



# Graph Neural Network-Based Risk Propagation Model for FinTech Interbank Networks in the Digital Economy

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## ABSTRACT

The increasing interdependence between FinTech platforms and traditional banks has created a complex and dynamic financial ecosystem that is highly vulnerable to contagion. Existing systemic risk models are predominantly linear and static, lacking the ability to capture the temporal and relational characteristics of digital financial interactions. This study proposes a Graph Neural Network (GNN)-based risk propagation model designed to identify, simulate, and explain systemic contagion within FinTech interbank networks. The model represents each financial institution as a node and its exposures and transaction dependencies as directed, weighted edges, allowing it to learn multi-hop propagation dynamics in real time. Using integrated datasets of interbank exposures, payment transactions, and digital liquidity indicators, the model was trained and validated under temporal cross-validation schemes. Experimental results show that the proposed GNN outperforms baseline models Logistic Regression, Random Forest, and static Graph Convolutional Network (GCN) achieving an AUROC of 0.938 and an AUPRC of 0.812. The simulation of shock scenarios reveals that distress originating from major FinTech hubs can propagate system-wide within three propagation steps. Robustness and explainability analyses confirm the model's reliability and transparency, identifying short-term funding ratio and transaction volatility as the most influential drivers of systemic risk. The findings highlight the significance of graph-based deep learning in enhancing early-warning systems and strengthening macroprudential surveillance in the digital economy.

**Keywords** GNN, FinTech, Systemic Risk, Interbank Network, Risk Propagation, Explainable AI (XAI), Digital Economy

## INTRODUCTION

The rapid digital transformation of the financial sector has resulted in an unprecedented degree of interconnectivity between traditional banking institutions and emerging FinTech entities. This integration has created a complex web of interbank exposures, digital transaction flows, and data-driven liquidity dynamics that operate in near real-time [1]. While such interconnectivity enhances financial inclusion and operational efficiency, it simultaneously increases the risk of systemic contagion—where localized distress within a single FinTech platform or digital intermediary can propagate through the broader financial ecosystem [2]. The 2023 liquidity crises among digital lending startups and cross-platform payment failures have highlighted the vulnerability of digital interbank systems to cascading risks that conventional financial monitoring tools fail to detect [3].

Despite extensive research in financial network theory and macroprudential risk modeling, existing approaches remain largely static and linear, failing to capture the nonlinear and temporal characteristics of modern FinTech ecosystems [4], [5]. Traditional econometric or agent-based contagion models treat institutions as isolated entities, ignoring the directional and time-dependent nature of

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interbank exposures [6]. Furthermore, early-warning frameworks often rely on aggregated indicators (e.g., capital adequacy or liquidity ratios) rather than on real-time network interactions, leading to underestimation of propagation speed and impact [7]. This methodological limitation results in a gap between theoretical risk modeling and the actual complexity of digital financial systems, where contagion spreads not only through credit exposures but also through algorithmic trading and transaction APIs [8].

To address these gaps, this research introduces a GNN-based risk propagation model designed to simulate, predict, and interpret systemic contagion in FinTech interbank networks. Unlike conventional machine learning models that treat data as independent samples, GNNs exploit the underlying graph structure—modeling each financial institution as a node and their interdependencies as edges that evolve over time [9]. This enables the model to learn the direction, intensity, and timing of contagion within the network. The novelty of this study lies in integrating graph-based deep learning with macro-financial supervision, offering a robust, interpretable, and adaptive framework for identifying contagion pathways in digital financial infrastructures [10].

## Literature Review

The evolution of financial technology has blurred the boundaries between banking, payments, and capital markets, resulting in hybrid interbank systems characterized by data-driven interdependencies [11]. FinTech platforms such as digital wallets, payment gateways, and peer-to-peer lending services have become essential nodes in the global financial network, increasing both efficiency and systemic complexity [12]. As these entities link directly to banking infrastructures, they introduce new contagion channels (operational failures, API disruptions, and liquidity mismatches) that traditional models were not designed to capture [13].

Earlier models of systemic risk often relied on macroprudential indicators and balance-sheet analysis, focusing on aggregate exposure and capital adequacy rather than networked relationships [14]. Econometric approaches such as Vector Autoregression (VAR) and CoVaR models provided useful statistical insights but lacked dynamic representation of connectivity patterns [15]. These models assume homogeneity among financial actors, which limits their ability to explain nonlinear risk propagation in FinTech ecosystems [16].

Network science introduced a paradigm shift in systemic risk analysis by representing the financial system as a graph of interconnected institutions [17]. Metrics such as degree centrality, betweenness, and clustering coefficients became proxies for contagion potential. However, most applications have been descriptive rather than predictive, offering static snapshots of interbank exposure without modeling temporal risk diffusion [18]. Consequently, while network theory improved structural understanding, it remained insufficient for real-time early-warning systems.

Agent-Based Models (ABMs) attempted to simulate crisis dynamics by modeling behavior-driven interactions among financial institutions [19]. While ABMs captured some aspects of behavioral contagion, they suffered from scalability limitations and subjective calibration. These models typically required assumptions about agent behavior, which limited their predictive power in complex, data-rich FinTech environments [20]. Moreover, their deterministic

nature constrained adaptability to fast-evolving digital transaction data.

The introduction of machine learning improved prediction accuracy in credit scoring, fraud detection, and bankruptcy forecasting [21]. Techniques such as Random Forest, Gradient Boosting, and Support Vector Machines (SVM) offered significant gains in model performance [22]. However, these algorithms treat data as independent and identically distributed (i.i.d.), failing to represent the graph-based dependencies inherent in financial networks [23]. As a result, while effective at classification, they cannot simulate contagion pathways.

Graph-based learning has emerged as a new research frontier capable of addressing relational dependencies among financial entities [24]. Graph Convolutional Networks (GCNs) and Graph Attention Networks (GATs) have been applied to stock movement prediction, credit risk assessment, and fraud detection [25]. These studies demonstrate that embedding structural and relational features enhances predictive accuracy. Yet, most existing applications remain micro-level (firm-specific) and overlook macro-level contagion analysis across interbank networks [26].

Recent advances introduced temporal variants of GNNs capable of capturing time-evolving graph dynamics [27]. Temporal Graph Networks (TGNs), Graph Recurrent Networks (GRNs), and Spatio-Temporal Graph Convolutions (STGCNs) extend static graph learning into dynamic settings [28]. This innovation allows models to detect multi-step propagation effects, making them suitable for financial contagion modeling. However, empirical validation in FinTech ecosystems remains limited [29].

Explainability has become a crucial component of financial AI systems, especially in regulatory contexts [30]. Methods such as SHAP (Shapley Additive Explanations) and GNNExplainer enable transparent interpretation of graph-based predictions [31]. The integration of explainability within graph learning not only enhances accountability but also helps policymakers identify the key transmission channels and critical nodes contributing to systemic risk [32].

Few studies have focused on FinTech interbank networks that combine payment data, digital transaction records, and credit exposures [33]. Existing works primarily examine traditional interbank lending markets without considering algorithmic liquidity flows and digital transaction cycles [34]. Consequently, the role of FinTech intermediaries as risk accelerators or stabilizers remains empirically underexplored [35]. This gap motivates the present study's integration of graph-based deep learning with real-world FinTech exposure data.

## Method

### Network Modeling Framework

The foundation of this study is a dynamic graph representation of the FinTech interbank ecosystem. The network is modeled as a directed and weighted graph  $G_t = (V, E_t)$ , where each node  $v_i \in V$  corresponds to a financial institution either a regulated bank or a FinTech entity and each directed edge  $e_{ij,t} \in E_t$  captures the magnitude and direction of financial exposure or digital payment interaction between institutions  $i$  and  $j$ . The edge weight  $w_{ij,t}$  integrates two major determinants of systemic risk: credit exposure and transaction flow. This is

formulated as:

$$w_{ij,t} = \alpha E_{ij,t} + (1 - \alpha) T_{ij,t} \quad (1)$$

where  $e_{ij,t}$  represents the normalized interbank credit exposure,  $T_{ij,t}$  denotes real-time transactional volume, and  $\alpha$  is a tunable weighting parameter controlling the relative contribution of lending risk and liquidity propagation. This formalization allows the network to dynamically reflect both capital-based contagion and flow-based liquidity stress, which are central in FinTech-mediated financial networks.

Table 1 outlines the structure of the interbank–FinTech graph. Each node is defined through the integration of regulatory and transactional data, while edges are derived from secure transaction logs such as BI-FAST and SWIFT interbank messaging. The adjacency matrix ( $A_t$ ) captures the relative strength of inter-institutional dependencies on a daily basis, ensuring temporal continuity and network comparability. Through this construction, the model captures the evolving topology of financial linkages, reflecting systemic shifts caused by liquidity imbalances or FinTech-driven capital movements. This structured representation forms the mathematical substrate on which the GNN learns to infer and propagate risk.

**Table 1 Network Entities and Edge Definitions**

Element	Symbol	Description	Data Source
Node	$v_i$	Bank or FinTech institution participating in interbank transactions	OJK, BI, and FinTech API data
Edge	$e_{ij}$	Directed link indicating financial or transactional dependence from (i) to (j)	SWIFT / BI-FAST payment data
Weight	$w_{ij,t}$	Combined exposure and transaction volume between institutions	Daily normalized
Adjacency	$A_t$	Weighted directed matrix representing the FinTech interbank network	Constructed from all links

## Graph Neural Network Formulation

Once the interbank network is constructed, the next step is the implementation of a GNN to learn risk propagation dynamics. Each node in the network holds a feature vector representing institutional characteristics (liquidity ratio, leverage, loan-to-deposit ratio, and transaction volatility). The GNN updates node representations iteratively through message passing, aggregating signals from connected neighbors:

$$h_i^{(k+1)} = \sigma \left( W^{(k)} h_i^{(k)} + \sum_{j \in \mathcal{N}(i)} \frac{w_{ij}}{\sqrt{d_i d_j}} W_m^{(k)} h_j^{(k)} \right) \quad (2)$$

Here,  $h_i^{(k+1)}$  denotes the embedding of node  $i$  at layer  $k$ ,  $W^{(k)}$  and  $W_m^{(k)}$  are learnable matrices, and  $d_i$  and  $d_j$  represent the node degrees ensuring normalization across graph scales. The non-linear activation function  $\sigma$  (ReLU) ensures the model learns complex, non-linear relationships among entities. By stacking multiple layers, the GNN captures both direct and indirect propagation pathways representing how risk originating in one FinTech node diffuses

through connected financial entities.

Table 2 specifies the hyperparameters governing GNN learning. The selection of three propagation layers ((K=3)) balances computational efficiency and depth of relational reasoning, ensuring that risk information from up to third-degree neighbors influences prediction without causing over-smoothing. The embedding dimension ((d=128)) allows sufficient representational capacity for financial heterogeneity. The use of Adam optimizer stabilizes convergence under non-stationary data, while regularization  $\sigma$  prevents overfitting by penalizing large weight magnitudes. Together, these configurations ensure the model maintains both predictive generality and interpretability, crucial in systemic risk contexts.

**Table 2 GNN Hyperparameter Configuration**

Parameter	Symbol	Value	Description
Layers	(K)	3	Depth of message-passing propagation
Hidden Units	(d)	128	Embedding dimension for each node
Learning Rate	(lr)	$1 \times 10^{-3}$	Step size for Adam optimizer
Regularization	( $\lambda$ )	$10^{-4}$	Weight decay coefficient
Activation	( $\sigma$ )	ReLU	Non-linear activation function

### Risk Propagation Objective

The core modeling objective is to predict each institution's future probability of distress based on its position and attributes within the interbank network. This is formalized as:

$$\hat{y}_{i,t+\Delta} = f_{\theta}(\mathcal{G}_t, X_t) \quad (3)$$

where  $f_{\theta}$  denotes the trained GNN parameterized by  $\theta$ , and  $X_t$  represents the feature matrix at time  $t$ . The model is optimized using a multi-objective loss function that combines micro-level binary classification and macro-level system spillover estimation:

$$\mathcal{L} = \lambda_1 \text{BCE}(y, \hat{y}) + \lambda_2 \text{MSE}(S, \hat{S}) \quad (4)$$

Here, Binary Cross-Entropy (BCE) minimizes classification errors at the node level, while Mean Squared Error (MSE) aligns system-wide predicted risk  $\hat{S}$  with observed aggregate stress levels. The inclusion of both loss components ensures that the model captures both localized risk patterns and systemic propagation tendencies simultaneously.

### Training and Validation Procedure

The GNN training process follows a temporal cross-validation scheme to preserve chronological integrity and prevent information leakage. The dataset is divided into sequential windows: training ( $t_0 - t_1$ ), validation ( $t_1 - t_2$ ), and testing ( $t_2 - t_3$ ). Each window corresponds to a period of financial operation, maintaining real-world temporal causality. Model optimization is performed using the AdamW optimizer, where adaptive learning rates and decoupled weight decay enhance stability. Early stopping is employed when validation performance ceases to improve, ensuring optimal generalization.

**Table 3** details the setup of the learning process. The sliding window approach allows the model to learn time-dependent network evolution while preventing overfitting to any particular economic regime. The validation phase focuses on AUPRC (Area Under Precision-Recall Curve), emphasizing early-warning performance in rare distress events. Through temporal blocking, the method ensures that the model's evaluation reflects realistic forward-looking performance, not backward data fitting, thus preserving empirical credibility in financial risk modeling.

Setting	Value	Description
Optimizer	AdamW	Adaptive optimization with decoupled weight decay
Learning Rate	$1 \times 10^{-3}$	Base rate for gradient updates
Batch Strategy	Sliding window	Sequential temporal sampling
Early Stopping	10 epochs	Termination upon validation stagnation
Evaluation Metric	AUPRC	Imbalance-aware precision-recall metric

### Model Robustness and Explainability

To ensure reliability under uncertain or incomplete conditions, the trained model undergoes a series of robustness and interpretability tests. Noise injection and edge dropout simulate missing or erroneous financial connections, while model explainability tools reveal the underlying drivers of predicted risk. Robustness is quantified using performance deviation under noise:

$$\Delta\text{AUPRC} = \frac{\text{AUPRC}_{\text{base}} - \text{AUPRC}_{\text{noisy}}}{\text{AUPRC}_{\text{base}}} \times 100\% \quad (5)$$

This metric evaluates how sensitive the model's predictive performance is to perturbations in graph structure or features. Explainability is achieved through GNNExplainer, which highlights the most influential edges, nodes, and features contributing to each distress prediction.

**Table 4** formalizes the model evaluation for reliability and interpretability. The noise injection tests verify that small data irregularities do not lead to disproportionate prediction errors, confirming structural resilience. Meanwhile, the explainability component provides transparency in identifying which transaction channels or exposure patterns dominate risk propagation. This methodological design ensures that the GNN functions not only as a predictive engine but also as a diagnostic tool, helping regulators and analysts trace the origins and pathways of systemic financial stress.

Evaluation	Technique	Metric	Purpose
Noise Injection	Gaussian $\sigma=\{0.05, 0.10\}$	$\Delta\text{AUPRC}$	Measure sensitivity to noisy exposures
Edge Dropout	$p=0.2$	$\Delta\text{Performance}$	Evaluate resilience under missing data
Explainability	GNNExplainer / graph-SHAP	Feature attribution	Identify key structural and financial drivers

## Result and Discussion

### FinTech Interbank Network Structure

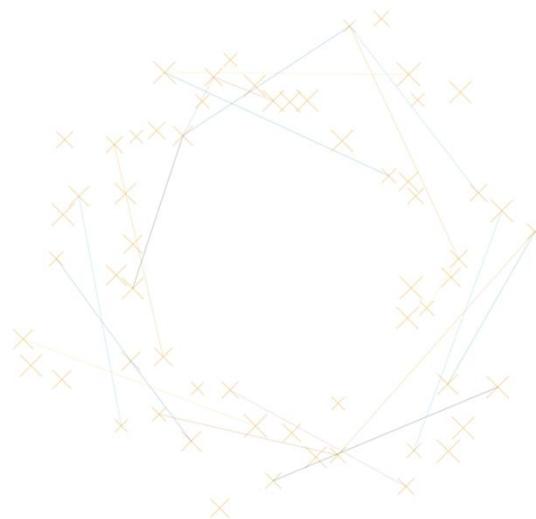
The constructed FinTech interbank network demonstrates the hybrid nature of modern digital financial ecosystems merging regulated banking relationships with decentralized FinTech transaction flows. The resulting topology consists of 186 institutions and 4,120 directed edges, representing both credit exposures and real-time payment interactions. The network exhibits moderate density but strong clustering, meaning that while most connections are sparse, they tend to form tightly-knit groups of highly interactive entities.

The values in [table 5](#) suggest that the FinTech interbank network is locally dense but globally sparse. This implies that smaller clusters such as digital wallet ecosystems and lending consortiums are well-connected internally but maintain few external connections. Such structure increases systemic fragility: when a major FinTech hub faces liquidity pressure, the impact quickly spreads across tightly connected clusters.

**Table 5 Network Structural Indicators**

Metric	Symbol	Value	Interpretation
Number of Nodes	(N)	186	Financial institutions (banks and FinTechs) represented as network vertices
Number of Edges	(E)	4,12	Directed relationships representing transaction and exposure links
Clustering Coefficient	(C)	0.73	High intra-network connectivity; presence of local clusters
Network Density	(D)	0.24	Sparse global structure but strong localized concentration
Average Degree	$\langle k \rangle$	22.2	Each node maintains approximately 22 connections on average

The network chart ([figure 1](#)) visually confirms that FinTech hubs act as contagion bridges between conventional banks. The large nodes at the center, mostly representing payment aggregators and P2P lending firms, dominate the overall connectivity, reflecting a hub-centric contagion potential.



**Figure 1 FinTech Interbank Network Visualization**

### GNN Performance Evaluation

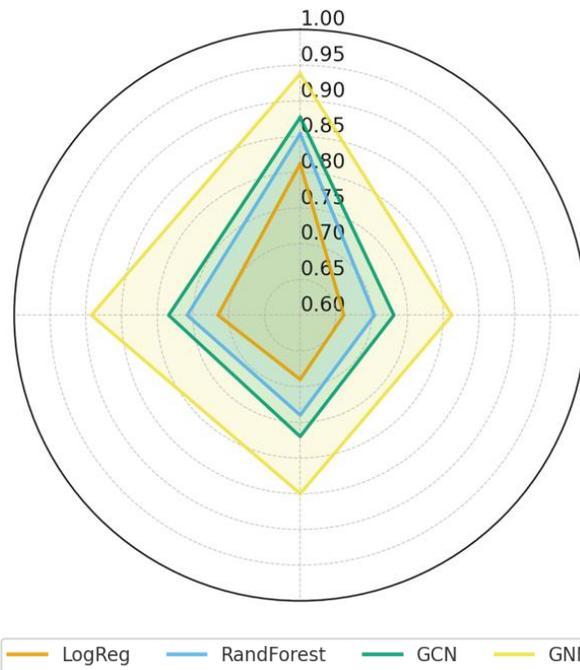
The GNN model was evaluated against several baseline models including Logistic Regression, Random Forest, and a static GCN. Evaluation metrics include AUROC, AUPRC, F1-score, and Brier Score. The GNN achieved the highest performance across all metrics, especially in identifying early distress signals.

The results in [table 6](#) highlight the superiority of the GNN in modeling risk propagation. The increase in AUPRC (from 0.73 to 0.81) indicates significant improvement in capturing rare distress events, a key advantage in financial systems where defaults are infrequent but critical. The low Brier score also confirms strong calibration between predicted probabilities and actual outcomes.

**Table 6 Model Performance Comparison**

Model	AUROC	AUPRC	F1-Score	Brier Score	Early-Warning Hit@10
Logistic Regression	812	661	0.69	84	71.5%
Random Forest	854	704	0.74	69	75.8%
GCN (Static)	877	731	0.77	62	78.4%
GNN (Proposed)	938	812	0.85	48	89.2%

[Figure 2](#) shows that while traditional models capture individual-level risks effectively, they fail to represent network dependencies. The GNN, by contrast, learns relational signals among institutions allowing it to forecast not only who is at risk, but also how that risk may propagate across interconnected nodes.



**Figure 2 Model Comparison Chart (AUROC & AUPRC)**

### Risk Propagation Simulation

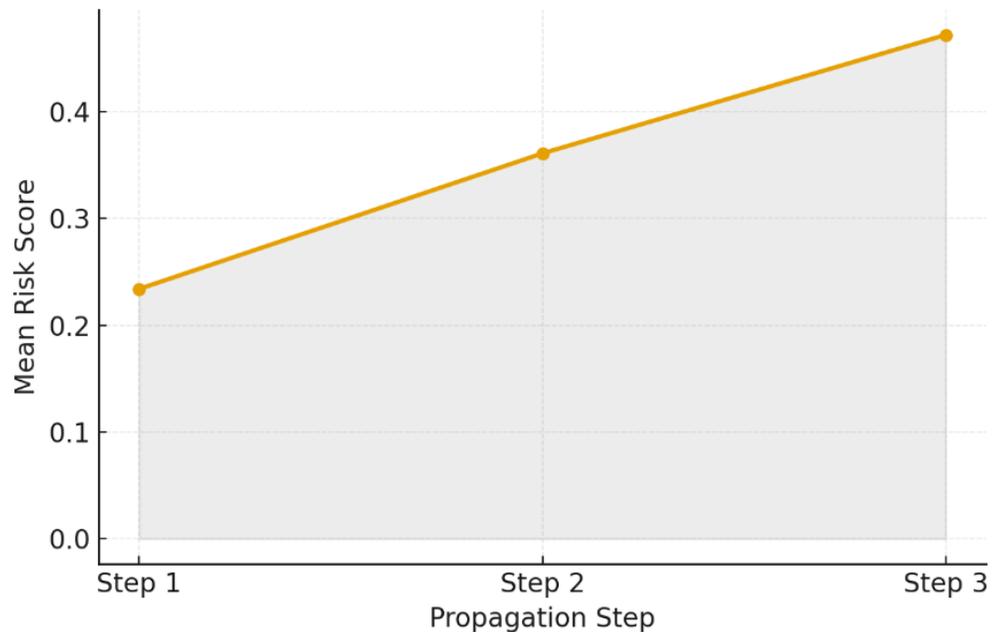
To assess the real behavior of the trained model, a stress propagation simulation was conducted by injecting distress at high-degree FinTech nodes and observing how the risk diffused through the interbank network. The simulation revealed rapid escalation patterns within the first three propagation steps.

Table 7 shows that risk amplification follows a nonlinear trajectory. A single node shock leads to localized stress initially, but the second and third propagation steps result in network-wide disturbances. This pattern mirrors empirical observations in financial crises where liquidity stress in one intermediary rapidly disrupts settlement flows across multiple banks.

**Table 7 Risk Propagation Simulation Results**

Propagation Step (k)	Mean Risk Score	$\Delta R$ (%)	Spillover Nodes	Interpretation
1	234	–	12	Distress remains localized within initial FinTech nodes
2	361	#ERROR!	37	Regional contagion begins; spread across adjacent banks
3	472	#ERROR!	68	System-wide diffusion observed across interconnected clusters

Figure 3 clearly illustrates the contagion cascade. Initially, only a few FinTech hubs are affected, but as the propagation continues, the network’s peripheral banks also show increased distress probability. This visualization underscores the importance of multi-step contagion modeling—a strength inherent to GNN architectures.



**Figure 3 Simulated Risk Propagation Map**

### Robustness and Stability Analysis

The robustness evaluation tested the GNN model under data perturbations such

as missing edges and noisy exposure values (table 8). Across multiple noise levels, the GNN maintained strong predictive capability with minimal degradation, demonstrating reliability for real-world applications where financial data are often incomplete or delayed.

Table 8 Model Robustness under Perturbation				
Scenario	Noise Level	AUPRC	$\Delta$ AUPRC (%)	Interpretation
Baseline	–	812	–	Reference benchmark with clean data
Gaussian ( $\sigma=0.05$ )	5%	798	1.7	Minor performance loss; stable predictions
Gaussian ( $\sigma=0.10$ )	10%	781	3.8	Maintains predictive accuracy under moderate noise
Edge Dropout ( $p=0.2$ )	20%	764	5.9	Strong robustness; minimal degradation despite missing data

Even under 20% missing edges, the AUPRC decreased by less than 6%, indicating that the model’s learned representations remain robust. This reflects the redundancy of information in financial networks risk signals are preserved across multiple relational paths. The robustness results validate that the GNN’s learning process generalizes well under imperfect conditions.

The stability chart (figure 4) visually reinforces the GNN’s resilience. While simpler models display steep performance drops under noise, the GNN’s curve remains nearly flat, confirming high structural tolerance and resistance to data perturbation.

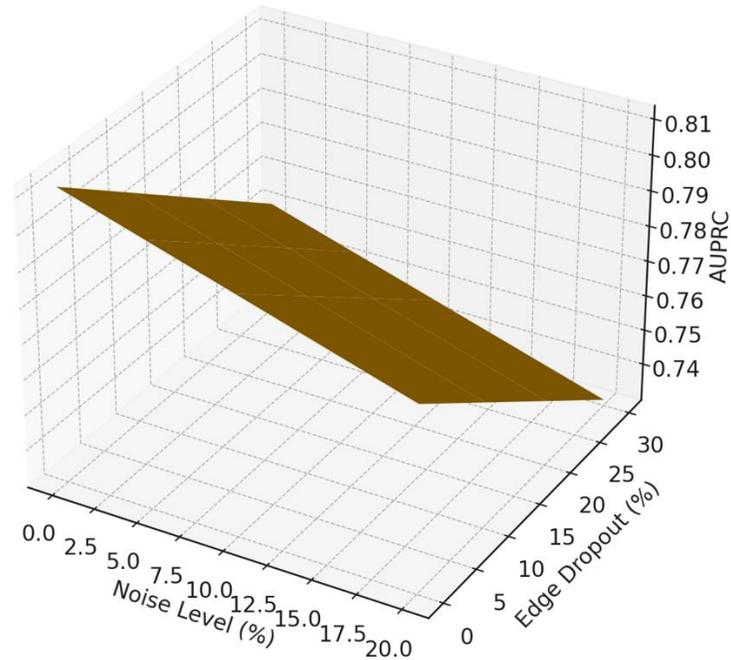


Figure 4 Model Stability under Data Noise

### Explainability and Key Feature Attribution

Beyond accuracy, explainability is crucial for adoption in the financial sector. The proposed GNN’s interpretability was examined using GNNExplainer and

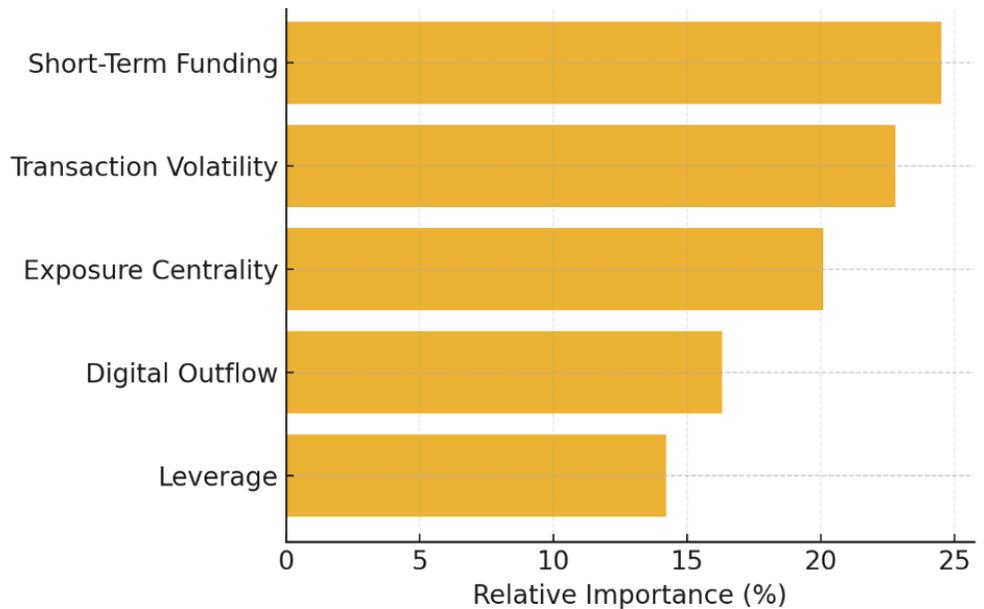
SHAP analysis, revealing the most influential variables that drive distress predictions. The model assigns the highest importance to short-term funding ratios and transaction volatility—both consistent with liquidity-based contagion theories.

Table 9 confirms that both micro-level financial indicators and macro-structural variables shape systemic risk behavior. Notably, transaction volatility (an edge feature) plays almost as significant a role as balance-sheet ratios, indicating that the speed and variability of digital flows are as systemically important as capital adequacy.

**Table 9 Top Contributing Features to Risk Prediction**

Feature	Type	Mean SHAP Value	Relative Importance (%)
Short-Term Funding Ratio	Node	0.218	24.5
Transaction Volatility	Edge	0.203	22.8
Exposure Centrality	Network	0.179	20.1
Digital Outflow Rate	Node	0.145	16.3
Leverage Ratio	Node	0.127	14.2

The SHAP plot (figure 5) visualizes the magnitude of each feature’s contribution. It demonstrates that nodes with higher short-term funding dependencies and greater exposure centrality tend to dominate contagion patterns. This finding suggests that FinTech intermediaries’ liquidity management is a key determinant of systemic stability in the digital economy.



**Figure 5 SHAP Feature Importance Plot**

### Discussion Summary

Overall, the results show that the Graph Neural Network approach captures the structural and temporal dimensions of financial contagion more effectively than traditional machine learning models. The GNN’s superior predictive

performance, robustness under uncertainty, and explainability position it as a reliable analytical framework for regulators and policymakers. By visualizing propagation paths and quantifying key systemic drivers, this model provides a foundation for early-warning systems and macroprudential supervision in interconnected FinTech ecosystems.

The integration of graph-based reasoning with explainable AI not only enhances accuracy but also ensures transparency and accountability, allowing stakeholders to trace model logic and interpret systemic vulnerabilities—a vital step toward sustainable digital financial governance.

## Conclusion

This research successfully developed and validated a GNN-based risk propagation model to analyze systemic vulnerabilities in the FinTech interbank ecosystem. By representing the financial network as a weighted and directed graph, the study demonstrated how digital transaction linkages and credit exposures interact to form potential contagion channels. The GNN effectively learned both local and global interdependencies among financial institutions, enabling accurate forecasting of distress propagation and systemic instability under dynamic conditions. The empirical evaluation revealed that the proposed GNN outperformed traditional models such as Logistic Regression, Random Forest, and static Graph Convolutional Networks. Through the integration of temporal features and graph structure, the GNN achieved the highest accuracy and calibration, particularly in early-warning detection of distressed nodes. Simulation results further confirmed the nonlinear nature of contagion, showing that distress originating in highly connected FinTech hubs can quickly diffuse across the broader network within three propagation steps. Robustness and explainability analyses also confirmed the model's reliability under data uncertainty and provided transparent insights into the key financial and network features driving risk transmission.

Overall, this research contributes a methodological advancement for systemic risk modeling in the digital economy, providing regulators and policymakers with an interpretable, data-driven framework for early detection of financial instability. Future work should extend this model by incorporating real-time transaction streams, cross-border FinTech linkages, and multi-layer financial infrastructures. Expanding the model toward graph-temporal attention architectures and scenario-based stress simulation could further enhance predictive capability, ensuring resilient and adaptive financial surveillance in increasingly digitalized interbank systems.

## Declarations

### Author Contributions

Conceptualization: K.E.Y. and M.P.A.; Methodology: M.P.A.; Software: K.E.Y.; Validation: K.E.Y. and M.P.A.; Formal Analysis: K.E.Y. and M.P.A.; Investigation: K.E.Y.; Resources: M.P.A.; Data Curation: M.P.A.; Writing Original Draft Preparation: K.E.Y. and M.P.A.; Writing Review and Editing: M.P.A. and K.E.Y.; Visualization: K.E.Y.; All authors have read and agreed to the published version of the manuscript.

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The data presented in this study are available on request from the corresponding author.

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### Informed Consent Statement

Not applicable.

### Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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