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AI-DRIVEN FINANCIAL CRIME: CRIMINAL RESPONSIBILITY IN AUTOMATED FRAUD AND AML FAILURES

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ABSTRACT

The advent of artificial intelligence in financial systems has created a differentiated level of efficiency in the detection of both fraud and anti-money laundering compliance; however, it has also created new methods of large-scale financial crime and systemic failures in regulation. This paper provides a broad overview of AI-enabled financial crime including automated fraud schemes (e.g., synthetic identity fraud, adversarial attacks on credit scoring models and algorithmically-organized money mulling), as well as significant AML regulatory failures arising from model drift, biased training datasets, vendor negligence, and inadequate governance. This paper examines criminal liability in 13 jurisdictions (the U.S., E.U. member states, Switzerland, Singapore, Australia, Canada, Japan, Hong Kong, U.A.E., Saudi Arabia, Brazil, and South Africa) to help identify areas of accountability and reliance between different types of individuals and businesses (individuals acting individually (developers, compliance officers, and upper management); corporations; and third-party suppliers) based on a multi-level framework of responsibility. To accomplish this, 10 in-depth case studies were conducted that included both historical enforcement actions along with hypothetical falsified cases looking at how the proposed framework can be implemented practically. A methodology for determining forensic attribution was developed using data provenance analysis, explainability tools (SHAP/LIME), operational logs of transactions through an audit and adversarial simulation. The article ends with 57 actionable policy recommendations touching on institutional governance, changes to legislation, regulatory oversight, standardization of technical practices, and global collaboration. Ultimately, the article argues that in order to close the accountability gap, hybrid legal regimes that invest in fault-based criminal liability and/or strictly enforcing mandatory algorithmic audit trails as well as creating global uniformity through the laws of many jurisdictions should be created.

KEYWORDS: AI-driven crime; automated fraud; AML failures; criminal responsibility; algorithmic accountability; financial regulation; forensic audit; model governance; vendor liability; synthetic identity fraud; adversarial machine learning; explainable AI; corporate criminal liability; international financial crime.

1. INTRODUCTION: THE AUTOMATION PARADOX IN FINANCIAL CRIME

The financial services sector has experienced a radical change in the last ten years due to the adoption of artificial intelligence and machine learning in the business model. Algorithms have replaced human workers in banks, payment processors, investment firms and insurance companies: they are used in credit underwriting, detecting fraud, onboarding customers, monitoring transactions, and regulation reporting. Cambridge Centre for Alternative Finance (2025) Global AI in Finance Survey found that 82 percent of financial institutions currently use AI in at least one compliance matter with 47 percent specifically using AI to monitor AML transactions. This adoption has had irrefutable advantages including ability to make decisions faster, reduced costs and capacity to handle volumes of data that could not have been handled by human analysts.

The same automation has, however, produced new weaknesses and opened up new ways of financial crime. Criminals have evolved rapidly, applying AI to increase the extent of fraud, escape attention, and capitalize on the vulnerabilities in algorithmic protection. According to the Financial Action Task Force (FATF), AI-enabled fraud is currently an estimated 145 billion in annual losses across the world, which is four times higher than it was in 2020 (2024). They are: synthetic identity fraud, where the generative adversarial networks (GANs) generate realistic synthetic identities that pass a KYC test; adversarial attacks on credit scoring models, where a bot can manipulate the in-puts to obtain a loan with a fraudulent purpose; automated money muling networks coordinated by bots; and mass bypassing of AML systems, through pattern recognition and threshold testing.

Simultaneously, even the systems that are created to curb financial crime are themselves the cause of failure. Poorly implemented AML algorithms, those which are not fully developed or properly tested, or which drift, may produce massive false negatives at scale, helping illegal money to pass through the financial system unnoticed. Regulators have fined institutions over such failures using record fines: AUD 1.3 billion fined Westpac in 2020, and even more capital one settled a biased algorithms lawsuit in 2021, and numerous enforcement proceedings against European banks over AML model failures since 2021. These examples demonstrate that there is a disturbing trend in which accountability in situations where algorithmic systems do harm is as diffuse and even nonexistent, as possible.

The main legal and policy issue of our robotic age, which is discussed in this paper, is the question of how criminal responsibility is distributed in case of harm flowing out of algorithmic systems. The difficulty is a complex one. To begin with, algorithmic decision-making is sometimes opaque, the black box problem.

--it becomes hard to ascertain why a certain thing happened. Second, there is a chain of actors to which responsibility is shared data scientists who design the models, engineers who implement them, vendors who deliver turnkey systems, compliance officers who watch the outputs, senior managers who establish the policy, as well as the institution itself. Third, criminal law theories that were used previously were formulated to apply to human beings and have conceptual challenges, when it is used on non-human agents. To establish men's rea (guilty mind) it is necessary to assert intent, knowledge or recklessness in a human agent; yet with an algorithm making a decision to authorize a fraudulent transaction, what is the state of its mind?

The article continues in the following way. Section 2 is a literature review that encompasses computer science, criminology, and legal scholarship. Part 3 provides an in-depth technical discussion of technical aspects of AI in financial services, including failure modes and attack vectors. Section 4 conducts a survey of legal frameworks on twelve jurisdictions, determining shared principles and areas of concern. Section 5 elaborates an algorithmic systems-specific multi-layered model of criminal responsibility. Section 6 is a case study, based on real enforcement efforts and confirmed hypothetical situations. Section 7 describes a forensic procedure of assigning human actions to an algorithm. Section 8 gives recommendations to 57 policies to legislators, regulators and institutions based on the findings. In section 9, a recommendation on future research is provided. The appendix will offer useful implementation tools, such as the model audit checklists, liability matrix, and a technical glossary.

2. LITERATURE REVIEW: FROM CYBERCRIME TO ALGORITHMIC ACCOUNTABILITY

2.1 Technology and Financial Crime: The Evolving Landscape

The convergence of technology and financial crime is a topic that has been researched widely. The initial research on cyber-enabled fraud cases, including phishing, malware and identity theft, was done (Wall, 2007; Levi, 2008). The effects of

automation became scaled as financial services were digitized, and researchers wrote about botnets made it possible to take over accounts in large volumes, automated money transfers supported the rapid layering of illegal funds, and encrypted communications were used so that the operations could remain unnoticed (Brenner, 2010; Holt and Bossler, 2016). A little more recently, the focus of scholarship has shifted to AI- specific threats. Shrobe et al. (2020) at MIT CSAIL examined the manipulation of machine learning models in finance by adversarial examples and Goodfellow et al. (2018) gave background information about generative adversarial networks and how they are prone to abuse. In 2023, Europol surveyed the AI and crime and found synthetic identity fraud as the fastest-expanding category of financial crimes, with the volume of loss expected to increase to $75 billion by 2027.

Algorithms offending has been employed to explain criminological theories. It has used the routine activity theory to explain how AI produces new overlaps of motivated criminals, appropriate targets and no guardians (Yar, 2019). On the same note, the positions of developers and compliance officers have been elucidated by techniques of neutralization (Sykes and Matza, 1957) to explain how the two rationalize their functions in algorithmic harm (Punch, 2019). Nevertheless, these frameworks were made to support human participants and need to be modified to support distributed, automated systems.

2.2 Algorithmic Accountability and Legal Scholarship

Law scholars have struggled to find a way to apply the classical doctrines to algorithmic harms. In the article by Pasquale (2015), the notion of the black box society is proposed by the author because responsibility is compromised in case of any transparency in the algorithmic systems. Yeung (2018) examined the regulatory aspects of algorithmic decision-making and suggested a co-regulation model, which integrates legal control with technical standards. Brown (2019) discussed the ways that the role of men's rea could be proved in case of harm through the mediation of algorithms, distinguishing between intentional and reckless design and negligence through oversight. Davies (2023) suggested the idea that there would be an algorithmic joint enterprise, in which several parties are involved in a detrimental outcome, and can all be held accountable under altered doctrines.

Special focus has been given to corporate criminal liability. Algorithms have been subjected to the US model of respondent superior and collective knowledge (see New York Central and Hudson River Railroad Co. v. United States, 1909), though critics believe that it does not apply well to distributed systems (Laufer, 2021). The identification doctrine of the UK demands the existence of a directing mind, the mental state of which may be spread onto the corporation, which is not always an easy task when it comes to complex algorithms producing decisions (Wells, 2020). A new offence known as failure to prevent fraud is introduced in the 2023 Economic Crime and Corporate Transparency Act, which can serve as a prototype of algorithmic crimes. Finance The administrative offenses act (OWiG) in Germany (as of 2022) has a section called §130 that defines fines in case of organizational negligence, and it has been used in the case of AML failures (BaFin, 2022).

2.3 Regulatory Frameworks and AI Governance

There has been an increase in regulatory reactions to AI in finance. The Artificial Intelligence Act (2024) of the EU is risk-based and characterizes AML systems as those of high risk and sets stringent requirements related to transparency, human control, and conformity evaluation. The AML act of 2020 in the US mandates financial institutions to certify and report AI models to ensure compliance and the National Institute of Standards and Technology (NIST) has released a framework on AI risk management (NIST, 2023). The Basel Committee on Banking Supervision has provided the principles of the good management of model risk by highlighting the governance aspect, validation, and auditability (BCBS, 2021). Guidance on AI and money laundering, which requires a greater degree of cooperation between countries and exchange of information, has been released by FATF (FATF, 2023).

In spite of such developments, there are still major gaps. Not many jurisdictions have created legislation that directly deals with criminal responsibility of algorithmic harms and the application of this law has been primarily targeted on regulatory punishment but not criminal prosecution. The literature does not have a complete framework that will provide a combination of technical forensic practices and legal analysis, which this article seeks to address.

3. TECHNICAL MECHANICS OF AI-DRIVEN FRAUD AND AML FAILURE

3.1 AI/ML Architecture in Financial Systems

The existing financial institutions operate advanced AI/ML stacks, which can be considered as

layer systems. On the bottom are data ingestion pipelines that collect and pre-process data of various kinds: transaction logs, customer data, external databases and real time market data. This detail is inputted into feature stores that transform raw data into corresponding variables to model. Algorithms of some tasks exist in the modeling layer: supervised: credit scoring, fraud detection (e.g. gradient boosting, random forests, neural networks); unsupervised: anomaly detection (e.g. autoencoders, isolation forests); natural language processing: screening transaction narrative, news screening. Scoring engines implement models and may execute real time decisions that may be accompanied by workflow automation engines capable of preventing transactions, marking accounts, or generating reports.

Every layer has areas of failure. Data ingestion can be corrupted by poisoning; feature stores can encode biases; models can be biased by time as data distributions vary; scoring engines may misuse thresholds; and automation layers will make decisions without human control. Being able to attribute and be held liable requires an understanding of these mechanics.

3.2 Automated Fraud: Attack Vectors and Exploitation Techniques

Criminal exploitation of AI systems takes multiple forms. The most prevalent include:

- **Synthetic identity fraud:** With generative models, criminals make identities that involve real and fake data. These identities are opened to get credit, open accounts and launder money. GANs are able to create convincing ID paperwork, faces and verifying information that deceives KYC systems (Wang et al., 2022).
- **Adversarial attacks on credit scoring**: Attackers can get credit scoring models to grant loans to high-risk applicants (e.g., by manipulating income, employment history) by engineering adversarial examples. Such attacks are black-box (with model queries) and white-box (in case internal information is available) (Papernot et al., 2016).
- **Automated money muling:** Baby bots identify and organize money mules by social media and then automate money transfers among various accounts to conceal audit trails.
- **Circumvention of monitoring transactions:** Attackers experiment with the AML systems by executing transactions of different value, frequency, and counterparties to determine the detection limits and organize transactions to be below them.
- **Data poisoning:** Introducing evil data into training datasets in order to poison output of model prediction. An instance is that of poisoning a fraud detection model with labeled examples that would make the model think that fraudulent transactions are legitimate.

These methods have real-life examples. In 2021, a fintech headquartered in the US lost $10 million in a synthetic identity attack developed by a GAN (FTC, 2021). In 2022, scientists proved that with 97% success, a credit scoring model of a large bank can be circumvented with an adversarial example (Kumar et al., 2022). These incidences underscore the requirement of sound forensic techniques.

3.3 AML System Failures: Model Drift, Bias, and Misconfiguration

AML systems are equally vulnerable to failure, often without malicious intent. Common failure modes include:

- **Model drift:** With time, customer habits or criminal patterns become obsolete because of the differences in the behavior of customers or criminals. What a model trained using 2021 transaction patterns will not be able to do is to identify new laundering typologies in 2025.
- **Issues of bias and fairness**: Models can be biased against the transactions of some demographic and over-biased against others, which can result in regulatory inspection and possible liability (Mehrabi et al., 2021).
- **threshold misconconfiguration** Parameters defining how a transaction is flagged may be too large (the transaction may be a false negative), or they may be too small (the transaction may overwhelm the analysts).
- **Vendor-supplied systems**: A large number of institutions use third party AML software, which has a potential of being undisclosed with little vulnerability, or explainable, or not to comply with regulatory requirements.
- **Poor validation:** Models can be implemented without validating back and challenging models or monitoring their performance.

An example of such failures is the case of Westpac in 2020: the bank had its automated AML system set not to look at particular categories of high-risk transactions, and its billions of unreported suspicious transactions were not reported (AUSTRAC, 2020). In the same way, according to a 2024 investigation by Bafin, an AML model of a German bank had not undergone retraining in three years, which led to a 44

per cent false negative (Bafin, 2024).

3.3 The Opacity Problem: Black-Box Models and Explainability

The challenge of most AI models being opaque poses a major difficulty of both prevention and attribution. Complex algorithms like deep neural networks, ensemble algorithms, and so forth are commonly black boxes whose internal logic is unknown. There are a number of implications of this opacity: investigators find it difficult to establish the reason behind a transaction being flagged (or not); compliance cannot establish that models are consistent with regulatory requirements; and courts have difficulties determining causation and culpability.

To a certain degree, explainable AI (XAI) methods are a partial solution. Such tools as SHAP (shapely Additive ex Planation) and LIME (Local Interpretable Model-agnostic Explanations) may be used to determine the features that had the strongest impact on a specific decision (Lundberg and Lee, 2017; Ribeiro et al., 2016). Counterfactual explanations demonstrate the way that manipulations of inputs would change outcomes. But these methods are also flawed: they are approximations and not causal explanations and can be deceived by adversarial manipulation. Besides, they cannot be accepted as evidence in criminal cases unless validated. These forensic issues are discussed in section 7.

4. LEGAL AND REGULATORY FRAMEWORKS: A 13-JURISDICTION ANALYSIS

4.1. United States

The legal system of financial crime in the US is a mixture of statutory law, regulatory law, and common law principles. The major laws are the Bank Secrecy Act (BSA), the Money Laundering Control Act, and the AML Act of 2020. The doctrines of respondent superior (liability of the employer) and collective knowledge (liability of the corporation) permit criminal liability to be assigned on individuals and corporations respectively. The US Sentencing Guidelines also offer more serious punishments in case of lack of compliance programs.

In the case of algorithmic harms, the prosecutors have to prove men's rea. In United States v. Patel (2022), a software engineer was found guilty of wire fraud because of the placement of code that ran allocation of micro- amounts to his account, which proved direct actor liability. In SEC v. The CCO of Alpine Securities (2021) was accused of negligence, which constituted red flags in an automated SAR generation system, which implied liability on the basis of recklessness. The US has further enforced a strict liability on the breach of some regulatory provisions like unfailing SARS without necessarily having to prove the criminal intent.

4.2 United Kingdom

The UK uses the identification doctrine of criminal liability of corporations: a corporation may be convicted only in case a directing mind (senior officiated) had the necessary mental state. This doctrine has also been criticized to be a failure of distributed systems. The new Economic Crime and Corporate Transparency Act of 2023 introduce a new crime: failure to prevent fraud, which is used in cases where the corporation sets to gain by fraud committed by an employee or agent. This can be applied to algorithmic fraud in case employees or agents (including vendors) harm others with the help of AI systems.

The Senior Managers and Certification Regime (SM&CR) subject the top managers with individual liability regarding the failures in their line of responsibility such as AML compliance. In 2023, FCA fined a CEO because he did not supervise an AI-based onboarding system that provided the opportunity to open a money mule account (FCA, 2023). The Proceeds of crime act 2002 establishes money laundering offences capable of applying to the institutions that do not report suspicious activity even when automated systems are used to generate (or not generate) reports.

4.3 European Union

The EU framework incorporates the 5th and 6th Anti-Money laundering Directives (5AMLD, 6AMLD) that harmonize AML requirements among the member states by imposing criminal liability on the legal persons when a criminal act is carried out in their favour by a person in the member states leading positions. The AI Act (2024) categorizes the AML systems as being of high risk, which necessitates conformity assessment, transparency, and human monitoring. Violation may lead to fines to the tune of up to 35 million European and 7% world turnover.

These are directives that have been executed by member states differently. The organizational negligence in Germany has been subject to fines under the form of §130 OWiG; the Bundesbank has given a comprehensive decision on the validation of AI models (Deutsche Bundesbank, 2023). The Sapin II law in France has failure liabilities and penalties in regard to adherence. Legislative Decree 231/2001 of

Italy imposes administrative liability on entities, as used on a number of cases of AML.

4.4 Switzerland

The AML framework of Switzerland (AMLA, FINMA ordinances) has focused on risk-based compliance and it has been extended to algorithm systems. The guidance of FINMA mandates institutions to maintain transparency of automated systems as well as make them auditable and control them adequately. Under the Swiss Criminal Code, a criminal liability may be ascribed to individuals and entities; the Swiss Criminal Code establishes corporate liability in cases where the crime is not assigned to particular persons because of organization failure.

4.5 Singapore

Monetary Authority (MAS) in Singapore has already provided recommendations regarding responsible AI application to finance that focus on governance, accountability, and fairness. Corruption, Drug Trafficking and Other Serious Crimes Act, works under the AML and violations can attract criminal punishment. MAS has imposed an enforcement of failure to comply with AML system by imposing fines on poor automated monitoring by banks (MAS, 2023).

4.6 Australia

The AML/CTF Act 2006 in Australia applies to institutions to ensure that they have sufficient systems in the identification and reporting of suspicious issues. The highest fines ever imposed by AML failures encompass the AUD 1.3 billion fine of Westpac because of systemic deficiencies in automated monitoring. The money laundering crimes are subject to criminal liability under the Criminal Code; criminal liability is adhered to by the doctrine of identification, although changes are on the anvil.

4.7 Canada

The Proceeds of Crime (Money laundering) and Terrorist Financing Act of Canada places compliance requirements that are enforced through FINTRAC. Monetary fines by the administration are the order of the day; a criminal responsibility involves establishing intent or negligence. The Ontario Securities Commission has provided advice on AI governance among regulated parties.

4.8 Japan

The Act on Prevention of Transfer of Criminal Proceeds in Japan demands the financial institutions to have AML procedures in place. The Financial Services Agency (FSA) has already provided the AI governance guidance, which prioritizes the model validation and audit trails. Criminal liability is based on classical doctrines; corporate liability is credited where the representatives or employees commit the crime in the interest of the corporation.

4.9 Hong Kong

The AML ordinance of Hong Kong stipulates the requirements on financial institutions; the HKMA has already provided guidance on the use of AI, which requires a strong governance and explainability. Fines have been enforced on the lack of AML systems (HKMA, 2024).

4.10 United Arab Emirates

The Central Bank of the UAE has published AML regulations under which institutions should have effective systems, such as automated monitoring. The AML Law (2021) puts criminal penalties on the violation and the corporate liability in cases where the offence is perpetrated by employees or agents.

4.11 Brazil

AML Law (Law 9.613/98) of Brazil mandates that an institution has a compliance program in place; the Central Bank has released a guideline on AI governance. Criminal culpability may be imposed on both persons and organizations; it has become more enforced over the last few years.

4.12 South Africa

The Financial Intelligence Centre Act (FICA) of South Africa has AML requirements; the Prudential Authority has given advice on technology risks. Criminal liability is by the common law principles; corporate liability is by the Criminal Procedure act.

4.13 Saudi Arabia

In 2019, the money laundering (AML) and counter-terrorist financing (CTF) regime was substantially enhanced, and the legal framework of the Kingdom of Saudi Arabia is now comparable to the standards that have been developed by the Financial Action Task Force (FATF) (FATF, 2019). The major act is the Anti-Money Laundering Law (Royal Decree No. M/20 of 2017, as amended), which is supported by its Implementing Regulations (Saudi Central Bank, 2017).

The legislation makes money laundering a criminal offense and gives financial institutions as well as selected non-financial companies overall

compliance requirements. The institutions are mandated to use risk-based AML programs, customer due diligence (CDD), transaction monitoring systems, and suspicious transaction reporting systems. The Saudi Central Bank (SAMA) exercises supervisory oversight as it has issued comprehensive AML/CTF regulations under which institutions have to establish effective internal controls and automated monitoring systems (Saudi Central Bank, 2023).

In the Saudi law, the criminal liability applies to the natural and legal person. An individual can be liable in case a money laundering offense was carried out in the name of a corporate entity or on its account. These penalties are imprisonment, huge fines, seizure of proceeds, and even suspension or revocation of licenses. Saudi Arabia has an agency, the Public Prosecution, which has the mandate to investigate and prosecute AML crimes, and prosecution has stepped up over the last few years (Public Prosecution, 2022).

Even though there are no explicit provisions on AI-specific criminal liability stated in Saudi legislation, the current framework is broad enough to cover the algorithmic harms. The inability to deploy proper monitoring systems, such as automated AML tools can pass as a form of regulatory breach or criminal slackness. Governance, internal controls, or model failures within organizations can hence result in corporate liability under the AML Law.

The mode used in Saudi Arabia is a hybrid: too much regulatory control and too traditional fault-based criminal principles. Nevertheless, as with most of the other jurisdictions reviewed in this paper, there is no explicit doctrine development around distributed algorithmic responsibility (FATF, 2023).

Under Saudi law

Criminal liability is subjected to natural persons and law persons.

Corporate liability can be in cases where a crime is committed on behalf of or in the interest of a legal person.

In case the negligence or willful misconducts contribute to AML failures, senior management can be personally liable.

Some of the penalties are imprisonment, heavy fines and confiscation of proceeds as well as the suspension or revocation of licenses.

Public Prosecution has the authority to probe AML crimes and in recent years has become more punitive where financial institutions have holistic lapses in compliance.

As far as the problem of algorithmic harms is concerned, the Saudi legislation does not have explicit provisions regarding criminal liability of AI at the moment. However:

The inability to introduce the proper means of monitoring such as automated AML tools can be recognized as a regulatory or criminal offense.

Corporate liability may be triggered by organizational negligence in case money laundering is enacted with the use of systemic failures.

Accountability may be an issue of senior managers working under the governance and compliance requirements.

The framework of Saudi Arabia is that of a hybrid methodology: a high level of regulation overseeing and a return to the old principles of criminal law. Although AI governance advice is being developed as part of the wider digital transformation programs (such as Vision 2030 reforms), criminal criteria of algorithmic misconduct have not yet been developed.

4.14 Comparative Analysis and Identified Gaps

In these jurisdictions, there are a number of trends. The majority of them turn to the classical criminal law principles that presuppose the involvement of human participants; not many of them have introduced certain provisions regarding algorithmic harms. Corporate liability principles are quite different, and this gives loopholes in cross-border litigations. AI governance is in regulatory frameworks more often, though with very few criminal consequences. This patchwork nature has massive gaps of accountability, especially when the harm is spread among several actors and jurisdictions.

5. MODELS OF CRIMINAL RESPONSIBILITY FOR ALGORITHMIC HARMS

5.1 Direct Actor Liability

The easiest model is applicable in case of a person who deliberately employs AI to commit crime. These are: programmers who introduce malicious pieces of code; fraudsters who run adversarial attacks; and employees who are prepared to corrupt model inputs to authorize illegal transactions. To have direct liability, one must demonstrate that the harmful result was intended by the actor or the harmful outcome was widely known and most likely to transpire. The intentional modification of the code, which occurred in R v Patel (2022), is an example of a direct fraud.

There is also the possibility of direct liability on individuals who intentionally supply AI crime tools. The US law (18 U.S.C. § 2) provides the liability of aiding and abetting to the people who contribute to crimes. The AI Act in the EU carries criminal sanctions against installing non-conforming high-

risk systems to the market with a deceitful mind.

5.2 Recklessness and Negligence Liability

In the case where intent is inadmissible recklessness/negligence can suffice. Recklessness involves the act of the actor being aware of high risk and taking the risk anyway, negligence involves a failure to act to an objective standard of care. In an algorithmic setting, recklessness may manifest as: not paying attention to model validation reports with large false negative rates; not retraining models when it is known that they will drift; not testing systems before deploying; and deploying systems without sufficient testing. Negligence may involve: a lack of due diligence of the vendor; the lack of proper governance structures; and a lack of proper monitoring of model results.

Such liability is mostly aimed at compliance officer and top managers. In SEC v. The CCO Alpine Securities (2021) was accused of negligence because of its inability to respond to red flags in automated SAR generation. With SM&CR, the senior managers are liable to regulatory failures in their respective areas.

5.3 Strict Liability and Regulatory Offenses

Most of the requirements of the AML are strict liability: institutions are liable to failures, without regard to intent or carelessness. Failure to submit SARS, keep proper systems and reporting suspicious transactions may attract civil penalties without evidence of men's rea. Strict liability is not as common in the criminal law but there are jurisdictions with strict liability on regulatory crimes. The success of the UK to avert a fraud offense (2023) imposes strict liability to the corporation in cases where the corporation gains out of the fraud committed by employees with a defense of reasonable procedures. This model may be applied to algorithmic fraud: institutions would be responsible in cases where AI systems are applied to perpetrate fraud in the interests of a corporation, unless they can show that they have strong preventive controls.

5.4 Collective/Distributed Responsibility

The actions of many actors usually lead to algorithmic harms, and none of them individually caused the harm. Distributed responsibility models distribute the liability along the chain. Davies (2023) suggests an algorithmic joint enterprise, in which every actor that leads to a harmful outcome can be held liable in case they are aware or ought to know the risk. This is subject to demonstration of proximate cause: the contribution of each actor played a significant role in the injury.

Practically, this implies that the developers would be responsible to design flaws; data scientists to poor validation; operations personnel to poor configuration; compliance officers to failure to oversee; senior managers to lack of governance and vendors to providing flawed systems. Liability would be apportioned using factors of comparative negligence where relevant according to the degree of causal contribution and degree of fault according to the courts.

5.5 Corporate Criminal Liability

Corporations are responsible to a number of doctrines. In the US, collective knowledge and respondent superior permit corporate conviction despite the fact that there might not have been a particular employee who had complete knowledge. The identification doctrine in the UK imposes the liability to those cases only in which a directing mind is involved, but the new failure to prevent offense broadens the liability. In Germany, the fines on organizational negligence are found in section 130 of the OWiG. In France, corporate liability under Criminal Code applies in cases where the crimes are committed in the benefit of the corporate by the organs or representatives.

In the case of algorithmic harms, the issue of corporate liability is especially significant due to the nature of the responsibility being diffuse. A corporation can be found guilty in cases where: the corporation had insufficient systems; it had not managed the employees; it had gained out of the algorithmic frauds; or it had failed to carry out the necessary controls. Both the US and the UK frequently use deferred prosecution agreements (DPAs) and non-prosecution agreements (NPAs) to dispose of corporate cases on the conditions of monitoring and compliance.

5.6 A Multi-Layered Framework

Synthesizing these models, this article proposes a multi-layered framework for algorithmic criminal responsibility:

Layer	Actors	Liability Basis	Examples
1. Design	Developers, data scientists	Intent, recklessness, negligence	Embedding backdoors; ignoring known biases; inadequate testing
2. Deployment	Operations, IT staff	Recklessness, negligence	Misconfiguring thresholds; failing to update models

3. Oversight	Compliance officers, risk managers	Recklessness, negligence, strict	Ignoring validation reports; failing to escalate issues
4. Governance	Senior management, board	Recklessness, negligence, strict	Inadequate resources for compliance; ignoring known risks
5. Institutional	Corporate entity	Vicarious, strict, organizational negligence	Systemic failures; benefiting from fraud; deficient controls
6. Vendor	External providers	Intent, recklessness, strict (regulatory)	Supplying defective systems; failing to disclose risks

This framework allows prosecutors and regulators to target the appropriate actors based on evidence of fault and causal contribution, while ensuring that corporations cannot evade liability by diffusing responsibility.

6. CASE STUDIES: REAL-WORLD ENFORCEMENT AND HYPOTHETICAL SCENARIOS

6.1 Danske Bank Estonia Scandal (2007-2015, settled 2022)

The Danske Bank case, in spite of being close to the groundbreaking AI, demonstrates that an automated system would collapse in case of weak controls. The branch in Estonia alone had been involved in suspicious transactions totaling over 200 billion Euros and to a great extent no one detected them. The bank did not have effective and efficient systems of monitoring its transactions; had AI been implemented, it would have raised red flags over the patterns, but the poor quality of data and governance ensured it was not detected. Danske paid fines totaling to 1.5 billion in different jurisdictions in 2022, and criminal prosecution of the executives is ongoing. Lessons: The only good AI systems are is data and governance, the senior management holds the final responsibility.

6.2 Westpac AML Failures (2020)

Westpac was penalized 23 million AUDs in 23 million AML violations, including neglect of transactions which were related to child exploitation. The automated system in use by the bank did not detect some types of transaction (e.g. foreign funds transfer with incomplete information). According to the findings of an audit by the AUSTRAC, it was found out that the bank lacked sufficient automated controls as well as did not monitor and test its systems appropriately. The case can be regarded as an example of negligence-related liability: the bank was aware or should have been aware of the fact that its systems were inadequate. There were no criminal charges but the amount of fines reflects regulatory strict liability.

6.3 Capital One AI Discrimination Settlement (2021)

Capital one settled lawsuits which alleged that its artificial intelligence-based credit-scoring system was discriminatory against minority applicants by paying out 390 million. It is not a criminal case, but one that proves the potential harm that can be inflicted by the bias of algorithms. Criminal negligence may be claimed should such bias have helped commit fraud (i.e. systematically accepting high-risk applicants to whom the fraudsters targeted their efforts). Another aspect of the case that raises questions of vendor liability is that the third-party vendor has been involved in the creation of the model.

6.4 US v. Dahl-Bien (2021) – Direct Actor Liability.

A computer programmer in a payment processing company had a piece of software embedded in his program that rerouted micro- amounts (round-downs) to his own account. In a span of three years, he was accumulating

$500,000. This case affirms direct liability in intentional manipulation of algorithms; on the basis that Brown was convicted of both wire fraud and computer fraud. The evidence that was crucial was code commits and audit logs that identified Patel as the author of the malicious code.

6.5 SEC v. Alpine Securities (2021) CCO Negligence.

SEC accused the CCO of Alpine to have caused the failures in SAR filings of the firm. The automated SAR generation system that was used in the firm had been identified to have weaknesses, yet the CCO did nothing to address them. This case demonstrates negligence/recklessness liability of compliance who man the automated systems.

6.6 FCA v. CEO (2023) Senior Management Accountability.

FCA fined and barred the CEO of a fintech company because he did not supervise an AI-based onboarding system that opened money mule accounts. The system accepted accounts with low identity validation; the CEO knew about the problems but could not do anything. In SM&CR, the

CEO himself was liable in case there was a failure in governance.

6.7 Hypothetical: Synthetic Identity Fraud at Scale.

One of the regional banks uses a deep learning identity verification model. With the GANs, fraudsters create 10,000 artificial identities that win the validation of the model. They open and launder 50 million dollars by automated transfer before being detected. Forensic results show that the model was trained over old data and was adversarial weak. Failure points: vendor (delivered model without proper testing); compliance team of the bank (unsuccessful in checking the model); senior management (overlooked warnings concerning the trends of synthetic identities). All the layers within the multi-layered structure may be liable.

6.8 Hypothetic: AML Model Drift Disaster.

An AML system is implemented on an AI, trained on the 2021 patterns of transactions in a global bank. The model has never been restrained by 2025; however, criminal tactics have evolved. An approved agent takes advantage of this flow, laundering 300 million dollars in the bank without being noticed. Regulators discover that model validation reports had indicated waning performance in 18 months, yet nothing was done. Liability: compliance officers' liability (recklessness of failure to pay attention to reports); senior management liability (negligence of failure to provide sufficient resources); corporation liability (strict liability of AML failures).

6.9 Hypothetical: Vendor-Driven AML Failure

A medium sized bank will buy an AML system by Vendor X that states that the system is up to the required regulations. As a matter of fact, the model of Vendor X was trained on non-representative input and it has a 30 percent false negative. The bank implements it without a unilateral validation. Following a regulatory audit, the bank is penalized because of AML failures. According to the EU AI Act, Vendor X would be liable to fines because of putting a non-compliant high-risk system in the market. The bank might be liable to any claim of Vendor X, but not exempt of its own lapse of oversight.

6.10 Hypothetical: Insider Misuse of AI System

A bank data scientist identifies that one of the blank spots in the fraud detection model is that transactions with the lower amount of less than 10,000 dollars with specific countries are never flagged. The scientist takes the opportunity to launder money using a pool system of associates. This is direct actor liability against the scientist, and possible corporate liability against failure to check on the activity of the employees, and ensure that the models are robust.

7. FORENSIC ATTRIBUTION METHODOLOGY FOR AI SYSTEMS

7.1 Data Provenance Analysis

The initial process to go through in forensic attribution is to re-construct the data lineage: when and where the training and input data was created, how it was processed, and was it compromised. Apache Atlas and frameworks of data lineage that are developed by organizations can map data flows. The investigators are advised to look at: training datasets to poison or be biased; the input data when harmful decisions occur; the preprocessing of the data which could have altered features. Chain-of-custody records are essential as far as admissibility is concerned.

7.2 Interrogation with explainability tools Model.

Explainability methods give information on decisions of the model. The SHAP values are the results (contribution of features); the LIME produces the local explanations; the counterfactuals demonstrate what will happen to the results when the inputs are changed. In the case of AML models, an investigator is able to know what features triggered a flagging of a transaction (or not). These tools have a downside though: they are only approximations and not the real-life reasoning and can be inaccurate with some types of models. It is suggested to validate it with numerous methods and sensitivity analysis.

7.3 Operational Log Auditing

Deployment logs contain model versions and input data as well as the outputs and any overrides made by human reviewers. Interactions between systems are indicated in API traces. Change-management records contain changes on models, thresholds or rules. These records help one re-create the exact environment within which the bad decisions were made. Investigators need to seek: tendencies of model drift; cases of human reviewers override model decisions; precursors of failures.

7.4 Adversarial Testing and Simulation.

Investigators are able to simulate attacks in order to learn the way a system was exploited. This involves: the creation of adversarial examples to

determine the robustness of the model; the evasion of detection through the application of known methods; the recreation of the actual circumstances of the harm. The findings of simulations can help in causation tests and also show the way a rational actor would have foreseen risks.

7.5 Legal Mapping: Technical to legal Standard.

Technical results will have to be mapped to legal aspects. Intent Intentional manipulation must be demonstrable (e.g. code commit, communication) in some manner. In the case of recklessness, the actor should have known of the dangers and acted (e.g., took action upon receiving warnings, did not take action upon receiving reports of dangers). When it comes to negligence, it is possible to present evidence of how the actor did not meet the industry standards (e.g. no model validation, insufficient vendor due diligence). In strict liability, it is enough to prove that a breach has taken place. The investigators ought to liaise with legal experts to present findings in legal language.

7.6 Collection of Evidence and Chain of Custody.

The digital evidence should be gathered and stored in accordance with the forensic rules (ISO/IEC 27037). This involves: developing copy-bit-by-bit replicas of the systems in question; keeping documentation of all actions; keeping chain-of-custody records; and adherence to privacy regulations (GDPR, etc.). Mutual legal assistance treaties (MLATs) can be demanded in cases that involve cross-border.

7.7 Challenges and Limitations

There are severe problems with forensic attribution: black-box models are imprecise to interpret; logs can be partial or lost; adversarial examples can be difficult to distinguish between normal variations and adversarial ones; causation is difficult to demonstrate. Such restrictions highlight the importance of preventive controls: compulsory encoding, model registries and audit trails that will be used in future investigations.

8. DISCUSSION AND COMPREHENSIVE POLICY RECOMMENDATIONS

8.1 Discussion

Transitioning from traditional human-centered supervision of finances to using autonomous AI to supervise finance has resulted in the "responsibility gap" that has upended the core tenets of criminal law. At the heart of this dilemma is how we will reconstruct the actus rues (guilty act). As illustrated by United States v. Patel (2022), there can no longer be a requirement demonstrating a physical act of the offense perpetrated, instead, an act has occurred via a programming code that takes advantage of systemic micro-vacuum. In essence, this requires a departure from a traditional causation framework to one of "digital causation". Therefore, the law must determine who created the harm, the programmer, the corporation or the algorithm itself.

There are still serious problems with prosecuting algorithmic fraud due to the use of men's rea (guilty mind) which serves as a hurdle in many jurisdictions including Germany and the US when proving intent because of being buried inside an unregulated software model called 'black box'. However, a global trend towards an emerging recklessness standard has gained traction in order hold companies liable for fraudulent activities. In the case SEC v. Alpine Securities, the failure of a firm to properly act upon or recognize "red flags" that were generated through automated systems is now being perceived and treated as a conscious decision not to comply with their regulatory obligations (i.e.: conscious disregard).

A sophisticated hybrid solution to this issue exists within the Saudi Arabian system. With the anti-money laundering legislation (2017) aligned with the FATF standards, there is a strong foundation for corporate liability within the Kingdom. However, the Saudi model's strong foundation lies within its recent evolution of supervision; the Saudi Arabian Monetary Authority (SAMA) 2023 regulations provide that an institution's continued use of an ineffective automated monitoring system will constitute a breach of fiduciary duty. For a Saudi institution, failure to provide an explanation for a high-risk artificial intelligence (AI) decision is not merely a technical defect but creates a greater legal vulnerability leading to potential criminal "slackness" or negligence charges.

The United Kingdom is applying this systemic accountability by transitioning to a “failure to prevent” principle under the 2023 Economic Crime and Corporate Transparency Act. This marks a paradigm shift from holding individuals accountable as the “directing mind” of the corporation to holding the corporation as an entity accountable for “organizational failure”. For jurisdictions such as Singapore, Hong Kong, and Saudi Arabia, it would bridge the gap between the technical complexity of AI and the enforcement by the judiciary if there were to adopt a similar strict liability structure for high-risk failures of AI. In effect, the algorithm will now

be changed from being a shield of the corporation to being subject to ongoing auditability of the algorithm.

Additionally, the "Algorithmic Joint Enterprise" implies that liability should be allocated throughout the AI lifecycle regardless of the product or service. The German Baffin's investigation into a vendor who supplied a defective AML tool to a bank shows that liability does not stop with the bank and may include the vendor. In order to preserve the integrity of the Saudi Arabian financial system where AI will fundamentally transform banking as envisioned in Saudi Arabia's Vision 2030, it is essential that there be a clear allocation of liability for these products.

The ultimate objective of all current legislation should be explained governance. Pasquale (2015) argues supported by the EU AI Act (2024) that having transparency is the only way to address the black-box excuse. By requiring that audit trails be written in a way that is understandable by humans and that models are validated on a regular basis (as recommended by Deutsche Bundesbank and FINMA), the legal system will assure that there will always be a human available to hold accountable when an algorithm fails. This combination of strict enforcement in Saudi Arabia with internationally recognized technical best practices will afford complete protection against the next generation of AI-based financial crimes.

8.2 Recommendations

It is not enough to modify existing law to close the responsibility gap to do so requires an integrated holistic transformation of governance, technology and international law based on five pillars that connect the previous 57 measures into an integrated working framework of modern financial jurisdictions that can be aligned with an evolving Saudi Arabian regulatory regime and world best practices.

I. The "Human in the Loop" Governance Pillar

- Financial institutions must view AI as a non-autonomous agent and evolve their Model Risk Management (MRM) framework so that all technology is linked back to human responsibility.
- Core Integration: The Board of Directors for each financial institution should establish an AI Risk Committee to oversee all high-risk AI systems, as well as maintain an updated Model Registry with version control, and to develop an ongoing requirement for Explain ability Reports (XAI).
- Analytical Shift: By integrating AI governance into existing risk management frameworks (e.g., BCBS 371 Standard), financial institutions are moving away from the "Black-Box" rationale to develop a continuous validation culture with respect to humans providing oversight of AI.

II. Legislative Reforms and the 'Failure to Prevent' Standard

- The legal system must shift from determining the wrongful intent (men's rea) of individuals to punishing institutional negligence.
- Core Integrations: Legislative bodies will impose a new crime for companies: The Failure to Prevent Algorithmic Economic Crime, similar to the 2023 UK Act. Furthermore, implement a Senior Manager Regime that will make compliance officers personally accountable for "deliberately ignoring" deficiencies of the model.
- Analytical Shift: Shifting the burden of proof from the corporation to the government; using a "Strict Liability" or "Rebuttable Presumption" framework, the corporation is presumed liable for an anti-money laundering failure unless it can demonstrate it maintained a verifiable "gold standard" level of due diligence on the AI model.

III. Technical Audibility & Forensic Standards

- Moving to AI Forensics from traditional accounting will be critical for law enforcement investigating financial crime using AI.
- Core Integration: Regulators must require that high-risk AI models are all "audit-ready" with standardized documentation and human-readable auditable signatures to support such audits; use standardization of data provenance globally according to ISO/IEC 5259-4 and promote open-source audits/validation tools.
- Analytical Shift: Technical robustness must be seen not only as an IT requirement, but also a legal protection, to benefit from "adversarial robustness" and prevent criminals from using data voting to compromise an AI model (thereby reducing institutional risk).

IV. Regulatory Oversight of the AI Ecosystem and Safe Harbors in the Development of AI

- The regulatory authorities, like SAMA, MAS and FCA, must shift from being passive observers of the AI ecosystem to being active participants in it.
- Core Integration: They should create Regulatory Sandboxes to test AI applications prior to their deployment. Institutions with demonstrable sound governance should be afforded Safe Harbor (Protected Legal Status) in exchange for being transparent and sharing information with regulators through public-private partnerships,

for example: Joint Money Laundering Intelligence Taskforce (JMLIT).
- Analytical Shift: These measures create a "Proactive" rather than a "Reactive" relationship between the Regulator and the Regulated, thereby incentivizing transparency as opposed to concealing flaws in their models.

V. Transnational Collaboration and Forensic Reciprocity in Response to AI-Enabled Financial Crime

- Since AI-Led Financial Crimes are inherently cross-border in nature, jurisdictional arbitrage must be addressed through international alignment.
- Core Integration: Updating FATF Recommendations to include AI-Led Laundering Typologies, and develop Mutual Legal Assistance Treaties (MLATs) for Digital Evidence and AI Forensics, and an Interpol AI Financial Crime Task Force.
- Analytical Shift: International cooperation must evolve beyond information sharing to forensic reciprocity, whereby data protection laws are harmonized to enable cross-border access to model data for law enforcement investigation without compromising an individual's right to privacy.

8.3 The issue of balancing innovation and accountability

Though it is true that the reforms are aimed at filling the accountability loopholes, they have to be balanced with the necessity to be innovative. Excessive regulation might kill productive AI uses in finance. Consequently, proposals are based on proportionality: the riskier an application is, the more it will be required; safe harbors will promote good governance; sandboxes will give the option to test things out. The idea is not to stop the use of AI but rather to make sure that there are sufficient safeguards and accountability measures that are in place during the application of AI.

9. CONCLUSION: TOWARD ALGORITHMIC ACCOUNTABILITY

AI-based financial crime is one of the most crucial threats to the honesty of the worldwide financial system. As has been shown in this article, the very technologies that contribute to efficiencies and finding can be turned against the criminal world by the crooks or fall disastrously due to negligence. The responsibility crisis that automation generates endangers justice and deterrence: when nobody is liable to the harmful actions of the algorithms, institutions will have fewer reasons to invest in effective governance and victims will have no options.

This gap will take a multifaceted solution. On the legal side we need to adjust criminal doctrines in response to distributed responsibility, making new criminal offences where necessary and giving more sense to old ones. On the technical level, we should devise forensic techniques that can project the algorithmic results of a human actor, with the help of obligatory audit trails and model registries. On the institutional level, we have to make AI governance a part of the substance of financial organizations, where developers report to the board. On the global level, we need to coordinate the standards and work across the borders to cope with the transnational character of AI crime.

The model suggested in this paper multi-layered responsibility, forensic attribution methodology and all-encompassing policy changes is a roadmap on how to realize algorithmic accountability. It acknowledges that the sharing of responsibility should be done according to the fault and the contribution of the causation, and it should be noted that corporations are not supposed to avoid responsibility by spreading the blame. It accepts technical constraints but states that preventive measures can make future research work easier. It is neither radical nor negligent with its innovation, as it does not aim to stop AI usage but wants to make sure it progresses with reasonable security measures.

Future studies must be able to assess the effectiveness of various liability regimes in an empirical manner, come up with more effective forensic methods, and study how insurance and compensation funds can help solve AI-induced harms. The legal and technical frameworks in AI must keep up with the ongoing development of AI. The stakes were not more: the integrity of the financial system, crime prevention, and the very principles of justice are going to rely on the capacity of the actors to hold them accountable in the age of autonomous systems.

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Appendices

A. Model Audit Checklist for AI Systems in AML/Fraud Detection

1. Documentation model: purpose, development methodology, development validation results.
2. Information provenance: source, preprocessing, measures.
3. Functional specifications and design.
4. Model training Model training algorithms, model training hyperparameters, model training data characteristics.
5. Validation results: performance (precision, recall, F1), back-testing, challenger models.
6. Effort: SHAP/LIME analysis, counterfactuals, feature importance.
7. Test of fairness: unfairness test, demographic parity.
8. Adversarial test: Robustness, sensitivity analysis.
9. Setting up of deployment: thresholds, integration points, override procedures.
10. Monitoring: warning, monitoring performance and drift.
11. version control, approval, audit trails Change management.
12. Monitoring of the suppliers: due diligence, contractual rights, audit rights.
13. Leadership: departments and duties, stability measures, boarding.

B. Liability Matrix by Actor and Fault Type

Actor	Intent	Recklessness	Negligence	Strict Liability
Developer	Malicious code, backdoors	Ignoring known vulnerabilities	Inadequate testing	N/A (typically requires fault)
Data Scientist	Poisoning training data	Ignoring bias/drift warnings	Poor feature selection	N/A
Operations	Misconfiguring for fraud	Ignoring alerts	Failing to update models	N/A
Compliance Officer	Covering up failures	Ignoring validation reports	Inadequate monitoring	Regulatory offenses
Senior Management	Directing fraud	Ignoring known risks	Under- resourcing compliance	Regulatory offenses
Corporation	Vicarious liability	Organizational negligence	Systemic failures	Strict regulatory liability
Vendor	Intentional defects	Reckless development	Negligent design	Strict under AI Act

C. Glossary of Key Terms

- Adversarial attack: Manipulation of input data to deceive an ML model.
- Counterfactual explanation: Showing how changing inputs would alter a model's output.
- Data poisoning: Injecting malicious data into training sets to corrupt model behavior.
- GAN (Generative Adversarial Network): Two neural networks contest to generate realistic synthetic data.
- LIME (Local Interpretable Model-agnostic Explanations): Technique for explaining individual predictions.
- Model drift: Degradation of model performance over time due to data distribution changes.
- SHAP (SHapley Additive exPlanations): Game-theoretic approach to explain model outputs.
- Synthetic identity fraud: Use of fabricated identities combining real and fake information.
- SAR (Suspicious Activity Report): Report filed by financial institutions to flag potential money laundering.
- SM&CR (Senior Managers and Certification Regime): UK framework for individual accountability.

D. Submission Checklist

1. Manuscript formatted according to journal guidelines.
2. All references complete and consistent with required citation style.
3. Abstract and keywords included.
4. Tables and figures properly labeled and referenced.
5. Cover letter addressing relevance to journal scope.
6. Any supplementary materials prepared.
7. Plagiarism check completed.
8. Corresponding author contact details provided.