07 The Application of Artificial Intelligence in Detecting Money Laundering in Kenyan Commercial Banks

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Abstract

Money laundering is a serious threat to financial stability and national security, made worse by systemic weaknesses. Traditional, rule-based anti-money laundering (AML) systems face challenges that often lead to data-collection issues and a high number of false positives. This study aimed to evaluate the use of artificial intelligence (AI) in AML operations within Kenya's commercial banking sector. It intended to address a significant gap in existing research by exploring how much AI is being used, the specific technologies involved, their perceived effectiveness, and the main challenges and opportunities for their application. Based on affordance actualization theory, this research used a practical mixed-methods approach. Data were collected through questionnaires from 76 respondents and detailed interviews with 15 participants. These included bank employees, officials from the Financial Reporting Centre, security agencies, and independent AML professionals. The findings show that AI applications in AML processes are diverse, with larger banks leading adoption. The study found a strong positive correlation between AI adoption and perceived effectiveness in combating money laundering. Based on these findings, the research recommends that leading banks share their success stories to motivate other institutions to adopt these technologies. It also suggests the need for clear guidelines and standards across the sector to ensure that AI is integrated consistently and effectively in the financial industry.

Keywords: Affordance actualisation theory, artificial intelligence, anti-money laundering, commercial banks, money laundering.

Introduction

Money laundering has been specifically discussed and regulated in Article 3.1 of the UN Vienna Convention of 1988, which defines it as:

> The conversion or transfer of property, knowing that such property is derived from any offence(s), for the purpose of concealing or disguising the illicit origin of the property or of assisting any person who is involved in the commission of such an offence or offences to evade the legal consequences of his actions; The concealment or disguise of the true nature, source, location, disposition, movement, rights with respect to, or ownership of property, knowing that such property is derived from an offence(s) or from an act of participation in such an offence(s) (UNODC, 1988, p. 3).

The National Security Policy of the Republic of Kenya (2021) lists money laundering as an emerging threat from trans-organised crime that undermines Kenya's social-political stability and, by extension, its economy. The policy adds that launderers can influence policy, decision-making, and political processes through their resources. Tiwari et al. (2020) add that prevalent underground activities that fuel money laundering encompass drug trafficking, cybercrime, and corruption.

The Financial Action Task Force (FATF), an international organisation responsible for establishing guidelines to prevent money laundering and counter the financing of terrorism (CFT), is dedicated to keeping abreast of cutting-edge technologies in the banking sector. The growing use of digital solutions relying on artificial intelligence (AI) and its subsets, machine learning (ML) and natural language processing (NLP), can enhance the identification, reaction, communication, and monitoring of suspicious activity for risk management purposes (FATF, 2021).

Anti-money laundering (AML) refers to the various legal frameworks, regulations, and protocols that financial institutions follow to prevent, detect, and report cases of money laundering (Dilmegani, 2023). These institutions, mainly banks and other credit-providing entities implement AML systems to detect money laundering. The systems aim to identify risks associated with money laundering, prospective individuals engaged in money laundering activities, and transactions related to money laundering (Han et al., 2020).

Much of the conventional AML workflow implemented in the banking industry follows a linear pipeline structure that establishes a connection between a data source and a rule-based system. Analysts subsequently integrate their research endeavour to ascertain the legitimacy or fraudulent nature of transactions (Han et al., 2020). The goAML application, created by the Information Technology Service

(ITS) in collaboration with the United Nations Office on Drugs and Crime (UNODC) Global Program against Money Laundering, Proceeds of Crime and the Financing of Terrorism (GPML), is a comprehensive software solution designed exclusively for implementation by Financial Intelligence Units (FIUs) (goAML - Anti-Money-Laundering System, n.d.). The system provides users with a comprehensive and adaptable rule-based analysis functionality, allowing for the creation of rules that incorporate dynamic risk scores (UNODC, 2016). IBM i2 Analyst's Notebook is another tool commonly employed by financial institutions, serving as a crucial asset for security agencies and the private sector. This tool is effective for detecting and investigating fraudulent activity, such as money laundering (Analysis Using i2 Analyst’s Notebook | NRD Cyber Security, n.d.). Although i2 Analyst's Notebook may not completely encompass the concept of a self-learning AI system, it effectively combines AI components to augment its analytical skills (I2 Analyst’s Notebook - Discover and Deliver Actionable Intelligence, n.d.).

Rule-based systems cannot learn information and expertise over time, resulting in a fixed and inflexible knowledge base. They have drawbacks that include data aggregation, the occurrence of false positives, and risk scoring due to false information (Dilmegani, 2023). Nevertheless, many of these challenges can be effectively addressed using AI-powered software. Dilmegani (2023) asserts that AI is essential in facilitating the automation of various investigation processes. It enables the automation of document screening through the use of NLP techniques. Additionally, AI aids in the examination of large databases and resources. It also detects money laundering transactions and regulates suspicious transaction reports (STRs). Furthermore, AI contributes to reducing false positive reports linked to money laundering.

Globally, AI has demonstrated effectiveness in combating money laundering. In 2019, HSBC used AI-AML procedures, decreasing the time required for reviews and reducing the cost by $400,000 per year. The same applied to Standard Chartered in 2020, leading to a 40% reduction in the time required for compliance reviews and an enhancement in the accuracy of AML procedures. In 2021, JPMorgan Chase successfully integrated an AI-driven system, resulting in a remarkable 95% reduction in false positives with a corresponding 95% enhancement in the accuracy of its AML program. The cases serve as a demonstration of AI’s potential to enhance AML efforts (Artificial Intelligence and Anti-Money Laundering, n.d.).

Statement of the Problem

Money laundering poses a significant threat to financial stability and national security due to vulnerabilities in economic systems, budget imbalances, and the persistence of the informal economies (Reznik et al., 2021), and is closely linked to criminal activities such as drug trafficking, terrorism financing, and financial offenses like corruption and tax fraud (Johari et al., 2020; Tiwari et al., 2020). The accelerated advancement of money laundering techniques presents significant challenges for financial institutions responsible for preventing these illegal financial operations (Han et al., 2020). Despite advancements in adopting digital technology in the financial sector, a considerable portion of AML systems still rely on conventional, rule-based approaches to monitor transactions (Godinho, 2023), which limits their capacity to respond to emerging money laundering techniques. Given the rising complexity and volume of financial transactions, there is an urgent need to explore more dynamic and flexible approaches to the AML processes.

Artificial intelligence (AI) has emerged as a powerful tool for transforming how financial institutions detect and mitigate money laundering. The financial industry is well-positioned to integrate AI due to its profound dependence on customer and transaction data, which banks continuously collect, organise, and analyse (Kruse et al., 2019). AI's adaptability makes it effective in intelligently responding to variations in the market and evolving risks, allowing banks to improve accuracy in detecting money laundering (Chelangat & Munene, 2023).

In Kenya, where the banking sector faces heightened risks of money laundering due to fraud, forgery, drug-related offenses, corruption, cybercrimes, human trafficking, smuggling, and tax irregularities (ESAAMLG, 2022), the adoption of AI in AML processes has become especially critical. However, despite the growing recognition of AI's potential in combating financial crimes, the current level of AI adoption in Kenyan banks remains inconsistent and underdeveloped (Ngari, 2023). This research sought to fill the gap by evaluating the current level of AI adoption in Kenyan banks' AML efforts.

Research Objective

The research objective was to assess the current level of AI adoption in AML operations by commercial banks in Kenya in support of national security measures against money laundering.

Significance of the Study

The study sought to address the existing knowledge gap by providing insights into the unique challenges and opportunities that AI technology presents in AML processes in Kenya's banking industry. Considering the significant national security risk presented by money laundering, this study investigated the successful integration of AI in commercial banks to enhance their AML efforts. Moreover, the study aimed to provide policymakers and regulatory authorities with crucial knowledge for formulating suitable legislative frameworks that facilitate the execution of AI-powered AML initiatives.

Scope and Limitations

Scope of the Study

This study focused on the AML compliance programs in Kenya's banking industry, specifically in Nairobi County. This location was chosen because it has a concentration of major banks that handle the most transactions. It also focused on AI adoption in AML solutions.

Limitations of the Study

The sensitive nature of banking operations presented challenges in collecting data from these entities. However, the researcher overcame these challenges by explicitly clarifying that the data collection exercise was solely for academic research.

Literature Review

Theoritical Framework

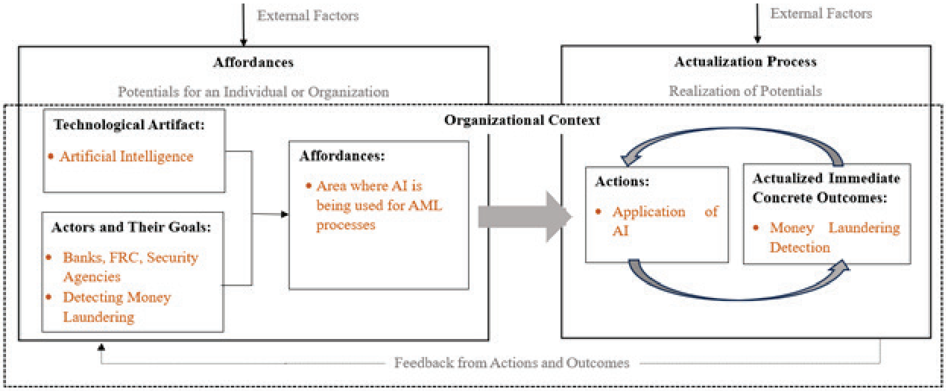
This study used affordance actualisation theory (AAT) to understand how AI technologies could be harnessed to detect instances of money laundering. Affordance actualisation refers to the process by which organisations effectively harness IT capabilities (Alraddadi, 2020). The theory examines the relationship between actors and technology and the interplay of roles within an environment. This encompasses organisational knowledge, processes, and other social functions (Liang et al., 2023). The theory was selected for the study because it offers robust analytical capabilities for examining technical and social elements without favouring one over the other when evaluating the correlation between IT artifacts, employees, and organisational objectives (Chatterjee et al., 2019). In this particular context, AI served as the artifact.

The theory has two main tenets: affordance and actualisation. The notion of affordances stems from the research conducted by ecological psychologist James J. Gibson, who characterised affordances as the complete range of potential actions or capabilities inherent in the environment and dependent upon the actors' capabilities (Jones, 2003). Affordances are also defined as how the capabilities of technology encourage, influence, and limit specific uses within an organisational setting (Jónasdóttir & Müller, 2020). When a person uses technology to take advantage of one or more opportunities to achieve a specific outcome that supports organisational goals, the potential actions become actualised (Strong et al., 2014). The actualisation of fundamental capabilities improves actors' understanding, allowing them to use sophisticated technologies (Liang et al., 2023).

Affordance actualisation theory in AI applications for detecting money laundering centers on understanding and using the potential capabilities and opportunities that AI technology can provide. It guided the evaluation of how adoption of AI and its utilisation in AML processes can help detect money laundering incidents.

Figure 1 illustrates the AAT framework utilised in this study.

FIGURE 1 ◢ Affordance actualisation framework



Adapted from Strong et al. (2014)

AAT's primary limitation is that it primarily examines the interpretive connection between users and technological devices that arises during their interaction with that technology in real-life contexts (Vyas et al., 2006). Nevertheless, this did not influence the study as it focused on technical outputs rather than social implications.

Money Laundering

Money laundering significantly threatens the financial and economic sectors' stability and the national security of all nations. Data provided by the UNODC shows that the estimated yearly volume of illicit funds involved in money laundering globally ranges from 2% to 5% of the global gross domestic product (GDP). This corresponds to a substantial amount ranging from $800 billion to $2 trillion (Dilmegani, 2023). In addition, just 0.2% of the funds laundered through the banking sector are believed to be seized. The scale of this criminal activity is becoming increasingly sophisticated, which exposes banks to a higher risk of being targeted (Kaur, 2023).

Criminals in Kenya use various methods to launder money, including investments and the exploitation of the country's financial system through layering and placement. This poses a national security concern, leading to individuals involved in illegal activities from other countries using Kenya's financial systems to launder and hide their substantial amounts of illicit funds (Tollaksen, 2023).

Naheem (2016) describes the traditional model of money laundering within banks that involves depositing cash into a bank (placement), subsequently layering the funds across multiple accounts (layering), and ultimately integrating the illicit money with legitimate funds to hide its origin and unlawful history (integrating). Han et al. (2020) postulate that AI methods can detect money laundering in each of these stages. Popular machine learning techniques such as support vector machines (SVMs) and random forest (RF) can categorise fraudulent transactions using extensive annotated bank datasets.

Level of AI Adoption in AML Operations

Commercial banks are increasingly incorporating AI into their AML operations. This trend aligns with global initiatives to improve financial security and regulatory compliance. Although specific information on Kenya is limited, global progress provides a solid framework.

Han et al. (2020) conducted a study on AI technologies for AML, highlighting the shortcomings of existing rule-based systems. They proposed a framework using advanced NLP and deep learning techniques to improve future AML technologies. The study found that existing systems had shortcomings that resulted in an overwhelming number of transactions being identified, requiring significant resources for analysis. The proposed framework aimed to reduce false identification of suspicious transactions, achieve regulatory compliance, and improve operational efficiency. It incorporated NLP semantic tasks designed to reduce time and cost to around 30% compared to manual methods.

Canhoto (2021) supported the study by Han et al. (2020) on the potential of machine learning algorithms in identifying and preventing money laundering and terrorism financing. The study employed AAT to understand the technical characteristics of machine learning-driven AML approaches and the social behaviors influencing their use. It employed qualitative methods and a single embedded case study of BANK, a UK-based financial services organisation. The study concluded that supervised machine learning has limited potential due to the lack of high-quality training datasets about money laundering methods.

The study by Gupta et al. (2023) concurred with Han et al. (2020), concluding that traditional rule-based monitoring systems were inadequate in identifying complex criminal tactics. AAT, based on direct perception psychology, was used to show that AI could improve operational efficiency and prediction accuracy while reducing operational costs. Goldbarsht (2023) noted that banks were integrating AI technologies into their data analysis operations to identify suspicious transactions more efficiently, leading to improved financial services. He added that AML regulatory authorities in the US, UK, and Australia are promoting AI use.

Chitimira and Ncube's 2021 study in Zimbabwe found that the costs of building efficient AML systems often outweigh the benefits. They recommended the use of AI to combat financial crimes. However, Zimbabwe's banking institutions have limited use of AI for deterring money laundering, unlike countries like Singapore, Italy, the USA, the UK, and Germany, which have successfully used AI in their banking industries.

A 2022 study by Maundu found that Kenyan commercial banks are implementing Fintech solutions to enhance anti-money laundering efforts. These include artificial intelligence, customer screening, digital identity verification, and big data analytics. However, banks are hesitant to adopt blockchain technology, suggesting that successfully integrating these technologies can significantly impact risk management and compliance.

Critical Analysis and Research Gap

The use of AI in financial systems has shown promising results, as suggested by Han et al. (2020). Nevertheless, there is a scarcity of research on its application for AML in actual financial systems, particularly in Kenya. A survey or interview-based study could provide a more thorough understanding. Canhoto's 2021 study depended on a single case study, which limits its generalisability. Additional research involving a larger sample of banks could offer more insights. Chitimira and Ncube's 2021 study inadequately examined factors contributing to the slow adoption of AI-based AML solutions in Zimbabwe and lacked empirical evidence to support AI's efficacy. Maundu's 2022 study used the Diffusion of Innovation-Technology, Organisation, and Environment (DOI-TOE) framework, which was inadequate for capturing the complexities of FinTech in the financial industry. This study extended Maundu's 2022 study using AAT and a pragmatic paradigm, adding a qualitative aspect and narrowing the technology to AI only.

Research Methodology

Research Approach

The study used a mixed-methods approach. It employed the pragmatic paradigm, allowing the researcher to simultaneously collect quantitative and qualitative data. This strategy embraced a pluralistic perspective to obtain all forms of data to address the research questions (Creswell & Clark, 2018). Combining the two approaches enabled the researcher to comprehensively address study questions and generalise the outcomes to the entire population.

Research Design

The study employed a convergent design that combines qualitative and quantitative data to comprehensively investigate the research problem. It offered a well-rounded understanding of the research problem from various perspectives, thus presenting a holistic view (Creswell, 2015). It allowed for a quick comparison between participants' perspectives from semi-structured interviews and researcher's perspectives obtained through questionnaires (Creswell & Clark, 2018).

Study Site/Research Setting

The study was conducted in Nairobi County, known as East Africa's financial powerhouse due to its high concentration of bank branches (Liman, 2023). In 2022, Nairobi City had the largest number of branches, 573, accounting for 40% of the total of 1,475 (Cowling, 2023). Some (2020) revealed a possible global money laundering network in Nairobi, including Chinese citizens operating fraudulent credit card schemes to purchase from Kenyan firms.

Target Population

The study involved compliance officers from commercial banks, as well as employees working on anti-money laundering matters from the National Intelligence Service (NIS), the Financial Reporting Centre (FRC), and the financial investigations unit of the Directorate of Criminal Investigation (DCI). The selection of compliance officers was determined by the banks' market share, with nine large banks accounting for 75.14%, eight medium banks for 16.29%, and seven small banks for 4.72%, representing 96.15% of the total market, as published by the Central Bank of Kenya (CBK) in 2022. Mathuva et al. (2020) found that the CBK imposed fines only on larger banks in the 2018 National Youth Service (NYS) scandal, justifying the study's choice of a lesser percentage of smaller banks. Specifically, four large and two medium peer group banks were penalised; however, no small banks were involved.

The questionnaire targeted 118 respondents, with 96 respondents from selected commercial banks and 22 from the FRC. For in-person interviews, the target population was 24 bank managers and two senior officers each from the NIS, FRC, and DCI, bringing the total to 30.

Sampling

Sampling Design

The quantitative research used proportionate stratified sampling to select items from commercial banks and FRC, the main users of anti-money laundering systems, in contrast to the NIS and DCI, which primarily focus on investigations. This approach ensures an accurate representation of the entire population.

The study used purposive sampling for interviews involving individuals with extensive expertise in the subject matter (Nikolopoulou, 2022), in this case, money laundering. Participants included bank risk managers and officers at the FRC, NIS, and DCI. AML experts from PricewaterhouseCoopers International Limited (PwC), Transparency International Kenya (TI-Kenya), and Amnesty International were also interviewed to mitigate response bias.

Sampling Size

The study used two sample sizes, with the quantitative sample significantly larger than the qualitative sample. This allowed for an in-depth qualitative investigation of the research topic, while the inclusion of a larger quantitative sample yielded a rigorous and statistically significant study (Creswell & Clark, 2018).

Table 1 specifies that the recommended sample size is 91 respondents with a confidence level of 95%. The researcher adapted it from an existing sample size table by Krejcie and Morgan (1970). The researcher used it to determine the sample size for the quantitative research.

TABLE 1 ◢ Quantitative research sample size

Respondent	Target Population	Stratified Sample	Percentage
Large Peer Group Banks	36	28	30.51%
Medium Peer Group Banks	32	25	27.12%
Small Peer Group Banks	28	22	23.73%
FRC	22	16	18.64%
Total	**118**	**91**	**100%**

Adopted from Krejcie and Morgan (1970)

The researcher recruited interview respondents as guided by Vasileiou et al. (2018) who contended that qualitative researchers performing interview-based studies with specified research questions generally discover that they obtain minimal new information after questioning approximately 20 individuals within a relevant participant category.

Senior management of banks were interviewed because of their vast knowledge of money laundering and were purposively selected from eight banks spread across the three tiers: three each from large and medium peer group banks and two from the small peer group banks (Central Bank of Kenya, 2022). Two officers from the NIS, FRC, and DCI were also purposively selected to understand the challenges of investigating money laundering and how AI could enhance these investigations. To mitigate potential response bias, three additional AML experts, one each from PwC, Amnesty International, and Transparency International Kenya (TI-Kenya), were interviewed. Table 2 shows the qualitative research sample size.

TABLE 2 ◢ Qualitative research sample size

Respondent	Sample	Method
Large Peer Group Banks	3	Purposive
Medium Peer Group Banks	3	Purposive
Small Peer Group Banks	2	Purposive
NIS	2	Purposive
FRC	2	Purposive
DCI	2	Purposive
Other AML Experts	3	Purposive
Total	**17**	

Adopted from Krejcie and Morgan (1970)

Data Collection Procedures and Tools

Data Collection Tools

The study utilised an online survey with open-ended and multiple-choice questions for fast and cost-effective data collection. However, questionnaires may have drawbacks as respondents may interpret questions differently, affecting their responses (Kabir, 2016). To address this, an interview schedule was used concurrently, providing a thorough understanding of the research questions and context. This allowed for comprehensive information from participants, clarified uncertainties, and enhanced response accuracy (Taherdoost, 2016).

Pre-testing

A pilot study was conducted to ensure the validity and effectiveness of the survey questions and research instrument (Bryman, 2012). The questionnaire was tested on individuals with extensive expertise in AML operations in the financial industry, with a sample size of 10% of the anticipated sample size for the parent study. To avoid using the same participants in both pilot and final studies (Ismail et al., 2018), the study selected respondents outside the research site, a commercial bank in Bomet town. This approach ensured the validity and effectiveness of the research instrument.

The study utilised Cronbach's alpha (ά) reliability, a widely accepted measure in social and organisational sciences (Bonett & Wright, 2014). Based on pilot test feedback, the study presented reliability statistics in Table 3, which display Cronbach's alpha values.

TABLE 3 ◢ Cronbach's reliability statistics

Cronbach's alpha	N of Items
0.970	47

Experts generally agree that a pilot study with an alpha reliability coefficient of 0.60 or higher is acceptable (Taherdoost, 2016). The SPSS Statistics output showed a Cronbach's alpha coefficient of 0.970 for 47 variables, indicating a strong correlation between the variables and consistent evaluation of the same underlying construct.

Data Analysis and Presentation Plan

The researcher transformed raw data into a meaningful format using IBM SPSS Statistics version 20. Descriptive statistics were used to uncover patterns and gain insights, while open-ended questions were analysed qualitatively to uncover overarching patterns. Transcribing textual data from interviews into word-processing files, coding, and grouping it into themes was done using Microsoft Excel 2019. The separate analyses of both datasets were then combined.

Quantitative data was displayed through tables and charts, whereas qualitative data was conveyed through narratives and quotes from participants to capture their perspectives and experiences.

Ethical Considerations

The study ensured participant anonymity by coding data and using it solely for academic research. Participants were informed about their rights, including voluntary participation and withdrawal options. To prevent privacy breaches, the confidentiality of the banks was protected through coding.

Findings

Response Rate

Creswell (2015) suggests that a questionnaire response rate of 50% or more is sufficient for most surveys. Table 4 indicates that 76 out of the 91 respondents in the study's quantitative sample size submitted their responses, resulting in a response rate of 83.52%. The researcher stopped collecting qualitative data when new insights or features were no longer evident (Creswell & Creswell, 2018). 15 participants from a 17-person sample were interviewed, resulting in a thorough understanding of the study objectives.

TABLE 4 ◢ Response rate of distributed questionnaires

Respondent	Sample	Method
Completed Questionnaires	76	83.52%
Unreturned Questionnaires	15	16.48%
Total	**91**	**100%**

Level of AI Adoption in Response to AML Operations

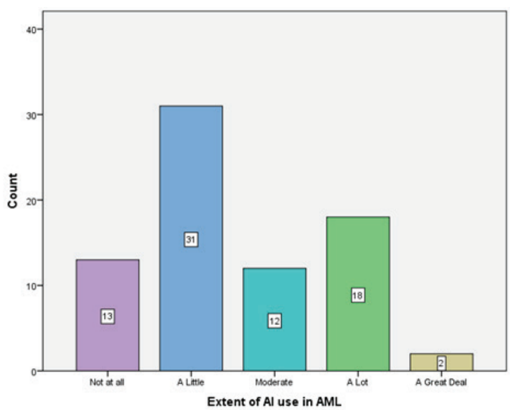
The study evaluated the adoption of AI in AML operations by Kenyan commercial banks to combat money laundering. It investigated the extent of AI integration, the specific AI systems used, and the perceived effectiveness of AI-based solutions in detecting and preventing money laundering.

◢ The Extent of AI Integration in AML Processes

Respondents were asked to indicate the extent to which AI technology is currently used in their institution's AML processes. Options ranged from "A Great Deal," scoring 5, to "Not at All," scoring 1. This aimed to capture the overall level of AI adoption within the banking sector.

Figure 2 demonstrates the levels of AI implementation in AML processes among institutions. The study showed that 17.11% of respondents have not yet integrated AI into their AML processes, with the majority (40.79%) using AI to a limited extent. This indicates that many institutions remained in the early phases of adopting AI. A small number (15.79%) had achieved a moderate level of AI adoption, while 18 (23.68%) had embraced AI to a significant degree. However, only two participants reported extensive use of AI, indicating that complete integration of AI was still scarce in the industry.

FIGURE 2 ◢ A Bar chart illustrating the current level of AI adoption in AML



The interview responses revealed that the adoption of AI in AML processes varies across banks, with some indicating widespread integration in larger institutions and others showing limited adoption in smaller ones. One respondent stated that:

> The banking industry is in the preliminary stages of AI implementation in Anti-Money Laundering (AML) systems, with many banks still using traditional rule-based systems. The limited adoption of AML measures can be attributed to a historical lack of focus on this issue. Only after the enactment of the Proceeds of Crime and Anti-Money Laundering Act (POCOLMA) was significant attention given to this matter. Although there has been an increase in AML efforts since 2019, the integration of advanced AI technologies has been slow and is yet to reach the desired level of progress (INT-IAE2-01).

Table 5 details the descriptive statistics for the level of adoption of AI-based AML solutions by various institutions. The mean score of 2.54 indicated an almost moderate AI adoption, suggesting that several institutions were in the initial phase of implementing AI technologies. The standard deviation of 1.113 indicated moderate variation in AI adoption levels among the various institutions under study. This showed that while some banks had fully incorporated AI, others used it to a limited extent.

TABLE 5 ◢ Descriptive Statistics of the Current Level of AI Adoption in AML

Respondent	N	Minimum	Maximum	Mean	Standard deviation
Extent of AI use in AML	76	1	5	2.54	1.113
Valid N (listwise)	76				

The study used SPSS Statistics to cross-tabulate industry and AI adoption levels in AML processes and analyse variation, as shown in Table 6 (*next page*).

The results indicated that AI adoption in AML procedures varied among industry categories. In small peer group banks, 42.1% of respondents indicated minimal use of AI, suggesting they might have been experimenting with it. Medium peer group banks showed a more even distribution, with 35% employing AI to a limited degree. The spread reflected a progressive rise in the use of AI by this category. Large peer group banks demonstrated a broader spectrum of AI implementation, with 42.3% using AI "A Little" and 46.2% using "A Lot" or "A Great Deal." This suggested they were at the forefront of AI integration due to their substantial resources and extensive AML measures. At the FRC, 36.4% reported not using AI, while the remaining 63.6% used it to a limited or moderate extent. This may have reflected the organisation's reliance on conservative systems like the goAML.

TABLE 6 ◢ Industry Vs. extent of AI use in AML crosstabulation

			Extent of AI use in AML					
			Not at all	A Little	Moderate	A Lot	A Great Deal	**Total**
Industry	Small Peer Banks	Count	3	8	4	4	0	19
		%	15.8%	42.1%	21.1%	21.1%	0.0%	100.0%
	Medium Peer Banks	Count	4	7	5	4	0	20
		%	20.0%	35.0%	25.0%	20.0%	0.0%	100.0%
	Large Peer Banks	Count	2	11	1	10	2	26
		%	7.7%	42.3%	3.8%	38.5%	7.7%	100.0%
	FRC	Count	4	5	2	0	0	11
		%	36.4%	45.5%	18.2%	0.0%	0.0%	100.0%
	Total	Count	13	31	12	18	2	76
		%	17.1%	40.8%	15.8%	23.7%	2.6%	100.0%

The interviews provided additional perspectives to back the diverse degrees of AI implementation within the industry categories. Respondents from smaller banks expressed that the implementation of AI was still restricted, with a dependence on conventional approaches and low use of AI. Respondent INT-B1-02 stated: "Our bank uses AI to a certain degree. Our primary focus is on using traditional methods while incorporating AI for fundamental transaction monitoring and customer verification."

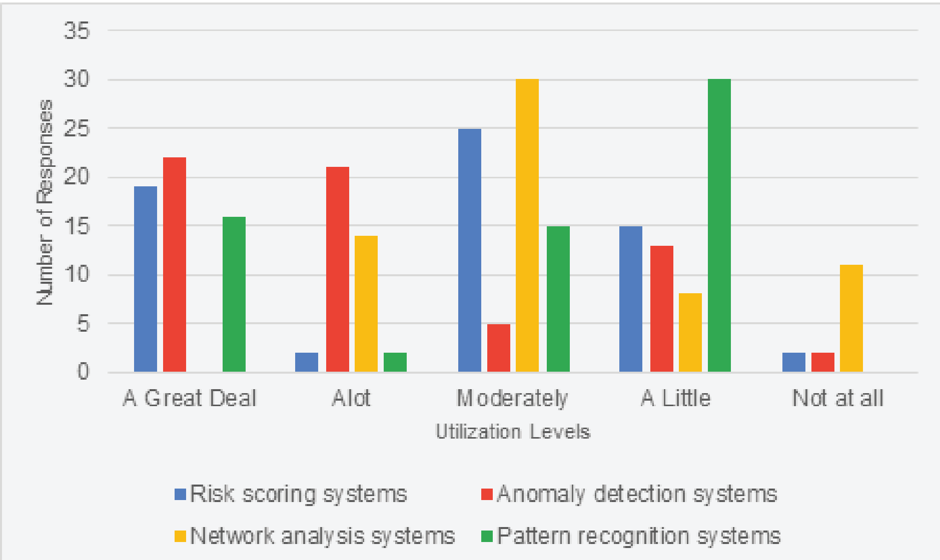
This finding concurs with Chitimira and Ncube (2021), who asserted that Singapore, Italy, the USA, the UK, and Germany have successfully used AI to combat money laundering in their banking industries, while Zimbabwe's institutions showed limited use. The affordance actualisation theory provided a framework for understanding AI adoption in AML processes. While AI affordance exists for adopting AI in AML processes, actualisation varies significantly, with larger banks extensively using AI and smaller institutions still in the early stages. This showed that factors like organisational readiness and resource availability influence the degree of actualisation.

◢ *Utilisation Levels of Various AI Systems in AML Strategies*

Institutions that indicated any level of AI use were requested to rate the utilisation of key AI systems like risk scoring, anomaly detection, network analysis, and pattern recognition in their AML strategies. Options ranged from "A Great Deal," scoring 5, to "Not at All," scoring 1. This detailed view provided a comprehensive understanding of the most frequently used AI tools and their extent of application.

The majority of respondents, 25 (39.68%), reported moderate usage of AI in risk scoring systems, with a significant number, 19 (30.16%), using it extensively, and 15 (23.81%) using it minimally. This indicated a significant dependence on risk scoring in AML procedures. Anomaly detection systems had high utilisation levels, with 22 (34.92%) rating it as "A Great Deal" and 21 (33.33%) as "A Lot," highlighting their importance in detecting unusual transaction patterns. AI-based network analysis systems were most frequently used at a moderate level, with 30 respondents (47.62%), 14 (22.22%) using it "A Lot," and 8 (12.7%) using it "A Little." However, none of the respondents indicated extensive use, and 11 (17.46%) reported not using it, possibly due to limited resources, lack of expertise or perceived lower importance in the AML process. Pattern recognition systems had the highest number of respondents, 30 (47.62%) using it "A Little," which might indicate possible early-stage adoption or limited institutional capabilities. Figure 3 shows this distribution.

FIGURE 3 ◢ Stacked bar chart of the current AI systems utilisation in AML



The systems most frequently mentioned by the interview respondents were the anomaly detection and risk scoring systems, with one of the participants stating:

> Banks commonly use AI technology for anomaly detection and risk scoring tasks. These AI applications are crucial in detecting and flagging suspicious patterns potentially linked to money laundering activities. By doing so, they contribute to national security by preventing the flow of illicit funds that could potentially support criminal and terrorist organisations (INT-F-01).

Some respondents mentioned using AI systems for pattern recognition and network analysis. Respondent INT-B3-01 highlighted: "AI systems can analyse routine transaction volumes through pattern recognition, or they can examine the various connections an entity engages with through network analysis."

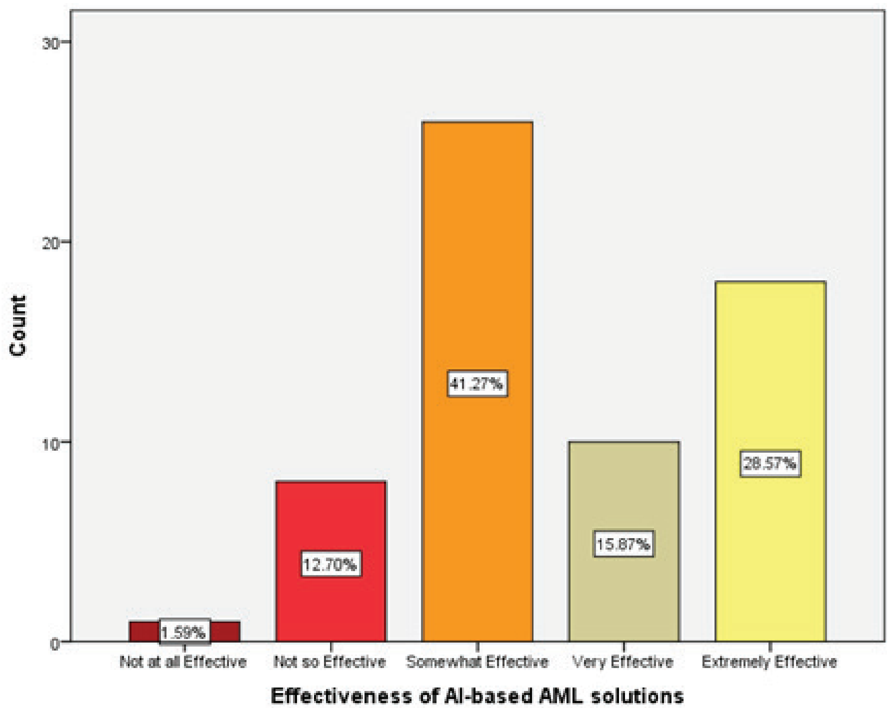
The finding aligned with Cameron's (2022) study, which highlighted AI's potential to improve anomaly detection and risk scoring in AML processes. The study revealed that anomaly detection and risk scoring systems were more frequently revealed that anomaly detection and risk scoring systems were more frequently actualised in AML than network analysis and pattern recognition systems, indicating that actualisation was influenced by perceived relevance, ease of use, and organisational needs.

◢ Effectiveness of Current AI-Based AML Solutions

Finally, respondents evaluated their institution's AI-based AML solutions' effectiveness, assessing their perception of the systems' practical performance and ability to meet their AML objectives. Options ranged from "Extremely Effective," scoring 5, to "Not at All Effective," scoring 1.

Figure 4 illustrates the effectiveness of AI-based AML solutions.

FIGURE 4 ◢ A bar chart illustrating the effectiveness of AI-based AML



The study showed that a minor fraction (1.59%) perceived these solutions as completely ineffective. In comparison, 12.70% regarded them as not very effective, suggesting that only a small number of participants believed that AI-based AML solutions are ineffective. Nonetheless, 41.27% of respondents found the AI-based solutions to be moderately effective, thus acknowledging the usefulness of the systems. 15.87% of the respondents stated that these solutions were very effective, while 28.57% declared them extremely effective. This implied a high level of confidence in AI's ability to deal with money laundering cases among the respondents. On average, the percentage of participants who found AI-based AML solutions to be somewhat effective, very effective, or extremely effective was 85.71%, indicating a positive perception of AI.

Thus, as illustrated in Table 7, AI-based AML solutions were considered fairly effective with the prospect of being highly effective. This pointed to a positive attitude toward the adoption of AI in AML processes. The 1.088 standard deviation showed that the respondents had varying perceptions of the effectiveness of AI-based AML solutions.

TABLE 7 ◢ Descriptive statistics on the effectiveness of AI-based AML

Respondent	N	Minimum	Maximum	Mean	Std. Deviation
Effectiveness of AI-based AML solutions	63	1	5	3.57	1.088
Valid N (listwise)	63				

This finding was similar to the responses gathered through interviews. Most respondents believed AI technology was highly effective in detecting money laundering because it could efficiently process and analyse large data volumes. Respondent INT-B3-02 narrated: “AI has proven to be extremely successful in identifying instances of money laundering. The system efficiently handles large volumes of data, quickly detects complex patterns, and minimises false alarms, enabling analysts to prioritise high-risk cases.”

In an earlier study, Kaur (2023) postulated that early adopters of AI technology see significant efficiency improvements and compliance with stricter regulations. Players in the financial services industry who possess adequate knowledge of AI were more likely to devise the right strategies for AI adoption. This study's findings highlighted that money laundering detection and prevention could be enhanced through the affordances presented by AI solutions. However, their effectiveness varied, suggesting an inequality in actualisation, with some organisations facing challenges that hinder their full realisation.

Table 8 (*next page*) shows the results of the one-way ANOVA test conducted to analyse the perceived effectiveness of AI-based AML solutions across different levels of AI adoption.

The study demonstrated a positive correlation between the extent of AI adoption and perceived effectiveness, with mean effectiveness scores increasing from “A Little” (2.68) to “A Lot” (5.00). The confidence interval for “A Lot” users is small, indicating high confidence in their responses. However, the intervals for “A Little” and “Moderate” users were wider, indicating greater variability in their perceived effectiveness. There was more variability in ratings among groups with lower AI use, such as “A Little” and “Moderate,” as indicated by the standard deviation of

TABLE 8 ◢ Descriptive statistics on the effectiveness of AI-based AML

	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum
					Lower Bound	Upper Bound		
A Little	31	2.68	.541	.097	2.48	2.88	1	3
Moderate	12	3.67	.492	.142	3.35	3.98	3	4
A Lot	18	5.00	.000	.000	5.00	5.00	5	5
A Great Deal	2	4.00	.000	.000	4.00	4.00	4	4
Total	63	3.57	1.088	.137	3.30	3.85	1	5

solutions to be somewhat effective, very effective, or extremely effective was 85.71%, indicating a positive perception of AI.

Implications

The study presents empirical data specific to Kenya, offering insights beyond single case studies and theoretical discussions (Canhoto, 2021; Han et al., 2020). The ANOVA results offered empirical proof of the correlation between AI adoption and the perceived effectiveness of AI-based AML.

Conclusion and Recommendations

Conclusion and Practical Implications

The study's findings had significant implications for implementation within the banking industry. It demonstrated that AI integration into AML practices is currently limited, especially for smaller banks. Larger banks that had extensively adopted AI reported greater perceived effectiveness, indicating the potential for AI to improve AML operations. Thus, targeted efforts are needed to address barriers to AI integration and fully utilise AI's potential.

The significant correlation between AI adoption levels and perceived effectiveness suggests that banks should prioritise expanding their use of AI to take advantage of these technologies. Shared resources and financial incentives should be offered, especially to smaller banks to help them overcome adoption challenges.

Recommendations

Sharing best practices from institutions already using AI extensively would help other institutions successfully integrate AI technologies into their operations. By analysing such experiences, other banks can gain insights and possible approaches to successfully implementing AI.

Policymakers should establish clear guidelines and standards to encourage consistent AI adoption in the financial sector. This would include financial support for smaller institutions and collaborations between banks, technology providers, and regulators.

Policymakers should strengthen regulatory frameworks to guarantee that AI implementation in AML processes aligns with national security goals while upholding high data privacy standards and ethical considerations.

Recommendations for Further Research

Further research could investigate the determinants affecting AI adoption rates and their correlation with measurable gains in AML outcomes. This could include exploring the barriers to AI adoption in smaller financial institutions and focusing on understanding how these barriers can be overcome.

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