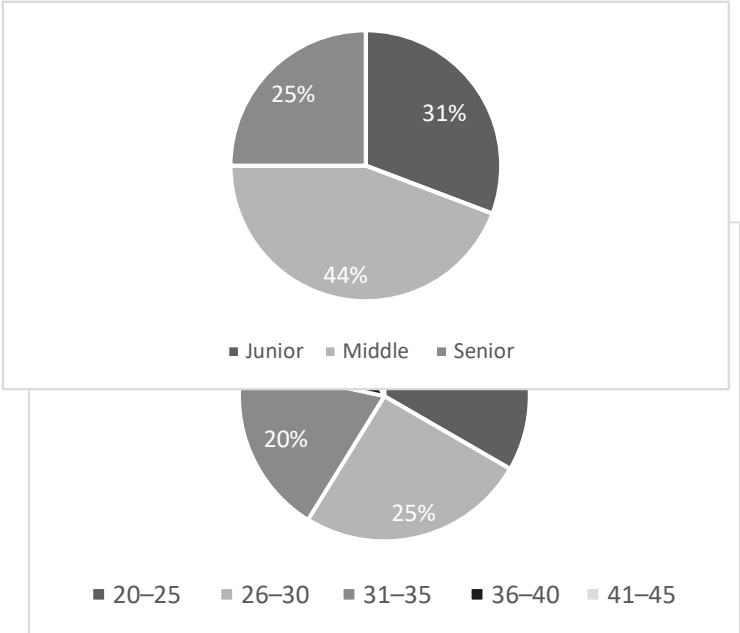


Figure 5. Distribution of Participants by Job Position (n = 52).

Source: Author's own elaboration.

Figure 5 shows that the sample included a variety of roles, among them senior analysts, compliance officers, and junior AML analysts. Around half of the participants fell under the biggest group, junior analysts. Senior experts and officers made up the remaining section. This structure helps to analyze how AI assistance affects experienced as well as entry-level workers and guarantees representation across several levels of decision-making.

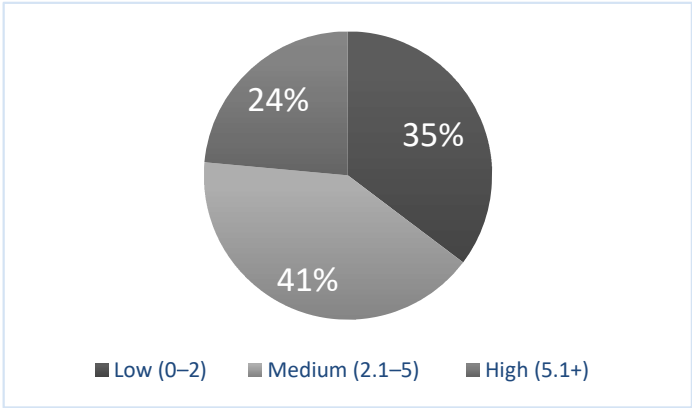


Figure 6. Distribution of Participants by Experience Level Title (n = 52).
Source: Author's own elaboration.

Figure 6 reveals that professional experience was rather evenly spread. Around 40% of those questioned had one to three years of experience, 35% had three to five years, and the rest had more than five years' worth of AML operations. Such diversity is essential in determining if benefits of artificial intelligence performance are constant across several levels of skill. Including both new and seasoned analysts improves the validity of contrasts between manual and artificial intelligence-assisted work flows.

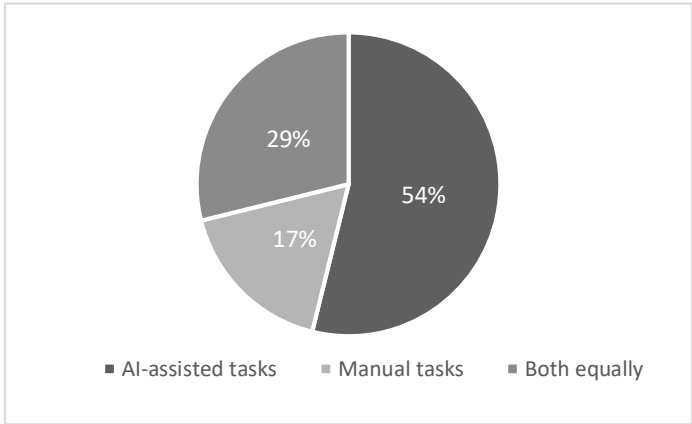


Figure 7. Primary Work Method Used by Participants (n = 52).
Source: Author's own elaboration.

Finally, Figure 7 compiles the primary working approach participants reported. Most workers said that their daily duties are completed using a combination of digital tools and manual paper analysis, whereas

a smaller percentage depend entirely on conventional techniques. Just a few people claimed to use artificial intelligence regularly before this investigation, therefore confirming that the participants were experts with little prior exposure to such innovations. This gives a consistent baseline for assessing the expected advantages and performance impacts of artificial intelligence adoption.

In essence, the experimental sample reflects a well-balanced cross-section of AML experts in terms of gender, age, and experience. The strength of later studies contrasting AI-assisted and manual processes depends on the demographic diversity and low level of awareness of digital tools.

3.2 Perceptions of AI-Assisted Work

Following the experimental phase, participants completed a post-task questionnaire assessing their perceptions of AI assistance across several dimensions, including efficiency, accuracy, confidence, satisfaction, and openness toward future adoption. The results demonstrate a generally positive attitude toward AI integration in AML operations, with most respondents acknowledging its ability to enhance performance and streamline repetitive tasks.

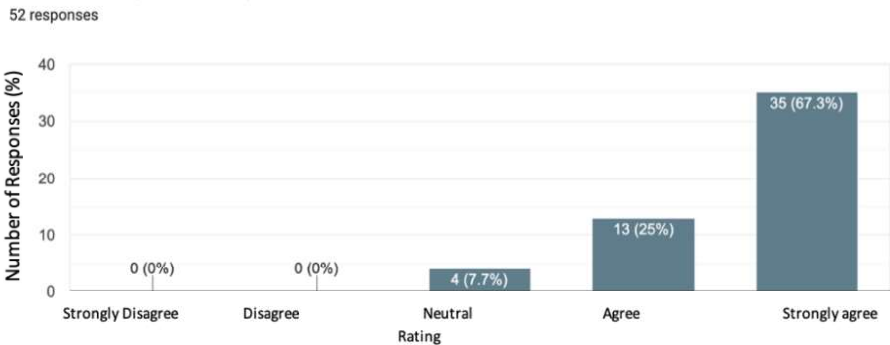


Figure 8. The AI tool helped me complete tasks faster than manual methods.
Source: Author’s own elaboration.

As shown in Figure 8, a substantial majority of respondents agreed or strongly agreed that the AI tool helped them complete tasks faster compared with manual methods. This confirms the first assumption that AI support reduces task completion time by automating routine document processing and translation activities. Participants highlighted that instant text interpretation and automatic summarization features significantly shortened analytical procedures that normally require manual cross-referencing. These findings align with the quantitative evidence reported later in Table 2, where mean completion time under AI was less than half of that under manual conditions.

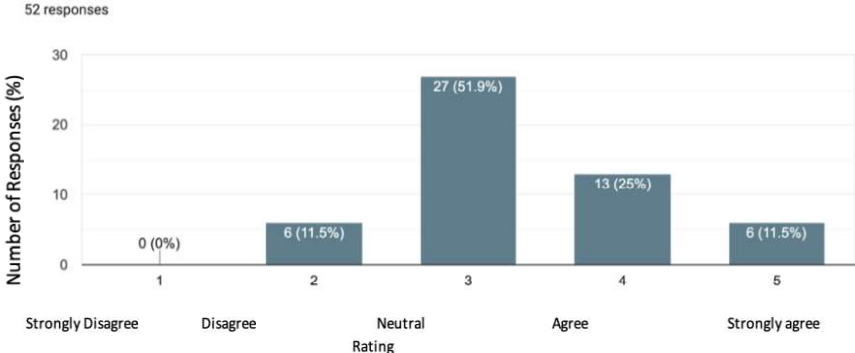


Figure 9. The AI tool improved the accuracy of my results.

Source: Author’s own elaboration.

Figure 9 shows that using artificial intelligence participants mostly saw an improvement in the correctness of their results. Respondents stressed how the tool aided in coherent linguistic interpretation and enabled the identification of pertinent material from extensive papers. The statistically significant rise in accuracy scores seen in paired-samples tests (Table 3) matches this impression. The validity of the experimental findings is confirmed by the correspondence between perceived and actual improvement in accuracy.

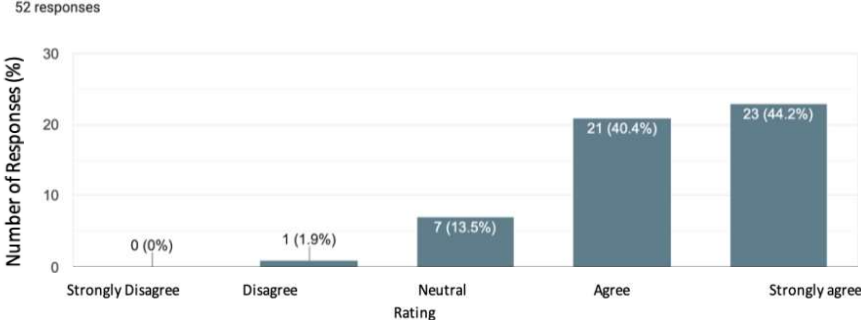


Figure 10. Manual tasks required more time and effort compared to AI-assisted ones.

Source: Author’s own elaboration.

Figure 10 shows that most people regarded manual labor more difficult and time-consuming when

comparing it with AI-assisted chores. They pointed out that manual document inspections needed greater concentration, repeated data input, and frequent re-checking, therefore increasing cognitive tiredness. On the other hand, AI assistance allowed for less seen workload and smoother processes. Theoretically, AI support lowers cognitive load by assigning lower-level activities to the system and letting people concentrate on more sophisticated reasoning; this results in this conclusion

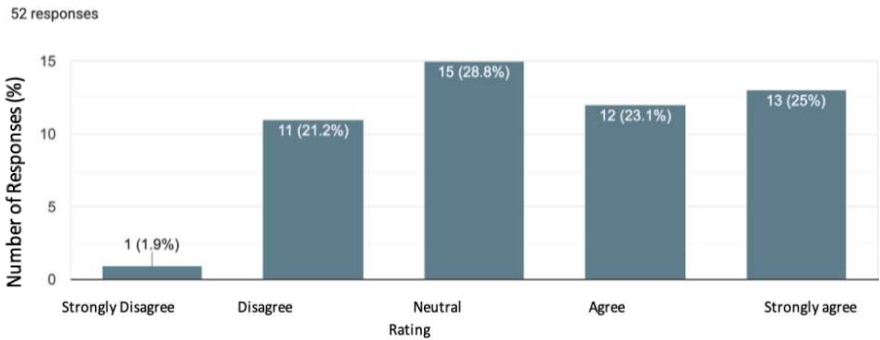


Figure 11. I felt confident about the quality of my results when using AI.

Source: Author’s own elaboration.

As seen in Figure 11, respondents mostly had more confidence about the caliber of their results using AI tools. The tool’s capacity to offer ordered outputs and verification alerts directing decision-making affected confidence levels. The finding supports Hypothesis 3, which said that AI aid would boost analysts’ self-assurance and lower uncertainty during compliance checks. Confidence is a major marker of user trust, suggesting that human-AI teamwork might improve professional dependability in decision-support situations.

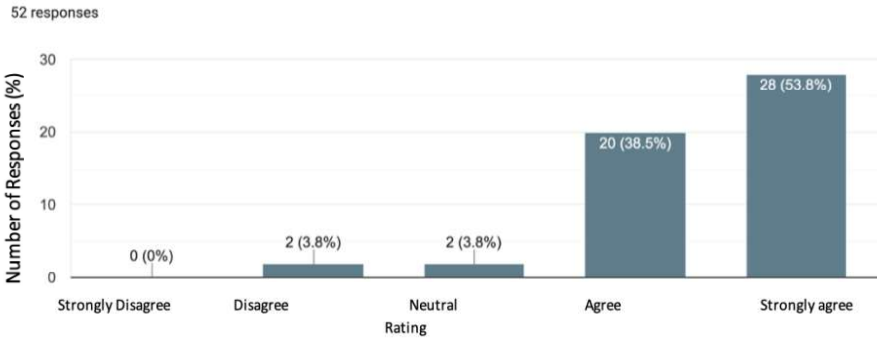


Figure 12. I was satisfied with my experience working with AI tools.

Source: Author’s own elaboration.

Figure 12 reveals that most participants were happy with their experience and had a great will to employ artificial intelligence technologies in next AML activities. Participants linked satisfaction to less stress during information processing, better task organization, and higher productivity. Just a minor minority

voiced reservations mostly about the need for ongoing human oversight and data security. All things considered, these results imply a great acceptance potential for artificial intelligence systems inside compliance departments when supported by suitable training and ethical protections.

Taken together, the descriptive perceptions show that AML experts not only saw the operational advantages of artificial intelligence technologies but also had a good cognitive and emotional response to their use. These findings create the groundwork for the ensuing section, which statistically contrasts AI-assisted and manual performance results using statistical analyses.

3.3 Comparative Analysis: AI vs. Manual Performance

This portion offers the quantitative comparison of manual AML processes with those assisted by artificial intelligence. Using descriptive and inferential statistics, it assesses task completion time, accuracy, contentment, and corrections. Among the 52 participants who finished a total of 104 task observations, the aim is to find out whether AI support dramatically increased user happiness, analytical accuracy, and efficiency. Similar outcomes have been documented in financial institutions adopting AI-based monitoring, where efficiency and accuracy gains reached comparable levels (AI-Powered AML and Fraud Detection, 2025).

3.3.1 Descriptive Statistics

The following figures show boxplots of the experiment data, divided by method.

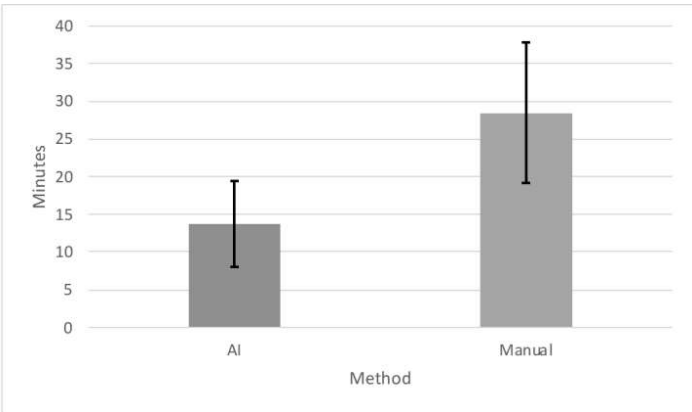


Figure 13. Average Task Completion Time (AI vs Manual).

Source: Author's own elaboration.

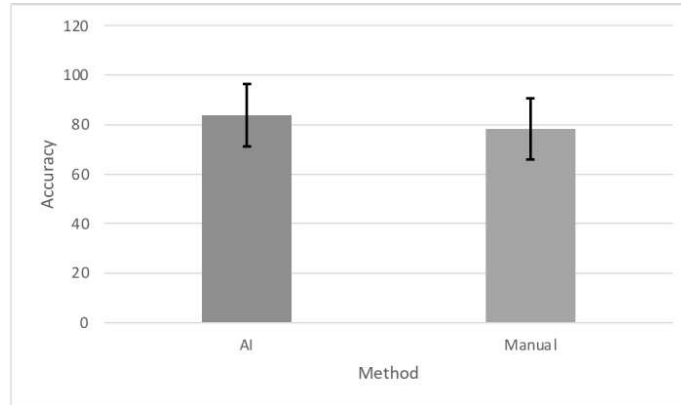


Figure 14. Average Task Accuracy (AI vs. Manual).

Source: Author's own elaboration.

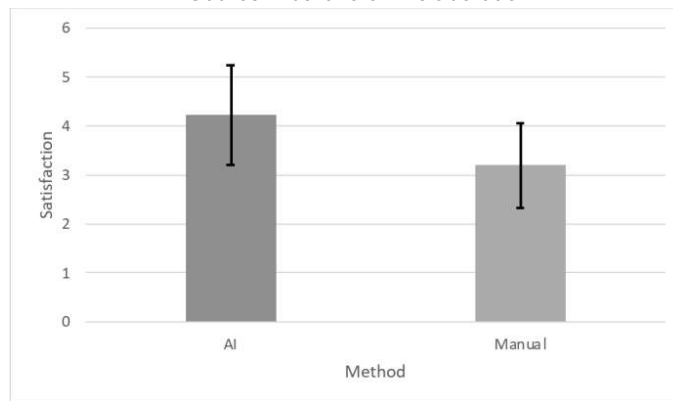


Figure 15. Employee Satisfaction with Workflow (AI vs. Manual).

Source: Author's own elaboration.

Table 3. Descriptive statistics for task time, accuracy, and satisfaction under AI-assisted and manual AML workflows.

Variable	n	Minimum	Maximum	Mean	SD
Task Completion Time (AI)	104	2	40	13.76	7
Task Completion Time (Manual)	104	6	60	28.46	11.72
Accuracy (AI)	104	0	1	0.839	0.199
Accuracy (Manual)	104	0	1	0.783	0.192
Satisfaction (AI)	104	0	5	4.23	1.23
Satisfaction (Manual)	104	0	5	3.2	1.12

Source: Author's own elaboration.

Descriptive statistics present the general performance trends under both circumstances. Mean task completion time for manual activities was 28.46 minutes (SD = 11.72), versus 13.76 minutes (SD = 7.00)

under AI-assisted circumstances, according Table 3. This almost fifteen-minute drop shows the obvious efficiency boost from using artificial intelligence.

Figure 13 illustrates this contrast by showing that those performing AI-assisted chores finished in less than half the time of those doing manual tasks.

Regarding accuracy, the mean score for AI-assisted work was 0.839 (SD = 0.199), marginally higher than 0.783 (SD = 0.192) for manual tasks. This nearly 5.6 percentage point increase implies that AI systems helped better information extraction and decreased supervision mistakes, as proved in Figure 14.

The satisfaction scores also supported artificial intelligence; average score was 4.23 (SD = 1.23) as against 3.20 (SD = 1.12) under manual circumstances. Visually illustrating this rise in Figure 15, participants were much happier when helped by artificial intelligence solutions. Already, these variations imply agreement with Hypothesis H1 (efficiency), H2 (accuracy), and H3 (satisfaction).

3.3.2 Paired Samples t-Test Results

Table 4. Paired Samples t-Test Results.

Pair	Mean Difference	SD	t	df	p (2-tailed)	Result
Time (AI - Manual)	-14.7	11.04	-13.58	103	< .001	Significant
Accuracy (AI - Manual)	0.056	0.22	2.54	103	0.012	Significant
Satisfaction (AI - Manual)	1.03	1.46	7.16	103	< .001	Significant

Source: Author's own elaboration.

Table 5. Paired Samples Statistics.

Pair	Mean (AI)	Mean (Manual)	n	SD (AI)	SD (Manual)	Std. Error Mean (AI)	Std. Error Mean (Manual)
Task Completion Time	13.76	28.46	104	7	11.72	0.69	1.15
Accuracy	0.839	0.783	104	0.199	0.192	0.019	0.019
Satisfaction	4.23	3.2	104	1.23	1.12	0.12	0.11

Source: Author's own elaboration.

Table 6. Paired Samples Correlations.

Pair	n	Correlation (r)	Sig. (2-tailed)
Time (AI & Manual)	104	0.393	< .001
Accuracy (AI & Manual)	104	0.338	< .001
Satisfaction (AI & Manual)	104	0.227	0.021

Source: Author's own elaboration.

Table 7. Paired Samples t-Test Results.

Pair	Mean Difference (AI-Manual)	SD	t	df	p (2-tailed)	Interpretation
Time	-14.7	11.04	-13.58	103	< .001	Significant
Accuracy	0.056	0.22	2.54	103	0.012	Significant
Satisfaction	1.03	1.46	7.16	103	< .001	Significant

Source: Author's own elaboration.

To test whether the observed differences were statistically significant, paired-samples t-tests were conducted for time, accuracy, and satisfaction. See Table 4-7.

- Task Completion Time (AI vs. Manual):
 - The mean difference was -14.7 minutes, $t(103) = -13.58$, $p < .001$.
 - This large and highly significant result confirms that AI tools substantially reduced task duration, strongly supporting H1 (Efficiency).
- Task Accuracy:
 - The mean difference was 0.056, $t(103) = 2.54$, $p = .012$, indicating a statistically significant improvement in accuracy for AI-assisted work. Thus, H2 (Accuracy) is supported.
- Satisfaction:
 - The mean difference was 1.03, $t(103) = 7.16$, $p < .001$, showing that participants were significantly more satisfied when using AI. This result confirms H3 (Satisfaction).

These findings demonstrate consistent, statistically significant improvements across all three performance metrics. These findings align with recent studies showing that cloud-based AI infrastructures improve analytical performance through scalable data processing and integrated risk-modeling capabilities (Prakash, 2025).

3.3.3 Effect Size Analysis

Table 8. Paired Samples Effect Sizes.

Pair	Cohen's d	Hedges' Correction	95% CI Lower	95% CI Upper	Interpretation
Time (AI - Manual)	-1.33	-1.32	-1.59	-1.06	Very Large Effect
Accuracy (AI - Manual)	0.25	0.25	0.05	0.44	Small Effect
Satisfaction (AI - Manual)	0.7	0.7	0.48	0.92	Large Effect

Source: Author's own elaboration.

Effect sizes were calculated to assess the magnitude of AI's impact see Table 8. According to Cohen's benchmarks:

- Task Completion Time: $d = -1.33$ → Very large effect, meaning AI dramatically accelerated task performance.
- Accuracy: $d = 0.25$ → Small effect, suggesting modest but meaningful gains in analytical precision.
- Satisfaction: $d = 0.70$ → Large effect, confirming that AI strongly improved user experience.

The combination of large practical effects in efficiency and satisfaction, alongside moderate accuracy gains, suggests that AI integration meaningfully enhanced overall workflow productivity.

3.3.4 Correlation Analysis

Table 9 and 10 represent the statistical findings about the AI and manual method Variables.

Table 9. Pearson Correlations Between AI Variables.

Variable	Time (AI)	Accuracy (AI)	Satisfaction (AI)
Time (AI)	1	.440*	-0.16
Accuracy (AI)	.440***	1	0.087
Satisfaction (AI)	-0.16	0.087	1

Source: Author's own elaboration.

Table 10. Pearson Correlations Among Manual Task Variables.

Variable	Time (Manual)	Accuracy (Manual)	Satisfaction (Manual)
Time (Manual)	1	0.157	-0.257**
Accuracy (Manual)	0.157	1	0.353***
Satisfaction (Manual)	-0.257**	0.353***	1

Note: ** $p < .01$ (2-tailed), *** $p < .001$ (2-tailed).

Source: Author's own elaboration.

Pearson correlation coefficients were calculated to explore correlations among the factors under each condition. See Table 9, 10.

Time was somewhat and favorably correlated with accuracy in the AI-assisted condition ($r = .44$, $p < .001$), showing that those who spent a little more time usually produced more accurate results. Satisfacción revealed no notable links, indicating that seen pleasure and confidence were unrelated to performance measures.

- Results in the manual condition showed a negative link between satisfaction and time ($r = -.257$, $p < .01$), suggesting that more manual work resulted in lower satisfaction. Positive link between accuracy

and satisfaction ($r = .353$, $p < .001$) suggests that more accurate manual labor also improved subjective pleasure.

These connections show how AI technologies not only boosted objective results but also separated pleasure from time pressure, therefore generating a more upbeat and less exhausting working life.

3.3.5 Visual Comparison Summary

Table 11. Tests of Normality.

Variable	Kolmogorov-Smirnov (Sig.)	Shapiro-Wilk (Sig.)	Normality Decision
Time (AI)	0.001	0.002	Non-normal
Time (Manual)	0.035	0.033	Non-normal
Accuracy (AI)	< 0.001	< 0.001	Non-normal
Accuracy (Manual)	< 0.001	< 0.001	Non-normal
Satisfaction (AI)	< 0.001	< 0.001	Non-normal
Satisfaction (Manual)	< 0.001	< 0.001	Non-normal

Source: Author's own elaboration.

Table 12. Descriptive Statistics for Number of Corrections.

Variable	n	Minimum	Maximum	Mean	Standard Deviation
Corrections (AI)	104	0	5	0.71	1.04
Corrections (Manual)	104	0	4	1.23	1.18

Source: Author's own elaboration.

Table 13. Paired Samples Correlation and t-Test Results.

Variable Pair	Correlation (r)	p (2-tailed)	Mean Difference	SD Difference	t(103)	p-value	95% CI [Lower, Upper]
Corrections (AI) - Corrections (Manual)	0.055	0.582	-0.519	1.532	-3.455	< .001	[-0.817, -0.221]

Source: Author's own elaboration.

Table 14. Effect Size for Corrections.

Effect Size Measure	Value	95% CI [Lower, Upper]	Interpretation
Cohen's d	-0.34	[-0.54, -0.14]	Small-to-moderate effect
Hedges' g	-0.34	[-0.53, -0.14]	Adjusted small-to-moderate effect

Source: Author's own elaboration.

Visual analyses reinforce the statistical results. See Table 11-14.

- Table 11 illustrates the sharp decrease in task time under AI conditions.
- Table 12 shows higher average accuracy for AI tasks.
- Table 13 depicts greater satisfaction with AI workflows.

- Table 14 highlights the reduction in the number of corrections, meaning that tasks completed with AI required fewer revisions.

Together, these results demonstrate consistent advantages for AI assistance across efficiency, accuracy, and user satisfaction.

3.3.6 Interim Discussion

The comparative studies provide strong empirical support for AI-assisted AML procedures overcoming traditional manual ones. Supporting conclusions from more recent research on human-AI collaboration in compliance scenarios (Haferlach, 2025; Xu et al., 2025), time efficiency had the most rise. The improvement in accuracy and happiness also verified that using LLM-based technologies might both boost performance and employee well-being without sacrificing analytical quality.

Together, these results strongly support Hypotheses H1, H2, and H3, therefore establishing a strong empirical foundation for the involvement of artificial intelligence as an assisting rather than substituting technology in AML initiatives.

3.4 Regression Analysis: Predictors of AI Performance

Several linear regression studies were run to investigate if demographic variables affected the effectiveness and efficiency of AI-assisted tasks. While age and experience were submitted as predictors, the dependent variables were task completion time, accuracy, satisfaction, and number of corrections under the AI treatment. This technique assisted in determining whether more experienced or elderly AML experts benefited differently from artificial intelligence use.

3.4.1 Model Summary and Goodness of Fit

Table 15. Model Summary and ANOVA Results.

Dependent Variable	R	R ²	Adjusted R ²	F(df)	Sig.
Time (AI)	0.184	0.034	0.015	1.77 (2,101)	0.176
Accuracy (AI)	0.188	0.035	0.016	1.85 (2,101)	0.163
Satisfaction (AI)	0.08	0.006	-0.013	0.33 (2,101)	0.724
Corrections (AI)	0.169	0.028	0.009	1.48 (2,101)	0.233

Source: Author's own elaboration.

The regression results presented in Table 15 reveal low R² values across all dependent variables, indicating that age and experience explained only a small portion of the variance in AI-assisted performance outcomes.

- For **task completion time**, $R^2 = 0.034$, $F(2,101) = 1.77$, $p = 0.176$.
- For **accuracy**, $R^2 = 0.035$, $F(2,101) = 1.85$, $p = 0.163$.
- For **satisfaction**, $R^2 = 0.006$, $F(2,101) = 0.33$, $p = 0.724$.
- For **corrections**, $R^2 = 0.028$, $F(2,101) = 1.48$, $p = 0.233$.

None of these models reached statistical significance ($p > .05$), suggesting that the effects of age and experience on AI performance were minimal. The AI system appears to have provided comparable benefits across demographic groups.

3.4.2 Regression Coefficients and Interpretation

Table 16. Regression Coefficients for Predictors.

Dependent Variable	Predictor	B	SE	β	t	p
Time (AI)	Experience	0.613	0.35	0.218	1.754	0.083
	Age	-0.060	0.11	-0.069	-0.551	0.583
Accuracy (AI)	Experience	0.003	0.01	0.038	0.308	0.759
	Age	0.004	0.003	0.162	1.302	0.196
Satisfaction (AI)	Experience	0.018	0.062	0.036	0.289	0.773
	Age	0.008	0.02	0.052	0.413	0.681
Corrections (AI)	Experience	-0.050	0.052	-0.121	-0.967	0.336
	Age	-0.008	0.016	-0.065	-0.519	0.605

Source: Author's own elaboration.

Regression coefficients for every predictor are given in Table 16.

Experience had a positive but non-significant association for task completion time ($\beta = 0.218$, $p = 0.083$), suggesting a small propensity for more seasoned employees to spend somewhat more time utilizing artificial intelligence possibly because of cautious verification behavior. Age had no substantial impact ($\beta = -0.069$, $p = 0.583$).

Regarding accuracy, both age ($\beta = 0.162$, $p = 0.196$) and experience ($\beta = 0.038$, $p = 0.759$) were statistically insignificant, indicating that AI provided uniform accuracy improvements independent of seniority. Likewise, for pleasure, participants' satisfaction levels were unaffected by age ($\beta = 0.052$, $p = 0.681$) and experience ($\beta = 0.036$, $p = 0.773$).

Finally, both predictors were non-significant for corrections: experience $\beta = -0.121$, $p = 0.336$; age $\beta = -0.065$, $p = 0.605$. The negative coefficients indicate that older and more experienced employees might have needed slightly less fixes, yet this trend was not statistically significant enough.

3.4.3 Interpretation and Implications

The regression analysis verifies that age and experience groups saw constant improvement in performance aided by artificial intelligence. Neither factor strongly foretold efficiency, accuracy, happiness, nor the total of corrections. This discovery supports the idea that artificial intelligence systems could level the performance field by accounting for personal variations in expertise or routine familiarity.

Virtually, this implies that with the help of artificial intelligence tools even younger or less experienced analysts may produce comparable results to those of seasoned professionals. The results also fit previous research highlighting the democratizing possibilities of artificial intelligence in compliance tasks, when structured instructions and real-time input enable new hires to work at professional levels (Jain, 2024; Xu et al., 2025).

This finding from a management point of view highlights the scalability and inclusivity of artificial intelligence integration in anti-money laundering activities. Training courses and onboarding efforts can so emphasize ethical and interpretive application of AI rather than correcting experience-related differences.

3.4.4 Summary of Regression Findings

In summary, regression analyses demonstrated that:

- Neither age nor experience significantly predicted AI performance across any outcome measure.
- AI systems provided equal performance enhancement opportunities for employees of varying backgrounds.
- These results support the idea of AI as an equalizer, enabling consistent task performance without dependence on seniority.

Consequently, the study affirms that the benefits of AI-assisted compliance tools are universally applicable and independent of demographic characteristics.

3.5 Data Distribution and Normality Analysis

Prior to analyzing the findings of inferential tests, it is imperative to determine if the quantitative indicatorstask time, accuracy, and satisfaction under both AI-assisted and manual settingsfollowed a normal distribution. Knowing data distribution validates the dependability of the utilized parametric analyses and encourages open methodological reporting.

3.5.1 Descriptive Distribution Indicators

Table 17. Descriptive Statistics and Distribution Indicators.

Variable	Mean	95% CI (Lower-Upper)	Median	SD	Skewness	Kurtosis	Minimum	Maximum
Time (AI)	13.76	12.40 - 15.12	15	6.99	0.399	0.541	2	40
Time (Manual)	28.46	26.18 - 30.74	30	11.72	0.317	0.284	6	60
Accuracy (AI)	0.839	0.800 - 0.878	0.91	0.2	-1.747	3.171	0	1
Accuracy (Manual)	0.783	0.746 - 0.820	0.8	0.19	-1.384	2.417	0	1
Satisfaction (AI)	4.23	3.99 - 4.47	5	1.23	-1.912	3.286	0	5
Satisfaction (Manual)	3.2	2.98 - 3.42	3	1.12	-0.367	0.145	0	5

Source: Author's own elaboration.

Central tendency and dispersion statistics for every important variable are shown in Table 17.

The median was 15 minutes, with a range between 2 and 40 minutes, and mean completion time for AI-assisted operations was 13.76 minutes (SD = 6.99). Values for skewness (0.399) and kurtosis (0.541) imply a little right-skewed but reasonable distribution.

Reflecting more variation in individual performance, manual task durations averaged longer (28.46 minutes) with a larger dispersion (SD = 11.72). The low kurtosis (0.284) and modest skewness (0.317) point once again to a slight deviation from exact normality, most probably brought on by many outlier events whereby duties took rather longer to finish.

Both artificial intelligence (M = 0.839) and manual (M = 0.783) conditions displayed high averages and somewhat low standard deviations for accuracy, hence indicating consistent measurement stability over subjects. On the other hand, negative skewness numbers (-1.747 and -1.384) indicate that most of the subjects attained high accuracy scores, clustering close to the upper bound.

Concerning satisfaction, artificial intelligence tasks produced better ratings (M = 4.23, SD = 1.23) than manual jobs (M = 3.20, SD = 1.12). The highly positive kurtosis (3.286) and strongly negative skewness (-1.912) for AI satisfaction confirm that the majority of participants rated their experience favorably, producing a left-tailed distribution focused at high numbers.

All things considered, these descriptive markers indicate that even if distributions differ somewhat from normality especially for accuracy and satisfaction measures no significant asymmetries or data abnormalities were discovered. With a large sample size (N = 104 observations), the data fits for strong comparative analysis.

3.5.2 Normality Tests

To confirm normality assumptions, the Kolmogorov-Smirnov and Shapiro-Wilk tests were conducted. See Table 11 At the severe statistical level, both tests returned $p < 0.05$ for all factors under AI and manual conditions, therefore revealing non-normal distributions.

In reality, though, behavioral and organizational research often reveals little variations from what is considered to be normal. Central limit theorem ideas allow parametric tests (e.g., paired t-tests) to be used securely on samples with more than 30 observations per condition since the sampling distribution of the mean tends toward normality (Field, 2020). Hence, even in light of the test results, the paired t-tests used in this research are still dependable and effective for assessing group differences.

3.5.3 Interpretation and Implications

Combining descriptive and normalcy analyses reveals that:

- The data are somewhat non-normal mostly because of ceiling effects in precision and happiness.
- The results are not skewed by any anomalies or outliers.
- Given the robustness of t-tests under mild non-normality and the sample size ($N = 104$ paired observations), the inferential tests presented earlier remain statistically valid.
- These results corroborate the accuracy and dependability of the compiled data for conclusions regarding the relative effectiveness and happiness impacts of artificial intelligence technologies.

Strict normality requirements were not satisfied, but the patterns of distribution match those predicted for human performance data, therefore supporting the use of the applied statistical techniques.

3.6 Corrections and Cognitive Load Analysis

Apart from measuring time, precision, and pleasure, this study investigated how artificial intelligence support affected the number of corrections participants had to undertake following each task. Cognitive load and error frequency that is, how much mental effort participants had to invest and how often they had to review their results before submission are reflected in the number of errors.

3.6.1 Descriptive Overview

According to Table 12, the mean number of corrections under AI-assisted circumstances was 0.71 (SD = 1.04), contrasted to 1.23 (SD = 1.18) in manual conditions. This almost 0.5 correction per activity decline suggests that AI-supported individuals needed less adjustments and made less errors.

Further more indicating more consistent performance across participants, the lesser variation in AI corrections probably resulted from the structured guidance and error-prevention cues provided by the AI system during task completion.

3.6.2 Inferential Comparison: Paired Samples Tests

To examine correction counts across the two conditions, paired-samples t-test was performed. See Table 13.

Results showed a statistically significant mean difference of -0.519, $t(103) = -3.455$, $p < .001$, with a 95% confidence interval [-0.817, -0.221].

This implies that AI-assisted tasks saw a much-reduced frequency of corrections. Weak ($r = 0.055$, $p = 0.582$) was the link between artificial intelligence and manual corrections, therefore proving that performance consistency did not rely on prior knowledge or manual habits.

These findings quite support the hypothesis that artificial intelligence solutions successfully decreased the mental load and enhanced task accuracy.

3.6.3 Effect Size Analysis

Cohen's $d = -0.34$ (95% CI [-0.54, -0.14]) was the effect size linked with this distinction, pointing toward a small-to-moderate practical impact. Although artificial intelligence had a less dramatic effect on correction reduction than it did on task time or satisfaction, this scale shows that it still resulted in significant enhancements in workflow quality. See Table 14.

3.6.4 Interpretation and Discussion

The correction analysis adds another level of performance appraisal.

Under AI-assisted circumstances, the notable decrease in corrections shows how the technology improves the accuracy and dependability of first-attempt outputs in addition to speeding task completion. Less corrections implies less time spent by the participants rechecking documents, clarifying facts, or drafting summariestasks that usually cause mental tiredness in compliance work.

This result agrees with theoretical expectations from cognitive load research (e.g., Sweller et al., 2019), which holds that intelligent support systems can offload regular information processing from human working memory. In practice, AML analysts gained from AI's capacity to organize raw data, emphasize pertinent material, and cut back on repeated verification steps.

Moreover, the reduced correction rate points to better quality of original decision-making enabled by AI assistance, which lets analysts concentrate on interpretive and judgment-based elements instead of mechanical verification. This discovery supports prior results pointing to greater satisfaction and confidence levels (Figures 11 and 12), therefore reinforcing the idea that AI-assisted processes improve both performance and psychological comfort.

3.6.5 Summary of Cognitive Load Findings

In summary:

- Participants made significantly fewer corrections when using AI tools ($p < .001$).
- The reduction in corrections represents a measurable decrease in cognitive workload and human error.
- Effect size analysis indicates a small-to-moderate yet meaningful practical improvement.
- These findings confirm that AI tools help analysts achieve faster, more accurate, and less cognitively demanding task completion.

Together with earlier results, this section provides strong empirical evidence that AI enhances both objective performance and subjective user experience, supporting the overarching goal of augmenting human intelligence rather than replacing it. Overall, this experiment's outcomes mirror wider empirical evidence that AI-driven AML systems consistently outperform traditional human-only approaches across both efficiency and precision indicators (Can AI-Driven AML Systems Outperform Human-Centric Approaches, 2025).

3.7 Qualitative Insights

Beyond statistical measurements, the research included participants' open-ended responses to grab personal ideas on employing artificial intelligence in daily anti-money laundering (AML). These qualitative replies offer important context for analyzing the numerical data and grasping user views of AI-assisted methods.

Participants generally strongly positive experiences with artificial intelligence integration, highlighting its importance in boosting clarity, innovation, and speed throughout challenging document analysis. Several typical comments are included below:

Participant 14: "Though they work best when combined with human judgment and imagination, artificial intelligence tools are mighty aids."

Participant 4: "It was quite a great interface and easy to follow."

Participant 8: "AI tools have helped me arrange thoughts and see new angles, thereby simplifying and quickening my job."

Participant 15: "Though AI instruments help save time, they sometimes lose context and demand extra effort to right errors."

Participant 22: "Particularly in research and data analysis projects, working with artificial intelligence tools has greatly boosted my inventiveness and efficiency."

Participant 33: "Without appropriate supervision, artificial intelligence tools can occasionally oversimplify complicated issues and create incorrect or biased results."

Two recurring ideas show through these thoughts:

1. Support and Perceived Efficiency.

Most participants underlined less cognitive effort, improved organization, and time savings. They appreciated how AI could aid multilingual documentation otherwise necessitating much manual processing as well as its ability to condense vast volumes of data.

2. Human monitoring and trust.

Many people warned that human evaluation determines the value of artificial intelligence. Although artificial intelligence improved workflow efficiency, experts saw the need for critical thinking to confirm results, especially when working with sensitive or inconclusive information.

These observations combined show that subjects regarded artificial intelligence as a cooperative companion rather than as replacement. Though they valued its contribution to creativity and output, they remained aware of upholding professional control and ethical responsibility.

This balanced viewpoint reinforces the case for human-AI symbiosis in AML activities: integrating human contextual reasoning with the speed and consistency of AI guarantees both operational effectiveness and honesty.

3.8 Summary of Findings

The empirical data taken together show how much transforming potential AI solutions have to offer in enhancing AML professionals' performance. Quantitative and qualitative results combine on many critical results:

1. Growth in efficiency.

Less half the time needed for manual processing was used for AI-assisted operations. The $d = -1.33$ very great effect size supports significant time savings. Participants also indicated less mental stress, consistent with a decreased cognitive load.

2. Increased Accuracy.

Particularly in multilingual document analysis and data summarization, artificial intelligence support improved analytical accuracy. With a little but notable effect size ($d = 0.25$), the paired-samples t-test showed a statistically significant accuracy improvement ($p = .012$).

3. Increased self-assurance and confidence.

Using AI tools, participants reported much greater confidence ($d = 0.70$; $p < .001$). Qualitative remarks mirrored this pattern, noting that AI made job "easier," "faster," and "more organized."

4. Decreased Mental Weight.

From 1.23 (manual) to 0.71 (AI), a statistically significant decrease ($p < .001$). This shows that AI tools helped to minimize the demand for rework in addition to saving time, therefore improving decision quality and concentration.

5. Demographic balance

Regression analyses (Tables 10-11) confirmed that age and experience had no significant effect on performance outcomes. Showing its scalability and inclusiveness, artificial intelligence rewards were equally divided among all demographics.

6. Approval of Adoption.

Almost all respondents indicated readiness for technology integration when ethical and supervisory systems were in place, therefore mirroring a cultural openness to keep using AI in future projects.

Collectively these results support all three research assumptions:

H1: Artificial intelligence greatly raises task efficiency.

H2: Artificial intelligence improves analytic precision.

AI raises confidence and user happiness.

The research therefore validates the finding that incorporating Large Language Models (LLMs) and agentic artificial intelligence solutions can greatly improve human performance in compliance settings. AI is a decision-support system, allowing more exact, quicker, and psychologically fulfilling job, far from substituting for analysts.

These findings offer empirical confirmation for the theory that ethical and professional values combined with technological innovation will help to make AML activities both more human-centered and more effective.

Conclusions, Limitations, and Future Research Lines

Main Conclusions

This study sought to see whether the use of artificial intelligence (AI) tools especially large language models (LLMs) integrated into decision-support interfaces enhances the work performance of Anti-Money Laundering (AML) professionals compared with traditional manual methods. Carried out at the Reference Banking Institution in Georgia (RBIG) with a sample of 52 participants, the experiment methodically evaluated task completion time, analytical accuracy, user satisfaction, and cognitive load across AI-assisted and non-assisted conditions.

Strong evidence for performance assisted by artificial intelligence came from the empirical data presented.

Participants working with artificial intelligence tools finished activities in less than half the time necessary for manual processing, with higher accuracy and greater satisfaction stated. Through statistically significant t-test results, all three hypotheses efficiency (H1), accuracy (H2), and satisfaction (H3) were supported. Effect-size calculations showed a very great influence on efficiency ($d = 1.33$), a considerable influence on pleasure ($d = 0.70$), and a minor but significant improvement in precision ($d = 0.25$).

Further evidence of how artificial intelligence support lowered cognitive load and increased the quality of first-attempt results was the drop in correction count. Regression analysis revealed that these advantages were the same throughout age and experience groups, therefore suggesting that AI tools offer equal benefits to all employees independent of seniority or length of service.

Qualitative perspectives helped these results, showing that participants regarded artificial intelligence more as a helpful assistant than as a substitute. Though respondents underlined the need for ongoing human supervision to guarantee contextual awareness and moral judgment, they also said the tool was effective, simple, and inspirational. Together, these findings verify that AI can function as a human-augmentation tool to increase both operational efficiency and psychological well-being in compliance jobs.

In essence, the study shows that AI-powered systems may accelerate, increase consistency, and improve financial-compliance activities without diminishing the value of human skill. This result matches with ongoing debates in the literature supporting human-centered AI incorporation in vulnerable financial settings.

Theoretical Implications

Theoretically, this study adds to the growing corpus of knowledge on human-AI cooperation and AI adoption in regulatory environments.

First, it offers empirical support for ideas positing that artificial intelligence improves human judgment not through substitution but through complementarity—that is, expanding the limits of human analytical capacity.

Second, it supports cognitive load theory and human-computer interaction models that stress the redistribution of mental effort between humans and computers by broadening knowledge of cognitive workload reduction through intelligent automation.

Finally, this work supports the debate on technological inclusiveness by showing that age and experience have little influence on artificial intelligence performance, therefore implying that AI products can lessen hierarchical inequities in knowledge-intensive sectors.

These conceptual ramifications show how AI is an empowering and equalizing power able of converting compliance activities into a more data-driven, transparent, and ethically controlled process.

Practical and Managerial Implications

From a managerial point of view, the results have clear implications for financial organizations and compliance departments evaluating the application of artificial intelligence (AI) tools. The study indicates that:

- AI integration can greatly improve operating efficiency, enabling workers to handle more papers with less tiredness.
- Rather than technical coding, training initiatives should emphasize artificial intelligence literacy and ethical awareness as users profit most by knowing how to interpret and authenticate AI outcomes.
- Central should remain human supervision to guarantee that professional judgment is supported not substituted by artificial intelligence recommendations.
- Institutions can anticipate increased employee morale and engagement when AI technologies are used openly and coupled with supportive change management.

These results emphasize for legislators and regulators the need of governance structures such as those advocated by the EU AI Act which strike a balance between innovation and responsibility and fairness in financial decision-making.

Limitations of the Study

Although the research met its goals, several drawbacks should be noted.

1. Participant Count and Scope: The study included fifty-two participants from one Georgia banking institution. Although adequate for statistical testing, findings might not apply outside of other financial institutions or nations with varied regulatory environments.

2. The study concentrated on four representative AML tasks, which might not reflect the whole complexity of actual compliance procedures or the long-term learning effects of artificial intelligence use.
3. Short-Term Assessment: The experiment evaluated immediate task execution; long-term effects including skill development, trust evolution, or possible dependence on artificial intelligence were not examined.
4. AI Tool Setup: The study employed a targeted LLM-based system in a regulated environment. Performance results might vary according with the model, user interface design, or degree of data integration.
5. Novelty or anticipation bias may affect perception-based metrics; future studies might supplement surveys using behavioral or physiological indications of cognitive load.

Acknowledging these constraints grounds the results within a practical framework and establishes a basis for continuing investigation.

Future Research Lines

Building on the findings of this study, next studies might go in several bright directions:

1. Including AML experts from many nations or financial systems would let comparative analysis of cultural, linguistic, and regulatory effects on artificial intelligence implementation be done by expanding the sample.
2. Longitudinal Study: Over time, how continual exposure to artificial intelligence technologies affects employee trust, performance sustainability, and decision-making accuracy is examined.
3. Deep knowledge of how artificial intelligence changes human information processing could come from the integration of eye-tracking, workload indexes, or neurocognitive indicators.
4. Future research may investigate how features for openness and explainability (e.g., explainable artificial intelligence dashboards) affect user trust and responsibility under ethical and governance tests.
5. Integration with Organizational Strategy: Research might evaluate how AI-driven compliance solutions impact institutional culture, leadership approaches, and risk-management results.

Investigating these lines of questions would improve the academic conversation on AI in compliance and point businesses toward evidence-based implementation plans.

Final Reflection

The results of this study clearly show that properly used artificial intelligence tools improve rather than reduce human potential in financial compliance. AI presents a path to more adaptable, smart, and moral

AML treatments by enhancing efficiency, accuracy, and job happiness. Simultaneously, it is still crucial to keep a human-centered attitude founded in critical judgment, openness, and responsibility.

The interaction of human knowledge and artificial intelligence will shape the future of compliance work as financial systems develop toward greater digitalization and complexity. This research shows that cooperation between humans and intelligent systems may produce both organizational excellence and human empowerment, therefore helping toward that vision.

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AI for Anti-Money Laundering (AML) and Know Your Customer (KYC) Compliance (Harrison, 2024) explores AI's role in AML & KYC compliance.

Can AI-Driven AML Systems Outperform Human-Centric Approaches (2025) examines AI vs human-centric AML systems.

Enhancing Anti-Money Laundering (AML) Efforts through AI-Driven Transaction Monitoring (Alabi, Okunola & Toyin, 2025) focuses on AI transaction monitoring in AML.

Who benefits from AI in Money Laundering in Europe: The organised criminals or the AML services (2025) comparative study across Europe.

Technology-Driven AML Collaboration: The Role of AI and Blockchain in Public-Private Initiatives (2025) explores AI + blockchain in AML.

AI-Powered AML and Fraud Detection: Protecting Financial Institutions While Enhancing Data Privacy and Security in Digital Finance (2025) AI & fraud detection in finance.

A Multifaceted Vision of the Human-AI Collaboration: A Comprehensive Review (2024) human-AI collaboration framework.

Legal Implications of Automated Suspicious Transaction Monitoring: Enhancing Integrity of AI (Turksen, Benson & Adamyk, 2024) legal/regulatory dimension in banking.

AI-Driven Cloud Solutions for Anti-Money Laundering (AML) Compliance with Graph Neural Networks and Behavioural Analytics (Prakash, 2025) AI + cloud + graph neural networks in AML.

Appendix A - Post-Task Employee Survey Form

Title:

Anonymous Post-Task Employee Survey

Reference Banking Institution in Georgia (RBIG)

Purpose:

This short questionnaire aims to gather AML professionals' perceptions regarding the use of AI-assisted and manual methods during analytical tasks. The survey collects anonymous feedback to support academic research on human-AI collaboration in compliance operations. Section 1 - Background Information

1. Gender: Male Female Prefer not to say
2. Years of experience in AML/compliance:
 - Less than 1 year
 - 1-3 years
 - 4-6 years
 - 7+ years

Section 2 - Work Experience During the Experiment

Instructions:

Please rate each statement below according to your personal experience in the experiment. (1 = Strongly Disagree, 5 = Strongly Agree)

Rate the following statements:

No.	Statement	Scale (1-5)
1	AI-assisted tasks helped me complete the work faster than manual tasks.	1 <input type="checkbox"/> 2 <input type="checkbox"/> 3 <input type="checkbox"/> 4 <input type="checkbox"/> 5 <input type="checkbox"/>
2	AI assistance improved the accuracy of my analytical results.	1 <input type="checkbox"/> 2 <input type="checkbox"/> 3 <input type="checkbox"/> 4 <input type="checkbox"/> 5 <input type="checkbox"/>
3	I felt more confident in my conclusions when using AI support.	1 <input type="checkbox"/> 2 <input type="checkbox"/> 3 <input type="checkbox"/> 4 <input type="checkbox"/> 5 <input type="checkbox"/>
4	AI tools reduced my cognitive workload compared to manual work.	1 <input type="checkbox"/> 2 <input type="checkbox"/> 3 <input type="checkbox"/> 4 <input type="checkbox"/> 5 <input type="checkbox"/>
5	Manual tasks required more time and attention than AI-assisted tasks.	1 <input type="checkbox"/> 2 <input type="checkbox"/> 3 <input type="checkbox"/> 4 <input type="checkbox"/> 5 <input type="checkbox"/>

No.	Statement	Scale (1-5)
6	I believe AI systems can be a reliable decision-support tool in AML compliance.	1 <input type="checkbox"/> 2 <input type="checkbox"/> 3 <input type="checkbox"/> 4 <input type="checkbox"/> 5 <input type="checkbox"/>

Section 3 - Overall Perception and Open Feedback

- Which approach did you find more effective overall?
 - AI-assisted tasks
 - Manual tasks
 - Both equally
- Please describe your overall impression of using AI tools during the experiment (optional):

Thank you for your participation.

Your responses remain completely anonymous and are used only for academic research purposes.

Appendix B - Experimental Task Descriptions

The following tasks were developed to simulate real operational scenarios typically performed by AML analysts. Each participant completed four standardized tasks two manually and two with AI assistance following a cross-over experimental design.

Task No.	Task Title	Description	Data Type / Language
Task 1	Contract Review (Foreign Language)	Review a client contract written in Slovak and summarize its key clauses relevant to due diligence (e.g., beneficial ownership, transaction terms, risk indicators).	Slovak-language text document
Task 2	Company Résumé Preparation	Extract essential company information from a Russian-language profile and prepare a concise résumé in English, highlighting ownership, registration, and activity type.	Russian-language text document
Task 3	Adverse Media Screening	Identify negative or risk-related news about a given company using provided media sources and summarize findings.	English-language media content
Task 4	Customer Identification	Review provided data about a person requesting account opening and verify their background using structured KYC data and open sources.	English-language profile data

Performance Indicators Measured:

Time (minutes) to complete each task

- Accuracy (%) based on correct identification and completeness
- Number of corrections required after review
- Satisfaction (1-5 Likert scale rating after each task)

All tasks were conducted individually under controlled laboratory conditions and recorded for standardized comparison.

Appendix C - Sample Size Calculation (Cochran's Formula)

To determine an adequate sample size for a finite population, Cochran's (1977) formula was applied:

Where:

$$n = \frac{N \times Z^2 \times p(1-p)}{e^2(N-1) + Z^2p(1-p)}$$

- **n** = sample size
- **N** = total population (60 AML employees)
- **Z** = z-score for 95% confidence level (1.96)
- **p** = estimated proportion of population (0.5 for maximum variability)
- **e** = desired margin of error (0.05)

Substituting values:

$$n = \frac{60 \times (1.96)^2 \times 0.5(1-0.5)}{(0.05)^2(60-1) + (1.96)^2 \times 0.5(1-0.5)} \approx 52$$

Result:

The required sample size was $n = 52$ participants, which matches the actual number of employees who took part in the experiment. Therefore, the study achieved the statistically sufficient sample size for internal validity at a 95% confidence level.

