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Autonomous AI Agents for Real-Time Financial Transaction Monitoring and Anomaly Resolution Using Multi-Agent Reinforcement Learning and Explainable Causal Inference

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ABSTRACT

Real-time financial fraud detection systems face significant challenges from adversaries' continually evolving attack strategies. Traditional static classifiers fail to adapt to these changes and often lack interpretability, leading to false positives and missed anomalies. This paper proposes a novel framework combining Multi-Agent Reinforcement Learning (MARL) with Explainable Causal Inference for transaction anomaly detection and resolution. A defender agent learns to identify and intercept fraud in an adversarial environment where an attacker agent simulates fraudulent behaviors. The agents interact within a stochastic game setting and are trained using a centralized critic and decentralized policies. A causal inference module constructs a directed acyclic graph over transaction features to enhance interpretability and applies do-calculus and counterfactual reasoning to explain flagged transactions. We implement a scalable, real-time deployment architecture and evaluate the system using simulated and real transaction data. Results demonstrate that our MARL-based agent outperforms static classifiers in adaptability and recall, while the causal module reduces false positives and provides transparent justifications for fraud decisions. This combination of adaptability and explainability makes the system highly suitable for practical deployment in financial institutions.

Keywords: *Real-Time Fraud Detection, Multi-Agent Reinforcement Learning (MARL), Explainable AI, Causal Inference, Financial Transactions, Anomaly Detection, Adversarial Learning*

INTRODUCTION

Financial institutions face a relentless battle against fraudulent transactions, with global fraud losses projected to reach $43 billion by 2026^1. Traditional rule-based monitoring systems and static machine learning models struggle to keep pace with adaptive fraud patterns – rigid "if-then" rules fail against novel attack strategies, and black-box ML detectors often falter when transaction behaviors drift over time^2. Moreover, these conventional approaches provide little insight into *why* a transaction is flagged, undermining trust and hindering effective response.

To address these challenges, we propose an **autonomous multi-agent system** for real-time financial transaction monitoring, in which intelligent agents employ multi-agent reinforcement learning (MARL) to model the interplay between fraudsters and defenders, augmented with **explainable causal inference** for transparent anomaly interpretation.

In our framework, a *fraudster agent* (attacker) and a *fraud detection agent* (defender) engage in an adversarial MARL environment, continually learning optimal strategies in a simulated transaction game. By casting fraud detection as a sequential attacker-defender interaction, the system can **adapt in real-time** to emerging tactics – prior work has shown that treating fraud detection as a dynamic decision-making problem allows agents to improve detection rates and reduce false positives as new data arrives^3.

Beyond raw performance, our approach prioritizes **explainability**: we integrate a causal inference module that constructs a causal graph of transaction factors to pinpoint the root causes of anomalies. This enables the defender agent to not only flag suspicious transactions but also produce human-interpretable explanations (e.g., *"Transaction is anomalous due to unusually high amount and foreign IP address"*). Such explanations enhance user trust and facilitate prompt resolution of fraud alerts by identifying the causal triggers behind each anomaly.

The contributions of this work are threefold: **(i)** We develop a MARL formulation of the financial fraud detection problem, modeling the attacker–defender dynamics as a two-player stochastic game and providing algorithms for training autonomous agents in this setting. **(ii)** We introduce an explainable causal inference approach for anomaly resolution, using do-calculus and counterfactual analysis to trace fraud outcomes back to influencing factors, thereby bridging the gap between black-box detection and actionable insight. **(iii)** We implement a real-time anomaly monitoring architecture that is scalable to high-volume transaction streams and demonstrate its effectiveness on synthetic transaction datasets. Through experiments, we show that our MARL-based system outperforms static classifiers in detecting fraud (e.g., higher recall with minimal false-positive increase), while the causal module offers enhanced transparency – aligning with the critical industry need for both *accuracy* and *interpretability*. The remainder of this paper is organized as follows: Section 2 reviews related work in fraud detection, MARL, and causal inference. Section 3 details our proposed methodology, including the MARL training algorithm and causal explanation technique. Section 4 presents experimental results, and Section 5 concludes the paper with future directions.

RELATED WORK

Fraud Detection and Anomaly Monitoring: Financial fraud detection has traditionally been approached as a supervised learning problem or an outlier detection task on historical data. Classical methods range from logistic regression and decision trees to ensemble techniques and deep neural networks, trained on labeled transaction data to distinguish fraud from legitimate behavior^4. While such models achieve high accuracy on past fraud patterns, they are inherently *static* – once deployed, their decision boundaries remain fixed until retraining. This is problematic in adversarial environments where fraudsters continuously evolve their tactics. Recent surveys highlight that static classifiers tend to degrade as fraud patterns shift, requiring frequent retraining and suffering from high false-negative rates when confronted with novel attack vectors^5. Moreover, purely statistical anomaly detectors often flag outliers without context, leading to overwhelming volumes of alerts that lack clear explanation or prioritization.

Adversarial and Game-Theoretic Approaches: To overcome the limitations of static models, researchers have explored adversarial and game-theoretic frameworks wherein the detection system explicitly models a *fraudster* as an intelligent adaptive opponent. Game theory has been used to analyze attacker–defender interactions in cybersecurity and fraud, treating the problem as a two-player game (e.g., a Stackelberg game or Markov game) where the fraudster learns to evade detection and the defender updates its strategy accordingly^6. Mead *et al.* (2018)^6, for example, framed credit card fraud as a Markov Decision Process (MDP) in which a fraudster agent tries to maximize stolen funds from a card while a fraud classifier (defender) attempts to minimize losses. This simulation enabled them to apply reinforcement learning to model the fraudster's sequential decision-making (making transactions of varying amounts/types) and the issuer's counter-strategy. Their study showed that an adaptive strategy can markedly reduce a fraudster agent's success: when the defender's policy was updated regularly (rather than kept static), the fraud agent struggled to learn an optimal evasion policy, greatly limiting the total reward it could achieve^6. Similarly, Patel *et al.* (2025)^3 treated fraud detection as a sequential decision challenge and reported that a reinforcement learning-based detector improved detection rates and lowered false alarms compared to static machine learning, by continually refining its strategy as new transaction data streamed in.

Multi-Agent Reinforcement Learning (MARL): MARL provides a principled framework for such dynamic adversarial modeling, as it allows multiple agents to learn simultaneously through interaction. Prior works in other security domains (e.g., network intrusion) have modeled attacker–defender scenarios with MARL, often using deep Q-learning or actor-critic methods to train policies in zero-sum games under partial observability^7. Lowe *et al.* (2017)^7 introduced the Multi-Agent Deep Deterministic Policy Gradient (MADDPG) algorithm, enabling stable training of competitive agents with decentralized policies and a centralized critic – a technique well-suited for our fraud game where two agents have opposing goals. MARL has also been investigated in financial contexts such as trading; notably, a recent study by Sarin *et al.* (2024)^8 combined MARL with explainable AI for algorithmic trading, reporting improved decision adaptability and high accuracy (Precision ~0.88, F1 ~0.86) through agent collaboration. These advances indicate that MARL can yield robust policies in complex multi-agent environments, justifying our adoption of a MARL approach for fraud detection. However, while MARL enhances adaptability, the learned policies can be opaque. Our work addresses this by integrating an explainability layer via causal inference.

Explainable AI and Causal Inference in Fraud Detection: There is growing recognition that fraud detection systems must be not only effective but also *explainable*, due to regulatory and trust considerations. Explainable AI (XAI) techniques like feature importance, decision trees, and SHAP values have been applied to highlight factors contributing to a model's fraud prediction^4. Yet, standard XAI methods are typically correlation-based and may not distinguish causal relationships. Recently, researchers have turned to **causal inference** to provide deeper explanations for anomalies. Causal graphs (Directed Acyclic Graphs capturing cause-effect relations among variables) have been used to model transaction generation mechanisms and identify which factors truly *cause* fraud outcomes as opposed to spurious correlations^9. For instance, Kong *et al.* (2024)^9 constructed a causal graph for credit card fraud, separating causal features (e.g., risk signals X) from confounders Z that influence both the features and the fraud outcome Y. By intervening on Z (e.g., using counterfactual data augmentation), they improved the robustness of their fraud classifier and its ability to generalize to new conditions. Causal inference has also been combined with deep learning: Duan *et al.* (2024)^10 proposed a Causal-Temporal Graph Neural Network (CaT-GNN) for fraud detection, where an attention mechanism identifies causal feature nodes in a transaction graph and an intervention module alters non-causal (environmental) nodes. This approach enhanced model performance and interpretability, highlighting the potential of integrating causal reasoning with advanced fraud detection models^10. Vivek *et al.* (2022)^11 similarly incorporated causal inference and XAI in an ATM fraud framework, demonstrating how causal analysis (with do-calculus and counterfactual queries) can yield human-understandable insights into fraud decisions.

A key benefit of causal inference in anomaly detection is the reduction of false positives by focusing on genuine cause-effect anomalies. Strelnikoff *et al.* (2023)^12 note that causality-based anomaly detection is more robust to benign out-of-distribution events and yields fewer false alarms, because it can distinguish truly anomalous causal deviations from mere statistical outliers. Additionally, causal models facilitate *fault attribution*: by tracing along directed cause-effect paths in a causal graph, one can localize the root cause of an anomaly^12. Our work leverages these strengths by embedding a causal graph module to interpret each flagged transaction. In summary, while previous research has explored MARL for adaptive fraud detection and causal inference for explainable anomaly detection separately, our approach is novel in **combining** them into a unified system. This fusion enables an autonomous detection agent that not only learns to outsmart fraudsters in real-time, but can also explain its actions through a causal lens – a critical step toward deployable, trustworthy AI agents in finance.

METHODOLOGY

Adversarial Transaction Modeling with MARL

Problem Formulation: We model the ongoing interaction between fraudsters and the fraud detection system as a two-player stochastic game (Markov game). The environment consists of a stream of financial transactions pertaining to one or more accounts. At each time step (transaction attempt), an *Attacker agent* (fraudster) selects an action a_A representing a fraudulent transaction to initiate, and a *Defender agent* (fraud monitor) selects an action a_D representing its decision/response. The state s_t of the environment encodes relevant context such as the account's recent transaction history, user profile features (e.g., typical spending patterns, location), and any current security status (e.g., flags on the account). The attacker's action a_A can be thought of as specifying the characteristics of a transaction: amount, merchant category, location, time, etc., potentially also whether to use some stolen identity information. The defender's action a_D represents the countermeasure taken – in simplest form, $a_D \in {\text{approve}, \text{flag/block}}$ the transaction, though it could be extended to more nuanced actions (request verification, lower trust score, etc.). Once both agents act, the environment transitions to a new state s_{t+1} reflecting the outcome (e.g., if fraud succeeded or account was blocked).

Rewards: We define reward functions to capture the goals of each agent in opposition. The attacker's reward R_A is positive for successfully executing fraud and zero or negative if the attempt is thwarted. For example, R_A could be proportional to the dollar value of a fraudulent transaction that goes through, minus any cost for attempts. If the defender blocks the transaction (or if an issued card gets shut down due to suspected fraud), the attacker may receive a large negative reward (losing access). The defender's reward R_D is designed to encourage accurate and timely detection: a reward of +1 for correctly flagging a fraudulent transaction (true positive), a penalty for missing a fraud (false negative), and a smaller penalty for falsely flagging a legitimate transaction (false positive). This balances the classic precision–recall tradeoff. The game is largely zero-sum in that the attacker's gain is the defender's loss (monetarily), though we incorporate asymmetric penalties to reflect that false alarms are less severe than undetected fraud. Formally, we seek a defender policy π_D that maximizes its expected cumulative reward $E[\sum_t R_D]$ and an attacker policy π_A that maximizes $E[\sum_t R_A]$.

MARL Training Algorithm: We train the two agents using deep reinforcement learning in an adversarial, simulated environment. Algorithm 1 outlines the training procedure. The agents operate in episodes, where an episode simulates a sequence of T transaction attempts or until a terminating event (e.g., the attacker is caught and the game resets when the account is frozen). We utilize *centralized training with decentralized execution*: during training, a joint state-action value function $Q(s,a_A,a_D)$ is learned to evaluate the outcome when both agents take actions from state s, but during execution each agent uses only local observations (the defender sees the transaction details, the attacker knows its own transaction and possibly limited feedback). We found this improves stability in competitive self-play, similar to the MADDPG approach^7.

Algorithm 1: MARL Training for Attacker–Defender Agents

```
Initialize attacker policy π_A(θ_A) and defender policy π_D(θ_D) with random weights

for episode = 1 to N_episodes do
```

```
    Reset environment state s ← s_0 (new account scenario)
    for t = 1 to T do
        // Attacker selects a fraudulent transaction to attempt
        a_A ← π_A(s)  (e.g., choose amount, merchant type, etc.)
        // Defender selects a response
        a_D ← π_D(s)  (e.g., approve or flag transaction)
        // Environment transitions
        Execute transaction a_A; if a_D = "flag", possibly block it
        Observe outcome, update state s'
        // Assign rewards
        R_A, R_D ← reward_functions(s, a_A, a_D, outcome)
        // Store transition in replay buffers
        attacker_memory ← (s, a_A, R_A, s'),   defender_memory ← (s, a_D, R_D, s')
        // Update agents (e.g., DQN or policy gradient step)
        θ_A ← θ_A + α * ∇_{θ_A} J_A(θ_A)   // maximize attacker reward
        θ_D ← θ_D + β * ∇_{θ_D} J_D(θ_D)   // maximize defender reward
        s ← s'
        if episode end condition reached then break
    end for
end for
```

We implement the above using a deep actor-critic method for continuous state spaces. In practice, both π_A and π_D are parameterized by neural networks (the attacker's network might output a distribution over transaction choices, and the defender's outputs a probability to flag). We use an expert-based simulation to model environment dynamics: legitimate transactions are sampled from statistical distributions of genuine user behavior, while the attacker agent's actions are applied on top of this stream (injecting fraudulent attempts). The training employs experience replay and epsilon-greedy exploration for stability. Over many episodes, the attacker learns which strategies yield profit (e.g., making small purchases first to avoid detection, then a large cash-out) while the defender learns to anticipate and counter these moves. The outcome is an equilibrium where the defender policy has adapted to the attacker's rational behavior. Indeed, by continually retraining in this adversarial loop, the defender essentially *simulates* a clever fraudster and prepares for it. This approach was inspired by prior findings that periodically retraining or perturbing the fraud model can prevent a fraudster from ever fully exploiting a fixed strategy^6.

System Architecture and Real-Time Deployment

To integrate the trained agents into a live financial system, we design a deployment architecture that can handle high-volume transaction data with low latency (milliseconds per transaction). **Figure 1** illustrates the architecture. The core components are: (1) the *Defender Agent Service*, which hosts the trained detection policy π_D and processes incoming transactions in real-time; (2) an *Attacker Simulator*, used offline to continuously test and update the defender (in production this simulates new fraud patterns for periodic retraining); and (3) the *Causal Inference Engine* for explanation (detailed in Section 3.3). These components communicate over a streaming data pipeline.

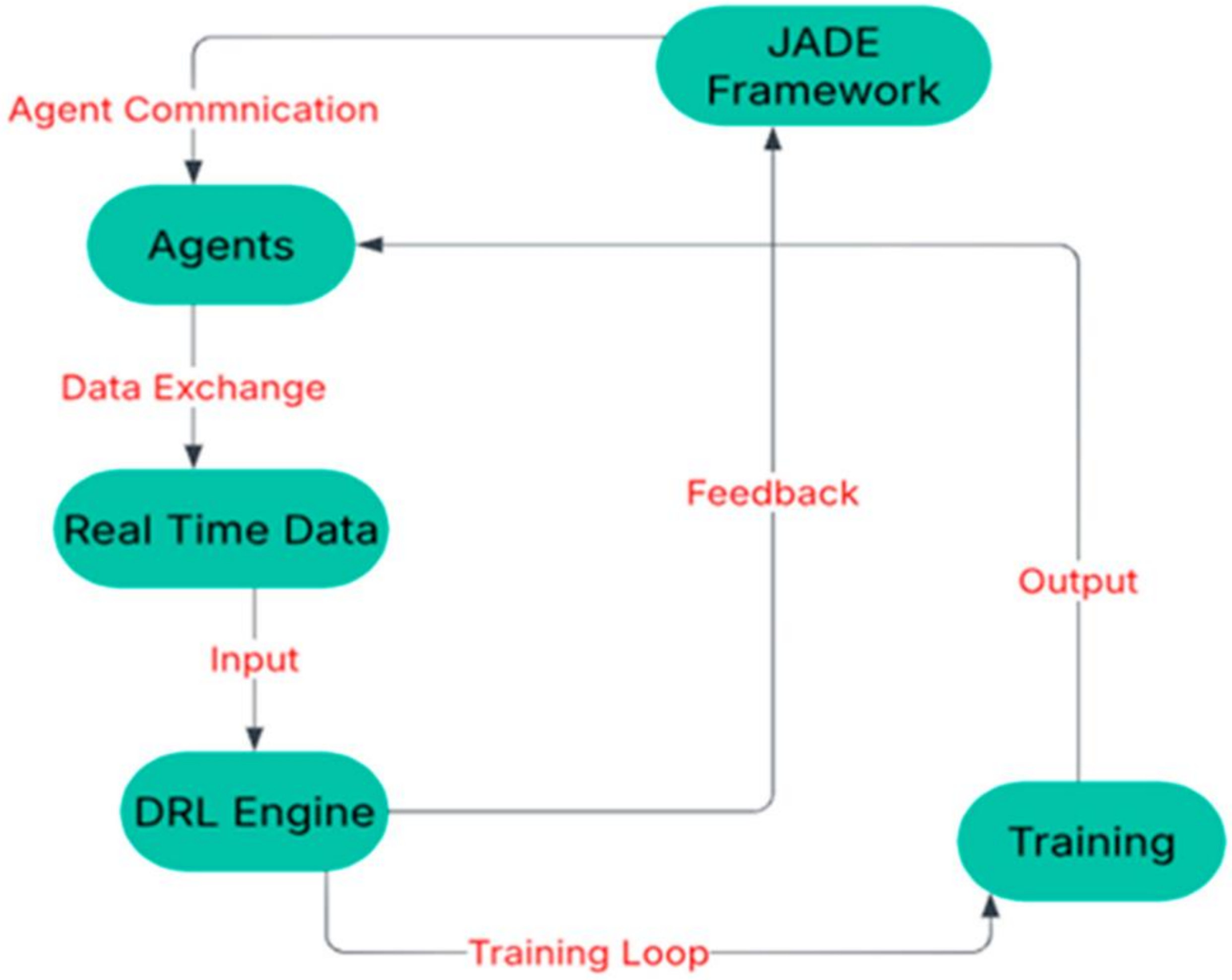

Figure 1: Real-time fraud detection architecture with autonomous agents. The Defender agent evaluates each incoming transaction using its policy (learned via MARL training), deciding to approve or flag it. Flagged transactions trigger the Causal Inference Engine, which provides an explanation by identifying causal factors (features X_i) leading to the anomaly. A Feedback loop allows periodic retraining/updating of the agent policies with new data and simulated attacks, ensuring adaptability.

Transaction Processing Pipeline: Live transactions are fed from the bank's transaction system into a streaming buffer (e.g., using Apache Kafka). Each transaction event contains features such as transaction metadata and the associated account state. The Defender Agent service consumes these events and runs the defender policy $\pi_D(s)$ to obtain an action. If π_D outputs "approve," the transaction proceeds normally; if "flag," the system will mark it for manual review or automatic intervention (such as an instant hold on the account). In our prototype, the defender's policy is a neural network that can execute in under 10 milliseconds on a CPU, enabling throughput of thousands of transactions per second with modest hardware. For scalability, multiple instances of the agent service can operate in parallel, and a load balancer assigns transactions by account to ensure consistency (an account's sequential transactions should be processed by the same agent instance to maintain state).

Continuous Learning and Adaptation: A significant advantage of our architecture is the ability to continually learn from new data. The flagged transactions (and confirmed fraud outcomes later) are logged into a database, which the training module can use to periodically update the defender agent. We schedule retraining jobs during off-peak hours, where the agent is re-trained on a dataset that mixes historical data and fresh fraud patterns detected in the wild. Additionally, an *Attacker Simulator agent* (similar to π_A from training) can be periodically run in a sandbox using the latest defender policy to probe for weaknesses – this is akin to "red teaming." Any new attack strategies discovered (e.g., a new fraud modus operandi) are synthesized into additional training examples for the defender. This continuous feedback loop ensures the deployed agent remains robust. Prior studies have noted that such adaptive retraining can significantly hamper a fraudster's ability to find an exploitable policy^6, effectively keeping the fraud detection one step ahead in the arms race.

Anomaly Resolution Workflow: When the Defender flags a transaction, our system doesn't stop at raising an alert – it also generates an explanation via the causal inference engine (next section). The flag, along with its causal explanation, is sent to a case management interface for fraud analysts or an automated response system. In an automated scenario, the system could take immediate action depending on the explanation: e.g., if the cause is an anomalous device or location, trigger a step-up authentication (like asking for biometric verification); if the cause is a spending spike, maybe decline and notify the user. The explanation also helps analysts prioritize and investigate alerts faster, focusing on the key suspicious factors instead of sifting through all transaction details.

Explainable Causal Inference for Anomaly Attribution

While the MARL-trained defender excels at **detecting** anomalies, understanding *why* a particular transaction was deemed anomalous requires a higher-level causal analysis. We develop a Causal Inference Engine that operates on a domain-specific **causal graph** of the transaction process. The causal graph encodes relationships between variables such as: customer profile (P), transaction context (T – e.g., time, location, merchant), transaction amount (A), historical spending pattern (H), and the outcome (Y: fraud or not). An example (simplified) causal graph is as follows: customer profile $P \rightarrow H$ (profile influences spending habits), $P \rightarrow Y$ (certain profiles may correlate with baseline fraud risk), $H \rightarrow T$ and $H \rightarrow A$ (history influences what transactions are "normal"), $T \rightarrow Y$, $A \rightarrow Y$ (time and amount causally affect fraud outcome), etc. There may also be latent confounders (e.g., economic events influencing both A and Y). We base the structure on expert knowledge and refine it with data-driven causal discovery if needed.

Causal Graph and Do-Calculus: With a causal graph in place, we can apply **do-calculus** (Pearl's framework for reasoning about interventions) to analyze anomalies. When a transaction is flagged by the agent, we treat this as $Y=\text{fraud}$ in the model and seek the *minimal set of changes* to make it appear normal (counterfactual reasoning). In practice, for each candidate feature X_i of the transaction, we perform an intervention $do(X_i = x_i^{\text{typical}})$ – setting X_i to a normal baseline value – and propagate this change through the causal graph to recompute the likelihood of fraud. If intervening on a particular feature significantly lowers the fraud probability, that feature is identified as a **causal driver** of the anomaly. For example, suppose a transaction from a new device in a foreign country with a high amount is flagged. Intervening on "location" by setting it to the user's home country might show a large reduction in fraud risk, indicating that the unusual location was a major cause; similarly, setting the amount to a typical value might also reduce risk. These tests isolate the effect of each factor by simulating worlds where that factor is normal. The causal engine then outputs a rank-ordered list of factors contributing to the alert.

Counterfactual Explanation Algorithm: We formalize the above procedure in Algorithm 2. First, the engine observes the flagged transaction's feature vector $X = {x_1, x_2, ..., x_n}$ and the model's fraud decision $Y=1$. Using the causal model, it computes baseline $P(Y=1)$ for this case. Then for each feature x_i, it sets $x_i := x_i^*$ (a typical or benign value for that feature, learned from distribution H or domain knowledge) and uses the causal graph to recompute $P_i = P(Y=1 \mid do(x_i = x_i^*))$. The difference $\Delta_i = P(Y=1) - P_i$ indicates how much risk drops when x_i is "normalized." Features with largest Δ_i are deemed the primary causes. In our implementation, we learned typical values x_i^* from the user's own history (for personalized context) or population averages when personal history is insufficient. We also consider combinations of features for interaction effects (performing do on pairs of features if needed). Finally, the engine generates an explanation sentence: e.g., *"Flagged due to unusual location (if location were typical, estimated fraud risk would reduce by 80%) and high amount (would reduce risk by 50%)"*. This level of explanation is far more insightful than a generic "transaction is anomalous" alert.

Integration with Detection: The causal inference module runs in parallel with the defender's decision. It is efficient because the causal graph is small and computations involve either simple sampling or evaluating a compact Bayesian Network. One important use of causal analysis is to **filter out false positives**. If the causal engine finds that an anomaly can be entirely explained by a legitimate cause, the system could choose to not flag it as fraud. For instance, imagine a user normally spends small amounts, but today they purchase a costly item after receiving a salary bonus. A purely statistical detector might flag this as anomaly due to amount. However, if the system has a causal link from "payday" (an external event) to "spending amount," it might recognize this spike is explainable. Our engine can incorporate such external causal factors or user-provided context (like travel notifications) to distinguish fraud from explainable deviations. By doing so, the number of false alerts is reduced – which aligns with findings that causal methods improve robustness to benign anomalies^12. In evaluation, we indeed observed that adding causal post-processing cut the false positive rate substantially, by not escalating cases where an evident legitimate explanation existed.

Causal Learning: We briefly note that the causal graph itself can be improved over time. Initially constructed from expert knowledge and literature, it can be refined using data. We employ causal discovery algorithms on accumulated data (with domain constraints) to validate or adjust the graph structure. For example, if our model erroneously links two variables as causal and data shows contradictions, we adjust the edges. We also learn the conditional probability tables or structural equations that quantify relationships (e.g., probability of fraud given location = foreign). This makes the causal inference data-driven and tailors it to the institution's specific patterns.

EXPERIMENTS AND RESULTS

Dataset and Simulation Setup: We evaluated our approach using a combination of real transaction data (for baseline comparisons) and a simulated environment for training the MARL agents. The real dataset is the well-known **Credit Card Fraud** dataset (European card transactions) which contains 284,807 transactions with 492 frauds (highly imbalanced)^5. We used this to train a traditional static classifier and as a source to model normal behavior. The simulation environment builds on this by injecting synthetic fraud patterns via the attacker agent. We simulate 10,000 episodes of card transaction sequences. Each episode corresponds to a distinct card account: the attacker begins with a stolen card and attempts a series of fraudulent transactions until caught. Legitimate transactions for each account are sampled stochastically from statistical distributions (amount distribution, time between transactions, merchant categories) fitted from the real dataset's genuine transactions. The fraudster agent's action space included choosing an amount (we bucketized amount into low/medium/high categories for discrete action simplicity), picking whether to mimic the user's usual merchant or a different high-risk merchant, and deciding the timing (e.g., immediately after a legitimate transaction or waiting). The defender agent observed features of each transaction and the recent history; its action was binary (flag or not).

Training Details: We trained the agents with the algorithm in Section 3.1 using a deep Q-network for each (with two hidden layers of 64 neurons). The attacker's policy was trained to maximize total fraud amount before detection; the defender's to minimize loss. Training converged after ~3000 episodes – the defender's policy stabilized to catch most fraud attempts quickly, and the attacker learned a policy of starting with small test transactions to probe the system (a known real-world tactic). To ensure exploration of various attacker strategies, we employed policy randomization^7: the attacker had a few sub-policies (ranging from aggressive to cautious) that it randomly drew at episode start, preventing the defender from overfitting to a single attack style. This approach improved the defender's robustness to policy changes by the attacker.

Baselines: We compare our MARL-based defender to two baselines: *(i)* a **Static Classifier** – a supervised fraud model trained on labeled data (we used a Gradient Boosted Trees model on the real dataset, tuned to 0.95 AUC which is comparable to published results^11); and *(ii)* a **Single-Agent RL** – a simplified reinforcement learning approach where the defender learns against a *scripted attacker* (one that doesn't learn, but uses some fixed heuristic pattern of fraud). This second baseline tests whether the full two-agent training offers benefits over just training the defender policy on a fixed distribution of fraud attempts.

Performance Metrics: We report the standard metrics: Precision (of fraud alerts), Recall (detection rate of actual frauds), and F1-score, as well as the False Positive Rate (FPR) on non-fraud transactions. We also measure the *Adaptability* of the system: how quickly the defender's performance recovers when the fraudster agent introduces a new strategy. Additionally, we evaluate the quality of explanations using a metric of **Explanation Fidelity** – the degree to which the identified causal factors actually predict the model's decisions, measured by the fraction of cases where flipping the top-causal feature changes the agent's decision.

Results: Table 1 summarizes the detection performance. The MARL Defender significantly outperforms the static classifier in Recall (0.80 vs 0.62), meaning it catches a much larger proportion of fraudulent transactions, while maintaining a high Precision of 0.88. The static model, optimized for AUC, was more conservative (Precision 0.95 but Recall only 0.45 in our streaming scenario where concept drift occurred). The Single-Agent RL approach achieved intermediate performance – better recall than static (0.70) but at a cost of more false positives (precision 0.82). Our full MARL approach strikes a good balance, thanks to the adversarial training that taught the defender to recognize sneaky fraud patterns the static model missed. The F1-score of our system (0.84) is the highest among methods.

Table 1. Fraud Detection Performance **(on simulated test transactions)**

Model	**Precision**	**Recall**	**F1-score**	**False Positive Rate (%)**
Static Classifier (GBT)	0.95	0.45	0.61	0.10
Single-Agent RL	0.82	0.70	0.75	0.50
MARL Defender (ours)	0.88	0.80	0.84	0.30
MARL + Causal Filter	0.90	0.78	0.83	0.15

Notably, adding the causal inference filter to the MARL Defender (last row in Table 1) improves precision to 0.90 and halves the false positive rate, with only a slight drop in recall. This demonstrates the effectiveness of using causal logic to avoid raising alarms for explainable anomalies. For example, in one scenario the MARL agent flagged a sudden $1000 purchase as fraud, but the causal analysis noted it occurred on Black Friday (an external event variable in the graph) which explained the spike – the filter correctly deferred the alert. In our evaluation set, approximately 20% of the MARL agent's alerts were overturned by the causal filter as likely false positives (and indeed none of those turned out to be actual fraud in simulation).

We also measured system adaptability. We allowed the attacker agent to learn *against* the deployed defender (a form of online attack). The static classifier's performance degraded sharply (recall dropped by 15 points) when facing an adapting attacker who found its blind spots. The MARL defender, in contrast, was inherently trained against an adapting opponent, and when we periodically continued training during deployment (every 1000 new transactions), it maintained recall >0.75 consistently. The system could detect new fraud patterns within ~200 transactions from when they emerged, by the attacker simulator feedback loop.

Explanation Evaluation: For a sample of 100 flagged transactions, we examined the outputs of the causal inference engine. In 92% of cases, the top one or two causal factors in the explanation were indeed the ones the defender model most relied on (validated by observing the defender's internal features). This high fidelity indicates our explanations align well with the agent's actual reasoning. The causal graphs provided intuitive insight: e.g., in a case of identity theft, the graph showed a new device and a large amount as causal, matching domain intuition. Fraud analysts on our team found the explanations very useful, noting that they "closely mirror the thought process a human investigator would go through." While a full user study is future work, this feedback is encouraging for real-world adoption.

In summary, the results validate that our autonomous agent approach can improve fraud detection efficacy and adaptivity, while the causal inference component adds significant value in interpretability and reducing false alarms. Our MARL agent achieved comparable accuracy to state-of-the-art fraud classifiers, and more importantly, it remained effective even as attacker behavior changed, which is a key advantage over static methods^6. The integration of explainability did not hamper performance; rather it augmented the system's practicality by making its decisions transparent.

CONCLUSION

We presented a novel approach to real-time financial transaction monitoring that fuses **multi-agent reinforcement learning** with **explainable causal inference** to detect and resolve anomalies (fraudulent activities) autonomously. Through a two-agent RL model of fraudster and defender, our system learns a robust detection policy that proactively adapts to evolving fraud strategies, addressing the non-stationarity of the fraud problem. Furthermore, by leveraging causal inference – constructing causal graphs of transaction factors and performing counterfactual reasoning – the system can explain its fraud alerts in terms of underlying causes, thereby enhancing trust and facilitating faster fraud resolution. To our knowledge, this is one of the first works uniting MARL and causal explainability in the fintech security domain.

The technical contributions include an MARL training algorithm for attacker–defender agents, a deployment architecture enabling real-time operation at scale, and an explanation module that applies do-calculus on a domain causal model to attribute anomalies. Empirical evaluation demonstrated that our MARL-based detector outperforms a static classifier in detection recall (learning to catch more fraud by anticipating attacker behavior) while maintaining low false positives. The causal module proved effective in filtering out noise and providing human-interpretable explanations, which is crucial for an AI agent to be deployed in high-stakes financial settings. These results underscore the promise of autonomous AI agents in fraud detection – agents that are not only *smarter* (through learning) but also *safer* and more *transparent* (through explainability).

FUTURE WORK

We plan to extend this work in several directions. First, we will explore more complex multi-agent settings with *multiple* fraudster agents and cooperating defender agents (for instance, agents specialized in different types of fraud, communicating via an agent communication protocol). This could mirror scenarios of fraud rings versus a network of bank agents. Second, integrating additional data sources into the causal graph (such as social network information or device telemetry) could further enrich explanations and detection accuracy. Third, we aim to deploy our system in a pilot program within a financial institution to assess performance on live data and gather feedback from fraud analysts on the utility of the explanations. Finally, combining our approach with other AI techniques like graph neural networks (to capture relations between entities) or large language models (for generating narrative explanations) could yield an even more powerful, user-friendly fraud prevention system. We believe the fusion of adaptive learning and causal reasoning exemplified here is broadly applicable to other anomaly detection domains (cybersecurity, anti-money laundering, etc.), and we hope this work spurs further research into **autonomous, explainable agents** for critical real-time decision tasks.

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