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THE ECONOMIC COST OF FRAUD IN THE U.S. AND HOW AI CAN REDUCE THESE LOSSES

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ABSTRACT
Fraud is a growing economic problem in the U.S. Consumer fraud costs businesses, government agencies, and individuals billions of dollars annually, eroding public confidence and financial security. Recent findings from both the Federal Trade Commission (FTC) and the FBI's IC3 reveal that fraud-related losses continue to increase across industries on a year-over-year basis. Organizations globally estimate that nearly 5% of annual revenues are lost due to fraudulent activity. Classical detection systems, primarily based on static, rule-based approaches, are not sufficient to counter the complexity and sophistication of fraud. In contrast, AI has become a game-changer in fighting fraud by leveraging cutting-edge strategies (machine learning, anomaly detection, behavior analysis, and natural language) to detect and prevent fraudulent behaviors as they happen. By continually changing to keep up with new behaviors, AI systems can cut financial losses and help companies operate more efficiently while strengthening trust in markets and institutions. This research illustrates the economic cost of fraud in the US and investigates how AI can curb these losses, highlighting their role in shifting from reactive responses to proactive judgments.
KEYWORDS: *Fraud; Artificial Intelligence; Economic Losses; Detection of Fraud; U.S. Economy*

INTRODUCTION

The financial toll of fraud in the United States is a massive and growing problem for Americans, businesses, and government organizations. In 2024, the FTC indicated that consumers lost more than $12.5 billion in fraud costs (Garriott, 2025), reflecting a rise over the previous year and highlighting investment and imposter scams as two especially expensive varieties (Nejad *et al*., 2025). This number is but a small share of the overall economic toll. Larger analyses from the FBI's Internet Crime Complaint Center (IC3) detail losses of more than $16.6 billion in 2019 (Dwight *et al*., 2025), and the Government Accountability Office estimates that fraud in federal programs alone could total between $233 billion and $521 billion annually (Sheets, 2025).

Artificial intelligence (AI) is a key and promising solution against this increasing threat. Unlike static, rule-based systems, AI and machine learning models can analyze vast amounts of data in real-time to detect nuanced anomalies and more complicated patterns (Bello *et al*., 2023) that would be difficult for humans or outmoded technologies to detect. AI-powered solutions deploy a variety of approaches, from behavior analysis that can alert on anomalous user activity to natural language processing (NLP) capabilities (Verma *et al*., 2025) that spot phishing emails and surface advanced anomaly detection that can preemptively recognize emerging threats. This pliability makes it possible for AI to continue learning and adapting in the face of new fraud schemes, a right that's especially important in a digital world where criminals are using AI. AI in fraud detection has had promising results already, with some deployments eliminating fraud losses and drastically increasing the speed at which it is detected (Bello *et al*., 2023). By turning the tide against reactive damage control to proactive defense, AI mitigates not only financial ruin but also improves operational efficiency and trust in financial and public institutions.

The financial cost of fraud in the United States is an enormous and expanding issue for Americans, business owners, and government entities. In 2024, the FTC reported that some $12.5 billion was lost by consumers in fraud (Greenblatt, 2025) compared to the year before and investment and imposter scams emerged as two of these most costly types.

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This figure is only a tiny fraction of the total economic cost. Additional reports from the FBI's Internet Crime Complaint Center (IC3) specify losses of more than $16.6 billion in 2019 (Sibtain *et al*., 2025), and the Government Accountability Office, for their portion, indicates that fraud as it relates to federal programs only could cost between $233 and $521 billion dollars every year (Sheets, 2025).

Artificial intelligence (AI) is one of the most important characteristics and an encouraging endowment to combat such adversity. Unlike the static, rule-driven platforms of years, AI or machine learning would have access to almost an infinite amount of rapidly analyzed data up to that point in time (Sarker, 2021), leading to being able to pinpoint nuanced anomalies and more complex patterns such as B(P)D leakage that might escape or elude humans from noticing it or obsolete technologies for that matter. AI-centered offerings harness a range of solutions which include behavior analysis that can raise an alert on anomalous user activity and NLP capabilities that detect phishing emails and surface advanced anomaly detection such as actionable threat identification to identify threats in their infancy stage. This elasticity also enables AI to keep learning and changing in response to novel fraud schemes (Samuel, 2023), treatment that is particularly important in a digital universe teeming with criminals who are using AI. AI in fraud detection has also shown promising outcomes, with some implementations reducing the fraud loses to zero and significantly shortening the time it takes for a fraud to be identified (Faisal *et al*., 2024) Shifting the pendulum from reactive damage control to proactive defense, AI serves to stem not only monetary ruination but also enhance operational efficiency and trust in financial and public services.

LITERATURE REVIEW

The fraud problem is a persistent and growing threat in the United States and results in an immense financial cost as well as damage to public and private sector confidence in institutions. The reported cases of fraud have escalated in recent years and are collectively costing consumers, workers, and public billions of dollars a year due to consumer fraud, occupational frauds/scams, and government program abuse (Federal Trade Commission, 2025; Federal Bureau of Investigation Internet Complaint Center, 2024). With these direct costs, studies reveal myriad cost implications that are hidden, which include reputational harm, and compliance expenditure in addition to lost productivity (O'Neill *et al*, 2014). Considering this, academic and industry literature has placed a growing emphasis on artificial intelligence (AI) and machine learning (ML) as next-generation transformational solutions for fraud detection and prevention, offering adaptive capabilities that go beyond traditional rule-based systems (Alonge *et al*., 2021). This paper collects major theories of fraud, economic effects, and the effectiveness of AI-based approaches in reducing losses.

Models and Analysis of Fraud Economics

Theory Much of the academic basis for understanding fraud is derived from theoretical frameworks. The Fraud Triangle hypothesis is still considered meaningful, denoting fraudsters' decisions or choices influenced by three factors: pressure, opportunity, and rationalization (Mandal *et al*., 2024). Building on this, the Fraud Diamond of Wolfe and Hermanson contained a fourth component: capability, to recognize that personal capabilities and attributes would determine success in committing fraud (Widyashanti, 2015). These models help explain why fraud never goes away, even in highly regulated environments. The economic impact is also substantial; the ACFE estimates that organizations lose 5% of their annual revenue due to occupational fraud (Fish, 2020). Whether at an individual level or a national level, fraud reduces profitability, interrupts the flow of business, damages image and credibility, and diminishes market stability. As we have seen from historical cases, such as Enron, fraud has the potential not only to destabilize entire industries but also to obfuscate investor mood.

Consumer and Cyber Fraud Trends

Consumer fraud is also one of the fastest-growing areas. The Federal Trade Commission (FTC) reported that the total consumer loss for 2023 exceeded $10 billion (Lin, 2025) and was driven primarily by investment and imposter scams. Digital channels, cryptocurrencies, and the social engineering exploits of adversaries enhance fraudsters' ability to hide their face (anonymity) (Khan, A. et al., 2025) and broadcast their advertisement for business across a larger market domain. The proliferation of digital payment platforms has also opened the door to new forms of exploitation, from phishing to crypto-related investment scams (Baloch *et al*., 2023) (Baloch *et al*., 2023). Such trends emphasize, analysts have identified, the advancement of modern fraud and the limitations of static detection methods, too.

Organizational and Occupational Fraud

Businesses are still losing money to corporate and occupational fraud. Occupational fraud schemes, including asset misappropriations, corruption, and financial statement fraud, continue to result in median losses in the hundreds of

thousands per case with an average duration of 14 months (Denman, 2019). The most recent covering of economic crime validates that procurement fraud and company fraud still top the list of the costliest crimes. Those losses are not only monetary in the form of stolen funds, but also come in the form of compliance fines, legal fees, and lost patient confidence. Research also emphasizes the reluctance of organizations to adopt complete quantification or disclosure of internal fraud, which may contribute to systematic under-reporting (iVelasco, 2025).

AI-Based Fraud Detection: Theoretical Models

AI systems for fraud prevention evolve on multiple theoretical and computational models. Anomaly detection systems set the profile of what is normal and flag deviations as suspicious, to be beneficial when monitoring transactions (Rahman *et al*., 2023). Supervised models are used for fraud detection by the training data set that labels all the training cases to classify new transactions (Tiwari *et al*., 2021), while unsupervised learning identifies novel fraud schemes without relying on historical data (Kumar *et al*, 2025). Graph-based machine learning, for example, can be used to reveal collusion in fraud rings among accounts and transactions represented as related networks (Li *et al*., 2022). Such methods present a dynamic and scalable alternative to rule-based systems.

Behavioral Studies and New Artificial Intelligence Problems

Recent work has focused on behavioral biometrics, where AI builds profiles of users from login habits, device data, and keystroke dynamics. These systems can identify account takeovers by identifying suspicious transactions that occur in accounts when the right credentials have been supplied (Vitla, 2023). Meanwhile, enemies of all stripes are also leveraging generative AI to produce deepfakes, synthetic identities, and targeted scams at an unprecedented scale. This phenomenon has led to an "AI vs. AI" arms race, wherein defensive AIs must constantly respond and adjust to the attackers' advancements. Researchers emphasize the stimulus and challenges of AI enablement, emphasizing the need for explainability, ethical frameworks, and governance (Olanrewaju, 2025).

Synthesis and Research Gaps

The literature shows that fraud carries high and nuanced economic costs to the U.S., including those on consumers, businesses, and government. AI-enabled global paywall considerations, including anomaly detection, graph analytics, and behavioral analysis, provide far more accurate, adaptable, and real-time prevention percent existing systems. However, challenges persist; a small number of longitudinal studies examine multidecade economic returns to AI incorporation. There is limited independent research on adversarial adaptation to implemented models, and no standard measures exist for assessing the performance of AI systems in fraud detection (Soyombo, 2024). Future research could more closely examine studies friction point and build on it by empirically estimating AI's ability to reduce the real economic losses associated with fraud in diverse households.

RESULTS AND DISCUSSIONS

Explosive Growth and Digital Evolution of Fraud Losses

The impact of fraud is not just static; the numbers prove it is moving at breakneck speed, as estimates paid out to keep fraudulent schemes have doubled in the past few years alone, primarily fueled by digitally enabled fraud. Consumer fraud losses in 2024 were estimated to have exceeded $12.5 billion, a substantial increase over the previous year (Kurshan *et al*., 2025). This rise of cybercrime to the attention of consumers is paralleled by the FBI's Internet Crime Complaint Center (IC3), which reports a total loss of $2.7 billion in 2018 (Iqbal *et al*., 2020). The surge is being driven by the move to high-yield scams such as investment scams and cryptocurrency fraud, which have harnessed the speed, scale, and anonymity of payments that are underpinned by digital technology. This shift underscores that those geographical and jurisdictional barriers, which had previously acted as physical constraints for fraud, have evaporated with technology and require sophisticated countermeasures.

AI Capabilities and the Evolution from Reactive to Proactive Detection

The technical literature review conducted asserts that AI and ML systems endow agent-based fraud management with the dynamic capabilities necessary to evolve from a reactive to a proactive stance in their fight against fraud. At the heart of this is anomaly detection, where ML models learn a 'normal' pattern of customer and transaction behavior, then raise alerts in real-time (Yang *et al.*, 2023). That's a clear improvement over static, rule-based systems that are only able to identify known fraud patterns once the loss has already happened. Supervised learning-based models have proven very successful in tuning detection rate and minimizing false positives (Dolesi *et al*., 2024) by learning from large amounts of labeled data, saving a substantial amount of operational time and improving customer satisfaction. On the other hand, Unsupervised learning models are great at recognizing completely new fraud patterns, such as

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elaborate synthetic identities (Anasuri, 2023) not seen before in anyone's database, ever empowering defense to stay ahead of attackers and catch them right after new fraudulent schemas begin to execute.

Cutting-Edge Concepts for Systemic Threat Protection with Artificial Intelligence

Beyond the identification of individual anomalies, advanced AI technologies tackle the complex and organized nature of contemporary financial crime (Bukhari *et al*., 2024). Graph-Based Machine Learning is an essential tool in this area as it models how accounts, transactions, and devices are related to each other, on a network basis, revealing invisible patterns of collusion or money laundering rings that would not otherwise be detected from single-transaction type checks, which are commonly used (Takahashi *et al*. 2025). It is a method that directs the lens of criminal networks in advertisement fraud, rather than onto the act of fraud itself. At the same time, Behavioral Analysis also offers strong protection against Account Takeovers (ATOs) by being able to establish a unique behavioral profile via keystroke dynamics (Bello, 2025), assigned device IDs, and common login habits; any significant shift logs an instantaneous alert in real-time, even if authorized usernames are provided. Use of these methods in combination results in a multi-layered defense approach that is now necessary to address the systemic and organized nature of contemporary fraud (Najar *et al*., 2025).

DISCUSSION

Implications for Theory and Implementation

The findings are discussed as a basis for debating the theoretical and policy repercussions of integrating AI into the fraud risk map, such as with respect to the development of criminology theories and ethically embedding technology.

Connecting AI to Criminological Theory: Attacking Opportunity and Capability

The overwhelming increase in technologically facilitated fraud losses further reinforces the idea that a modification from the traditional Fraud Triangle to a Fraud Diamond (Capability is added as an additional factor) was necessary (Thomas 2024). The massive magnitude and success of the present digital scams are due to prospective scammers' technical expertise in using generative AI towards personalized scams and deepfakes. Fraud detection of AI challenges the very basis of the diamond, opportunity, and capability (Aldemir *et al*., 2025). Thanks to real-time anomaly detection and solid behavioral systems, AI is the kind of tech that shrinks the time window in which crime could happen; if traditional occupational fraud took months to spot, now it can be detected in milliseconds. Moreover, by promptly recognizing the output of AI-enabled scams (e.g., new synthetic identities), detection AI raises the technology bar, and in doing so implicitly challenges the specialist ability of fraudsters while driving continued costly reengineering (Zhao *et al*., 2021).

The Systemwide Effect of AI on Economic Efficiency and Trust

The shift to AI-based technologies is an opportunity to reduce the systemic costs of fraud through improved economic efficiency and rebuilding trust (Kothandapani, 2025). High false positive rates (the excess of legitimate transactions wrongly classified as the result of fraud) due to old, rule-based systems then lead to avoidable costs incurred, with delays in processing, dissatisfied customers, all of which contribute to the Fraud Multiplier. (Jeyachandran, 2024). The superior precision and efficiency of AI can be evidenced in the ability to cut down on false positives while speeding up processing time directly leads to less operational friction and lower compliance costs for businesses (Rahman *et al*., 2023). By rapidly identifying and stopping threats that are systemic, such as program fraud across government systems or network-level money laundering rings, AI also keeps public resources safe while instilling confidence in financial institutions (Marzouk, 2023). This capability extends well beyond the ability to simply reduce loss and enable a more robust, secure digital economy for all participants.

Governance and the "Black Box" Problem

As powerful as it may be, the pervasive use of AI raises important governance and ethical issues that must be addressed to maintain trust and compliance. A major consideration is the risk of algorithmic bias. Training AI models on incomplete or historically biased data can result in unfair discrimination against innocent transactions (Zaman *et al*., 2022), and against users based on race, gender, or other characteristics, leading to systemic inequalities. In addition, the black box or opaque nature of many complex machine learning algorithms contradicts management expectations for model interpretability (Lopardo, 2024). There are also legal responsibilities that stalk financial and government organizations that automate decisions that affect people (e.g., blocking assets or refusing entitlements). And so, AI is only as good as the systems used to build it around, and those systems need a lot of investment in terms of transparent

models and continual auditing, robust ethical frameworks that ensure gains made in technology don't become losses in fairness or accountability.

The Emergent "AI vs. AI" Running Epic and Future Requirements of the Field

The final power of AI is now tested in the "AI vs AI" arms race, which has emerged as a finding prominently displayed in the CAI computer-aided instruction Stack. New AI fraud detection examines tools that have raised awareness of the consequences of fraud, and criminals are increasingly investing in Generative AI technology to produce better deepfakes and social engineering scams, making the threat more advanced (Lin, 2025). This reality calls for a change in the focus of future research. What is needed now is not a show of how AI can spot fraud that is already known, but longitudinal independent measures as net economic value after some kind of high cost in implementation and data governance. There is a pressing need for community-wide standardized open-source metrics for assessing real-world AI model performance in production as well as empirically studying the longitudinal adversarial adaptations of human-led fraud rings against constantly adapting AI models.

CONCLUSION

Fraud's economic burden on the United States has risen to epidemic proportions, affecting individuals, corporations, and administrative bodies, with the national economy annually losing billions of dollars. Furthermore, this suffering is not only immediate financial losses, but it also includes reputational damage, regulatory costs, and consumer distrust. Recent traditional fraud detection systems no longer function with the increasing fraud schemes in the context of digital transformation and globalization, and the world economy. Thus, artificial intelligence seems like a tool for reducing these costs. Artificial intelligence can help reduce these costs by providing a means of setting up fraud prevention based on dynamic adjustments responsive to the latest threat intelligence. Such systems can identify previously unknown threats by learning fraud patterns, analyzing anomalies, and studying behaviors. The experience of using them in real cases such as financial services, insurance, and government programs suggests that their implementation in the United States has the potential to save billions, improve operations, and help restore consumer trust. The use of artificial intelligence for fraud prevention in the United States should not be seen as a kind of excellent opportunity but as a strategic initiative for safeguarding the economy, stakeholders, and ensuring a secure future in the fraud area.

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