The FinTech-AI Nexus: A Paradigm Shift in Anti-Money Laundering Surveillance and Enforcement

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Abstract

This study examines how the convergence of FinTech capabilities and AI-driven solutions is reshaping Anti-Money Laundering (AML) surveillance and enforcement. Drawing on the Resource-Based View (RBV) and Institutional Theory (IT), it develops a framework to evaluate the role of technological capabilities and institutional pressures (IP) in strengthening AML outcomes. A theoretical model was constructed, and primary data will be collected from AML professionals, FinTech experts and compliance officers in the banking and financial services. SmartPLS 4.0 will be applied to test the hypotheses and validate the conceptual model. The study is expected to demonstrate that FinTech and AI capabilities significantly improve AML surveillance efficiency, which in turn enhances enforcement outcomes. Regulatory support is expected to strengthen the link between surveillance and enforcement, while institutional pressures may further drive the adoption of the technology. The study contributes to digital financial governance by identifying the key enablers and constraints in technology-driven AML practices. The findings provide actionable insights for regulators, financial institutions and technology developers, emphasising that while advanced technologies are crucial, effective regulatory support remains essential for maximising enforcement success and safeguarding financial integrity in the digital age.

Keywords

FinTech; artificial intelligence; anti-money laundering; regulatory support; digital financial governance.

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1 Introduction

The accelerating convergence of financial technology (FinTech) and artificial intelligence (AI) is transforming the global financial landscape, introducing both unprecedented efficiencies and new vulnerabilities.[1] Amongst the most pressing challenges in money laundering are those that threaten financial integrity, economic stability and institutional credibility. Traditional AML systems, largely rule-based and reactive, have struggled to keep pace with the evolving sophistication of financial crimes.[2] Their limited surveillance capabilities fail to detect hidden, network-based and real-time laundering patterns, leaving critical monitoring gaps and increasing systemic risk. This study addresses the important research question of how the integration of AI-driven FinTech solutions can enhance surveillance and enforcement, thereby creating a paradigm shift in AML practices.

The relevance of this study lies in its positioning at the intersection of financial governance, digital technology and regulatory compliance. As financial transactions become more digitised, decentralised and cross-border in nature, regulators and financial institutions face mounting pressure to adopt intelligent systems capable of real-time change detection, predictive analytics and adaptive enforcement.[3] The integration of FinTech innovations with AI-driven surveillance offers an avenue for strengthening AML efforts. While implementation is capital-intensive and operationally expensive in the short term, in the long run it can significantly reduce compliance costs and false positives, while enhancing accuracy and timeliness in enforcement.[4] By situating the research within the broader discourse on digital finance and regulatory technology, this study offers insights of immediate value to academics, industry practitioners and policymakers.

The study adopts a pragmatic approach grounded in structural equation modelling to test hypothesised relationships between FinTech capabilities, AI applications, Regulatory Support (RS), and AML enforcement outcomes. Data collected from compliance officers, financial services professionals

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1 Allioui and Mourdi 2023 *Sensors*.

2 Gandhi *et al* 2024 *International Journal on Smart Sensing and Intelligent Systems*.

3 Raza *et al* "Regulatory, Governance and Future Trends in the Financial System".

4 Saiyed 2025 *International Journal of Electrical and Computer Engineering Research*.

and FinTech experts enables the study to capture the structural enablers, institutional influences and managerial decisions shaping adoption across the regulatory, technological and organisational contexts within the AML ecosystem. This methodological design not only facilitates severe hypothesis testing but also helps bridge the gap between theoretical debates and real-world practices. Significantly, the study emphasises the need to integrate external pressures, internal competencies and cognitive judgments to better understand the multi-level dynamics of AML transformation in digital financial environments.

The significance of this research is twofold. From a practical perspective, it provides evidence-based insights into how financial institutions can leverage AI-powered FinTech tools to build more robust and cost-effective AML systems. From an academic standpoint, it addresses a clear gap in the literature, where studies on FinTech, AI and AML often remain fragmented, examining technological, organisational or regulatory aspects in isolation. By bringing these dimensions together, the research contributes to a more comprehensive understanding of the FinTech–AI nexus, advancing theory-building in financial governance and regulatory innovation.[5] The findings thus hold the potential to guide global policy debates, shape institutional strategies and provide a roadmap for strengthening AML ecosystems in the digital era.

The theoretical foundation of the study is built on an integrated framework that synthesises the Institutional Theory (IT) and the Resource-Based View (RBV). The IT explains how regulatory pressures, legitimacy concerns and compliance obligations drive financial institutions toward adopting advanced AML technologies.[6] The RBV highlights the strategic role of internal resources – such as technological infrastructure, AI expertise, and data assets – in enabling sustainable competitive advantages in AML enforcement. Complementing these, the Theory of Planned Behaviour (TPB) captures the behavioural and cognitive aspects of decision-making, illustrating how attitudes, perceived control and organisational norms shape managerial intentions to adopt FinTech and AI-driven surveillance. Together, these perspectives provide a holistic lens through which the study examines how external environments, organisational resources and decision-maker cognition interact to drive AML innovation.

By integrating these theoretical perspectives, the research not only contributes to existing scholarship but also addresses a critical gap: the lack of holistic frameworks that link structural enablers, internal resources and behavioural dynamics in the adoption of AI-enabled FinTech solutions for AML. The article is structured to first introduce FinTech, AI and AML

5 Cubric and Li 2024 *Technovation*.
6 Shibin *et al* 2020 *Annals of Operations Research*.

surveillance. This introduction is followed by a review of the literature and the development of hypotheses grounded in the integrated framework. This is then supported by a detailed methodology section, the presentation of results, and a discussion of the theoretical and practical implications. The study concludes by outlining its limitations and identifying avenues for future research. In this way, the research flows systematically from the contextual background to theoretical framing, empirical analysis, and forward-looking insights, offering a comprehensive contribution to the field of digital financial governance.

2 Literature review and hypotheses

2.1 Theoretical review

This study utilises an integrated theoretical lens combining RBV and IT. Such a synthesis enables a comprehensive examination of external institutional pressures (IP), firm-level capabilities and managerial cognition that collectively shape sustainability investment decisions in resource-constrained contexts.

The RBV directs attention to firm-level capabilities, emphasising how internal resources shape competitive advantage. As argued by Barney and Arikan,[7] resources that are valuable, rare, inimitable, and non-substitutable (VRIN) enable organisations to sustain superior performance. Within the context of AML, the RBV underscores the importance of FinTech capabilities and AI adoption as critical technological resources.[8] These capabilities, ranging from blockchain-enabled transparency to machine learning driven anomaly detection, equip financial institutions with advanced tools to monitor and mitigate money laundering risks. Prior research supports this logic. Akartuna, Johnson and Thornton[9] show that firms leveraging advanced analytics outperform their peers in compliance accuracy, and demonstrate that digital infrastructure investments significantly strengthen financial governance outcomes. Nonetheless, a limitation of RBV lies in its tendency to focus on resource possession, without addressing how regulatory environments or institutional pressures shape the effective deployment of such technologies.[10] This is particularly relevant in AML, where compliance outcomes depend not only on technological strength but also on the alignment with external rules and enforcement mechanisms.

Bridging this gap, IT highlights the influence of external pressures on organisational behaviour, particularly coercive, normative and mimetic

7 Barney and Arikan "Resource-based View".
8 Akinwunmi 2025 *Applied Sciences, Computing, and Energy*.
9 Akartuna, Johnson and Thornton 2023 *Security Journal*.
10 Zhang and Dhaliwal 2009 *International Journal of Production Economics*.

forces. In the AML context, regulatory mandates and global compliance standards represent coercive pressures that guide technology adoption. NP emerge from industry best practices, client expectations and professional compliance norms, which push financial institutions to enhance their AML frameworks. Empirical evidence supports these dynamics. Shehu[11] found that strong regulatory backing accelerates AI-enabled compliance adoption. Jørgensen, Gunasekaran and Ma[12] revealed that peer influence within the financial sector fosters the diffusion of RegTech solutions (RS). RegTech solutions refer to technology-driven tools that use AI, automation, and data analytics to help financial institutions comply with regulations more efficiently, accurately, and in real time. Mutually, IT suggests that RS and NP do not merely complement firm-level resources but actively condition their effectiveness in combating illicit financial flows.

Taken together, the integration of RBV and IT provides a holistic perspective for examining AML practices in the digital era. While RBV highlights the strategic value of internal resources, capabilities and dynamic competencies in shaping compliance performance, IT explains how regulatory pressures, norms and legitimacy demands drive organisations to adopt and standardise AI-driven AML systems.[13] This dual-theory approach not only explains how technological adoption enhances AML surveillance efficiency (AMLSE), but also clarifies why enforcement success ultimately depends on the interaction between organisational readiness and external RS (Table 1).

Table 1: Theoretical mapping of core constructs and dimensions

Constructs	Dimensions	Strengths	References
FinTech Capabilities (FTC)	Technological Integration, Compliance Enhancement	Use of digital KYC, blockchain, and real-time transaction analysis	Ashta and Herrmann 2021 *Strategic Change*
AI Adoption in AML (AIAML),	Analytical Intelligence, Predictive Intelligence, Adaptive Learning	Use of ML algorithms, AI-driven fraud detection, and predictive analytics	Rincón-Flores *et al* "Adaptive Learning Based on AI with Predictive Algorithms"

11 Shehu 2010 *JMLC*.
12 Jørgensen, Gunasekaran and Ma 2025 *Energies*.
13 Lagna and Ravishankar 2022 *Information Systems Journal.*

AML Surveillance Efficiency (AMLSE)	Speed of Detection, Accuracy of Monitoring, Proactive Risk Management	Speed, accuracy, and proactive detection of suspicious transactions.	Malik, Muthalagu and Pawar 2024 *IEEE Access*
AML Enforcement Outcomes (AMEO)	Case Resolution Effectiveness, Reduction in Incidents, Enforcement Impact	Number of successful interventions, and reduced money laundering cases	Huang 2025 *JMLC*
Regulatory Support (RS)	Regulatory Clarity, Regulatory Responsiveness, Technical/Procedural Support	Clarity of regulations, availability of technical guidance, and legal infrastructure	Patel *et al* 2025 *Journal of Robotic Surgery*

2.2 Hypothesis (Hy)

Grounded in the RBV and IT, this study proposes that both internal technological capabilities and external regulatory pressures shape AMLSE and enforcement outcomes. RBV explains how FinTech and AI act as strategic resources, while IT highlights how normative and regulatory forces drive adoption and legitimacy. Together, these perspectives suggest that surveillance efficiency is the key mechanism linking digital capabilities to effective AML enforcement, leading to the following hypotheses.

Hy 1 FinTech Capabilities (FTC) → AML Surveillance Efficiency (AMLSE)

A literature review suggests that FinTech capabilities have a significant influence on the efficiency of AML surveillance mechanisms. The adoption of digital innovations, like blockchain, digital payment infrastructure and automated transaction monitoring tools, enables financial institutions' systems to detect irregularities with greater speed and precision.[14] FinTech offers the technological infrastructure that supports real-time surveillance and enhances data integration across platforms, thereby strengthening AML systems from the RBV. FinTech capabilities can be understood as valuable, rare and inimitable resources that enhance organisational competence in compliance.[15] The IT theory suggests that regulatory

14 Paramesha, Rane and Rane 2024 *Partners Universal Multidisciplinary Research Journal*.

15 Reyes-Mercado *FinTech Strategy*.

environments encourage the integration of FinTech solutions into AML frameworks, thereby legitimising their role in surveillance efficiency.

Hy 2 AI in AML (AIAML) → AML Surveillance Efficiency (AMLSE)

The application of AI has emerged as a transformative enabler in AML surveillance. Scholars argue that AI-powered systems, like machine learning algorithms, anomaly detection models and predictive analytics, can reduce false positives and improve the accuracy and privacy of suspicious transaction monitoring.[16] AI augments existing FinTech infrastructure by enabling the detection of complex money-laundering patterns that traditional rule-based systems often overlook. Within the RBV framework, AI represents an advanced capability that provides financial institutions with a sustainable advantage in fraud prevention and compliance.[17] From an institutional perspective, the growing global regulatory acceptance of AI tools further strengthens their legitimacy and accelerates their adoption in AML practices.

Hy 3 Normative Pressures (NP) → AML Surveillance Efficiency (AMLSE)

NP, rooted in IT, are identified as a main driver of AML surveillance adoption and efficiency. Industry-wide norms, professional standards and global AML directives (for example, Financial Action Task Force (FATF) recommendations) create expectations that financial institutions must adhere to in order to maintain legitimacy.[18] Prior research highlights that compliance with international norms not only mitigates reputational and legal risks, but also compels organisations to adopt more robust surveillance systems.[19] These pressures, derived from professional associations, international task forces and industry benchmarks, act as structural enablers, ensuring that AML surveillance systems evolve in line with global best practices. Thus, normative forces play a critical role in shaping surveillance efficiency beyond internal technological capabilities.

Hy 4 AML Surveillance Efficiency (AMLSE) → AML Enforcement Outcomes (AMEO)

A strong body of literature[20] emphasises that efficient surveillance mechanisms are central to enhancing AML enforcement outcomes. Effective surveillance enables the early detection of illicit financial activities, reduces compliance issues and facilitates more accurate reporting of suspicious transactions.[21] Furthermore, studies suggest that surveillance

16 Owen, Maddog and Moore "AI-powered Fraud Detection Systems".
17 Aakula, Zhang and Ahmad 2024 *Journal of Artificial Intelligence & Research*.
18 Burdon and Sorour 2020 *Journal of Business Ethics*.
19 Taherdoost 2021 *Electronics*.
20 Reznik, Utkina and Bondarenko 2023 *JMLC*.
21 Kelkar 2024 *Mayo Communication Journal*.

efficiency translates into enforcement success by providing regulators with actionable intelligence and strengthening the overall integrity of financial systems. From a theoretical perspective, RBV underscores surveillance as an internal organisational competency that supports strategic enforcement outcomes, while IT links surveillance efficiency to the external legitimacy of enforcement practices within regulatory frameworks.

Hy 5 Moderation of Regulatory Support (RS) on AMLSE → AML Enforcement Outcomes (AMEO)

Regulatory support is frequently highlighted in the literature as a pivotal factor that enhances AML outcomes by reinforcing surveillance mechanisms.

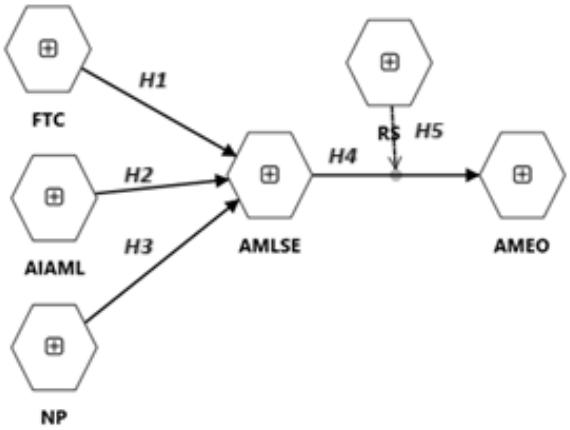


Figure 1: Conceptual model and theory-based hypotheses

Note: This figure 1 shows theory-based hypothesised links, evaluated to determine if evidence supports rejecting the null of no effect This study used the simplest evaluation method suited to study data, presenting links by relative strength rather than positive or negative effects.

This study proposes a unique conceptual framework that integrates the RBV and IT to examine how FinTech and AI capabilities, alongside normative pressures (NP), enhance AML enforcement through improved surveillance efficiency.[22] Unlike prior studies, it positions AMLSE as a mediator and RS as a moderator, highlighting that technological gains translate into enforcement success only when reinforced by strong institutional backing.

22 Al-Sharafi *et al* 2025 *Information Discovery and Delivery*.

3 Research methods and data

3.1 Design and approach

The present study employs a descriptive cross-sectional research design, which is particularly effective for analysing interactions among variables at a specific point in time. This design is well suited to the study's focus on understanding how FinTech capabilities and AI-driven solutions are transforming AML surveillance and enforcement and capturing the perceptions, behaviours and institutional practices of stakeholders in real-world contexts. The cross-sectional approach enables a comprehensive assessment of existing patterns, characteristics and relationships without manipulating the variables under study. The methodology involves systematic data collection from a diverse sample of AML professionals, compliance officers and FinTech experts, thereby ensuring a broad representation of insights from across the financial ecosystem.[23] The design is particularly advantageous when exploring behavioural dimensions, like trust, decision-making and RS, which often shape the adoption and effectiveness of new technologies.

3.2 Sample and data collection

The study specifically included professionals from government, the finance, compliance and technology sectors, who had recent experience, having actively participated in AML and financial governance practices over the last six months. Given the challenges of accessing a broad randomised pool of such specialised experts, a snowball sampling strategy was employed. This method allowed the recruitment of respondents through professional referrals, ensuring that participants possessed relevant expertise in FinTech adoption, AI integration and AML enforcement.

Data collection was carried out over four months (February to June 2025). A total of 500 responses were initially gathered in line with Cochran's formula for sample size determination.[24] After a rigorous screening process, 48 responses were found to be received after the deadline, 82 entries were found invalid or incomplete, and 42 participants did not meet the required expertise criteria. Following these exclusions, the final dataset comprised 328 valid responses, which is considered robust and statistically appropriate for Structural Equation Modelling (SEM) analysis using SmartPLS 4.

3.3 Instrument design

The measurement scales employed in this study are presented in Table 3, with items carefully adapted and refined to align with the study's objectives.

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23 Hamdi 2026 *Qualitative Research in Financial Markets*.

24 Woolson, Bean and Rojas 1986 *Biometrics*.

Each questionnaire item was systematically mapped to the constructs under investigation to ensure that the questions accurately reflected the underlying theoretical concepts, while demographic information was captured separately (Table 2). To establish face validity, the questionnaire was reviewed by a panel of ten domain experts drawn from both academia and industry.[25] The panel comprised:

- Academic experts: Five professors and researchers specialising in financial governance, compliance and FinTech adoption, affiliated with leading universities in India and abroad.

- Industry experts: Five senior professionals with extensive experience in FinTech applications, AI-driven compliance solutions, and AML enforcement, including managers, consultants, and executives from financial institutions and regulatory bodies.

The experts assessed the questionnaire for clarity, relevance and comprehensiveness, providing feedback that was instrumental in enhancing item precision and contextual appropriateness.

All constructs were measured using a 7-point Likert scale, ranging from 1 (strongly disagree) to 7 (strongly agree).[26] The scale consisted of a total of six constructs. Each construct consisted of three items designed to capture the multi-dimensional aspects of the variables (Figure 2). The hypothesised relationships among variables are depicted in Figure 1.

Table 2: Demographic characteristics of respondents (N 328)

Variable	Category	Frequency (n)	Percentage (%)
Gender	Male	198	60.4
	Female	130	39.6
Age (years)	18–25	72	22.0
	26–35	104	31.7
	36–45	86	26.2
	46 and above	66	20.1
Education Level	Undergraduate	88	26.8
	Postgraduate	146	44.5

25 Jangir *et al* 2023 *Journal of Risk and Financial Management*.
26 Sharma *et al* 2025 *Journal of Risk and Financial Management*.

	Professional/PhD	94	28.7
Occupation	Student	64	19.5
	Academic/Research	72	22.0
	Finance Professional	116	35.4
	Other	76	23.1
Experience in Finance/AML	Less than 5 years	122	37.2
	6–10 years	104	31.7
	More than 10 years	102	31.1
Note: N denotes number of respondents			
Source: author's work			

Table 3: Operationalisation of study variables and their measurement scales

Constructs	Measures	Construct Type and Theoretical Basis
FinTech Capabilities (FTC)[27]	1. Our organisation uses advanced FinTech solutions (e.g., blockchain, digital KYC) for AML compliance. 2. We have integrated real-time transaction monitoring through FinTech platforms. 3. FinTech adoption has significantly improved our ability to detect suspicious transactions.	Exogenous (RBV)

27 Bunnell, Osei-Bryson and Yoon 2021 *Expert Systems with Applications*.

AI Capabilities (AIC)[28]	1. We use AI algorithms to analyse large transaction datasets for potential money laundering risks. 2. AI tools in our organisation can predict suspicious activities before they occur. 3. AI-enabled AML systems in our organisation continuously improve through machine learning.	Exogenous (RBV)
Regulatory Support (RS)[29]	1. Regulatory authorities provide clear guidelines for using FinTech and AI in AML. 2. Our organisation receives timely updates from regulators on AML compliance requirements. 3. Regulators offer sufficient technical and procedural support for AML technology adoption.	Moderator (IT)
Normative Pressure (NP)[30]	1. Industry best practices influence our adoption of FinTech and AI for AML. 2. Our clients expect us to use advanced technologies to prevent money laundering. 3. Competitors' use of AML technologies motivates us to enhance our capabilities.	Exogenous (IT)
AML Surveillance Efficiency (AMLSE)[31]	1. Our AML systems can detect suspicious transactions more quickly than before. 2. Technology has improved the accuracy of our AML surveillance activities. 3. Our AML systems proactively flag potential risks before regulatory intervention is required.	Performer (Mediator)

28 Kumar *et al* 2024 *IEEE Transactions on Engineering Management*.
29 Zee, Bolger and Higgins 2020 *Journal of Personality and Social Psychology*.
30 Firmansyah, Yasirandi and Utomo 2022 *Procedia Computer Science*.
31 Pontes *et al* 2022 *JMLC*.

AML Enforcement Outcomes (AMEO)[32]	1. The adoption of FinTech and AI has led to more successful AML case resolutions. 2. Our organisation has reduced incidents of money laundering through technology-driven enforcement. 3. Our AML enforcement actions are more effective due to improved surveillance capabilities.	Outcome (Endogenous)

Source: author's work

A pre-screening process was conducted to ensure the suitability of respondents and the relevance of the sample.[33] The first qualifying question asked was: "Do you have experience and knowledge of FinTech applications, AI-driven compliance, and Anti-Money Laundering (AML) governance in financial institutions?" Only participants who responded affirmatively were permitted to complete the full survey. Since no centralised database or official estimate exists for professionals working at the intersection of FinTech, AI and AML enforcement, a non-probability convenience sampling strategy was employed. This approach is well-suited for exploratory research involving specialised, hard-to-reach professional groups and ensures access to respondents with practical expertise, even though it limits statistical generalisability.

Given the study's emphasis on FinTech platforms and AI-enabled surveillance systems, SEM was adopted as the primary analytical technique. SEM is particularly valuable in exploring complex relationships between latent constructs and their observed indicators, allowing for the testing of theoretical pathways. Its capacity to examine causal linkages makes it especially appropriate for evaluating how AI-driven FinTech adoption influences AML surveillance, enforcement efficiency and regulatory compliance within the financial ecosystem.

4 Results

4.1 Measurement model evaluation

The reliability and validity of the measurement model were tested via Cronbach's alpha, composite reliability, and average variance extracted (AVE) (Table 4). All the constructs recorded Cronbach's alpha measures

32 AlQudah, Mazhar Al Zoubi and Al Haddad 2024 *Advances in Decision Sciences*.
33 DeSimone and Harms 2018 *Journal of Business and Psychology*.

that were greater than the specified 0.70, which indicated that internal consistency was satisfactory.[34] Composite reliability estimates (ρa and ρc) also surpassed the critical value of 0.70, which reflected strong construct reliability.[35] Convergent validity was confirmed since AVE values for all constructs were greater than 0.50, establishing that each construct accounts for more than 50% of the variance of its indicators.[36] These findings collectively establish that the measurement model meets standards of reliability and convergent validity and serves as a sound basis for structural model evaluation.

Discriminant validity (Table 5) was also tested through the Fornell–Larcker (Table 6) criterion and correlation matrix. As stated by Fornell and Larcker,[37] the square root of AVE for every construct is supposed to be higher than its correlations with other constructs. As appears in Table 4, the diagonal elements (square roots of AVE) are always greater than the related inter-construct correlations, proving sufficient discriminant validity. For example, the square root of AVE for AIAML (0.861) was greater than its correlations with AMEO (0.579), AMLSE (0.556), FTC (0.624), and NP (0.556). Likewise, AMLSE (0.806) was greater than its correlations with other constructs, followed by FTC (0.830) and RS (0.821) as well. Further, the correlation values between constructs were less than the limit of 0.85, meaning that multicollinearity is not a problem.[38] Together, these findings show that the constructs are empirically separate, thus confirming the discriminant validity of the measurement model.

To test collinearity, Variance Inflation Factor (VIF) values were inspected for every item (Table 4). Based on Hair *et al*,[39] VIF values less than the critical value of 5 confirm that there is no problematic multicollinearity. The findings indicate that all VIF values varied from 1.124 (NP3) to 2.307 (AMLSE2), well below the critical cut-off point, thereby confirming that multicollinearity is not a threat to the estimation of the structural model. Interestingly, the interaction term (RS × AMLSE) captured a VIF of 1.000, further indicating stability in the moderation analysis. Thus, in the current study, collinearity is not an issue, and the constructs can be used confidently for hypothesis testing.

Table 4: Construct reliability and validity

Constructs	Items	VIF	Cronbach's alpha	Composite	Composite	Average variance

34 Khan *et al* 2025 *Journal of Hospitality and Tourism Insights*.
35 Shmueli *et al* 2019 *European Journal of Marketing*.
36 Fornell and Larcker 1981 *Journal of Marketing Research*.
37 Fornell and Larcker 1981 *Journal of Marketing Research*.
38 Hair, Ringle and Sarstedt 2011 *Journal of Marketing Theory and Practice*.
39 Hair *et al* 2017 *International Journal of Multivariate Data Analysis*.

				reliability (rho_a)	reliability (rho_c)	extracted (AVE)
AIAML	AIAML1 AIAML2 AIAML3	1.769 1.934 1.965	0.827	0.836	0.896	0.742
AMEO	AMEO1 AMEO2 AMEO3	1.399 1.380 1.212	0.971	0.987	0.820	0.604
AMLSE	AMLSE1 AMLSE2 AMLSE3	2.047 2.307 1.212	0.721	0.746	0.846	0.650
FTC	FTC1 FTC2 FTC3	1.390 1.788 1.896	0.775	0.780	0.869	0.689
NP	NP1 NP2 NP3	1.176 1.183 1.124	0.744	0.760	0.771	0.528
RS	RS1 RS2 RS3	1.570 1.488 2.053	0.756	0.820	0.860	0.673
	RS x AMLSE	1.000				

Source: created by SEM-PLS

Note: FinTech Capabilities (FTC), AI Adoption in AML (AIAML), AML Surveillance Efficiency (AMLSE), AML Enforcement Outcomes (AMEO), Regulatory Support (RS)

Table 5: Discriminant validity

Constructs	AIAML	AMEO	AMLSE	FTC	NP	RS
AIAML						

AMEO	0.762					
AMLSE	0.716	0.760				
FTC	0.768	0.711	0.732			
NP	0.830	0.720	0.702	0.870		
RS	0.693	0.720	0.705	0.894	0.774	
RS x AMLSE	0.134	0.179	0.193	0.207	0.196	0.359

Source: created by SEM-PLS

Table 6: Fornell-Larcker criterion

Constructs	AIAML	AMEO	AMLSE	FTC	NP
AIAML	0.861				
AMEO	0.579	0.777			
AMLSE	0.556	0.540	0.806		
FTC	0.624	0.662	0.560	0.830	
NP	0.556	0.551	0.830	0.561	0.727
RS	0.548	0.678	0.535	0.689	0.493

Source: created by SEM-PLS

4.2 Structural model analysis

After verifying the reliability and validity of the measurement model, the structural model was assessed to check the speculated associations (Table 7). In PLS-SEM, standardised path coefficients (β) typically range between −1 and +1, where the sign indicates the direction of the relationship and the magnitude reflects its strength. Following common guidelines,[40] coefficients around 0.02 are considered weak, 0.10 small, 0.30 moderate, and 0.50 or above strong effects. Positive values indicate a direct relationship, while negative values indicate an inverse relationship. Accordingly, the findings indicate that FinTech capacities (FTC) have a marginal but positive effect on AML watchfulness effectiveness (AMLSE) (β = 0.096, t = 1.945, p = 0.052), which implies that technology-driven mechanisms like blockchain and electronic payment systems improve monitoring but with a weaker comparative impact. Conversely, Artificial Intelligence in AML (AIAML) reflects a strong positive effect on AMLSE (β = 0.093, t = 2.095, p = 0.036),

40 Hair and Alamer 2022 *Research Methods in Applied Linguistics*.

reaffirming that AI tools, machine learning algorithms and natural language processing are substantially helpful in helping identify anomalies and minimising false positives, although the effect size is low.

NP becomes the most significant predictor of AMLSE ($\beta = 0.725$, $t = 17.762$, $p < 0.001$), noting that regulatory requirements, compliance obligations, and institution legitimacy issues are powerful drivers for banks to enhance surveillance systems. The findings also support that AMLSE has a positive impact on AMEO ($\beta = 0.245$, $t = 4.547$, $p < 0.001$), suggesting that effectiveness in transaction monitoring and suspicious activity detection translates to better reporting, investigation and prosecution of cases of money laundering.

Further, RS has a dual impact on influencing enforcement outcomes. The direct link from RS to AMEO is robust and strongly significant ($\beta = 0.571$, $t = 11.607$, $p < 0.001$), emphasising regulators' central position in driving enforcement success through harmonised reporting requirements, cross-jurisdictional coordination, and RegTech-facilitated supervision. In addition, RS strongly moderates AMLSE and AMEO ($\beta = 0.069$, $t = 2.179$, $p = 0.029$), suggesting that enforcement results are enhanced where surveillance competence is boosted by supportive regulatory systems.

In PLS-SEM, standardised path coefficients (β) typically range between −1 and +1, where the sign indicates the direction of the relationship and the magnitude reflects its strength. Following common guidelines,[41] coefficients around 0.02 are considered weak, 0.10 small, 0.30 moderate, and 0.50 or above strong effects. Positive values indicate a direct relationship, while negative values indicate an inverse relationship. In general, the model exhibits significant explanatory capability, with R^2 measures of 0.707 for AMLSE and 0.508 for AMEO, which suggest that the antecedent factors explain a substantial portion of variance in surveillance efficiency and enforcement results. The combined results support Hy2–Hy5, whereas Hy1 is partially supported, capturing the comparatively weaker impact of FinTech capabilities over AI adoption and normative pressures.

The explanatory potential of the structural model was determined by the R^2 values of the endogenous constructs (Table 8). The findings show strong predictive power, with AMLSE recording an R^2 value of 0.707 (adjusted $R^2 = 0.705$). This shows that fintech capabilities, AI adoption and normative pressures combined explain more than 70% of AMLSE variance, a high level of model robustness. Likewise, AMEO have an R^2 value of 0.508 (adjusted $R^2 = 0.504$), indicating that surveillance effectiveness and regulatory assistance explain over 50% of the variance in enforcement

41 Hair and Alamer 2022 *Research Methods in Applied Linguistics*.

outcomes.[42] These results demonstrate that the model has good explanatory power beyond the 0.50 threshold set for meaningful predictive accuracy in behavioural research.[43]

Table 7: Path coefficients analysis

Path and constructs	(O)	(M)	(STDEV)	T statistics	P-values	Significant (Y/N)
AIAML -> AMLSE	0.093	0.095	0.045	2.095	0.036*	Y
AMLSE -> AMEO	0.245	0.244	0.054	4.547	0.000***	Y
FTC -> AMLSE	0.096	0.098	0.049	1.945	0.052	N
NP -> AMLSE	0.725	0.723	0.041	17.762	0.000***	Y
RS -> AMEO	0.571	0.573	0.049	11.607	0.000***	Y
RS x AMLSE -> AMEO	0.069	0.071	0.032	2.179	0.029**	Y

Note: Retrench – Original sample (O), Sample mean (M), Standard deviation (STDEV), T statistics (|O/STDEV|)

*Converging Validity Pointer, Notes: ***= p < 0.01, **= p < 0.05*

Table 8: Quality criteria

Performance & Outcome constructs	**R-square**	**R-square adjusted**
AMEO	0.508	0.504
AMLSE	0.707	0.705

Source: created by SEM-PLS

42 Sharma *et al.* 2024 *International Journal of Information Management Data Insights*.
43 Hair *et al* 2017 *International Journal of Multivariate Data Analysis*.

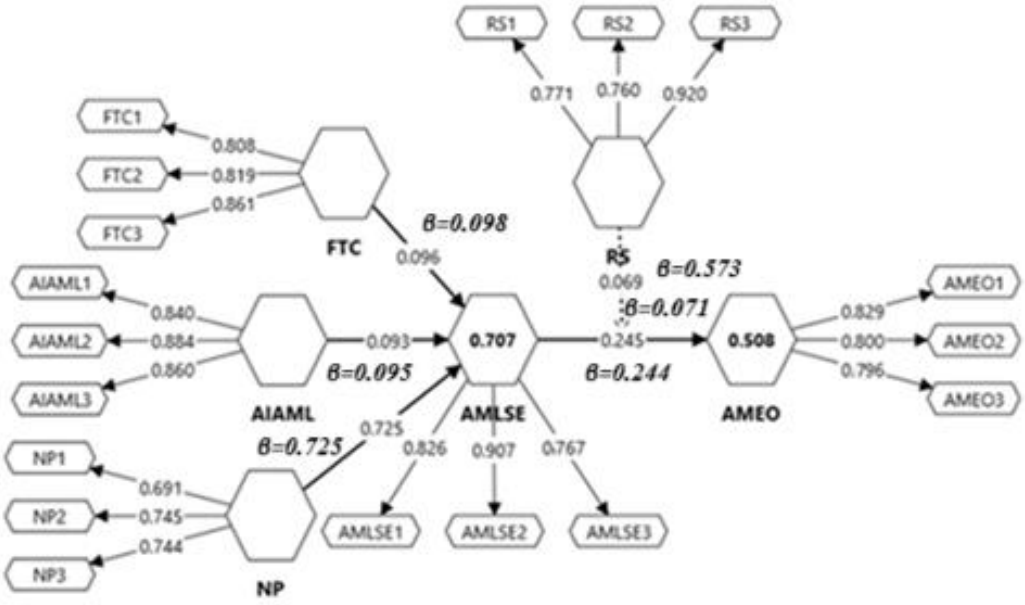


Figure 2: Path coefficients and results with beta value

4.3 Importance-performance map of AMEO

The IPMA results emphasise the relative contribution of each construct through total effects, providing clear guidance on where strategic efforts should be directed to strengthen financing outcomes.

Table 9: IPMA outcomes

Constructs	AMEO (total effects)	Performance
AIAML	0.023	57.530
AMLSE	0.245	60.777
FTC	0.023	67.764
NP	0.177	56.718
RS	0.571	70.397

Table 9 shows that RS has the highest importance (0.571) and performance (70.397), making it the strongest driver of AMEO. AMLSE (0.245; 60.777) and Normative Pressure (0.177; 56.718) hold moderate importance but have scope for performance improvement. In contrast, AIAML (0.023; 57.530) and FinTech Capabilities (0.023; 67.764) exhibit minimal direct

influence despite reasonable performance levels, indicating their role may be more supportive than decisive in shaping AML enforcement outcomes.[44]

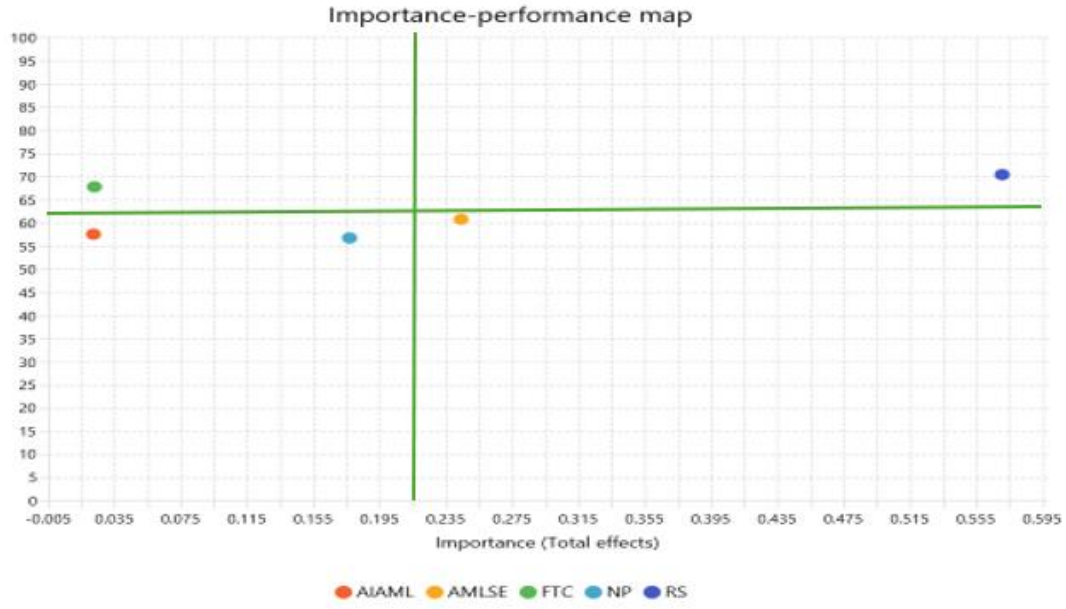


Figure 3 Total effects

Figure 3 shows the gridline averages (total effects average = 0.208, performance average = 61.35) and highlights RS as the strongest driver, positioned above both benchmarks. AMLSE is balanced, aligning closely with the averages. FTC shows good performance but low importance, while NP performs moderately with limited impact. AIAML scores below both averages, marking it as the weakest area needing improvement.[45]

44 Streukens, Leroi-Werelds and Willems "Dealing with Nonlinearity IPMA".

45 García-Fernández *et al* 2020 *International Journal of Environmental Research and Public Health*.

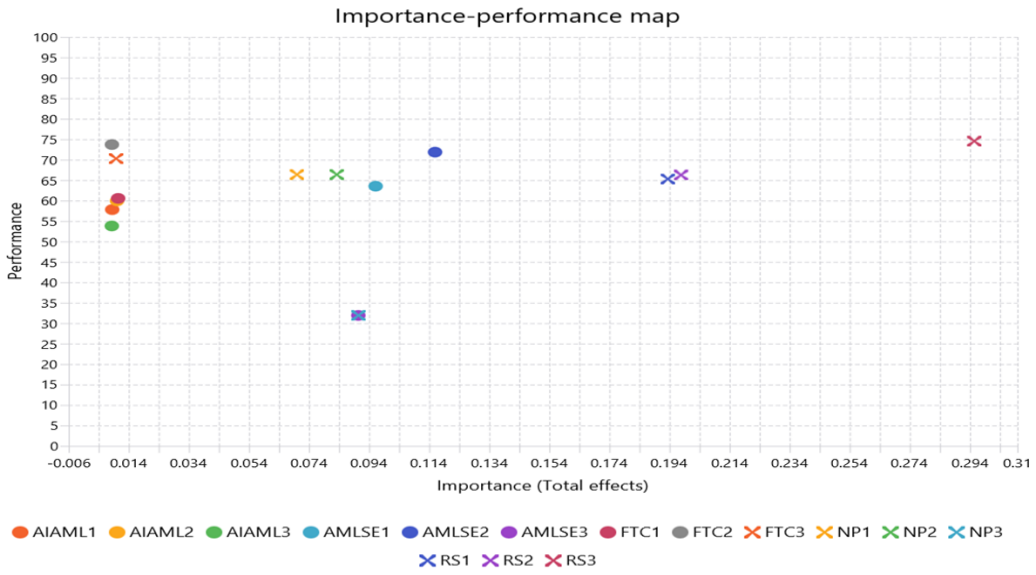


Figure 4: IPMA analysis

The Importance-Performance Map Analysis (IPMA) (Figure 4) shows that regulatory support (RS3) and normative pressures (NP2, NP3) have the highest importance and strong performance, making them the most critical drivers of AML enforcement outcomes. AI capabilities (AIAML1–3) and FinTech capabilities (FTC1–3) display good performance but relatively lower importance, suggesting that while these technologies are functioning well, their direct impact is less pronounced. AML surveillance efficiency (AMLSE1–3) lies in the mid-range, highlighting scope for further strengthening. Overall, the IPMA indicates that institutional factors (regulatory and normative pressures) outweigh technological capabilities in driving AML effectiveness, though better integration of AI and FinTech could enhance their importance.

5 Discussion

The results of this research offer strong empirical evidence for hypothesised relationships, validating the theoretical integration of IT, and the RBV. The measurement model proved to exhibit adequate reliability and validity to provide assurance about the robustness of subsequent structural analysis. Structural model results indicate that AMLSE captures a significant amount of variance (R^2 = 0.707), whereas AMEO are moderately explained (R^2 = 0.508). The findings indicate that surveillance efficiency is a mediating mechanism by which technological capabilities and institutional pressures are translated into enforcement success.[46]

[46] Liao, Weng and Shen 2020 *Sustainable Development*.

To begin, as predicted by RBV, FTC and AI adoption (AIAML) surfaced as strategic assets that substantially boost surveillance efficiency. This finding is consistent with Ballou, Grenier and Reffett,[47] who highlighted the role of analytics-driven practices in strengthening compliance and suggested that digital infrastructure can support more effective governance. By proving that FTC and AIAML enhance AMLSE, the findings authenticate them as valuable, rare and inimitable resources that provide institutions with better monitoring capacity. Nevertheless, as IT implies, these resources realise effectiveness within institutionalised contexts. The findings affirm this perspective, demonstrating that NP have a strong effect on AMLSE, as postulated by Munir and Baird,[48] who highlight the importance of regulatory and peer pressure in influencing adoption of RegTech. Therefore, technological capability and institutional legitimacy interact together, not in separation, in influencing AML performance.

Next, AMLSE showed a high and substantial impact on AMEO, in support of Hypothesis 4. This result is consistent with the literature highlighting that surveillance controls enhance the success of enforcement through facilitating the timely detection of illegal transactions and actionable intelligence.[49] Under the RBV lens, AMLSE is an internal resource that enhances strategic outcomes, whereas from an institutional view it improves legitimacy through guaranteeing the fulfilment of regulatory requirements. The explanatory capability of AMLSE ($R^2 = 0.707$) highlights its central position as a mediator, enhancing the impact of internal technological capacities and external institutional pressures on enforcement outcomes.

Importantly, the moderate explanatory power of AMEO ($R^2 = 0.508$) indicates that while surveillance efficiency is important to drive enforcement outcomes, it could also be influenced by complementary variables like regulatory support, inter-agency cooperation, and the allocation of resources variables emphasised in earlier research.

The IPMA offers a more in-depth understanding of the relative importance of institutional versus technological variables in determining AMEO. The results draw attention to the fact that RS is the strongest and highest performing driver, corroborating the salience of robust institutional frameworks in the effective implementation of AML. This is consistent with earlier studies highlighting that regulatory stringency and compliance culture tend to be the pillars of financial integrity mechanisms.[50] Normative Pressure (NP) and AMLSE also reflect moderate significance, indicating that although organisations are reacting to institutional forces and engaging

47 Ballou, Grenier and Reffett 2021 *Accounting Horizons*.
48 Munir and Baird 2016 *Journal of Accounting & Organizational Change*.
49 Nazzari and Reuter 2025 *Crime and Justice*.
50 Streukens, Leroi-Werelds and Willems "Dealing with Nonlinearity IPMA".

surveillance systems, additional improvements could achieve more effective enforcement outcomes. On the other hand, AI capabilities (AIAML) and FTC, as strong as their performance is relatively, have little immediate importance, which suggests their existing function is complementary rather than determining in driving the outcomes of enforcement.[51] This imbalance itself highlights the essential point: institutional drivers still dominate over technological levers in AML settings. Still, as surveillance by AI- and FinTech-powered systems increasingly develops at breakneck pace, the unrealised potential suggests a potential for intensified integration into regulatory frameworks. Strategically, policymakers and financial institutions must thus not only be firming up regulatory backing and compliance requirements, but also establishing avenues whereby AI and FinTech systems can shift from auxiliary facilitators to overarching drivers of AML enforcement effectiveness.

Overall, the results together emphasise that AML enforcement results are influenced mainly by institutional drivers, specifically regulatory support and normative pressures, and are assisted by technological enablers like AI and FinTech capabilities to a lesser extent. Moderation analysis emphasises how regulatory support not only directly influences but also magnifies the strength of surveillance mechanisms, solidifying its role as a decisive driver of enforcement. In addition, the IPMA findings indicate that although institutional forces continue to be determinative, there is unexploited potential in the use of technological instruments to be more efficient in AML in the future. All in all, this research contributes to theory by bridging institutional and technological viewpoints within an AML lens and offers practical recommendations to policymakers, regulators, and financial institutions aiming to balance compliance requirements with innovation. Finally, the discussion calls for a synergistic strategy grounding enforcement in robust rulebooks and increasingly integrating cutting-edge technologies – to maintain effectiveness in a growingly complex financial environment.

6 Contribution of the study

6.1 Theoretical implications

This study makes several key contributions. First, by combining the RBV with IT, it identifies the complementary relationship between internal ability and external pressure in determining AML outcomes. The decisive impact of FinTech and AI capacities on the efficiency of AML monitoring validates the RBV hypothesis that expensive, scarce, unique, and non-replicable higher-order technological assets, when valuable, rare, inimitable, and non-

[51] García-Fernández *et al* 2020 *International Journal of Environmental Research and Public Health*.

substitutable, represent a strategic asset.[52]Concurrently, the influence of normative pressures and regulatory assistance reinforces IT's hypothesis that organisational action is conditioned by the external institutional environments. The robust explanatory ability of AML surveillance effectiveness over enforcement results ($R^2 = 0.508$) further attests to how organisational capabilities are converted to effective regulatory compliance, further enriching the RBV debate by positioning compliance as a performance-driving capability.

Second, the results enrich AML research by empirically confirming the AI–FinTech intersection as a decisive driver of surveillance efficacy. Previous research prioritised technology-enabled governance, but the current research builds further by illustrating how AI, in addition to minimising false positives, also enhances the efficacy of FinTech infrastructure in sophisticated money-laundering detection. Furthermore, the role of regulatory support as a moderator of heightened surveillance–enforcement linkages progresses IT by indicating that institutional pressures are dynamic rather than static and engage interactively with technological capacities.

The IPMA further reinforces the theoretical relevance of distinguishing between institutional and technological drivers in shaping AML effectiveness.

6.2 Practical implications

The results have significant implications for regulators, policymakers and practitioners. For financial institutions, the research highlights the importance of investing in AI-driven analytics and FinTech infrastructure as strategic assets that directly increase surveillance efficiency. Exceeding compliance requirements, such investments generate sustainable benefits by lowering operational risks, minimising false positives, and enhancing detection accuracy, hence driving lower enforcement costs.

For the regulators, the research identifies the pivotal role of enabling regulatory environments to validate the efficacy of surveillance systems. In addition to enacting mandates of compliance, regulators must enable infrastructure, protocol standardisation and technological advice to guarantee the optimal deployment of AI–FinTech systems. International cooperation, such as conformity to FATF standards, can promote harmonisation across jurisdictions and enhance cross-border enforcement. For policy-making, the conclusions indicate that normative pressures and institutional backing must be utilised tactically to expedite the adoption of next-generation RegTech solutions. Industry associations, compliance forums, and professional organisations can assist in spreading best

52 Casati *et al* 2024 *Supply Chain Management.*

practices and establishing legitimacy for AI-driven AML tools. Lastly, for compliance officers and managers, the behaviourally informed insights from TPB suggest that building a compliance-focussed culture that cherishes technological adoption is crucial. Training, awareness-raising and managerial rewards can influence attitudes and intentions toward AI–FinTech adoption so that surveillance and enforcement systems are not regulatory to-do lists but organisational staples.

7 Conclusion

This research focussed on the contribution of AI-powered FinTech abilities to enhancing AML monitoring and enforcement in the finance sector. Based on the RBV, IT and the TPB, the results illustrated that FinTech and AI constitute essential resources that heighten AML monitoring effectiveness, which ultimately enhances enforcement results. In addition, regulatory support was identified to be an effective institutional driver that supports the surveillance enforcement connection. With R^2 values of 0.707 for AML surveillance effectiveness and 0.508 for AML enforcement results, the model affirms the strength of technological and institutional integration in the explanation of AML effectiveness. By reconciling organisational assets, institutional forces and managerial behavioural intentions, the research adds a multi-dimensional perspective on how the FinTech–AI interface reimagines compliance and governance in the finance industry.

7.1 Limitations

Notwithstanding its contributions, the research is open to a number of limitations. To begin with, the cross-sectional study design precludes causality, limiting understanding of long-term AI and FinTech usage in AML systems. Second, the data were obtained from a particular regional setting (Northern India), which will limit the generalisability of the results to other nations with varying regulatory regimes, technology development or institutional settings. Third, the research used self-reported measures, which could lead to biases like social desirability or subjective response inflation. Last but not least, the model concentrated predominantly on technological and institutional dimensions, and other dimensions that are applicable - organisational culture, human capital, and inter-organisation collaborations - were not taken into account explicitly.

7.2 Future research directions

Future research can overcome these restrictions and expand the existing study in various ways. Longitudinal studies can recognise the changing influence of AI and FinTech uptake on AML effectiveness over time, particularly as financial crimes evolve with increasing complexity. Cross-country comparison studies may explore how differences in regulatory

frameworks, institutional forces and technological environments influence AML performance. Moreover, combining qualitative methods like interviews of compliance officers and regulators can offer more contextualised information beyond numerical measures. Emerging models may also include factors like employee digital proficiency, ethical implications of AI applications, and international data-sharing arrangements that are becoming ever more pertinent in globalised AML systems. Finally, analysis of new technologies like blockchain, decentralised finance (DeFi), and explainable AI (XAI) against the background of AML may shed new theoretical and practical light on next-generation compliance and enforcement systems.

Bibliography

Literature

Aakula, Zhang and Ahmad 2024 *Journal of Artificial Intelligence & Research*
Aakula A, Zhang C and Ahmad T "Leveraging AI and Blockchain for Strategic Advantage in Digital Transformation" 2024 *Journal of Artificial Intelligence & Research* 356-395

Akartuna, Johnson and Thornton 2023 *Security Journal*
Akartuna EA, Johnson SD and Thornton AE "The Money Laundering and Terrorist Financing Risks of New and Disruptive Technologies: A Futures-oriented Scoping Review" 2023 *Security Journal* 615-650 https://doi.org/10.1057/s41284-022-00356-z

Akinwunmi 2025 *Applied Sciences, Computing, and Energy*
Akinwunmi T "Artificial Intelligence (AI) and Firm Survival of Deposit Money Banks" 2025 *Applied Sciences, Computing, and Energy* 21-38 https://doi.org/10.5281/zenodo.21428157

Allioui and Mourdi 2023 *Sensors*
Allioui H and Mourdi Y "Exploring the Full Potentials of IoT for Better Financial Growth and Stability: A Comprehensive Survey" 2023 *Sensors* 1-68 https://doi.org/10.3390/s23198015

Al-Sharafi *et al* 2025 *Information Discovery and Delivery*
Al-Sharafi MA *et al* "Factors Shaping FinTech Adoption: A Systematic Review, Key Determinants, Theoretical Insights, Conceptual Framework and Future Research Directions" 2025 *Information Discovery and Delivery* https://doi.org/10.1108/IDD-04-2025-0098

AlQudah, Mazhar Al Zoubi and Al Haddad 2024 *Advances in Decision Sciences*
AlQudah A, Mazhar Al Zoubi N and Al Haddad L "Mitigating Financial Crimes: How Anti-money Laundering Mechanisms Shape Bank Outcomes"

2024 *Advances in Decision Sciences* 79-105 https://dx.doi.org/10.2139/ssrn.5318862

Ashta and Herrmann 2021 *Strategic Change*
Ashta A and Herrmann H "Artificial Intelligence and Fintech: An Overview of Opportunities and Risks for Banking, Investments, and Microfinance" 2021 *Strategic Change* 211-222 https://doi.org/10.1002/jsc.2404

Ballou, Grenier and Reffett 2021 *Accounting Horizons*
Ballou B, Grenier JH and Reffett A "Stakeholder Perceptions of Data and Analytics Based Auditing Techniques" 2021 *Accounting Horizons* 47-68 https://doi.org/10.2308/HORIZONS-19-116

Barney and Arikan "Resource-based View"
Barney JB and Arikan AM "The Resource-based View: Origins and Implications" in Hitt MA, Freeman RE and Harrison JS (eds) *The Blackwell Handbook of Strategic Management* (Blackwell Hoboken 2005) 123-182 https://doi.org/10.1111/b.9780631218616.2006.00006.x

Bunnell, Osei-Bryson and Yoon 2021 *Expert Systems with Applications*
Bunnell L, Osei-Bryson K-M and Yoon VY "Development of a Consumer Financial Goals Ontology for Use with FinTech Applications for Improving Financial Capability" 2021 *Expert Systems with Applications* 113843 https://doi.org/10.1016/j.eswa.2020.113843

Burdon and Sorour 2020 *Journal of Business Ethics*
Burdon WM and Sorour MK "Institutional Theory and Evolution of 'a Legitimate' Compliance Culture: The Case of the UK Financial Service Sector" 2020 *Journal of Business Ethics* 47-80 https://doi.org/10.1007/s10551-018-3981-4

Casati *et al* 2024 *Supply Chain Management*
Casati M *et al* "Impacts of Blockchain Technology in Agrifood: Exploring the Interplay Between Transactions and Firms' Strategic Resources" 2024 *Supply Chain Management: An International Journal* 51-70 https://doi.org/10.1108/SCM-09-2023-0443

Cubric and Li 2024 *Technovation*
Cubric M and Li F "Bridging the 'Concept–Product' Gap in New Product Development: Emerging Insights from the Application of Artificial Intelligence in FinTech" 2024 *Technovation* 103017 https://doi.org/10.1016/j.technovation.2024.103017

DeSimone and Harms 2018 *Journal of Business and Psychology*
DeSimone JA and Harms PD "Dirty Data: The Effects of Screening Respondents Who Provide Low-quality Data in Survey Research" 2018

Journal of Business and Psychology 559-577 https://doi.org/10.1007/s10869-017-9514-9

Firmansyah, Yasirandi and Utomo 2022 *Procedia Computer Science*
Firmansyah IA, Yasirandi R and Utomo RG "The Influence of Efficacy, Credibility, and Normative Pressure to M-banking Adoption Level in Indonesia" 2022 *Procedia Computer Science* 51-60 https://doi.org/10.1016/j.procs.2021.12.117

Fornell and Larcker 1981 *Journal of Marketing Research*
Fornell C and Larcker DF "Evaluating Structural Equation Models with Unobservable Variables and Measurement Error" 1981 *Journal of Marketing Research* 39-50 https://doi.org/10.1177/002224378101800104

Gandhi *et al* 2024 *International Journal on Smart Sensing and Intelligent Systems*
Gandhi H *et al* "Navigating the Complexity of Money Laundering: Anti-money Laundering Advancements with AI/ML Insights" 2024 *International Journal on Smart Sensing and Intelligent Systems* 1-29 https://doi.org/10.2478/ijssis-2024-0024

García-Fernández *et al* 2020 *International Journal of Environmental Research and Public Health*
García-Fernández J *et al* "Importance-performance Matrix Analysis (IPMA) to Evaluate Servicescape Fitness Consumer by Gender and Age" 2020 *International Journal of Environmental Research and Public Health* 1-19 https://doi.org/10.3390/ijerph17186562

Hair, Ringle and Sarstedt 2011 *Journal of Marketing Theory and Practice*
Hair JF, Ringle CM and Sarstedt M "PLS-SEM: Indeed a Silver Bullet" 2011 *Journal of Marketing Theory and Practice* 139-152 https://doi.org/10.2753/MTP1069-6679190202

Hair *et al* 2017 *International Journal of Multivariate Data Analysis*
Hair JF Jr *et al* "PLS-SEM or CB-SEM: Updated Guidelines on Which Method to Use" 2017 *International Journal of Multivariate Data Analysis* 107-123 https://doi.org/10.1504/IJMDA.2017.087624

Hair and Alamer 2022 *Research Methods in Applied Linguistics*
Hair J and Alamer A "Partial Least Squares Structural Equation Modeling (PLS-SEM) in Second Language and Education Research: Guidelines Using an Applied Example" 2022 *Research Methods in Applied Linguistics* 1-16 https://doi.org/10.1016/j.rmal.2022.100027

Hamdi 2026 *Qualitative Research in Financial Markets*
Hamdi FM "Assessing International Anti-money Laundering Preventive Measures in Islamic Banks: A Directed Content Analysis Approach" 2026

Qualitative Research in Financial Markets 808-835 https://doi.org/10.1108/QRFM-06-2024-0163

Huang 2025 *JMLC*
Huang JY "Effectiveness of US Anti-money Laundering Regulations and HSBC Case Study" 2025 *JMLC* 525-532 https://doi.org/10.1108/JMLC-05-2015-0018

Jangir *et al* 2023 *Journal of Risk and Financial Management*
Jangir K *et al* "The Moderating Effect of Perceived Risk on Users' Continuance Intention for FinTech Services" 2023 *Journal of Risk and Financial Management* 1-16 https://doi.org/10.3390/jrfm16010021

Jørgensen, Gunasekaran and Ma 2025 *Energies*
Jørgensen BN, Gunasekaran SS and Ma ZG "Impact of EU Laws on AI Adoption in Smart Grids: A Review of Regulatory Barriers, Technological Challenges, and Stakeholder Benefits" 2025 *Energies* 1-33 https://doi.org/10.3390/en18123002

Kelkar 2024 *Mayo Communication Journal*
Kelkar U "Addressing Illicit Financial Flows: International Legal Efforts to Strengthen Economic Stability" 2024 *Mayo Communication Journal* 86-96

Khan *et al* 2025 *Journal of Hospitality and Tourism Insights*
Khan S *et al* "Understanding Tourists' Adoption of Edible Food Packaging: The Role of Environmental Awareness" 2025 *Journal of Hospitality and Tourism Insights* 2317-2337 https://doi.org/10.1108/JHTI-07-2024-0662

Kumar *et al* 2024 *IEEE Transactions on Engineering Management*
Kumar V *et al* "Artificial Intelligence (AI) Capabilities and the R&D Performance of Organizations: The Moderating Role of Environmental Dynamism" 2024 *IEEE Transactions on Engineering Management* 11522-11532 https://doi.org/10.1109/TEM.2024.3423669

Lagna and Ravishankar 2022 *Information Systems Journal*
Lagna A and Ravishankar MN "Making the World a Better Place with Fintech Research" 2022 *Information Systems Journal* 61-102 https://doi.org/10.1111/isj.12333

Liao, Weng and Shen 2020 *Sustainable Development*
Liao Z, Weng C and Shen C "Can Public Surveillance Promote Corporate Environmental Innovation? The Mediating Role of Environmental Law Enforcement" 2020 *Sustainable Development* 1519-1527 https://doi.org/10.1002/sd.2101

Malik, Muthalagu and Pawar 2024 *IEEE Access*
Malik J, Muthalagu R and Pawar PM "A Systematic Review of Adversarial Machine Learning Attacks, Defensive Controls, and Technologies" 2024 *IEEE Access* 99382-99421 https://doi.org/10.1109/ACCESS.2024.3423323

Munir and Baird 2016 *Journal of Accounting & Organizational Change*
Munir R and Baird K "Influence of Institutional Pressures on Performance Measurement Systems" 2016 *Journal of Accounting & Organizational Change* 106-128 https://doi.org/10.1108/JAOC-09-2014-0051

Nazzari and Reuter 2025 *Crime and Justice*
Nazzari M and Reuter P "How Well Does the Money Laundering Control System Work?" 2025 *Crime and Justice* 67-152 https://doi.org/10.1086/735665

Owen, Maddog and Moore "AI-powered Fraud Detection Systems"
Owen A, Maddog M and Moore J "AI-powered Fraud Detection Systems: Creating a Machine Learning Model to Identify and Prevent Fraudulent Transactions by Analyzing Patterns and Anomalies in User Data" (August 2020) (research manuscript on file with the authors)

Paramesha, Rane and Rane 2024 *Partners Universal Multidisciplinary Research Journal*
Paramesha M, Rane N and Rane J "Artificial Intelligence, Machine Learning, Deep Learning, and Blockchain in Financial and Banking Services: A Comprehensive Review" 2024 *Partners Universal Multidisciplinary Research Journal* 68-83 https://doi.org/10.5281/zenodo.12826933

Patel *et al* 2025 *Journal of Robotic Surgery*
Patel V *et al* "Best Practices in Telesurgery: Framework and Recommendations from the Society of Robotic Surgery (SRS) for Safe and Effective Implementation" 2025 *Journal of Robotic Surgery* 370 https://doi.org/10.1007/s11701-025-02523-x

Pontes *et al* 2022 *JMLC*
Pontes R *et al* "Anti-money Laundering in the United Kingdom: New Directions for a More Effective Regime" 2022 *JMLC* 401-413 https://doi.org/10.1108/JMLC-04-2021-0041

Raza *et al* "Regulatory, Governance and Future Trends in the Financial System"
Raza SA *et al* "Regulatory, Governance and Future Trends in the Financial System" in Raza SA *et al* (eds) *The Global Evolution, Changing Landscape and Future of Financial Markets: From Traditional to Digital* (Emerald Leeds 2025) 97-118 https://doi.org/10.1108/978-1-83549-330-420251009

Reyes-Mercado *FinTech Strategy*
Reyes-Mercado P *FinTech Strategy: Linking Entrepreneurship, Finance, and Technology* (Springer London 2021)

Rincón-Flores *et al* "Adaptive Learning Based on AI with Predictive Algorithms"
Rincón-Flores EG *et al* "Adaptive Learning Based on AI with Predictive Algorithms" in *Proceedings of the Seventh International Conference on Technological Ecosystems for Enhancing Multiculturality* (16-18 October 2019 León) 607-612 https://doi.org/10.1145/3362789.3362869

Reznik, Utkina and Bondarenko 2023 *JMLC*
Reznik O, Utkina M and Bondarenko O "Financial Intelligence (Monitoring) as an Effective Way in the Field of Combating Money Laundering" 2023 *JMLC* 94-105 https://doi.org/10.1108/JMLC-09-2021-0102

Saiyed 2025 *International Journal of Electrical and Computer Engineering Research*
Saiyed A "AI-driven Innovations in Fintech: Applications, Challenges, and Future Trends" 2025 *International Journal of Electrical and Computer Engineering Research* 8-15 https://doi.org/10.53375/ijecer.2025.437

Sharma *et al* 2024 *International Journal of Information Management Data Insights*
Sharma V *et al* "Does Service Quality Matter in FinTech Payment Services? An Integrated SERVQUAL and TAM Approach" 2024 *International Journal of Information Management Data Insights* 1-16 https://doi.org/10.1016/j.jjimei.2024.100252

Sharma *et al* 2025 *Journal of Risk and Financial Management*
Sharma V *et al* "Sustainable Investments in the Blue Economy: Leveraging Fintech and Adoption Theories" 2025 *Journal of Risk and Financial Management* 1-28 https://doi.org/10.3390/jrfm18070368

Shehu 2010 *JMLC*
Shehu AY "Promoting Financial Sector Stability Through an Effective AML/CFT Regime" 2010 *JMLC* 139-154 https://doi.org/10.1108/13685201011034087

Shibin *et al* 2020 *Annals of Operations Research*
Shibin KT *et al* "Examining Sustainable Supply Chain Management of SMEs Using Resource Based View and Institutional Theory" 2020 *Annals of Operations Research* 301-326 https://doi.org/10.1007/s10479-017-2706-x

Shmueli *et al* 2019 *European Journal of Marketing*
Shmueli G *et al* "Predictive Model Assessment in PLS-SEM: Guidelines for Using PLSpredict" 2019 *European Journal of Marketing* 2322-2347 https://doi.org/10.1108/EJM-02-2019-0189

Streukens, Leroi-Werelds and Willems "Dealing with Nonlinearity IPMA"
Streukens S, Leroi-Werelds S and Willems K "Dealing with Nonlinearity in Importance-Performance Map Analysis (IPMA): An Integrative Framework in a PLS-SEM Context" in Latan H and Noonan R (eds) *Partial Least Squares Path Modeling: Basic Concepts, Methodological Issues and Applications* (Springer Cham 2017) 367-403 https://doi.org/10.1007/978-3-319-64069-3_17

Taherdoost 2021 *Electronics*
Taherdoost H "A Review on Risk Management in Information Systems: Risk Policy, Control and Fraud Detection" 2021 *Electronics* 1-23 https://doi.org/10.3390/electronics10243065

Woolson, Bean and Rojas 1986 *Biometrics*
Woolson RF, Bean JA and Rojas PB "Sample Size for Case-control Studies Using Cochran's Statistic" 1986 *Biometrics* 927-932

Zee, Bolger and Higgins 2020 *Journal of Personality and Social Psychology*
Zee KS, Bolger N and Higgins ET "Regulatory Effectiveness of Social Support" 2020 *Journal of Personality and Social Psychology* 1316-1358 https://psycnet.apa.org/doi/10.1037/pspi0000235

Zhang and Dhaliwal 2009 *International Journal of Production Economics*
Zhang C and Dhaliwal J "An Investigation of Resource-based and Institutional Theoretic Factors in Technology Adoption for Operations and Supply Chain Management" 2009 *International Journal of Production Economics* 252-269 https://doi.org/10.1016/j.ijpe.2008.07.023

List of Abbreviations

AI	artificial intelligence
AMEO	AML enforcement outcomes
AML	Anti-Money Laundering
AMLSE	AML surveillance efficiency
AVE	average variance extracted
FATF	Financial Action Task Force
FinTech	financial technology
FTC	FinTech capabilities
IP	institutional pressures
IPMA	Importance-Performance Map Analysis
IT	Institutional Theory

JMLC	Journal of Money Laundering Control
NP	normative pressures
RBV	Resource-Based View
RS	Regulatory Support
SEM	Structural Equation Modelling
TPB	Theory of Planned Behaviour
VIF	Variance Inflation Factor