An Explainable Graph Neural Network Framework for Detecting Fraudulent Financial Transactions in Dynamic Banking Networks

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Abstract

Financial fraud is relational, adaptive and time dependent. Isolated transaction classifiers overlook shared devices, rapid fund circulation, mule account chains and evolving interaction patterns. This paper proposes an explainable temporal heterogeneous graph neural network (ETHGNN) that jointly models accounts, customers, devices and transactions; encodes recency and directional cash flow; and produces evidence-backed explanations for investigators. A leakage-aware evaluation protocol, imbalance-sensitive training objective, explanation faithfulness tests and operational governance controls are specified. To demonstrate reporting requirements without misrepresenting experiments, numeric results in this manuscript are illustrative scenario values, not measured outcomes of a trained model. The proposed validation uses chronological holdouts and tests precision, recall, area under the precision–recall curve, alert burden, calibration and explanation stability. The architecture offers a reproducible research agenda for combining fraud sensitivity with interpretable banking decisions.

Keywords: Financial fraud; graph neural networks; temporal graphs; explainable AI; banking networks; anomaly detection; class imbalance.

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1. Introduction

Banking networks as relational systems

Digital banking creates large volumes of card payments, account transfers, merchant settlements and device interactions. Fraud is rarely confined to a single payment. A low-value transfer may be ordinary in isolation but suspicious when preceded by account creation, a new-device login and a cascade of transfers to recently opened beneficiaries. Such patterns are naturally represented as relationships between entities rather than as independent rows in a database.

Operationally, this distinction requires explicit event-time feature construction, controlled data access, reproducible model snapshots and analyst feedback loops. Every reported alert should be traceable to the underlying authorized observations and a documented threshold selection policy. The framework is therefore designed as a decision-support layer, with human review for high-impact interventions.

Fraud typologies and temporal behavior

Fraudsters adapt to thresholds and operational controls. Account takeover can produce abrupt changes in device usage, location and beneficiary behavior. Mule networks can split funds across many recipients, then reconverge funds through layered intermediaries. Velocity and temporal ordering are therefore central to risk assessment: a chain of transfers within minutes differs materially from the same relationships distributed across several months.

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Limits of conventional classification

Rules and tabular machine-learning systems remain important because they are fast, auditable and straightforward to deploy. Nevertheless, engineered aggregates may miss longer-range dependencies and hidden shared infrastructure. Graph neural networks can aggregate contextual signals from linked accounts, customers and devices. However, naïve graph learning can also propagate noise, create leakage and learn spurious associations that raise false alarms.

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Why explainability matters

Fraud alerts impose investigation costs and can inconvenience legitimate customers. Banks need defensible reasons for review, intervention and escalation. An attention weight alone is not necessarily a causal explanation. Explanations should identify influential relations, time intervals and features; remain stable under irrelevant perturbations; and provide actionable evidence that analysts can verify against transaction records.

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Research problem

The central challenge is to score a new transaction using only information available at decision time while accounting for heterogeneous relations, evolving behavior, scarce positive labels and the need for meaningful explanations. Performance must be judged not only by classification accuracy but also by precision at a constrained review capacity, latency, calibration and fairness across customer segments.

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Objectives and contributions

This paper specifies a temporal heterogeneous graph architecture, an imbalance-aware learning objective, a local subgraph explanation procedure and an evaluation design suitable for retrospective banking records. It separates model design from observed results and supplies illustrative numerical tables to show how future findings should be presented. The intended contribution is a testable integrated framework, not a claim of newly established empirical superiority.

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2. Literature Review

Graph learning for illicit finance

Weber et al. (2019) introduced the Elliptic transaction graph, demonstrating the value and complexity of relational financial forensics. Their comparisons also caution that graph models do not automatically outperform strong tabular baselines. Public cryptocurrency graphs provide useful methodology benchmarks but do not reproduce the full operational structure of retail banking.

A rigorous comparison should report dataset coverage, graph construction assumptions, label timing, split methodology, class prevalence and computation budget. Otherwise, apparently strong results can arise from non-comparable datasets or from information that would not be available when a transaction actually occurs. These methodological differences motivate the controlled protocol proposed below.

Heterogeneous fraud detection

Rao et al. (2020) proposed xFraud, which combines heterogeneous graph prediction with explanations. Its design motivates typed entities and investigator-facing evidence. In banking applications, relations may include account ownership, device use, common beneficiary and funds transfer; each relation has different semantics and different privacy implications.

A rigorous comparison should report dataset coverage, graph construction assumptions, label timing, split methodology, class prevalence and computation budget. Otherwise, apparently strong results can arise from non-comparable datasets or from information that would not be available when a transaction actually occurs. These methodological differences motivate the controlled protocol proposed below.

Temporal transaction networks

Saldaña-Ulloa et al. (2024) studied temporal graph networks for payment fraud, showing the importance of interaction events. Kim et al. (2024) examined temporal graph networks for anomaly detection in financial networks. These studies support event-driven representation, while raising questions about delayed labels, temporal drift and streaming inference cost.

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non-comparable datasets or from information that would not be available when a transaction actually occurs. These methodological differences motivate the controlled protocol proposed below.

Graph explanations

GNNExplainer (Ying et al., 2019) seeks informative subgraphs and feature subsets for a prediction. PGExplainer (Luo et al., 2020) learns an explanation mechanism that can generalize across instances. Faithfulness, stability and plausibility must be evaluated separately; visually persuasive graphs may still omit decisive evidence.

A rigorous comparison should report dataset coverage, graph construction assumptions, label timing, split methodology, class prevalence and computation budget. Otherwise, apparently strong results can arise from non-comparable datasets or from information that would not be available when a transaction actually occurs. These methodological differences motivate the controlled protocol proposed below.

Imbalanced learning and calibration

Fraud positives are rare and investigation budgets are limited. Focal loss (Lin et al., 2017), class-weighted losses and hard-negative mining are candidate training strategies. Precision–recall curves are particularly informative for rare events (Saito and Rehmsmeier, 2015). Probability calibration and threshold selection should be assessed on temporally separated validation data.

A rigorous comparison should report dataset coverage, graph construction assumptions, label timing, split methodology, class prevalence and computation budget. Otherwise, apparently strong results can arise from non-comparable datasets or from information that would not be available when a transaction actually occurs. These methodological differences motivate the controlled protocol proposed below.

Research gap and synthesis

Prior work provides strong individual components, yet integrated evaluation of temporal heterogeneity, explanation fidelity, alert operations and governance is less standardized. An effective framework should explicitly prevent future-information leakage, handle cold-start entities, measure drift, and distinguish predictive association from a verified fraud narrative.

A rigorous comparison should report dataset coverage, graph construction assumptions, label timing, split methodology, class prevalence and computation budget. Otherwise, apparently strong results can arise from non-comparable datasets or from information that would not be available when a transaction actually occurs. These methodological differences motivate the controlled protocol proposed below.

3. Research Methodology

3.1 Research design and data governance

The proposed study is retrospective and observational. An authorized bank would provide pseudonymized transaction events, account metadata, beneficiary relationships, device links and confirmed investigation outcomes. Customer identity and direct identifiers must be excluded from model-development exports. A transaction receives its final label only after an investigation or defined maturity period. Unknown labels are not treated as legitimate negatives.

The unit of prediction is a newly initiated transfer. Event time, ingestion time and label-availability time are recorded separately. Training uses earlier events; validation and test sets use later non-overlapping windows. Any rolling feature is computed only from events preceding the scored transaction. Access controls, audit trails and retention schedules govern the graph store.

3.2 Workflow and system architecture

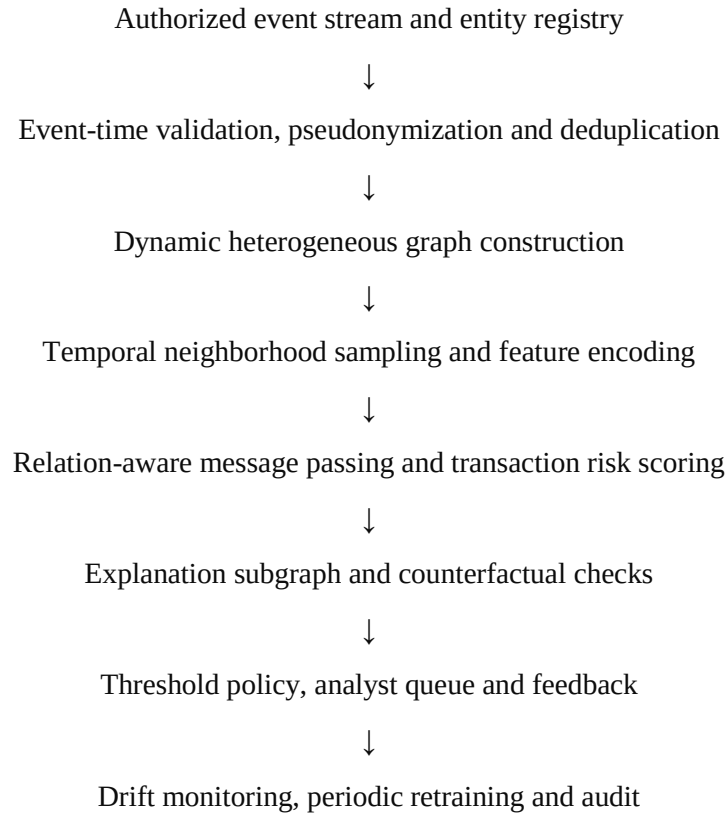

Figure 1. Proposed end-to-end research workflow (editable text flowchart).

3.3 Graph definition and temporal representation

Let the graph contain customer, account, device, merchant and transaction entities. Directed time-stamped edges describe transfer, ownership, login and shared-device relationships. Each event includes transaction amount, channel, location abstraction, device age, account tenure and elapsed time since related activity. Relation-specific normalization prevents high-degree hubs from dominating messages.

$$G(t) = (V(t), E(t), R, X(t))$$

Here G is the graph at decision time t; V is the entity set; E is the observed edge set; R is the relation-type vocabulary; and X contains authorized features. Only events with timestamps no later than t are included.

$$d(t, \tau) = exp(-\lambda(t - \tau))$$

The function d discounts an event observed at time τ relative to decision time t. The positive parameter λ controls the decay rate. Time decay is learned or selected using validation data, not the final test window.

3.4 Relation-aware graph message passing

Entity features are projected into a common latent dimension. A two-layer temporal heterogeneous encoder aggregates incoming and outgoing interactions separately. Each relation has its own transformation matrix and attention parameters. Sampling retains recent events and a limited number of older high-relevance links to control memory usage.

$$m(v,t) = \Sigma_r \Sigma_u \in N_r(v,t)\, \alpha(u,v,r,t)\, W_r\, h(u,t)$$

m is the aggregated message for target entity v; r indexes relation types; u denotes a prior neighbor; N is the eligible historical neighborhood; α is normalized temporal attention; W is a trainable relation transformation; and h is the previous entity embedding.

$$h(v,t) = ReLU(W_0\, x(v,t) + m(v,t))$$

h is the updated representation, x is the entity feature vector, W_0 is a learned projection, and ReLU is the rectified linear activation. Residual connections and dropout can stabilize learning.

3.5 Transaction scoring and loss

The risk head concatenates source-account, destination-account and transaction representations with event features. The output is a calibrated fraud probability. Labels are assigned according to confirmed outcomes available at the chosen training cutoff.

$$p = 1 / (1 + exp(-z))$$

p denotes the predicted fraud probability and z is the risk logit produced by a multilayer perceptron.

$$L = -\Sigma_i [w_1\, y_i\, log(p_i) + w_0(1 - y_i) log(1 - p_i)]$$

L is weighted binary cross entropy; i indexes labeled training transactions; y equals one for confirmed fraud and zero for confirmed legitimate activity; w_1 and w_0 compensate for class imbalance. Weights are estimated only from the training set.

3.6 Explanation engine

For each flagged transaction, the explainer identifies a compact time-respecting subgraph and feature subset that preserves the risk score. The explanation may highlight a new device shared with previously confirmed fraud, unusual transfer velocity, or a short-lived intermediary chain. It must never reveal protected customer details beyond the analyst's authorization.

$$S = p(G) - p(G \setminus M)$$

S is deletion faithfulness; p(G) is the original predicted risk and p(G \ M) is the risk after masking the selected explanatory evidence M. A larger drop indicates that the selected evidence contributed materially to the model prediction, although it does not establish real-world causation.

$$C = |M| / |G_l|$$

C measures explanation compactness: |M| is the number of selected elements and $|G_l|$ is the number of elements in the candidate local graph. Smaller values are preferable at similar faithfulness.

3.7 Experimental protocol and baselines

Proposed baselines are logistic regression, gradient-boosted trees, static graph convolution, graph attention and a temporal graph network without explanation regularization. All models use comparable authorized information and identical chronological splits. Hyperparameters and alert thresholds are chosen on validation data. Multiple random seeds and confidence intervals are required for final claims.

A suggested protocol uses early observations for training, an intermediate time window for validation and a later window for testing, with an embargo where labels mature slowly. Report results separately for account takeover, mule transfers, new entities and high-value transactions when sufficient labels exist. Evaluate throughput and 95th-percentile latency on specified hardware.

3.8 Evaluation measures and statistical testing

$$Precision = TP / (TP + FP)$$

$$Recall = TP / (TP + FN)$$

$$F1 = 2\,Precision\,Recall / (Precision + Recall)$$

TP and FP are true and false positive alerts; FN is missed confirmed fraud. Area under the precision–recall curve measures performance across thresholds. Alert volume, false positives per thousand transactions, calibration error, explanation faithfulness and analyst acceptance rate complement classification measures. Confidence intervals should use time-block bootstrap resampling to respect dependence.

3.9 Deployment, drift and safeguards

The online service fetches bounded recent neighborhoods, computes a score and stores model version, graph snapshot time and explanation provenance. Alerts can trigger enhanced review rather than automatic account blocking. Drift monitors feature distributions, score calibration, graph degree shifts and label prevalence. Human analysts can dispute explanations and record confirmed typologies for controlled retraining.

Ethical assessment should test disparate false-positive burdens across legally permissible audit cohorts, evaluate privacy leakage from shared-entity links and document appeal mechanisms. Governance must also specify escalation ownership, retention, security reviews and rollback criteria.

4. Illustrative Results and Discussion

IMPORTANT: The following numbers are constructed examples demonstrating the intended reporting format. No dataset was downloaded, no model was trained and no empirical performance is claimed. Replace these tables and graphs with actual test results before submitting as experimental research.

Model	Precision	Recall	F1	PR AUC
Logistic regression	0.71	0.58	0.64	0.69
Gradient boosting	0.8	0.68	0.74	0.78
Static GCN	0.82	0.73	0.77	0.82

Temporal GNN	0.86	0.79	0.82	0.87
Proposed explainable model	0.88	0.82	0.85	0.9

Table 1. Hypothetical comparative classification metrics. The illustrative pattern suggests that relational and temporal context could improve recall and precision, but the magnitude of any real improvement remains unknown.

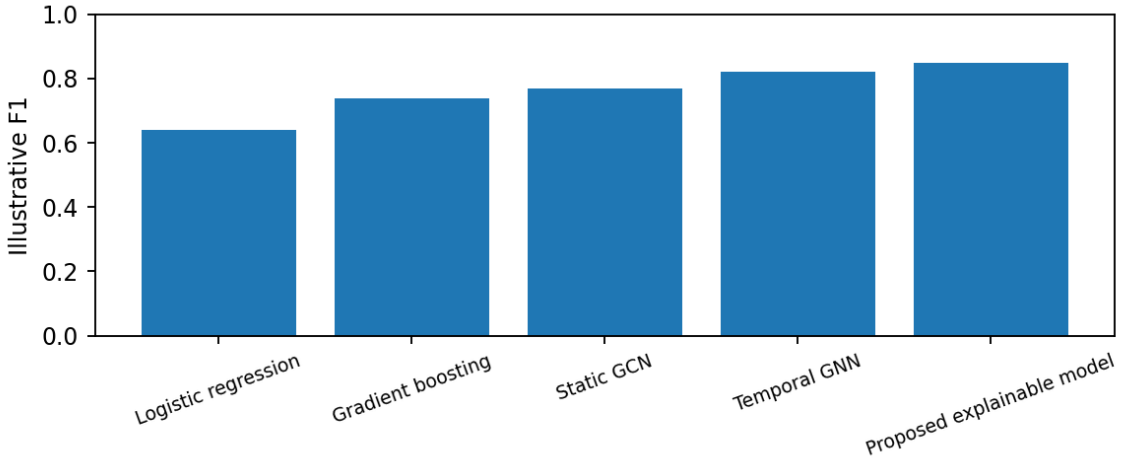

Figure 2. Illustrative F1 comparison (not experimental evidence).

Variant	Illustrative PR AUC	Illustrative F1
Full model	0.9	0.85
Without time encoding	0.86	0.81
Without relation types	0.84	0.79
Without neighborhood context	0.8	0.75

Table 2. Hypothetical ablation study. Each row should be estimated through a controlled retraining run, with uncertainty intervals and identical splits.

Measure	Illustrative value	Interpretation
Alerts per 10,000 transfers	55	Investigation workload
Fraud cases detected per 10,000	41	Detected confirmed cases
Deletion faithfulness	0.24	Average risk reduction after masking
Explanation compactness	0.18	Fraction of local evidence

		retained
95th percentile latency	72 ms	Online scoring time

Table 3. Example operational and explanation measures. Values are invented to show required reporting fields, not banking deployment measurements.

Interpretation requires care: an increase in recall can still create an unsustainable alert queue if prevalence is low. Explainability scores must be accompanied by human assessment, and strong discrimination does not guarantee probability calibration. Future experiments should also assess cross-bank portability, adversarial behavior, delayed investigations and fairness under distribution shifts.

5. Conclusion

This manuscript develops a testable framework for explainable fraud detection in dynamic banking networks using temporal, relation-aware graph representation learning. The architecture combines event-time graph construction, class-sensitive prediction, compact local explanations and operational safeguards. The proposed evaluation emphasizes chronological validity, rare-event precision and recall, explanation faithfulness, calibration, throughput and governance. Its principal limitation is that the numeric results are illustrative rather than experimental. A complete empirical study should implement the model on authorized banking data or a clearly qualified public proxy, benchmark against strong baselines and report reproducible results with uncertainty. This approach can help align predictive fraud analytics with accountable financial decision-making.

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