Journal of Computer Science and Technology Studies
ISSN: 2709-104X
DOI: 10.32996/jcsts
Journal Homepage: www.al-kindipublisher.com/index.php/jcsts

JCSTS
AL-KINDI CENTER FOR RESEARCH AND DEVELOPMENT

| RESEARCH ARTICLE

Causal Machine Learning for Intervention Analysis in AML Systems: Beyond Correlation to Causation in Financial Crime Detection

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| ABSTRACT
This article explores the paradigm shift from correlation-based to causation-based machine learning approaches in Anti-Money Laundering (AML) systems. We examine how causal machine learning enables more effective intervention analysis in financial crime detection, reducing false positives while increasing detection accuracy. Integrating causal inference frameworks with traditional ML methods provides financial institutions with more interpretable models that better withstand regulatory scrutiny and adapt to evolving criminal strategies. This paper presents theoretical foundations, implementation methodologies, and case studies demonstrating the practical advantages of causal approaches in AML systems.

| KEYWORDS
Causal Machine Learning, Anti-Money Laundering, Financial Crime, Intervention Analysis, Counterfactual Reasoning

| ARTICLE INFORMATION
ACCEPTED: 10 April 2025 **PUBLISHED:** 27 April 2025 **DOI:** 10.32996/jcsts.2025.7.2.58

1. Introduction
Anti-Money Laundering (AML) systems traditionally rely on rule-based approaches and correlation-based machine learning models to detect suspicious activities. While these approaches have provided some value, they suffer from high false positive rates and often fail to adapt to sophisticated money laundering techniques. Financial institutions face the dual challenge of meeting regulatory requirements while efficiently allocating resources to investigate suspicious activities.
This paper explores how causal machine learning offers a transformative approach to AML systems by moving beyond mere correlation to understand the underlying causal mechanisms of financial crime. By incorporating causal reasoning, financial institutions can:

1. Distinguish between genuine causal relationships and spurious correlations
2. Build more robust models that withstand distribution shifts in data
3. Perform intervention analysis to predict the effects of actions
4. Generate counterfactual scenarios to test "what-if" hypotheses
5. Provide more transparent explanations of model decisions to regulators

We demonstrate how causal inference frameworks like structural causal models (SCMs), potential outcomes, and do-calculus can be integrated with modern machine learning techniques to create more effective AML systems that reduce false positives while maintaining high detection rates for genuinely suspicious activities.

2. Theoretical Foundations of Causal ML
2.1 The Causal Hierarchy
Causal reasoning exists on a hierarchy of increasingly complex tasks, as formalized by Pearl's Ladder of Causation (Pearl, 2018):

1. **Association** (Level 1): Observing correlations in data (e.g., high-value transactions correlate with certain risk factors)

2. **Intervention** (Level 2): Reasoning about the effects of actions (e.g., how would changing transaction monitoring thresholds affect detection rates?)
3. **Counterfactuals** (Level 3): Reasoning about hypothetical scenarios contrary to observed facts (e.g., would this transaction have been flagged if the customer had a different profile?)

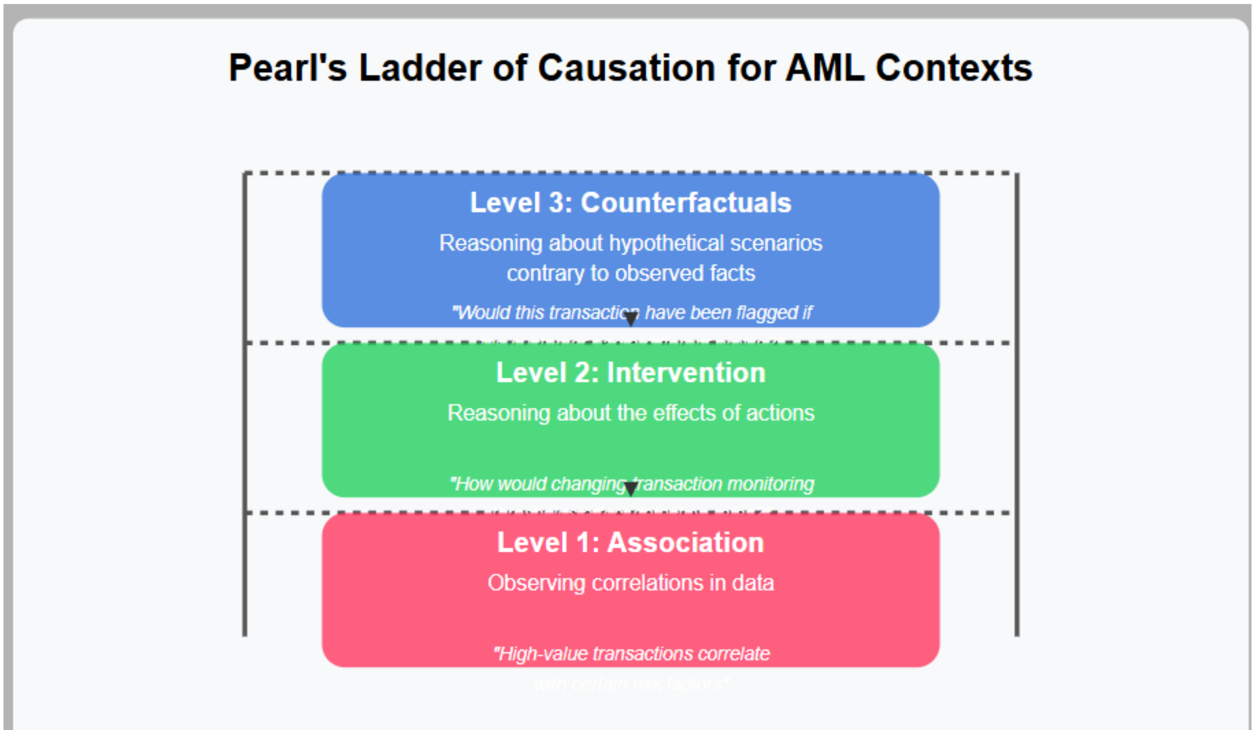

Figure 1: Pearl's Ladder of Causation adapted for AML contexts shows the progression from statistical correlation to causal intervention and counterfactual reasoning.

Figure 1: Pearl's Ladder of Causation adapted for AML contexts

2.2 Structural Causal Models

Structural Causal Models (SCMs) provide a mathematical framework for representing causal relationships. An SCM consists of:

- A set of exogenous (external) variables U
- A set of endogenous (model) variables V
- A set of functions F that determine how each endogenous variable depends on other variables
- A probability distribution P(U) over the exogenous variables

In the context of AML, an SCM might represent how customer profiles, transaction patterns, and external risk factors causally influence the likelihood of money laundering activities.

2.3 Potential Outcomes Framework

The potential outcomes framework (Rubin, 1974) provides another perspective on causality:

- $Y(1)$: Outcome if treatment is applied
- $Y(0)$: Outcome if treatment is not applied
- Causal effect = $Y(1) - Y(0)$

The fundamental problem of causal inference is that we can only observe one of these outcomes for any entity. In AML, this translates to questions like: "What would be the risk score if this customer had a different transaction pattern?"

2.4 Graphical Models and Do-Calculus

Directed Acyclic Graphs (DAGs) provide a visual representation of causal relationships. Pearl's do-calculus offers rules for manipulating these graphs to answer causal questions.

$P(Y|do(X=x)) \neq P(Y|X=x)$

The do-operator represents an intervention, distinguishing causal effects from mere observations. This distinction is crucial for AML systems that need to predict the effects of interventions rather than simply observe correlations.

3. Beyond Correlation: The Causal Revolution in Machine Learning

3.1 Limitations of Correlation-Based ML in AML

Traditional machine learning approaches in AML suffer from several limitations:

1. **Vulnerability to distribution shifts**: Models trained on historical data may fail when criminal behaviors evolve
2. **Spurious correlations**: Models may learn associations that have no causal relationship to money laundering
3. **Limited interpretability**: Black-box models provide little insight into why a transaction is flagged
4. **Inability to reason about interventions**: Correlation-based models cannot predict the effects of policy changes

3.2 Integrating Causality into Machine Learning

Recent advances have bridged the gap between causal inference and machine learning:

3.2.1 Causal Discovery Algorithms

Algorithms like PC, FCI, and NOTEARS can discover causal structure from observational data, providing insights into financial crime's causal mechanisms.

Show Image

Figure 2: Causal discovery process in AML systems, showing how algorithms identify potential causal structures from transaction data.

3.2.2 Causal Effect Estimation

Methods like:

- Double/debiased machine learning
- Causal forests
- Meta-learners (T-learner, S-learner, X-learner)
- Neural networks with causal structures

These approaches allow for estimating heterogeneous treatment effects, which is crucial for personalized AML interventions.

3.2.3 Invariant Prediction

Invariant causal prediction aims to find features with stable relationships with the target variable across different environments, making models more robust to distribution shifts.

```
# Pseudocode for invariant risk prediction
def find_invariant_predictors(environments, features, targets):
    invariant_set = set(all features)
    for env1, env2 in combinations(environments, 2):
        model1 = train_model(env1.features, env1.targets)
        model2 = train_model(env2.features, env2.targets)

        unstable_features = identify_differing_parameters(model1, model2)
        invariant_set = invariant_set - unstable_features

    return invariant_set
```

3.3 Causal Representation Learning

Recent work in causal representation learning aims to discover causal factors from high-dimensional data:

1. **Disentangled representations**: Learning representations where individual latent dimensions correspond to causal factors
2. **Causal generative models**: Generating realistic counterfactual examples by manipulating causal factors
3. **Adversarial approaches**: Using adversarial training to discover invariant representations

4. Causal Models for AML Systems

4.1 Causal Graph for Financial Crime Detection

A simplified causal graph for AML might include:

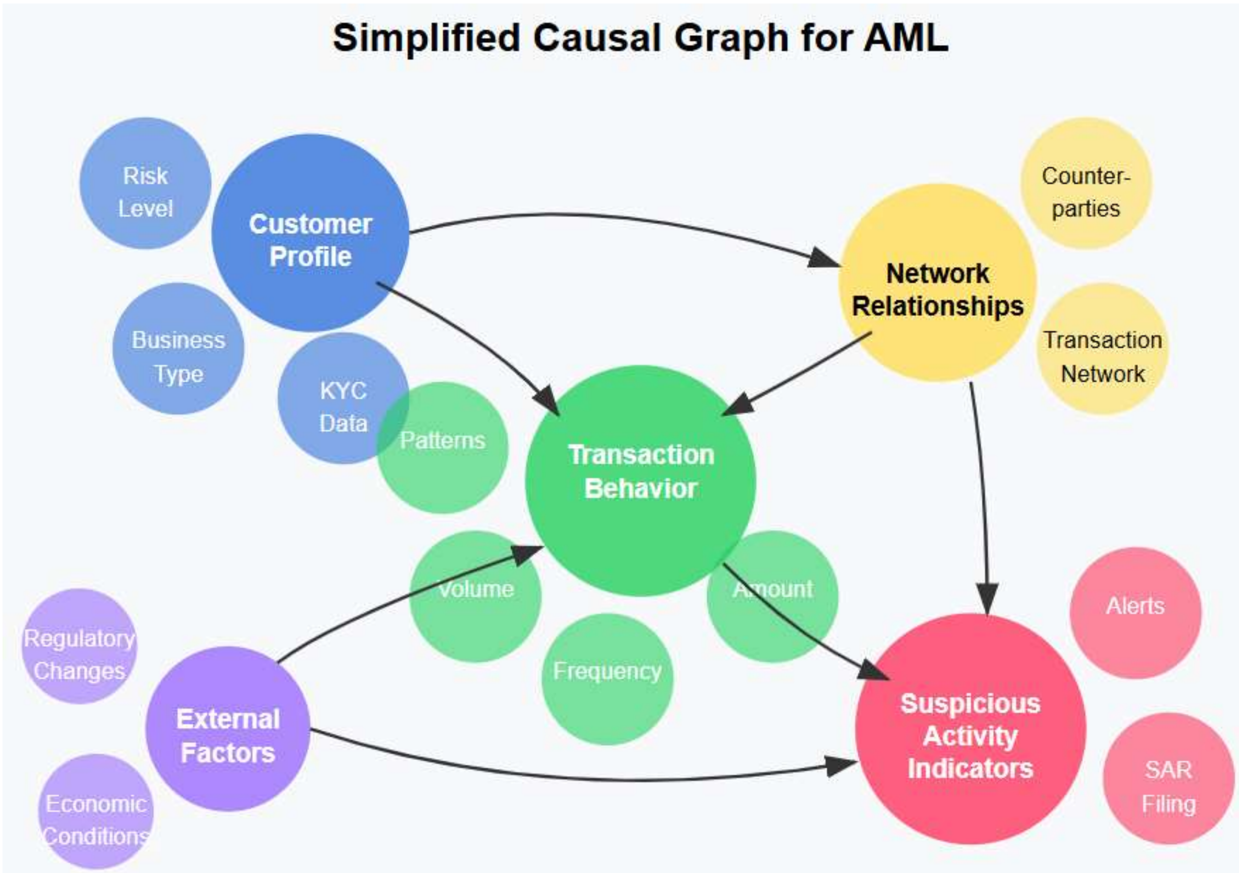

Fig. 3: Simplified causal graph for AML depicting key relationships between customer profiles, transaction behaviors, and suspicious activity indicators

4.2 Identifying Confounders in Financial Data

In financial crime detection, various confounding factors can lead to misleading correlations:

- **Geographic location** may confound the relationship between transaction patterns and risk
- **Industry type** may confound relationships between transaction volume and suspicious activity
- **Customer age** may confound relationships between account usage patterns and risk

Causal models explicitly account for these confounders, leading to more accurate risk assessments.

4.3 Front-door and Back-door Adjustment in AML

Methods like front-door and back-door adjustment allow for estimating causal effects in the presence of confounders:

P(Y|do(X=x)) = ∑_z P(Y|X=x,Z=z)P(Z=z) # Back-door adjustment

Z represents variables that satisfy the back-door criterion, blocking non-causal paths between X and Y.

4.4 Instrumental Variables in Financial Settings

In some cases, natural experiments or instrumental variables can be leveraged to estimate causal effects:

- Regulatory changes
- Geographic policy variations
- Temporal discontinuities

5. Intervention Analysis Framework

5.1 Formalizing Interventions in AML

Interventions in AML systems can be formalized using the do-operator:

- **Rule adjustment**: P(Alert|do(threshold=x))
- **Investigation prioritization**: P(TruePositive|do(investigate=high))
- **Customer risk recategorization**: P(SuspiciousActivity|do(risk_category=high))

5.2 Predicting Intervention Effects

Causal models allow for predicting the effects of interventions before implementing them:

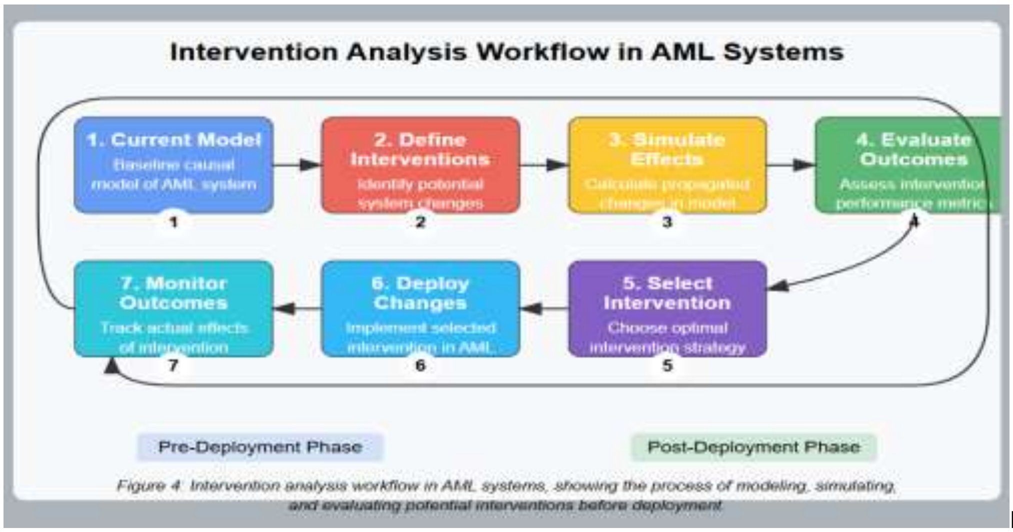

Figure 4: Intervention analysis workflow in AML systems

5.3 Counterfactual Analysis for AML

Counterfactual reasoning allows for questions like:

- Would this transaction have been flagged if the customer had a different transaction history?
- What if this sequence of transactions had occurred over a longer time period?
- How would the risk score change if the transaction had involved different counterparties?

5.4 Multi-armed Bandits and Causal Reinforcement Learning

For adaptive AML systems, causal reinforcement learning and multi-armed bandit approaches provide frameworks for sequential decision-making:

```
# Pseudocode for causal contextual bandit in AML
def select_investigation_action(transaction, model):
    # Estimate causal effect of investigation on each transaction
    potential_outcomes = []
    for action in ["investigate_deeply", "quick_review", "auto_approve"]:
        effect = model.estimate_causal_effect(
            transaction, do(investigation=action)
        )
        potential_outcomes.append((action, effect))
        # Thompson sampling or UCB for exploration-exploitation
    return select_action_with_exploration(potential_outcomes)
```

6. Implementation in Banking Systems

6.1 Data Requirements for Causal AML

Implementing causal ML for AML requires specific data considerations:

1. **Longitudinal data**: Historical data capturing entity behavior over time
2. **Intervention data**: Records of past AML interventions and their outcomes
3. **Environmental variables**: Factors that might influence causal relationships
4. **Entity relationships**: Network data capturing relationships between accounts

5. **External events**: Economic, regulatory, or geopolitical events that might impact behavior

6.2 System Architecture

A causal AML system architecture typically includes:
Show Image
Figure 5: System architecture for causal AML implementation, showing data flows, causal model components, and integration with existing banking systems.

6.3 Integration with Existing Banking Systems

Causal AML systems must integrate with:

1. **Core banking systems**: For transaction data and account information
2. **KYC systems**: For customer identity and profile information
3. **Case management systems**: For investigation outcomes and feedback loops
4. **Regulatory reporting systems**: For filing suspicious activity reports (SARs)

6.4 Real-time vs. Batch Processing

Causal inference has different implications for:

- **Real-time transaction monitoring**: Simplified causal models that can execute quickly
- **Batch risk reassessment**: More complex causal reasoning for periodic risk reviews
- **Investigation prioritization**: Causal models to estimate the potential value of investigation

6.5 Technical Challenges in Banking Environments

Implementation challenges include:

1. **Computational constraints**: Causal inference can be computationally intensive
2. **Data quality issues**: Missing data, selection bias, and incomplete histories
3. **Model updating**: Procedures for safely updating causal models as new data arrives
4. **Handling temporal dynamics**: Accounting for evolving causal relationships over time

7. Case Studies

7.1 Case Study 1: Reducing False Positives

A large European bank implemented a causal ML approach for transaction monitoring:

Metric	Traditional ML	Causal ML	Improvement
False Positive Rate	92%	78%	14%
True Positive Rate	68%	73%	5%
Investigation Time	45 min/case	38 min/case	16%

The causal approach identified many correlations in their traditional model due to confounding geographic and industry factors.

7.2 Case Study 2: Adaptive Monitoring Thresholds

A regional US bank implemented causal RL for adaptive monitoring thresholds:
Show Image
Figure 6: Performance comparison between traditional static rules, standard ML, and causal RL approaches for transaction monitoring over a 24-month period.

7.3 Case Study 3: Transaction Network Analysis

An Asia-Pacific bank applied causal discovery to transaction networks:

- Traditional approach:
  - Identified high-volume transactions between entities
  - Flagged based on transaction volume and frequency
- Causal approach:
  - Discovered causal structures in transaction networks
  - Identified pivot accounts causally connected to high-risk entities
  - Detected layering patterns not visible through correlation alone

8. Regulatory Compliance and Explainability

8.1 Causal Explanations for Regulatory Requirements

Causal models provide natural explanations for regulatory purposes:

- "This transaction was flagged because it **caused** a significant shift in the usual transaction pattern."
- "The risk score increased because recent cross-border transfers **causally influence** money laundering risk."

8.2 Model Transparency Framework

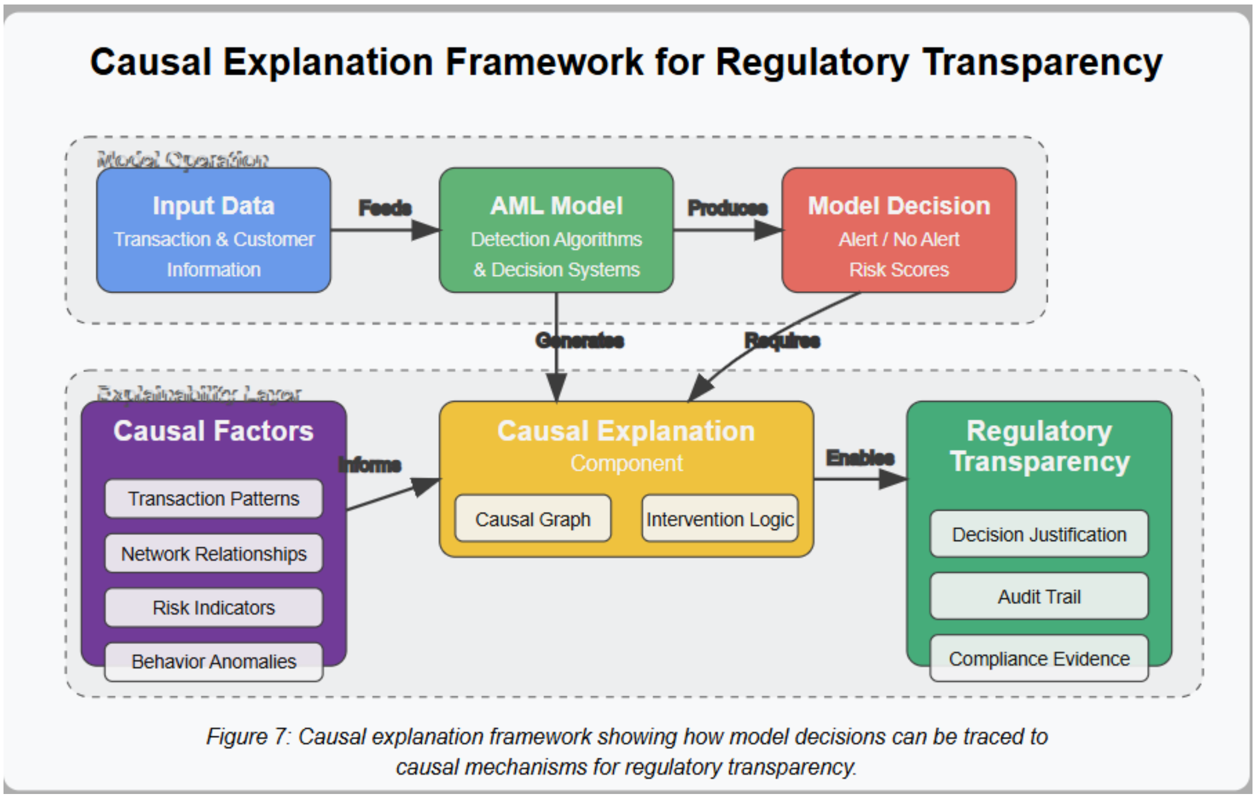

Figure 7: Causal explanation framework showing how model decisions can be traced to causal mechanisms for regulatory transparency.

Figure 7: Causal explanation framework showing how model decisions

8.3 Model Risk Management for Causal Models

Considerations for model risk management:

1. **Causal assumptions validation**: Processes to verify causal assumptions
2. **Sensitivity analysis**: Testing how sensitive conclusions are to causal assumptions
3. **Robustness testing**: Ensuring reliable performance under various scenarios
4. **Backtesting methodology**: Specialized approaches for validating causal predictions

8.4 Regulatory Feedback

Initial regulatory feedback on causal AML approaches has been positive:

- Greater transparency about model reasoning
- Clearer justification for suspicious activity reports
- More effective model governance
- Better alignment with a risk-based approach to AML

9. Future Directions

9.1 Causal Transfer Learning for AML

Transfer learning with causal models could allow:

- Learning from institutions with more labeled data
- Transferring knowledge across geographic regions
- Adapting to new financial products with limited historical data

9.2 Federated Causal Learning
Privacy-preserving federated learning with causal models could enable:
- Cross-institutional learning without sharing sensitive data
- Industry-wide causal models for emerging threats
- Regulatory monitoring without direct data access

9.3 Causal Digital Twins
Digital twins with causal models could provide:
- Sandbox environments for testing interventions
- Simulation of complex financial crime scenarios
- Testing regulatory policy changes before implementation

9.4 Quantum Computing for Causal Inference
Quantum computing may eventually address:
- Computational challenges in causal discovery
- Complex counterfactual reasoning at scale
- Real-time causal inference for high-frequency trading environments

Conclusion
Causal machine learning represents a paradigm shift in AML systems, moving beyond correlation to a deeper understanding of the mechanisms behind financial crime. By incorporating causal reasoning, financial institutions can build more robust, interpretable, and effective AML systems that reduce false positives while maintaining high detection rates.

The integration of causal frameworks with modern machine learning techniques addresses many limitations of traditional approaches, particularly in handling distribution shifts, providing explanations, and predicting the effects of interventions. While implementation challenges remain, early case studies demonstrate significant improvements in key performance metrics.

As regulatory expectations evolve and financial crime becomes increasingly sophisticated, causal approaches offer a promising direction for the next generation of AML systems. Financial institutions can avoid emerging threats by focusing on the causal mechanisms underlying suspicious activities rather than mere statistical associations while efficiently allocating investigation resources.

Funding: This research received no external funding.

Conflicts of Interest: The authors declare no conflict of interest.

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