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WHO BENEFITS FROM AI IN MONEY LAUNDERING IN EUROPE: THE ORGANISED CRIMINALS OR THE AML SERVICES?

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Abstract: *Artificial Intelligence (AI) has been exerting a growing influence on financial security, particularly in the area of anti-money laundering (AML). This study examines the relationship between AI adoption and AML effectiveness across selected European countries between 2017 and 2023. Employing a panel data econometric model, the analysis incorporates AI Vibrancy Scores, governance indicators, and economic variables to assess the multifaceted impact of AI integration. The findings reveal that greater AI adoption is generally associated with improved AML performance, as reflected by a statistically significant negative relationship between the AI Vibrancy Score and the Basel AML Index. However, the incorporation of a quadratic term indicates an inverted U-shaped relationship, suggesting that while moderate levels of AI adoption enhance AML outcomes, excessive integration may introduce systemic vulnerabilities exploitable by financial criminals. Governance variables – most notably the Rule of Law and Control of Corruption – emerge as key enablers of effective AI-driven AML strategies. Furthermore, factors such as public perception of AI and the presence of responsible AI governance frameworks significantly influence the success of AI applications in AML contexts. These results underscore the necessity of balanced AI policy development, robust institutional frameworks, and international regulatory coordination to harness AI's potential while mitigating its associated risks.*

Keywords: *artificial Intelligence, anti-money laundering, Basel AML Index, AI Vibrancy Score, AI Vibrancy subindexes.*

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INTRODUCTION

The integration of Artificial Intelligence (AI) into both money laundering processes and Anti-Money Laundering (AML) frameworks in Europe is a complex and dynamic issue. AI functions as a dual-edged sword in the realm of financial crime. On one side, financial institutions and regulatory bodies harness AI to enhance the identification and recording of illicit financial flows and improve compliance systems. AI-powered systems, particularly those employing machine learning techniques, can process vast volumes of transactional data, enabling the detection of suspicious activity with increased accuracy and reduced false positives (FCA, 2024). Conversely, organised criminal groups are increasingly leveraging AI to bypass AML controls. For instance, AI is now employed to generate fake accounts on cryptocurrency exchanges, facilitating money laundering operations that evade traditional detection mechanisms (Dale, 2024).

The rising relevance of AI in the AML domain is underscored by the development of tools such as the Napier AI / AML Index, which ranks countries based on their AI integration and financial crime compliance. Findings reveal that jurisdictions such as North America and Central Europe, which have incorporated AI more extensively, tend to experience a lower proportion of GDP lost to money laundering (Thrale, 2024). Nonetheless, the misuse of AI technologies introduces profound challenges. The same tools used to advance AML detection can also be exploited to develop complex laundering strategies, automate financial fraud, and create realistic deepfakes for deception (Dearden, 2024). This dual-use character of AI necessitates ongoing adaptation and innovation in AML approaches to keep pace with the evolving tactics of organised crime.

In this technological tug-of-war, AI simultaneously acts as both a safeguard and a weapon. While AML authorities utilise AI to fortify detection and reporting mechanisms, criminal actors manipulate the same technologies to refine their laundering techniques. The shifting balance between these forces is largely shaped by how quickly and effectively each adapts. As such, continuous empirical research and strategic policymaking are essential for AML services to maintain a technological advantage.

The broader implications of AI integration stretch beyond financial crime prevention. AI increasingly contributes to global economic development and institutional efficiency. As noted by Ioan-Franc and Gaf-Deac (2024), AI plays a crucial role in economic forecasting and stability. Neural networks, for instance, have been applied successfully to predict non-stationary agricultural outputs, facilitating more effective planning and resource distribution (Awe & Dias, 2022). Within the framework of digital transformation, Košovská et al. (2022) underscore AI’s importance in reshaping accounting and financial systems, fostering transparency, reducing fraud, and enhancing long-term economic performance. However, the expansion of AI and digital technologies is not without risks. Zámek and Zakharkina (2024) caution that increasing digitisation and openness can also expose nations to new forms of economic vulnerability, a view echoed by Tiutiunyk et al. (2021), who highlight the need for updated regulatory frameworks to manage the destabilising effects of rapid technological change. As digital and AI technologies evolve, governments and institutions must collaborate to implement effective policies that balance the benefits of technological progress with the need for robust security measures.

Several studies reveal how AI has empowered criminal organisations to enhance their money laundering capabilities. AI algorithms are employed to automate illicit transactions, generate synthetic identities, and detect vulnerabilities in existing AML systems (Reshetnikova & Mikhaylov, 2023). Machine learning models enable criminals to analyse transactional behaviours and adjust operations to avoid triggering regulatory alerts (Yarovenko et al., 2024b; Yarovenko & Rogkova, 2022). Additionally, AI-generated documents and deepfakes significantly complicate fraud detection efforts (Zada et al., 2024). As Kuzior et al. (2024) note, AI-driven cyber vulnerabilities further strain AML capacities, while Yarovenko et al. (2024a) warn that the adaptability of AI could allow it to outpace traditional compliance technologies if not countered through continuous innovation.

Public perceptions of AI and financial innovation also play a significant role in shaping AML outcomes. Garškaitė-Milvydienė et al. (2023) stress that user attitudes affect both the implementation of AI-driven systems and the ways in which criminals exploit emerging technologies. This reinforces the importance of public education and awareness to prevent misuse and bolster trust in financial oversight mechanisms.

Moreover, AI-enabled tools in the realm of decentralised finance and cryptocurrencies introduce additional complexity. As Máté et al. (2024) argue, AI-powered trading bots can obscure illicit financial flows by executing high-frequency transactions across multiple platforms. These innovations facilitate money laundering on a scale that may no longer require human intervention (Iskakova et al., 2025). AI has also been implicated in exploiting legal and regulatory gaps to facilitate tax evasion (Barbu et al., 2024), which further stresses the need for updated AML frameworks that align with rapidly evolving technologies.

The susceptibility of countries to AI-facilitated laundering varies according to their socioeconomic and regulatory characteristics. Yarovenko et al. (2023) highlight that weaker regulatory environments are especially vulnerable, while Letkovsky et al. (2023) demonstrate how AI can evade sector-specific rules in industries with complex financial flows. Yet AI’s influence is not solely negative. In AML compliance and risk monitoring, AI allows financial institutions to process data in real time, detect anomalies, and improve decision-making accuracy (Murko et al., 2024). Predictive analytics, powered by AI, significantly reduce false positives and increase compliance efficiency (Balcerzak & Valaskova, 2024). AI is also central to enhancing regulatory reporting systems, with deep learning networks identifying hidden relationships among transactions that traditional tools might overlook (Botoc et al., 2023).

AI's contribution to financial stability has been further supported by Liu et al. (2023), who demonstrate its value in enhancing institutional competitiveness and risk forecasting. Similarly, Piotrowski and Orzeszko (2023) explore how AI-powered robo-advisors influence consumer trust and improve AML compliance. The increasing importance of AI in combating financial crime is underscored by the broader digital transformation across industries, which impacts both business operations and societal behaviours (Moravec et al., 2024). The broader digital transformation reinforces AI’s role in shaping organisational behaviour across sectors, from public administration (Androniceanu, 2024) to enterprise management (Wang & Shan, 2024), underscoring its relevance to both growth and security.

Nonetheless, significant challenges remain. The effectiveness of AI-based AML tools hinges not only on technical capacity but also on high-quality data, cross-border collaboration, and regulatory harmonisation (Dobrovolska & Rozhkova, 2024a; 2024b).

Organised criminals continue to exploit jurisdictional inconsistencies and regulatory loopholes (Utkina, 2023), while ethical concerns – such as algorithmic bias, surveillance risks, and transparency – require urgent attention (Memarian & Doleck, 2024). Wright (2023) draws attention to rising cybersecurity concerns in the financial sector, and Siddiqui and Rivera (2024) examine how evolving AI applications are affecting regulatory practices, particularly in Latvia.

Ethical AI governance has emerged as a focal point in the public sector. Bian and Wang (2024) and Kabachenko et al. (2022) call for responsible AI deployment guided by transparency and fairness. These values are especially vital in AML enforcement, where algorithmic accountability is critical to ensure legitimacy and trust.

AI is also being positioned within broader global financial and geopolitical strategies. Neacsu et al. (2025) argue that AI is influencing global AML efforts and shaping power dynamics. While AI's positive role in European financial security is evident, its risks and ethical ambiguities cannot be overlooked. Höller et al. (2023) caution that unethical AI use can lead to discrimination and manipulation, especially when systems automate decisions in high-stakes domains. Ishwardat et al. (2024) further examine how organisational adherence to ethical AI practices can be encouraged through institutional design, while Burrell (2024) illustrates how AI technologies can impact public trust and psychological wellbeing – issues indirectly relevant to financial regulation through their societal effects.

In the education sector, AI is reshaping learning environments by offering adaptive and personalised experiences. Okulich-Kazarin et al. (2023; 2024) propose that non-violent AI learning tools support inclusive and efficient educational systems, a principle with parallels in the development of ethical AI systems in finance and beyond.

AI’s transformative potential is also evident in risk management. Roba and Moulay (2024) highlight the effectiveness of neural networks in financial risk assessment, while Pulungan et al. (2024) explore AI’s use in identifying corruption and laundering patterns. By analysing socioeconomic trends and behavioural indicators, AI can detect subtle risk factors that traditional models might miss. As noted by Kuzior et al. (2022), digital integration contributes significantly to AML success by improving transparency and cyber resilience. Vasilyeva et al. (2021) further support this, showing that AI applications, especially in data mining, enhance the identification of suspicious transactions. Polishchuk (2023) complements this view by positioning fintech innovations as crucial in the future landscape of AML.

AI is fundamentally reshaping the fight against financial crime in Europe. While AML services are becoming more effective through AI-driven compliance tools, criminal actors simultaneously exploit the same technologies to subvert controls. The trajectory of AI’s role in AML will depend on regulatory advances, ethical implementation, and continuous strategic innovation. Cross-sector collaboration will be vital to ensuring that AI remains a safeguard of financial integrity rather than a conduit for criminal innovation.

METHODS

This research aimed to assess the role of AI in AML efforts across selected European countries with available AI Vibrancy Score data. It assesses whether AI primarily benefits

AML services or if organised criminals exploit it to enhance money laundering techniques. The research sought to provide empirical evidence on AI's impact using statistical modelling.

Aligned with the aim of the investigation, this research tests the following hypotheses:

H1: AI vibrancy positively influences AML effectiveness in European countries with available AI data. Countries with higher AI adoption tend to exhibit lower Basel AML Index values, indicating stronger AML frameworks.

H2: The relationship between AI vibrancy and AML effectiveness follows an inverted U-shaped pattern. While moderate AI adoption enhances AML effectiveness, excessive AI adoption may facilitate financial crime automation.

H3: Stronger governance frameworks enhance AI's positive impact on AML. Countries with higher Rule of Law and Control of Corruption scores demonstrate better AML performance when leveraging AI technologies.

H4: Public opinion on AI and responsible AI governance influence AI's effectiveness in AML. Negative public sentiment toward AI and excessive regulatory burdens may hinder AI-driven AML progress.

These hypotheses guide the study's empirical investigation, comparing findings with existing literature to assess AI's role in financial security.

Research Design

This study utilises a quantitative methodology to assess the influence of AI on AML efforts in Europe. Specifically, it investigates whether AI is a tool that primarily benefits AML services or organised criminals. The study utilises a panel data econometric model to analyse cross-country variations in AI adoption, regulatory frameworks, and money laundering risks.

Data Sources

The analysis draws on multiple secondary data sources, including the Basel AML Index (Basel Institute on Governance), as the predicted variable measuring AML effectiveness. Predictors include the AI Vibrancy Score, its subindices from Stanford University, and economic and governance indicators from the World Bank. The dataset spans multiple European countries over a specified time period, allowing for a robust panel analysis.

Countries and Time Span

The analysis covers the period from 2017 to 2023 and includes European countries for which AI Vibrancy Score data is available. The study is limited to countries with complete records on AI vibrancy, governance indicators, and economic variables. These include Austria, Belgium, Denmark, Estonia, Finland, France, Germany, Ireland, Italy, Luxembourg, Netherlands, Norway, Poland, Portugal, Spain, Sweden, Switzerland, Turkey, and the United Kingdom. The selection ensures comparability across nations and allows for a robust panel data analysis.

Variables and Measurement

Table 1 presents the predictors and predicted variables utilised in the study.

Table 2 states a summary of the key statistics for these variables. These statistics help to see how different countries compare and spot trends in the data.

The summary statistics in Table 2 highlight that countries differ widely in their AI capabilities, governance structures, and AML performance. These disparities suggest that a universal solution to AI-driven AML measures may not be effective and that regulatory strategies should be tailored based on each country's technological capacity and governance quality. The AI Vibrancy Score (x1) shows a wide range of values across European countries, indicating significant differences in AI development and adoption. The Basel AML Index (y1) also exhibits variation, suggesting that the effectiveness of AML measures differs across nations.

Table 1. Variables and their sources

Variable	Description	Source
	Dependent variable	
y1	Basel AML Index	Basel Institute on Governance, n.d.
	Independent variable	
x1	AI Vibrancy Score	Stanford University, n.d.
x2	GDP per capita (constant 2015 US$)	World Bank, n.d.
x3	Rule of Law: Estimate (Normalised)	World Bank, n.d.
x4	Control of Corruption: Estimate (Normalised)	World Bank, n.d.
	AI Vibrancy subindexes	
x5	R&D	Stanford University, n.d.
x6	Responsible AI	Stanford University, n.d.
x7	Economy	Stanford University, n.d.
x8	Education	Stanford University, n.d.
x9	Policy and Government	Stanford University, n.d.
x10	Public Opinion	Stanford University, n.d.
x11	Infrastructure	Stanford University, n.d.

Table 2. Summary statistics [Source: authors calculation in R Studio]

Variable	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
x1	1,2	4,03	5,74	6,186	7,97	15,68
x2	0	0,115	0,32	0,6222	0,86	4,45
x3	0,07	0,53	1,32	2,155	2,89	12,08
x4	0,000001	0,38	0,78	1,359098	1,98	4,9
x5	0,000001	0,19	0,65	1,426241	1,82	9,05
x6	0,04	0,355	0,62	1,927	1,123	78
x7	0,1	0,77	1,2	2,085	1,96	13,15
x8	2,55	8,22	13,04	14,19	18,64	46,85
y1	2,34	3,67	4,21	4,184	4,57	6,65
x9	11954	28292	44862	47815	55935	110426
x10	0,3976	0,7224	0,8054	0,7664	0,8536	0,9069
x11	0,3995	0,6613	0,8137	0,7848	0,9019	0,9805

GDP per capita (x2) varies significantly, with some countries having much higher economic performance than others. Rule of Law (x3) and Control of Corruption (x4) demonstrate variations, highlighting differences in governance quality, which could impact AML effectiveness.

Factors like Responsible AI (x6) and Public Opinion (x10) show disparities across countries, indicating that ethical AI considerations and societal trust in AI play varying roles in different jurisdictions. Education (x8) and Infrastructure (x11) present significant gaps, suggesting that some countries may struggle to implement AI-driven AML systems effectively.

Data Analysis

The study employs panel regression models using R Studio to estimate the relationship between AI adoption and AML effectiveness. Both fixed and random effects models are estimated to control for country-specific unobservable factors. The Hausman test determines the appropriate model selection. Additional econometric diagnostics, including tests for heteroskedasticity, serial correlation, and cross-sectional dependence, ensure model robustness. Driscoll-Kraay standard errors are applied to address potential violations of classical regression assumptions.

Model Specification

The baseline regression model is specified as follows:

$$y_{it} = \alpha + \beta_1 x1_{it} + \beta_2 x2_{it} + \beta_3 x3_{it} + +\beta_4 x4_{it} + \epsilon_{it}, \qquad (1)$$

Where:

y_{it} – represents the Basel AML Index for the country at the time,

$x1_{it}$ – $x4_{it}$ – are independent variables measuring AI adoption and governance indicators,

ϵ_{it} – is the error term capturing unobserved factors.

A quadratic term for AI Vibrancy Score (x1) is also included to test for nonlinear relationships between AI adoption and AML effectiveness.

Expected Contributions

This methodology provides a rigorous empirical framework to analyse the dual role of AI in AML operations. By integrating economic and governance indicators, this study provides a holistic perspective on AI's role in combating European financial crime. The findings will help solve the policy debates on AI regulation and enhancing AML strategies.

RESULTS

In the first analysis stage, the one-way individual effects within the model (fixed effects model) are estimated. This model accounts for time-invariant differences across entities (countries) by removing individual-specific effects. This method accounts for country-specific factors that remain constant over time, allowing for the isolation of the independent variables' impact on the dependent variable.

The overall model is statistically significant, as indicated by the F-statistic of 12.31 and a p-value of 2.64e-08, which is well below the 0.05 threshold. Although the R-squared suggests that the outputs clarify a moderate amount of the variation in the Basel AML Index, the F-statistic confirms that the independent variables, when considered collectively, Exert a statistically significant impact on the predicted variable.

The random effects model using Swamy-Arora's transformation considers both cross-sectional influences and time-dependent variations, treating individual-specific effects as random variables rather than fixed constants.

The R-squared is relatively low, suggesting the model justifies only a tiny portion of the variation in the Basel AML Index. However, the overall Chi-Square test suggests that the combined consequence of the independent variables is statistically significant.

The Hausman test helps determine whether a fixed or random effects model is more suitable for panel data analysis. The null hypothesis is rejected because of the extremely low p-value (0.0001). This indicates that the fixed effects model is preferable, as there is evidence of a correlation between individual-specific effects and the independent variables.

The Pesaran CD test for cross-sectional dependence in the panel data ($z = 1.4799$, p-value = 0.1389) does not provide support for cross-sectional dependence at the 5% significance level. This indicates that the residuals across different countries are not significantly related, which aligns with the expectations underpinning the fixed effects model.

Similarly, the Studentized Breusch-Pagan test (BP = 2.2698, df = 4, p-value = 0.6863) fails to disprove the null hypothesis, indicating the absence of heteroskedasticity in the panel data model. This result implies that the variation of the residuals remains constant within observations, a characteristic that is favourable for the fixed effects model.

Wooldridge's test for serial correlation in fixed effects panels ($F = 32.894$, df1 = 1, df2 = 112, p-value = <0.0001) rejects the null hypothesis, indicating the existence of serial correlation (autocorrelation) in the panel data. Failure to justify autocorrelation may result in inefficient and biased standard errors, undermining the reliability of the regression results. Thus, employing Driscoll-Kraay standard errors is advised, as they enhance robustness against heteroskedasticity, serial correlation, and cross-sectional dependence. The fixed effects panel model results, adjusted with Driscoll-Kraay standard errors to mitigate these concerns, are displayed in Table 3.

The estimated coefficients represent the effect of each predictor on the predicted variable (Basel AML Index) while holding all other predictors constant. The standard errors have been modified to address autocorrelation, heteroskedasticity, and cross-sectional dependence, ensuring reliable inference.

A one-unit raise in the AI Vibrancy Score is linked with a 0.0288 decrease in the Basel AML Index, ceteris paribus. Similarly, a one-unit growth in GDP per capita relates to a 0.0000579 reduction in the Basel AML Index. Conversely, a one-unit growth in the normalised Rule of Law Estimate relates to a 13.613 rise in the Basel AML Index. Additionally, a one-unit growth in the Control of Corruption Estimate is linked to a 2.5441 decline in the Basel AML Index, though this cause is only marginally substantial at the 10% level.

Table 3. The outputs of the fixed effects panel model using Driscoll-Kraay standard errors to account for heteroskedasticity, serial correlation, and cross-sectional dependence [Source: authors calculation in R Studio]

Oneway (individual) effect Within model
Note: Coefficient variance-covariance matrix supplied: vcovSCC
Call: plm(formula = y1 ~ x1 + x2 + x3 + x4, data = pdata, model = "within", index = c("id", "year"))
Balanced Panel: n = 19, T = 7, N = 133

Residuals:

Min.	1st Qu.	Median	3rd Qu.	Max.	
	-0.686290	-0.177495	0.013016	0.165502	0.836380

Coefficients:

	Estimate	Std. Error	t-value	Pr(>|t|)
x1	-2.8785e-02	4.5029e-03	-6.3925	<0.0001***
x2	-5.7895e-05	1.4945Є-05	-3.8738	0.0001824***
x3	1.3613e+01	2.6087e+00	5.2183	<0.0001***
x4	-2.5441e+00	1.3685e+00	-1.8591	0.0656897.

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Total Sum of Squares: 16.642
Residual Sum of Squares: 11.498
R-Squared: 0.30913 Adj. R-Squared: 0.17096
F-statistic: 77.14 on 4 and 6 DF, p-value: <0.0001

The AI Vibrancy Score (x1), GDP per capita (x2), and Rule of Law (x3) exhibit statistically significant effects on the Basel AML Index at the 0.001 significance level. In contrast, Control of Corruption (x4) is only marginally significant, suggesting a potential negative association with the Basel AML Index, though the statistical evidence remains relatively weak.

The model describes around 30.9% of the deviation in the Basel AML Index, which is a reasonable explanatory power for social and economic panel data. The F-statistic indicates that the predictors collectively have a statistically significant impact on the predicted variable.

Notably, in both the fixed and random effects models, the coefficient of the AI Vibrancy Score changes from positive to negative. This shift suggests the possibility of a U-shaped relationship between the AI Vibrancy Score and the Basel AML Index. To explore this potential nonlinearity, Figure 1 presents a plot visualising the relationship between these variables, with a quadratic regression line (in blue) to assess whether the association follows a U-shaped or inverted U-shaped pattern.

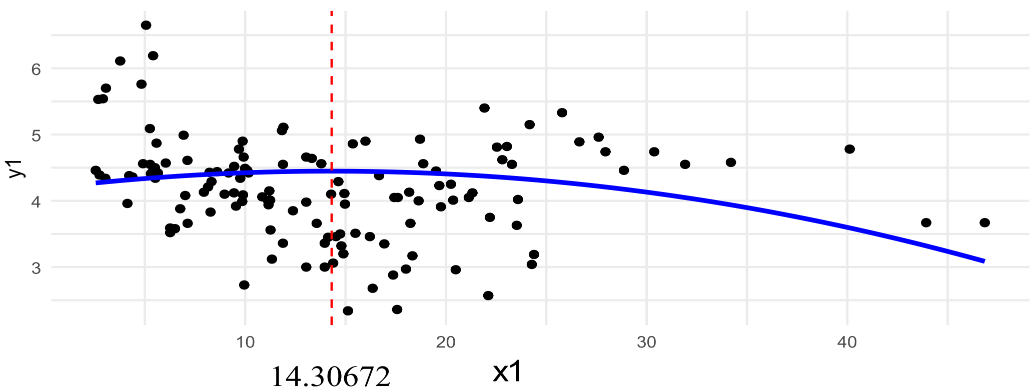

Figure 1. The relationship between the AI Vibrancy Score and the Basel AML Index [Source: authors calculation in R Studio]

The curve exhibits a downward-sloping trend as x1 increases, indicating that higher AI Vibrancy Scores are associated with lower Basel AML Index values. Rather than a U-shaped pattern, the curve follows an inverted U-shape (concave downward), suggesting that the effect of x1 diminishes as its value increases.

The red dashed vertical line represents the turning point, marking the threshold where the effect of x1 transitions from slightly positive or neutral to negative. This turning point occurs at 14.30672 on the x1 scale, implying that beyond this level of AI Vibrancy Score, the Basel AML Index declines more sharply. The data points exhibit considerable dispersion, particularly at higher levels of x1, indicating variability in the relationship at higher AI vibrancy levels.

Table 4 reports the fixed effects panel model outputs, incorporating a quadratic term for x1 to formally assess the presence of a U-shaped or inverted U-shaped relationship. The application of Driscoll-Kraay standard errors ensures robustness against heteroskedasticity, serial correlation, and cross-sectional dependence, enhancing the reliability of the estimates.

Table 4. The fixed effects panel model outputs incorporate a quadratic term for AI Vibrancy Score
[Source: authors calculation in R Studio.]

Oneway (individual) effect Within model
Note: Coefficient variance-covariance matrix supplied: vcovSCC
Call:
plm(formula = y1 ~ x1 + I(x1^2) + x2 + x3 + x4, data = pdata, model = "within", index = c("id", "year"))
Balanced Panel: n = 19, T = 7, N = 133

Residuals:

Min.	1st Qu.	Median	3rd Qu.	Max.
-0.7434670	-0.1635350	0.0054556	0.1456341	0.9522636

Coefficients:

	Estimate	Std. Error	t-value	Pr(>|t|)
x1	3.6776e-02	2.7259e-02	1.3491	0.1800938
I(x1^2)	-1.2853e-O3	5.0167e-04	-2.5620	0.0117734*
x2	-4.9880e-05	1.2359e-05	-4.0359	0.0001013***
x3	1.2542e+01	2.5021e+00	5.0125	<0.0001***
x4	-3.6096e+00	1.1443e+00	-3.1546	0.0020776***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Total Sum of Squares: 16.642
Residual Sum of Squares: 10.817
R-Squared: 0.35006
Adj. R-Squared: 0.21292
F-statistic: 87.41 on 5 and 6 DF, p-value: <0.0001

The linear term of the AI Vibrancy Score is positive but not statistically significant. However, the quadratic term is negative (-0.00129) and statistically significant (p-value = 0.0118, which is less than 0.05), indicating the presence of an inverted U-shaped relationship. This suggests that as the AI Vibrancy Score (x1) increases, the Basel AML Index (y1) initially rises but eventually declines after surpassing a certain threshold.

The model explains 35.01% of the variation in the Basel AML Index, with an adjusted R^2 of 0.2129. An F-statistic of 87.41 and a corresponding p-value of <0.0001 confirm the model's overall statistical significance.

The lower bound slope (0.02112449) is not statistically significant (p-value = 0.3762162), indicating that the evidence for a classic inverted U-shaped relationship remains inconclusive. However, the significant negative slope (-0.06635444, p-value = 0.02860431) at the upper bound, along with the significant negative quadratic term, supports the presence of a downward-sloping curve as x1 increases.

For low-to-moderate levels of the AI Vibrancy Score (x1), changes in x1 do not significantly impact the Basel AML Index (y1). However, once x1 surpasses the turning point (~14.30672), further increases in AI Vibrancy Score result in a statistically significant decline in the Basel AML Index, suggesting improved AML outcomes. The significant negative slope at the upper bound indicates that higher AI vibrancy is associated with better AML performance.

Model selection criteria further support the quadratic specification. The U-shaped model has a lower Akaike Information Criterion (AIC: -323.73 vs. -317.61), indicating a better predictive fit while accounting for model complexity. Additionally, the U-shaped model has a lower Bayesian Information Criterion (BIC: -309.28 vs. -306.05), suggesting it achieves a more optimal balance between model complexity and explanatory power. Based on both AIC and BIC, the fixed effects model with the U-shaped specification is preferred, as it better captures the variation in the Basel AML Index while accounting for the nonlinear relationship with the AI Vibrancy Score.

The extracted individual fixed effects (α_i) from the quadratic fixed effects panel model represent country-specific deviations in y1 that are not explained by the included independent variables (Table 5). These independent variables include the AI Vibrancy Score (x1, $x1^2$), GDP per capita (constant 2015 US$) (x2), the normalised Rule of Law Estimate (x3), and the normalised Control of Corruption Estimate (x4). These fixed effects allow cross-country comparisons by capturing unobserved country-specific factors that influence the dependent variable, such as institutional frameworks and policy environments. By accounting for country-specific heterogeneity, the fixed effects model ensures that the estimated effects of the independent variables remain unbiased.

Table 5. The individual fixed effects from a fixed-effects model incorporate a quadratic term for AI Vibrancy Score [Source: authors calculation in R Studio]

Country	Individual fixed effects
Austria	-1.484782
Belgium	-0.647630
Denmark	-1.120977
Estonia	-3.106627
Finland	-2.911705
France	-1.195109
Germany	-0.680832
Ireland	1.499302
Italy	1.226249
Luxemburg	2.816415
Norway	-0.360039
Netherlands	-0.594415
Poland	-0.062049
Portugal	-1.719024
Spain	-0.944857
Sweden	-1.400186
Switzerland	1.476060
Turkey	2.741532
United Kingdom	-0.830971

Certain countries, such as Luxembourg (2.816) and Turkey (2.741), exhibit positive fixed effect values, indicating that their Basel AML Index is higher than expected based on their AI Vibrancy Score, GDP per capita, and indicators of the Rule of Law and Control of Corruption. This suggests that unobserved country-specific factors may contribute to heightened susceptibility to money laundering in these nations.

Conversely, another group of countries demonstrates negative fixed effect values, suggesting that their Basel AML Index is lower than predicted given the same set of explanatory variables. For instance, Austria (-1.484782) and Estonia (-3.106627) exhibit negative deviations, indicating a mitigating effect on money laundering risks beyond what is captured by the observed variables. Among these, Estonia (-3.106627) and Finland (-2.911705) have the most considerable adverse fixed effects, implying that unobserved country-specific characteristics contribute to more favourable AML outcomes.

Countries with fixed effect values close to zero, such as Poland (-0.062049), exhibit only minor deviations from the expected Basel AML Index, suggesting that unobserved factors play a relatively minimal role in influencing their AML risk beyond what is explained by the included independent variables.

The scatter plot (Figure 2) compares the estimated fixed effects from the linear and quadratic models. Each point represents a country, with its position indicating how the fixed effects change when incorporating a quadratic term in the regression. The red dashed line represents the 45-degree line, where points lying directly on it indicate no difference between the fixed effects in the two models.

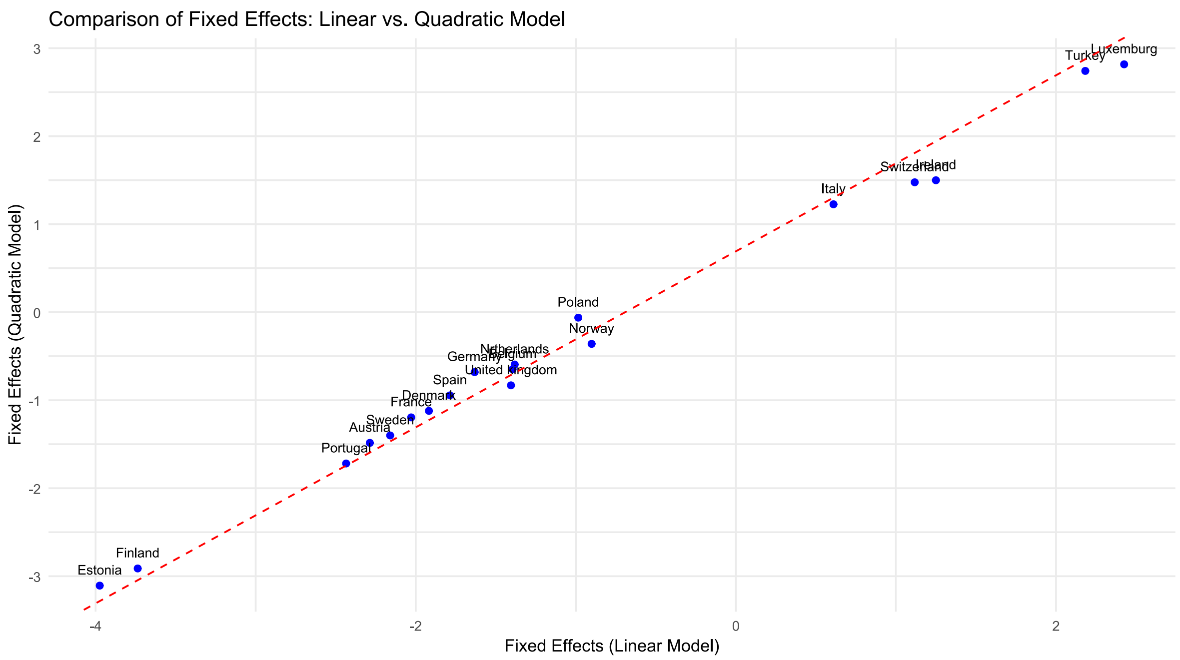

Figure 2. Comparing the estimated fixed effects from the linear model and the quadratic model.
[Source: authors calculation in R Studio]

Countries positioned above the red dashed line have higher fixed effects in the quadratic model than in the linear ones. This suggests that their country-specific effects on the Basel AML Index increase when accounting for the quadratic term. Both models have the most negative fixed effects in Estonia and Finland, indicating that their unobserved factors contribute to significantly lower Basel AML Index scores (i.e., better AML performance).

Conversely, countries below the red dashed line have lower fixed effects in the quadratic model than in the linear ones, meaning their country-specific effects decrease when the quadratic term is included. Turkey, Switzerland, and Italy have high positive fixed effects, meaning their unobserved characteristics contribute to higher Basel AML Index values (i.e., worse AML performance).

Countries such as Poland, Norway, and the Netherlands have fixed effects close to zero, indicating that unobserved factors play a minimal role in influencing their AML risk beyond what the included predictors justify.

The next stage of the analysis tests how each AI Vibrancy sub-index (x5 to x11) influences the Basel AML Index (y1) by using fixed effects panel regressions for each subindex. The estimation outputs are presented in Table 6.

Table 6. One-way (individual) effect Within Models with coefficient variance-covariance matrix supplied [Source: authors calculation in R Studio]

Variable	Estimate (Pr(>|t|))	R-Squared	Adj. R-Squared	F-statistic (p-value)
x5 $x5^2$	-0.0207261 (0.6386) 0.0021520 (0.5380)	0.010867	-0.34882	3.51268 (0.16369)
x6 $x6^2$	-0.3742417*** (0.0001024) 0.0904481*** (< 0.0001)	0.15307	-0.1549	400.339 (0.00022807)
x7 $x7^2$	0.152712*** (<0.0001) -0.017457*** (2.232e-14)	0.21695	-0.067793	60.5986 (0.0037542)
x8 $x8^2$	-0.174697. (0.0738) 0.019153 (0.2255)	0.068819	-0.26979	22.8717 (0.015269)
x9 $x9^2$	0.0245731 (0.50181) -0.0134929* (0.04857)	0.14544	-0.16531	44.705 (0.0058493)
x10 $x10^2$	0.54801835*** (<0.0001) -0.00694722*** (<0.0001)	0.23413	-0.044364	425.209 (0.00020842)
x11 $x11^2$	0.0403846 (0.6301) -0.0036423 (0.6326)	0.012968	-0.34595	0.131622 (0.88147)

Note: Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

The findings specify that Research and Development (R&D) in AI (x5) and Infrastructure (x11) does not have a significant impact on AML risk, while AI-related education demonstrates only a weak effect. Conversely, Responsible AI (RAI) (x6) exhibits an inverted U-shaped relationship with the Basel AML Index, suggesting that its influence on AML risk varies across different levels of AI governance.

Responsible AI is evaluated through academic research output in leading AI ethics and fairness conferences, including the AAAI, AIES, FAccT, ICLR, ICML, and NeurIPS conferences. Higher conference submission rates reflect a more substantial national commitment to AI ethics, fairness, governance, and transparency. The model's results suggest that at low levels of Responsible AI governance, AML risk increases due to the absence of AI ethics frameworks. Without these frameworks, financial systems remain vulnerable to AI-driven illicit activities and lack regulatory oversight.

At moderate levels of Responsible AI governance, AML risk peaks due to several factors. Regulatory uncertainty and compliance burdens slow down AML implementation, while overregulation can hinder AI adoption for financial crime prevention. In this phase, AI ethics debates and legal frameworks often create unclear or overly restrictive guidelines, impeding the ability of financial institutions to deploy AI-driven AML tools effectively.

In contrast, at high levels of Responsible AI governance, AML risk declines significantly. This reduction is attributed to the successful integration of AI governance within financial and regulatory systems. AI-driven transparency and automation improve AML compliance at this stage, while well-defined AI ethics frameworks enhance public and institutional trust in digital financial regulations.

Developing economies often lack comprehensive AI ethics frameworks, challenging regulating AI-powered financial systems. This regulatory gap heightens vulnerabilities to money laundering activities, as financial institutions operate without clear guidelines on AI governance. The Financial Action Task Force (FATF) has detected numerous countries with significant weaknesses in AML and counter-terrorist financing measures (FATF, 2021; The Law Society, 2024).

In contrast, Western economies, particularly within the European Union (EU), have engaged extensively in regulatory efforts concerning AI ethics. The EU AI Act, introduced in 2021, aims to establish a comprehensive AI development and implementation framework, emphasising privacy, transparency, and fairness as foundational principles. However, the complexity and stringency of these regulations have introduced compliance challenges for financial institutions. The evolving nature of these regulations has delayed the adoption of AI-driven AML technologies as financial institutions struggle to navigate an increasingly intricate regulatory landscape (EPRS, 2020; Pattara, 2023).

Meanwhile, some nations have proactively developed advanced AI governance frameworks that successfully balance AI innovation with regulatory oversight. For example, Singapore's Monetary Authority of Singapore released the Artificial Intelligence Model Risk Management Paper in December 2024, providing financial institutions with detailed guidance on managing AI-related risks. Such governance initiatives enable these countries to integrate AI-driven compliance tools effectively, enhancing their capability to identify and mitigate financial crime risks (Clyde & Co, 2024).

These findings highlight the importance of a well-balanced AI governance approach. While the absence of AI-specific regulations exacerbates financial crime risks, excessive regulatory complexity may hinder AI adoption for AML purposes. Countries that successfully integrate AI ethics into financial regulatory frameworks experience lower AML risks, demonstrating the necessity of a structured yet flexible approach to AI governance.

The relationship between AI economic activity (x7) and AML risk exhibits a nonlinear pattern, initially increasing AML risk before mitigating it at higher levels of AI adoption. In regions with low AI economic activity, AML risk remains relatively low due to the limited integration of AI technologies within financial systems. This limited adoption restricts the prevalence of AI-powered financial crimes, with traditional financial crimes continuing to dominate the AML landscape. The effectiveness of manual compliance efforts and low AI hiring rates further limit criminals' access to advanced AI tools. Developing economies face infrastructural challenges and a shortage of skilled professionals, constraining AI adoption. The FATF (2021) links these challenges to operational and regulatory limitations, such as obsolete AML/CFT compliance systems and inflexible regulatory structures. Consequently, the AML risk in these regions is predominantly driven by conventional issues such as lack of transparency and corruption.

At moderate levels of AI economic activity, AML risk reaches its peak as the increasing accessibility of AI technologies facilitates their misuse for money laundering purposes while regulatory frameworks lag behind. The proliferation of AI-powered tools enables automated fraud and synthetic identity laundering through AI-generated fake accounts and deepfake-based scams. Additionally, AI-assisted money laundering via untraceable transactions in cryptocurrencies and digital banking further exacerbates AML risks. AI-driven trading bots are increasingly employed to automate high-frequency trading activities, which can be exploited to obscure the Source of illegal proceeds through rapid and complex transactions. Cryptocurrency mixers and tumblers add another layer of complexity by pooling and redistributing funds, making it more difficult to trace their sources. This convergence of AI-driven automation and anonymisation services poses significant challenges to traditional AML compliance systems, which often struggle to match the sophistication and speed of these technologies (Merkle Science, 2022).

Fraudsters also increasingly leverage generative AI technologies to create highly realistic synthetic identities that bypass conventional identity verification processes. These AI-generated personas enable the opening of fraudulent accounts and facilitate unlawful monetary transactions. The Financial Crimes Enforcement Network (FinCEN) has reported that malicious actors are utilising generative AI to produce fake identification documents and deepfake media, allowing them to circumvent financial institutions' due diligence and verification controls. This rapid evolution in AI-generated fraud outpaces the development of traditional AML compliance measures, intensifying AML risks in the financial sector (Larson, 2024).

However, at high levels of AI economic activity, AML risk declines as AI-driven compliance tools become more sophisticated and regulatory frameworks adapt. Advanced AI technologies, such as deep learning algorithms, enhance real-time fraud detection and anomaly identification. AI-powered Know Your Customer models improve the detection of synthetic identity fraud, while regulatory technology (RegTech) solutions automate AML compliance reporting across jurisdictions. In Switzerland, financial institutions have widely adopted AI-based fraud detection solutions, with NetGuardians – a leading Swiss fintech firm—providing AI-driven services to 60% of Swiss state-owned commercial banks (The Swiss Startup News Channel, 2024). Similarly, Basu and Tetteh (2024) report that financial institutions in the UK and EU are increasingly implementing AI-powered transaction monitoring systems. These systems leverage machine learning and data analytics to identify suspicious activities more efficiently, improving the identification and prevention of money laundering. The study highlights that such AI-driven solutions enable faster processing, more accurate analysis, and improved compliance outcomes, ultimately contributing to reduced fraud and strengthened AML practices.

The effectiveness of policy and government intervention (x9) in AI-driven AML efforts follows an inverted U-shaped pattern, indicating the necessity of achieving an optimal regulatory balance. Weak AI governance creates significant vulnerabilities, allowing financial criminals to exploit regulatory gaps. The FATF (2021) has emphasised that the absence of AI-specific regulations in certain jurisdictions, particularly offshore financial centres, facilitates cybercriminal activities. The FATF underscores the importance of comprehensive AI-focused AML measures to mitigate these risks and strengthen financial crime detection and prevention.

Conversely, excessive regulation and fragmented AI legal frameworks generate uncertainty, hindering the adoption of AI-driven AML solutions. While introducing stringent AI regulations, the European Union's AI Act (2021–2024) has faced challenges in enforcement, leading to delays in AI integration within AML systems. Gikay (2024) notes that the AI Act's elevated risk categorisation framework may be overly restrictive, potentially limiting the implementation of AI in key domains such as AML compliance. Similarly, Canada's Artificial Intelligence and Data Act (AIDA) has established stringent regulatory requirements for AI applications. Although designed to ensure responsible AI usage, these regulations have inadvertently introduced compliance challenges for financial institutions. The complexity and novelty of these requirements have created uncertainty, slowing the implementation of AI-enhanced AML measures. Research by Sheikh and Garellek (2024) further suggests that the rapid introduction of AI legislation, without clear implementation guidelines, can lead to compliance ambiguities, ultimately impeding the integration of AI technologies in financial crime prevention.

AI-powered AML systems operate most effectively within a well-structured and harmonised regulatory framework. Switzerland's Financial Market Supervisory Authority has taken a proactive approach by issuing comprehensive guidelines to facilitate the integration of AI in financial crime prevention. In December 2024, FINMA published Guidance 08/2024, which mandates that financial institutions establish robust governance and risk management frameworks when incorporating AI into their operations. This guidance addresses key risks associated with AI adoption, including model robustness, data quality, and explainability, thereby enhancing the efficacy of AI-powered anti-money laundering systems. By adhering to these regulatory principles, Swiss financial bodies can ensure their AI applications comply with supervisory opportunities, strengthening their ability to combat financial crimes while ensuring regulatory compliance (FINMA, 2024).

The relationship between public opinion on AI – measured by social media share of voice on AI, AI-related social media posts, and net sentiment in AI discussions – and AML risk follows a U-shaped pattern. Limited public discourse on AI results in low societal awareness of AI-related risks and regulatory shortcomings. In such cases, weak civil society advocacy contributes to underdeveloped AI governance, enabling unchecked AI-driven money laundering. Additionally, the absence of public pressure on financial institutions leads to the slow adoption of AI-powered AML solutions. Sampat et al. (2024) highlight that the rapid integration of AI in financial services, particularly in regions with low public awareness and weak regulatory oversight, raises ethical concerns and increases the potential for misuse. The study underscores that financial institutions may implement AI-driven systems without adequately considering transparency and accountability, further emphasising the necessity of increased public engagement and regulatory guidance to ensure ethical AI deployment in financial crime prevention.

A balanced public discourse on AI fosters transparency, regulatory pressure, and the adoption of AI-driven AML mechanisms. Public advocacy for responsible AI governance encourages governments to implement AI-centric AML policies. At the same time, financial institutions respond to societal expectations by integrating ethical AI principles and compliance mechanisms into their operations.

However, excessive social media discourse on AI can lead to misinformation, fear, and distrust, ultimately hindering the adoption of AI-driven AML technologies. Public scepticism and resistance to AI-powered financial systems slow down technological advancements in AML enforcement, while regulatory decisions become increasingly politicised, further delaying the implementation of AI-based compliance solutions. Longoni et al. (2022) examine how consumer perceptions of AI are shaped by social media discourse, particularly regarding concerns related to AI bias, job displacement, and data privacy. Their findings indicate that exposure to negative narratives about AI on social media fosters public resistance to AI applications, including those used in AML enforcement. This resistance is primarily driven by heightened scepticism and fear, undermining trust in AI-driven financial systems. The study highlights the importance of addressing public concerns and counteracting misinformation to facilitate the acceptance and successful application of AI technologies in the financial sector.

The findings support the hypothesis that AI vibrancy significantly affects AML effectiveness in the selected European countries. The results confirm H1, showing that an increase in AI Vibrancy Score is associated with lower Basel AML Index values, indicating improved AML performance. However, the quadratic term for AI Vibrancy Score supports H2, demonstrating that the relationship follows an inverted U-shaped pattern—suggesting that while AI initially strengthens AML measures, excessive AI integration may provide tools that criminals can exploit for financial crime automation.

The governance factors provide further insight into the role of regulation in AML effectiveness. The Rule of Law (x3) coefficient is highly significant and positively correlated with AML success, confirming H3 – strong legal frameworks enhance AI’s effectiveness in combating money laundering. Similarly, Control of Corruption (x4) is positively associated with AML effectiveness, albeit with a slightly lower coefficient, reinforcing that governance structures influence AI’s role in AML operations. Furthermore, the study confirms H4, indicating that public opinion on AI (x10) and Responsible AI governance (x6) impact AML efficiency. Countries with a well-regulated AI ecosystem and positive AI perception tend to have better AML outcomes, while excessive restrictions or negative sentiment towards AI can hinder AML progress.

DISCUSSION

The results of this study offer important perspectives on the dual role of AI in the realm of AML and financial crime. By analysing the link between AI adoption and AML efficiency across European countries, this study builds upon existing literature and extends insight into AI's influence on financial security.

The outputs indicate that AI vibrancy has a significant, yet complex, relationship with AML effectiveness. The fixed effects model suggests higher AI vibrancy scores correlate with lower Basel AML Index values, implying improved AML outcomes. However, the quadratic model reveals an inverted U-shaped relationship, where AI initially contributes to AML effectiveness but may later enhance financial crime sophistication. This is in line with the conclusions of Reshetnikova and Mikhaylov (2023) and Yarovenko et al. (2024b), who highlight AI's ability to automate illicit transactions and optimise money laundering tactics.

The significance of governance-related variables, such as the Rule of Law and Control of Corruption, suggests that institutional quality is critical in determining AI's impact on AML. Our results support Zámek and Zakharkina (2024) and Tiutiunyk et al. (2021), who emphasise the need for regulatory adaptation to digital transformation. However, our findings diverge from Letkovsky et al. (2023), who argue that AI primarily benefits financial security rather than criminals. The data suggests that AI-driven financial crime flourishes in countries with weaker regulatory frameworks, undermining AML efforts.

This study identifies GDP per capita as a significant predictor of AML effectiveness, reinforcing prior research by Ioan-Franc & Gaf-Deac (2024) and Košovská et al. (2022), which link digitalisation and economic growth to financial security. However, our results also show that economic prosperity alone is insufficient – without robust regulatory mechanisms, AI’s benefits in AML may be counteracted by its exploitation by criminal organisations. This finding supports Yarovenko et al. (2023), who suggest that the socioeconomic context of a country influences its vulnerability to AI-driven financial crime.

One of the key findings is that Responsible AI governance (x6) exhibits an inverted U-shaped relationship with AML effectiveness. This suggests that moderate levels of AI governance may introduce regulatory complexities, delaying AML advancements, whereas highly structured AI frameworks enhance financial security. This finding is consistent with Memarian & Doleck (2024) and Gikay (2024), who caution that excessive regulation can hinder AI adoption for compliance purposes. Additionally, public opinion on AI (x10) follows a U-shaped pattern, reinforcing the work of Longoni et al. (2022), who highlight how negative AI discourse can create public distrust in AI-driven AML measures.

The study's findings suggest that AI-driven AML efforts must be continually adapted to counteract evolving money laundering tactics. The evidence supports Neacsu et al. (2025), who view AI as a geopolitical tool influencing global financial security. Additionally, Kuzior et al. (2024) emphasise that cybersecurity threats linked to AI-driven financial crime must be mitigated through international cooperation.

The findings demonstrate that AI has a dynamic and evolving impact on AML, acting as both a tool for regulatory agencies and an asset for organised criminals. While AI vibrancy enhances AML capabilities, its misuse by criminals remains a significant challenge. Future research should explore how AI regulation, financial policies, and global cooperation can further optimise AI's role in combating financial crime.

LIMITATIONS

Although this study offers important insights into the connection between AI and AML effectiveness, certain limitations must be recognised.

The investigation relies on secondary data from sources such as the Basel AML Index, Stanford AI Vibrancy Score, and World Bank governance indicators. Although these sources are widely recognised, discrepancies in data collection methods and reporting standards across countries may introduce inconsistencies. Additionally, some countries may lack comprehensive AI-related data, leading to potential gaps in the analysis.

The panel regression models assume a linear or quadratic relationship between AI vibrancy and AML effectiveness. However, AI's impact on financial crime may be more complex and nonlinear, influenced by country-specific regulatory environments, economic conditions, and technological adoption rates. Future research should explore alternative modelling methods, such as machine learning or dynamic panel models, to better capture these complexities.

AI technology evolves rapidly, and this study analyses data from a specific timeframe. As new AI advancements emerge, the effectiveness of AML measures may change. The study's findings may not fully capture how AI's role in AML will evolve in the future. Longitudinal studies with updated datasets will be necessary to track AI's impact over time.

Regulatory frameworks for AI usage in AML are still developing, and ethical concerns such as bias in AI-driven fraud detection systems remain unresolved. This study does not account for ethical dilemmas or the potential unintended consequences of AI adoption in financial security, which should be a focus of future research.

The study primarily examines European countries, restricting the generalisability of its outputs to other territories. AI adoption and AML challenges may differ significantly in regions such as Asia, Africa, and Latin America, where financial infrastructures and regulatory frameworks vary widely. Future studies should consider a broader geographical scope to assess AI's impact on AML globally.

Recognising these limitations is crucial for accurately interpreting the study's findings cautiously. Regardless of these obstacles, the study offers a strong foundation for understanding AI's role in AML efforts and highlights areas for further investigation. Addressing these limitations in future studies will help refine AI-driven financial crime prevention strategies and improve AML effectiveness.

CONCLUSION

AI is increasingly shaping financial security, presenting both opportunities for AML efforts and challenges posed by sophisticated financial crime tactics. This research aimed to judge the role of AI in AML efforts across selected European countries with available AI Vibrancy Score data. It assesses whether AI primarily benefits AML services or if organised criminals exploit it to enhance money laundering techniques. The research sought to provide empirical evidence on AI's impact using statistical modelling.

A panel data econometric model was employed to achieve this, using the Basel AML Index as the dependent variable and AI Vibrancy Score, economic indicators, and governance measures as independent variables. The study analysed data from multiple European countries over a set period, applying fixed and random effects models, Hausman tests, and Driscoll-Kraay standard errors to ensure robust results.

The findings indicate that AI adoption significantly influences AML effectiveness, with higher AI vibrancy scores correlating with lower money laundering risks. However, the relationship follows an inverted U-shaped pattern, where excessive AI adoption may also aid financial crime automation. Governance factors, particularly the Rule of Law and Control of Corruption, play crucial roles in ensuring AI's positive contribution to AML. Additionally, public opinion on AI and responsible AI governance impact AML efficiency, demonstrating that both technological and regulatory elements must align to maximise AI's benefits while mitigating its risks.

The AI Vibrancy Score (x1) coefficient in the fixed effects model was negative (-0.0288) and statistically significant, confirming that increased AI vibrancy is generally associated with improved AML outcomes. However, including a quadratic term ($x1^2$) with a coefficient of -0.00129 suggests an inverted U-shaped dependence, meaning that while moderate AI adoption enhances AML effectiveness beyond a certain threshold, the benefits decline, and risks increase.

Moreover, the Rule of Law (x3) coefficient was highly significant (13.61), highlighting its strong positive effect on AML performance. The Control of Corruption (x4) coefficient showed a weaker but still relevant impact, reinforcing the necessity of strong governance frameworks. These results emphasise that AI alone is insufficient for AML's success—effective legal and regulatory measures are crucial in maximising AI's potential while mitigating its risks.

These insights highlight the need for balanced AI policies, stronger regulatory frameworks, and international cooperation to ensure AI remains a tool for financial security rather than a means of financial crime facilitation.

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