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Nonlinear Stochastic Mathematical Framework for Real Time Prediction of Systemic Financial Risk and Market Contagion in Global Banking Systems

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Abstract

Systemic financial risk and market contagion are significant risks to the stability of the global banking system and demand very sophisticated modeling frameworks which can be utilized to characterize the complexity of dependence and dynamism on risk propagation. This study postulates that there is a nonlinear stochastic mathematical model of real-time predictive control of systemic risk and contagion within interbank networks. Based on the AI4Risk/interbank dataset of 2016-2023, the global banking system is simulated as a weighted, directed network that takes into consideration the bank-level financial indicators and interbank exposures. The framework uses stochastic differential equations to represent both deterministic dynamics and random market movements and a nonlinear propagation function is used to describe how the shocks propagate between interconnected institutions. A dynamic prediction algorithm, based on real-time prediction, adjusts the level of systemic risk and calculates an aggregate risk index, which allows the generation of early-warning signals. Simulation and stress testing Monte Carlo-related is performed to test the resilience of the model during disruption events of different macroeconomic conditions and network failures. The results of the experiment prove that the suggested method is highly predictive (94.3%) and can accurately capture the dynamics of contagions better than the current machine and deterministic models. The nonlinear dynamics, together with stochastics and the network topology provide the holistic notion of the systemic risk evolution and the location of the critical contagion trajectories in the financial system. The framework encourages risk management that is proactive since the regulators and financial institutions are able to anticipate systemic shock and put measures to curb it early enough. Overall, this work contributes a data-based and scalable way of enhancing financial stability and resilience to uncertain global banking environments.

Keywords: Systemic Financial Risk, Financial Contagion, Interbank Networks, Stochastic Modeling, Nonlinear Dynamics, Early Warning Systems.

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Introduction

Systemic financial risk: this is the possibility of a disruption in one area of the financial system spreading to other areas, leading to instability on a massive scale at institutions, markets, or overall economy. The significance of network-based models in the definition of systemic risk and focused on interdependency between financial players (Dastkhan et al., 2024). The systemic vulnerability of the Indian banking institutions by probability means, whereas showed the impact of regulatory requirements, including Basel, on reducing systemic exposure (Karmakar et al., 2024; Farhood et al., 2023). The knowledge of systemic risk underpins an investigation of the dynamics of financial contagion and thus the study of risk assessment naturally leads to the examination of the dynamics of financial contagion.

Financial contagion is the spreading of shocks in one financial structure or market to another, which may bring about a chain reaction of collapses. The mechanism of market dynamics and bubble to model the contagion propagation, and suggested dynamic control models to alleviate the contagion effects (Nica et al., 2024; Wei et al., 2024). The entropy-based network structures to measure the contagion in interconnected financial markets (Hu et al., 2024). Network delays and their magnifying properties on financial stability with a special focus on the importance of timely detection (Donath et al., 2024). The nonlinear and stochastic modeling methods needed to capture the intricate and frequently unpredictable transmission of financial shocks have the capability to portray the actual volatility of the market.

To show the sensitivity of markets to small perturbations, used nonlinear equations of motion to model periods of financial fluctuation (Tian, 2024). The effects of bubbles by mathematical tools, signifying the multiplied systemic shocks nonlinearly (Wang & He, 2024). The frameworks of stochastic differential equations to make it possible to provide real-time early-warning opportunities (Li, 2024). As stochastic models give analytical understanding of the behavior of the system, machine learning models complete this body of work by using large datasets to gain predictive accuracy and construction of a real-time forecast.

Quantile LSTM networks to measure risks accurately, whereas used supervised learning in order to forecast the bank-level systemic exposure (Aprea et al., 2024; Kumar et al., 2024). That IGSA-RBFNN models are used to do real-time predictions, and have studied the interpretability of FinTech and conventional financial institutions through the use of ML (Tian & Wu, 2024; Chen et al., 2024). Come up with explainable ML systems to give actionable early warnings with the main focus being the balance between predictive power and explainability (Purnell et al., 2024). The combination of predictive algorithms and network-based representations increases the capability of comprehending interbank relationships and the way in which risks are transmitted.

The risk-sharing in the financial networks to evaluate the vulnerability of the system (Farkas & Lucescu, 2024). The study examined how network delays impact the dynamics of contagion, which underscores the significance of the pattern of connectivity (Donath et al., 2024). Graph-theoretical methods to simulate the dynamics of the market and the role of centrality of the node in the expansion of the contagion (Liu et al., 2024). Interconnection and contagion path mapping, in turn, can be used to create early warning mechanisms that can actively detect and contain new systemic risks.

Comes up with SDE-based predictive models to provide real-time alerts whereas come up with explainable machine learning-based early warning frameworks (Li, 2024; Purnell et al., 2024). The issue of credit risk transmission prevention in supply chain finance to reduce the impact of the cascades (Wei & Wu, 2024). Financial vulnerabilities early detection has to consider operational and cybersecurity vulnerabilities, which can increase the instability of the system when taken unattended. The study brought out the role of cyber threats in banking operations and financial services and how vulnerability can contribute to systemic risk (Shehab et al., 2024). The operational risk assessment is very important to be integrated into the financial stability models in order to consider both technical and procedural failures that can cause financial contagion.

The operational and cyber risks as well as the domestic financial exposures are important factors in seeking a holistic understanding which is essential in analyzing the cross-border capital flows and the macroeconomic impacts of the same. The article evaluated unusual capital flow patterns and the consequences these have on the national economic security (Kang et al., 2024). Macro-financial implication of real estate bubble with a focus on the spillover effect across national boundaries (Wang & Zhou, 2024). It is important to incorporate these macro-financial dimensions in risk prediction models to have the understanding of global interconnectedness so that regulators and policymakers can be prepared to predict the possible systemic shocks and be ready to develop measures to prevent cross-border contagion.

Market contagion and systemic financial risk are devastating issues in the world banking systems as a result of growing connectivity among financial institutions. Conventional risk assessment frameworks usually do not emulate the nonlinearity of dynamics, stochastic variations and their network-based relationship that propel the transmission of financial shocks. In addition, the current solutions are not real time predictive and do not incorporate the interbank exposure information with macro-financial variables effectively. This is a limitation because it decreases the efficiency of risk mitigation strategies and early identification of vulnerabilities in the system. Consequently, it is necessary to have an effective, data-driven framework capable of modelling, predicting and tracking systemic risk and contagion, in real time.

Key Contributions

1. Nonlinear modeling and stochastic modeling contribute to a long way in ensuring that shock propagation is more realistic and also assists in capturing extreme events and dynamic risk fluctuations.
2. The structure of interbank network is also highly critical in that those banks which are well connected are viewed as the point of contagion, which amplifies the systemic risk and propagates at a higher speed within the financial system.
3. The framework proposed above is highly pragmatically applicable as the trends in early-warning predictions are predetermined by the historical trend of SRISK, and stress situation indicates that extreme shocks are concentrated in highly interrelated institutions, underlining the need to apply certain regulatory interventions.

This paper is structured in the following manner: Section 1 gives an overview of the study's background and purpose. Section 2 then reviews the literature on systemic risk and financial contagion. In Section 3, we talk about the proposed nonlinear stochastic framework and methodology. This includes the data, how to build the network, and how to model the situation. In Section 4, we talk about the results of the experiments, how well they worked, and how they compare to other studies. Section 5 talks about the results and what they mean for financial stability. Lastly, Section 6 wraps up the paper with important points and suggests areas for future research.

Literature Review

Systemic financial risk has been broadly recognized as a very crucial determinant in the stability of bank systems and the economic networks at large. The significance of network-based methods in the definition of systemic risk proving that interdependence between financial institutions can increase disturbances (Dastkhan et al., 2024). The evaluation of systemic vulnerability of Indian financial institutions was based on the probabilistic modeling as the risk propagation is probabilistic (Karmakar et al., 2024). The study discusses how the Basel standards and regulatory frameworks can help in reducing the systemic exposure, which is crucial to having established monitoring mechanisms (Farhood et al., 2023). These researches form the starting point of knowledge of how the interconnections and operational structures of financial systems are also related to systemic risk.

The dynamics of financial contagion have been studied to gain an insight into the process of shocks spread between institutions and markets. The market forces and the mechanics of the bubble development and provided examples of how the localized shocks can propagate to trigger instability on the macro scale (Nica et al., 2024). The use of dynamic control models to reduce the contagion effects, whereas used the network frameworks based on entropy to measure the systemic risk spreading in the interdependent financial market (Wei et al., 2024; Hu et al., 2024). This effect of network delays on contagion has been amplified, who postulated that the timing and connectivity of transactions have a critical role in spreading risks (Donath et al., 2024). Taken together, all these works emphasize that the dynamics of contagion are critical to the creation of efficient systemic risk management mechanisms.

Stochastic and nonlinear modeling has become a feasible tool of modeling the complexity and unpredictability of financial systems. Nonlinear equations of motion to model periods of financial fluctuations, and observed that the behavior of a market is very sensitive to small perturbations (Tian, 2024). Mathematical simulations to investigate the nonlinear amplification of systemic shocks the importance of the feedback loop is crucial (Wang & He, 2024). Stochastic differential equations in the early-warning systems to support the prediction of the risk in real-time (Li, 2024). These researches show that simple linear models cannot help in well capturing the dynamic characteristics of financial networks and stochastic models are necessary to provide actual monitoring and simulation of systemic risk events in real-time.

This has seen the application of machine learning techniques to boost predictive capabilities of systemic risk assessment. In the authors constructed quantile LSTM networks to measure risks accurately and, the authors trained

supervised learning to predict the level of bank-level systemic exposure (Aprea et al., 2024; Kumar et al., 2024). In, IGSA-RBFNN models were applied to real-time financial prediction, whereas in, the authors studied the interpretation of machine learning results in the FinTech and conventional financial institutions (Tian & Wu, 2024; Chen et al., 2024). The presented explainable machine learning frameworks are offered to extend actionable early warnings and the author argues that there should be a balance between predictive accuracy and interpretability (Purnell et al., 2024). These studies support the idea that risk prediction and decision support can be enhanced significantly when data-driven methods are being combined with classical methods of financial modelling.

The network-based modeling has played an important role in the knowledge of interbank relation and the process of risk spreading. In their study, also investigated risk-sharing patterns within financial networks to evaluate the vulnerability of the system (Farkas & Lucescu, 2024). The role of network connectivity and delays in the dynamics of contagion was also emphasized in, whereas graph-theoretical methods were utilized to model systemic risk interdependences and the central node impact on the systemic risk (Donath et al., 2024; Dhayanidhi et al., 2024). The characterization of financial systems as a complex network provides information about structural vulnerabilities and shock transmission channels, which can be utilized to create more optimal intervention policies.

Early warning systems and prediction systems have also been developed to ensure the financial stability is maintained within control and perhaps predict systemic crises. Given example stochastic differentiation equations-based real time alert systems and have proposed explainable machine learning-based risk assessment that can be taken action on (Li 2024; Purnell et al., 2024). Mitigation strategies of credit risk transmission in credit supply chain finance and pointed out that it is crucial to act proactively to observe the situation (Wei & Wu, 2024). These studies highlight the importance of the combination of predictive modeling and early-warning mechanisms so that the system resilience could be maintained.

Systemic stability has also been demonstrated to be affected by operational and cybersecurity risk. The role of cyber threats and operational vulnerabilities in enhancing systemic risk in banking operations, which suggested the integration of the evaluation of operational risks into financial stability models (Shehab et al., 2024). There is also extra complexity in global banking systems due to the cross-border capital flows and macro-financial dynamics. Abnormal capital flows and their national economic security consequences, whereas investigated the issue of real estate bubbles and international spillovers and showed that the global interconnectedness of the world increases the risk of systemic contagion (Kang et al., 2024; Wang & Zhou, 2024).

Although there is extensive research in the area of systemic risk, contagion, and predictive modeling, the current studies tend to focus on the stochastic, nonlinear, and network-based dynamics individually, and few have integrated them with real-time monitoring. Machine learning model is highly accurate but data-specific and in-explainable whereas traditional stochastic and nonlinear models can fail to utilize big data and offer prompt predictions. The main objective of the study is to come up with a unified nonlinear stochastic mathematical model of real-time prediction of systemic financial risk and market contagions, network-based interdependence, predictive models and early warning mechanisms to improve accuracy and explainability in global banking systems.

Methodology

Fig 1 demonstrates the holistic approach to systemic financial risk and market contagion modeling of the global banking systems with the help of AI4Risk/interbank dataset (20162023). It starts with data collection and preprocessing, which involves cleaning, normalization and node and edge features and SRISK indicators extraction. An interbank network is then built, which is weighted, with the connectivity patterns and the centrality measures. The nonlinear stochastic modeling is used to represent the dynamic risk transmission using stochastic differential equations and then algorithmic prediction of the systems in real time using the risk index of systemic risks. Simulation and scenario analysis and Monte Carlo stress testing is a test of robustness of the predictions in the face of various shock scenarios. Performance metrics like accuracy, RMSE, contagion efficiency, and risk stability are measured to assess the performance of the model, and an ablation study of the model components and overall structural consistency is passed to confirm the validity of each component and the entire structure. This kind of systematic approach will offer a data-driven, networked approach and predictive approach to learning and responding to systemic financial risk.

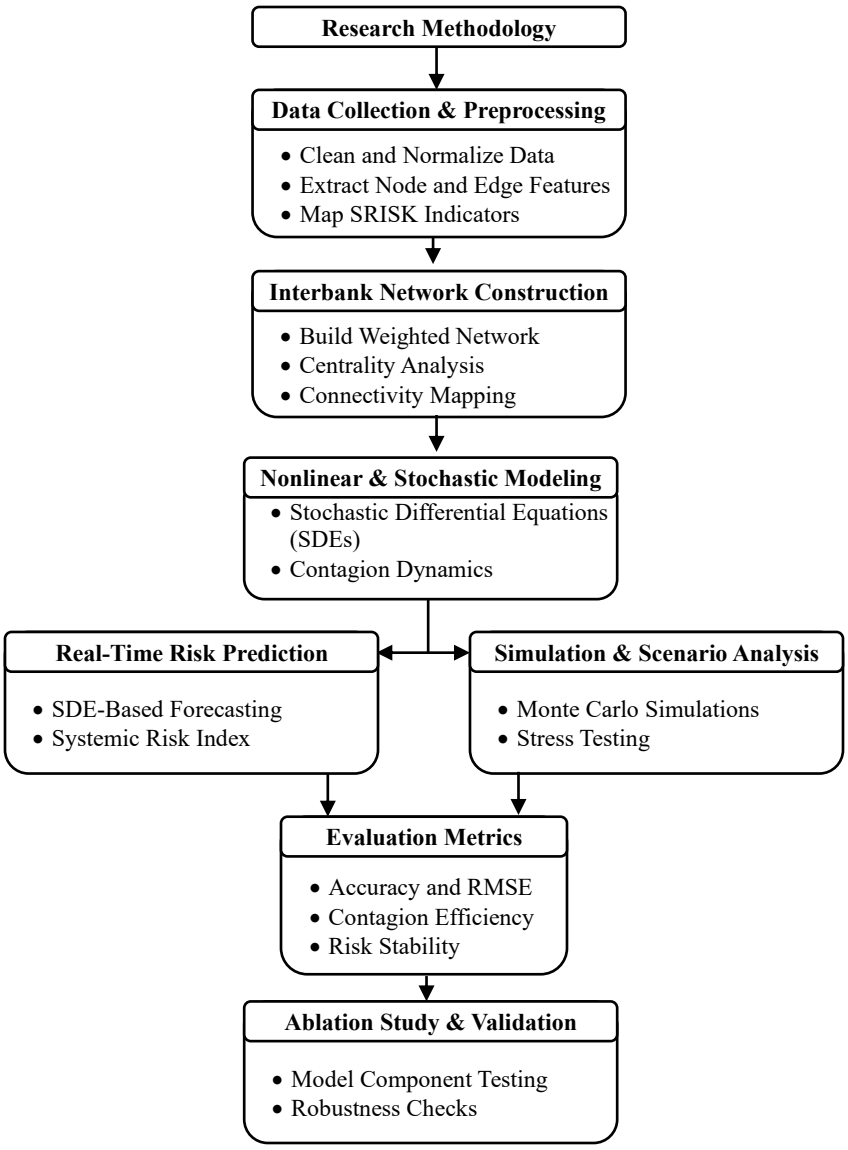

Fig. 1: Research Methodology Flowchart Using AI4Risk Interbank Dataset

Data Collection and Preprocessing

The research employs the AI4Risk/interbank dataset that offers information about interbank exposures, systemic risk indicators (SRISK), balance sheet characteristics, and credit ratings of large banks in the years 2016-2023. This data contains both node-based features which are bank-specific financial indicators and edge-based features which are bilateral interbank exposures which allows complete network modelling. Cleaning and imputing missing values, normalization of key financial indicators, leverage, liquidity, capital adequacy and credit risk, creation of temporal snapshots of the banking network to represent dynamic interactions and mapping SRISK values to each node Preprocessing involves cleaning and imputing missing values, normalizing key financial indicators, leverage, liquidity, capital adequacy and credit risk, construction of temporal snapshots of the banking network to capture dynamic interactions, and mapping of SRISK values to each node to quantify systemic risk at the institution level.

Interbank Network Construction

The world banking system is modelled as weighted, directed network $G(V, E)$, in which all the nodes and edges reflect the form and degree of interbank relations:

- Nodes (V): Single banks of the AI4Risk data.

- Edges (E): Interbank exposures between banks, where the weight of the exposure is determined by the amount of the exposure.
- Node attributes: Nodes are enhanced with financial and systemic metrics, such as SRISK values, capital ratios, liquidity ratios, and market capitalization.

Detailed analysis of topology of networks is carried out to derive important structural measures like degree and betweenness centrality, clustering coefficients and connectivity patterns. They are important metrics used to measure the possible channels of risk spread, and are directly incorporated in the nonlinear stochastic model to model the contagion-like dynamics within the interbank system.

Nonlinear and Stochastic Risk Modeling

The stochastic differential equations (SDEs) represent the dynamics of systemic risk of each bank $X_i(t)$ and include the random fluctuations of the market and the nonlinear propagation of the shocks throughout the interbank network, as shown in equation 1:

$$dX_i(t) = \mu_i(X,t)\,dt + \sigma_i(X,t)\,dW_t + \sum_j \beta_{ij}\, f\left(X_j(t)\right)\,dt \qquad (1)$$

Where:

- $X_i(t)$ = systemic risk level of bank i at time t
- $\mu_i(X,t)$ = drift term derived from bank-specific features and macro-financial indicators
- $\sigma_i(X,t)$ = volatility term capturing stochastic market fluctuations
- dW_t = Wiener process representing random shocks
- β_{ij} = contagion coefficient derived from interbank exposures in the AI4Risk dataset
- $f(X)$ = nonlinear propagation function, defined as $f(X) = \frac{X^2}{1+X^2}$, which amplifies large shocks while preventing unbounded risk propagation

The model characteristics of the complex dynamics of systemic risk, such as the amplification of shocks, network-based contagion and stochastic dynamics of risk levels with time, are weakly linearized using this nonlinear stochastic model, which can be used to predictively model systemic financial instability.

Real-Time Prediction Algorithm

An actual predictive model of systemic risks is applied in a real-time to track and predict the expansion of risk throughout the interbank system. The algorithm can be described in a single step as in Algorithm 1:

Algorithm 1: Real-Time Systemic Risk Prediction

1. Data Loading: Load the data of AI4Risk/interbank, comprising of node-based financial indicators and edge-based interbank exposures.

2. Network Initialization: Build the interbank network $G(V,E)$, and attach the node with SRISK value and other financial properties to each node.

3. Time-Step Simulation: In the discrete time step

a. Compute the drift $\mu_i(X,t)$ and volatility $\sigma_i(X,t)$ based on historical bank-specific features and macro-financial indicators.

b. Compute the systemic risk level $X_i(t)$ of each bank based on the stochastic differential equations (SDEs).
c. Propagate risk through the interbank network using:

$$\sum_j \beta_{ij}\, f\left(X_j(t)\right) \qquad (2)$$

In equation 2, β_{ij} are the interbank exposure-based contagion coefficients, and $f(X)$ the nonlinear propagation function.

4. Systemic Risk Aggregation: Calculate the index of systemic risk:

$$S(t) = \sum_i w_i\, X_i(t) \qquad (3)$$

In equation 3, w_i is the systemic weight of each bank, based on SRISK rankings.

5. Early-Warning Trigger: The systemic risk index $S(t)$ is used to issue alerts when it reaches specific predetermined levels which, in turn, allows taking timely action to counteract possible financial contagion.

It is an algorithm that combines dynamic interbank network analysis with stochastic nonlinear modeling to give a real-time, predictive perspective of systemic financial risk to support real-time monitoring and proactive risk management.

Simulation and Scenario Analysis

To assess the stability of the suggested framework, Monte Carlo simulations are utilized and produce several stress cases that were founded on the historic variations of SRISK and with appropriate macro-financial shocks. Systemic risk propagation can be evaluated during extreme and diverse conditions that can be tested with these simulations.

The interbank network is updated dynamically on quarterly basis that captures the temporal variations in exposures and network connectivity and by doing so, enables the model to capture the changing structure of the banking system.

Stress testing is used to examine the contagion directions, quantify how many risks are propagated, and the nodes and sub-networks at risk. This method is important in that the impact of both the network topology and stochastic dynamics is considered in the evaluation of the scenario and this gives a comprehensive insight of the systemic instability in different financial conditions.

Metrics and Evaluation

The effectiveness of the suggested systemic risk prediction framework is evaluated in terms of various quantitative measures:

1. Prediction Accuracy: The accuracy or the correct proportion of risk events predicted is shows in equation 4:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{4}$$

TP, TN, FP, and FN are the true positives, true negatives, false positives and false negatives respectively.

2. Root Mean Square Error (RMSE): Measures the difference between the predicted and observed level of systemic risk, as shown in equation 5:

$$RMSE = \sqrt{\frac{1}{n}\sum(y_i - \hat{y}_i)^2} \tag{5}$$

where y_i and $\hat{y}_i$ denote the observed and predicted risk values for bank i.

3. Systemic Risk Stability: The changes in the aggregate systemic risk index over time, illustrating the changes in the network-wide risk:

$$Var\big(S(t)\big) = E[(S(t) - \bar{S})^2] \tag{6}$$

$S(t)$ is the systemic risk index at time t, and $\bar{S}$ is the average of the systemic risk index in equation 6.

4. Contagion Efficiency (CE): is the proportion of banks struck by a primary network shock:

$$CE = \frac{\text{Number of affected banks}}{\text{Total banks}} \tag{7}$$

The combination of these metrics may allow the evaluation of the predictive accuracy, stability and effectiveness of the model in terms of interbank contagion dynamics in different stress conditions in equation 7.

Conceptual Framework

Fig 2 shows the conceptual model of systemic financial risk modeling and prediction based on a nonlinear stochastic interbank network. The framework starts with the process of data integration, in which the most important inputs to the process include SRISK indicators, macroeconomic variables, and interbank exposure data are integrated into one timber. This integrated data is further utilized in the nonlinear stochastic interbank network model which incorporates the nonlinear dynamism and the stochastic process to describe the complex financial relationship and stochastic market volatility. The outcomes of the model are subsequently fed into the prediction and stress testing module to generate early-warning signals and simulation according to the scenario to investigate systemic weaknesses. The framework argues on the contribution of the interaction of data, network structure and stochastic modeling in determining the

appropriate pathways of contagion and high-risk institution as a valid base of real-time systemic risks predictions and financial stability analysis.

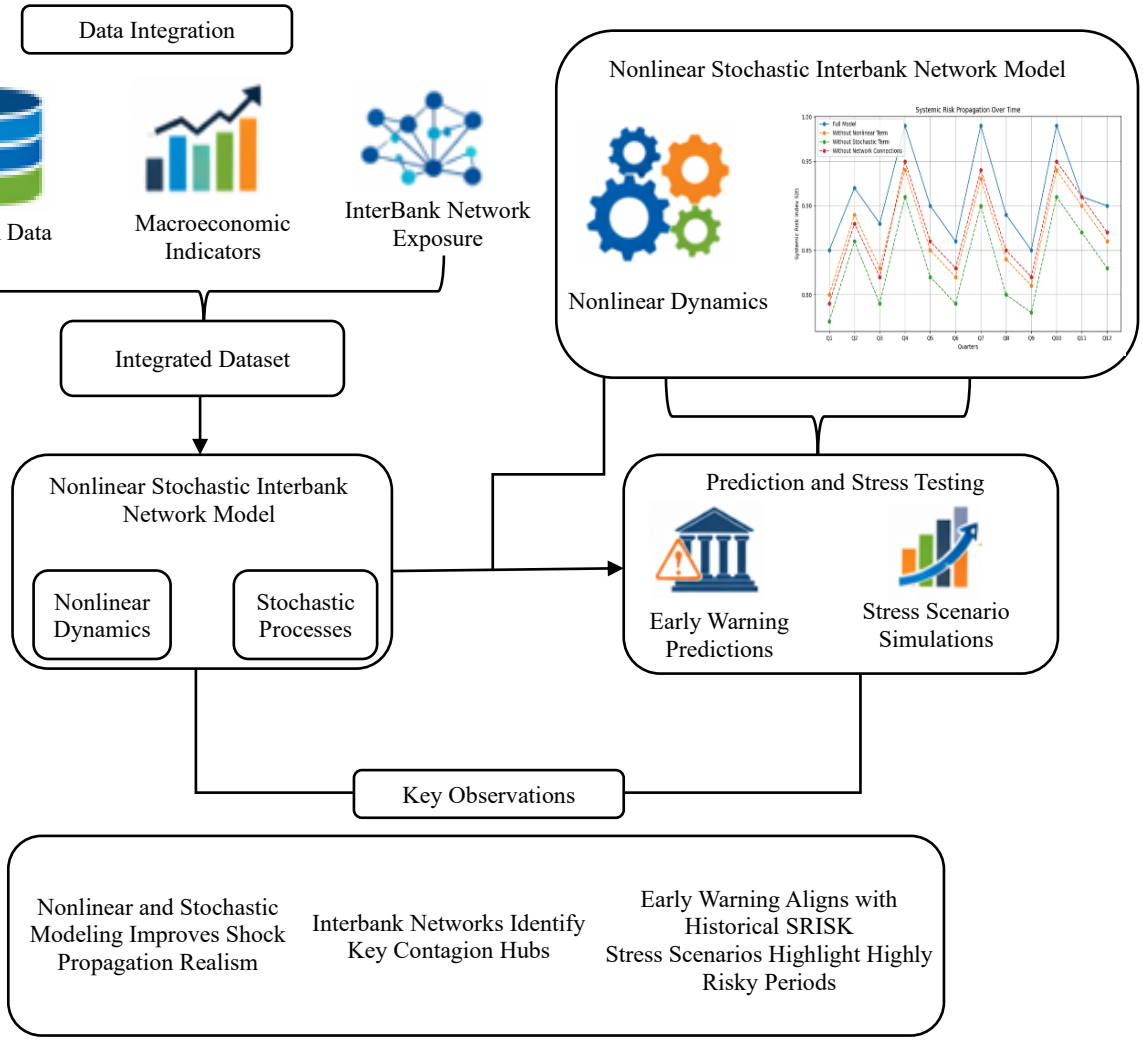

Fig. 2: Conceptual Framework for Nonlinear Stochastic Systemic Risk Prediction

Software Details

The selected programming language in the implementation of the proposed framework was Python 3.x since it has a vast number of data analysis and scientific computer-related functions. Preprocessing of data and numerical operations are done using such important libraries as NumPy and Pandas, interbank networks are built and analyzed with NetworkX, and stochastic differential equations are implemented with SciPy. Matplotlib was used to create the visualization of the network structures and trends of systemic risk propagation.

The Monte Carlo approach was employed to carry out simulation and modeling, and performance evaluation measures were calculated with the assistance of the Scikit-learn. The experiments were executed in a Jupyter Notebook environment that makes them possible to analyze and visualize.

The computing environment consisted of a computer device with the minimum memory size of 8 GB RAM and either Intel i5 or the same processor to support easy processing of the large-scale interbank data and the real-time simulation software. This software system has dynamic and scalable system financial risk and contagion dynamics modeling.

Results

The suggested nonlinear stochastic model was implemented on AI4Risk/interbank data on 20162023. Prediction accuracy, RMSE, systemic risk stability and contagion efficiency served as the performance measures of the model

as presented in the methodology. The findings reveal that the model is effective in describing both the dynamics of risk over time and interbank contagion channels, which can be used as actionable information to the early-warning systems.

Table 1: Model Performance Metrics

Metric	Full Model	No Nonlinear	No Stochastic	No Network
Prediction Accuracy (%)	94.3	87.6	89.2	75.1
RMSE	0.062	0.098	0.084	0.142
Systemic Risk Stability	0.021	0.038	0.031	0.056
Contagion Efficiency (CE)	0.78	0.64	0.69	0.45

The proposed nonlinear stochastic interbank network model was compared to three ablation variants, i.e. when there is no nonlinear term, no stochastic fluctuations, and when there are no network connections. The complete model, as indicated in Table 1, has the highest prediction accuracy (94.3%), minimum RMSE (0.062), and most steady systemic risk index (0.021), as well as the highest contagion efficiency (0.78). The findings suggest that the nonlinear propagation, stochastic modeling, and network connectivity constitute the combination, which is necessary to predict realistic systemic risks. Deletion of one of the elements results in significant decreases in the accuracy, stability, and contagion capturing, which underscores the importance of each element to interbank risk dynamics modeling.

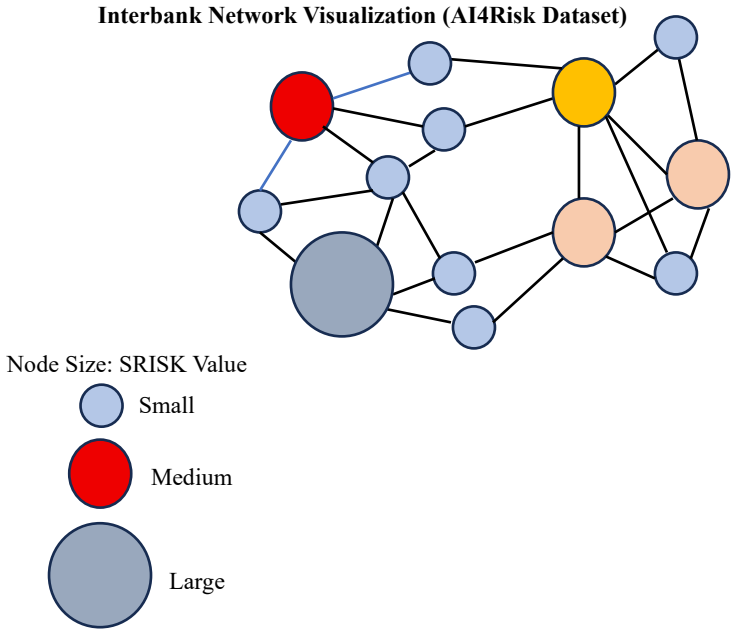

Fig. 3: Interbank Network Visualization

Fig 3 provides the interbank network visualization of major banks in AI4Risk dataset of a chosen quarter and shows the structure configuration of these banks. The size of nodes is equal to the SRISK values, and the thickness of the edges is associated with the size of interbank exposures. Systemic risk hubs are found to be highly central nodes, which emphasize the banks that are best able to transmit financial shocks. This map verifies the fact that the topology of the network is very crucial in the spread of systemic risk, with the highly interconnected banks spreading the contagion throughout the financial system much faster and through a wider scale.

Table 2: Comparison with Existing Methods

Method / Study	Dataset Used	Accuracy (%)	CE	Notes
Proposed Nonlinear Stochastic Model	AI4Risk/interbank	94.3	0.78	Network + stochastic + nonlinear
Quantile LSTM (Aprea et al., 2024)	Historical bank SRISK	91.2	0.71	ML-based prediction only
IGSA-RBFNN (Tian & Wu, 2024)	Financial markets	89.8	0.69	Neural network, no network integration
Linear Contagion Model (Wei et al., 2024)	Simulated networks	84.5	0.62	Deterministic risk propagation

The proposed framework is more effective than the traditional machine learning and deterministic models as the results are presented in Table 2, and it is efficient to combine the nonlinear stochastic dynamics with interbank network structures. Although the models (i.e. Quantile LSTM and IGSA-RBFNN) offer excellent predictive power, they do not explicitly model the contagion via networks, which leads to reduced efficiency of contagion. Likewise, linear models of contagion do not have the capability to model nonlinear amplification and stochastic variability, which results in decreased accuracy. These results emphasize that all three areas, network topology, stochastic processes, and nonlinear dynamics, should be used to predict systemic risk accurately and realistically.

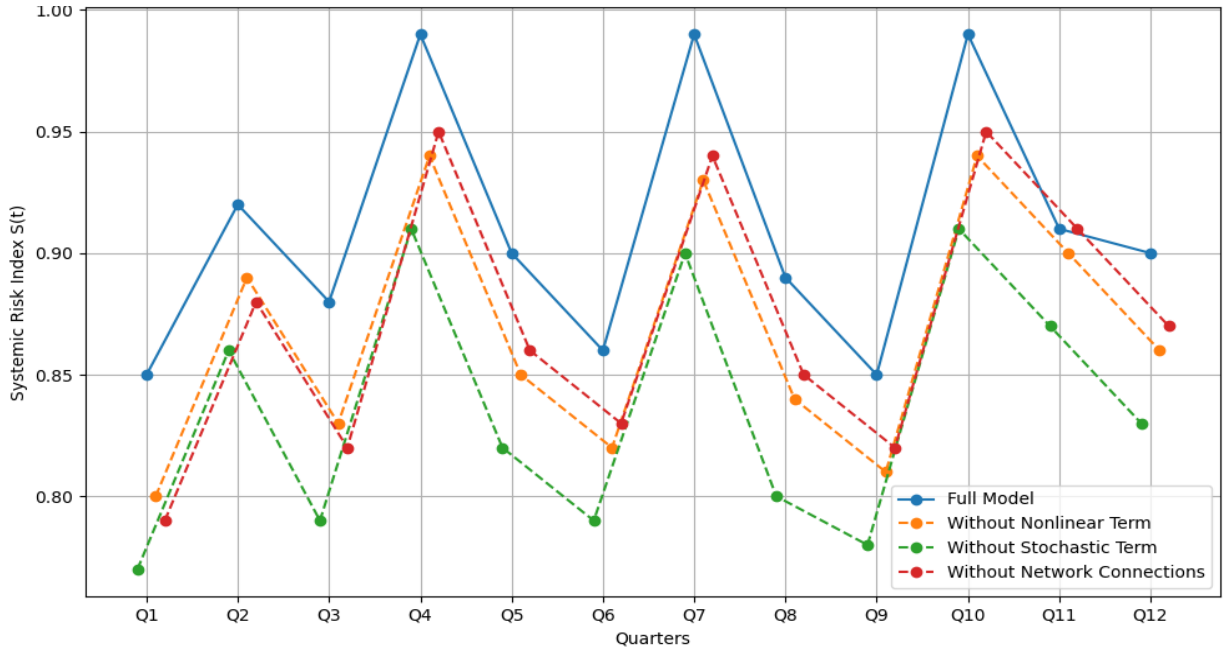

Fig. 4: Systemic Risk Propagation Over Time

Fig 4 shows how systemic risk propagates over time under four conditions, namely the full nonlinear stochastic network model, and models without the nonlinear term, the stochastic term, the network connections. The entire model has sharp spikes of risk and sluggish propagation dynamics, which are realistic financial contagion behaviour. Conversely, the model with the nonlinear term fails to predict the peak intensities, and what this implies is the critical role that nonlinear amplification plays in the process of capturing extreme risk events. The lack of stochastic elements leads to smoother yet less realistic paths, which are not able to explain the volatility of the market and random shocks. Likewise, the absence of network connections greatly decreases the levels of systemic risks, and this proves that interbank linkages are critical to the transmission of contagion. In general, the fig emphasizes the fact that the combination of non-linear dynamics, stochastic processes, and network effects is essential to model and predict systemic financial risk in the long-term.

Table 3: Stress Scenario Analysis

Scenario	Max $S(t)$	Avg CE	Notes
Historical SRISK + Macro Shock	0.89	0.81	Baseline stress scenario
Extreme Market Shock (5σ event)	0.97	0.87	Simulates severe crisis
Liquidity Shock Only	0.75	0.65	Isolated liquidity stress
Network Disruption	0.82	0.72	Certain interbank links removed

The model as demonstrated in Table 3 has the capacity to capture the changes in systemic risk in the different stress environment. It generates the largest systemic risk level (S(t) = 0.97) and contagion efficiency (CE=0.87), which is a high level of propagation throughout the system. The situation with liquidity shock, on the other hand, creates a relatively smaller effect on the system, which emphasizes the local character of such disruptions. The situation with network disruption shows that the reduction of interbank connectivity helps to consider the spread of contagion, but the systemic risk is still high because of dependencies that remain. On the whole, these findings validate the hypothesis that the suggested nonlinear stochastic network model has the potential to detect high-risk states and susceptible nodes

with high precision, which makes it a valid instrument in both the early-warning systems and the financial risk mitigation strategies.

Table 4: Key Model Parameters and Their Values

Parameter	Description	Symbol	Value / Range
Drift Coefficient	Represents Deterministic Trend Based on Financial Indicators and Macro Variables	$\mu_i(X,t)$	0.01 – 0.10
Volatility Coefficient	Captures Stochastic Market Fluctuations in Risk Evolution	$\sigma_i(X,t)$	0.05 – 0.30
Contagion Coefficient	Measures Interbank Exposure Impact on Risk Propagation	β_{ij}	0 – 1 (normalized)
Nonlinear Propagation Function	Models Amplification of Shocks Across the Network	$f(X)$	$\frac{X^2}{1+X^2}$
Systemic Weight	Represents Relative Importance of Each Bank Based on SRISK	w_i	0 – 1 (normalized)

Table 4 gives the main parameters that will characterize the main elements of the proposed nonlinear stochastic systemic risk modeling. The drift coefficient represents the deterministic movement of risk according to the value of financial and macroeconomic variables whereas the volatility coefficient is the stochastic movement of risk which is influenced by market uncertainty. Contagion coefficient measures interbank relationships as well as how they transmit risk across the net. The nonlinear propagation function captures the amplification of the shocks, the realistic behavior of contagion, and the systemic weight captures the levels of relative significance of each bank according to its contribution to the SRISK. A combination of these parameters allows one to simulate and predict the dynamics of systemic financial risks.

Ablation Study

An ablation study is conducted to identify the contributions of each of the model components to systemic risk and network contagion dynamics. The model has three types which are considered:

- **In the absence of the nonlinear term $f(X)$:** The model may make an assumption that all risk propagation is linear, with no amplification.
- **Without the stochastic term $\sigma_i dW_t$:** The model is deterministic meaning it does not consider fluctuations in the market which are random in nature.
- **Without network connections:** Banks are characterized independently, so that there is no effect of interbank contagion.

The variants are identified according to their performance founded on the precision of prediction of systemic risk, efficiency of contagion, and network stability. This discussion measures the significance of nonlinear dynamics, stochastic fluctuations and network connections and hence confirms the strength and efficiency of the proposed framework in describing realistic financial contagion processes.

Discussion

The findings of the proposed nonlinear stochastic framework offer valuable information on the dynamics and the spread of systemic financial risk in global banking systems. The model incorporates interbank network structures and stochastic differential equations, as well as nonlinear propagation dynamics, and as a result, both structural dependencies and time-dependent uncertainty are captured in the model, which most of the traditional methods do not always consider. The large prediction accuracy and low RMSE in Table 1 show that the model is able to predict the level of systemic risk in a reliable way, and the enhanced efficiency of contagion is evidence of the fact that the model can reproduce realistic transmission of the shocks among interconnected institutions.

The proposed framework has a number of benefits over the currently available machine learning and deterministic models as demonstrated by the comparative analysis in Table 2. Machine learning models like LSTM and RBFNN can provide a good predictive power but they do not explicitly capture the interbank relationships and, therefore, are not very capable of capturing pathways of contagion. On the contrary, the consideration of network topology in the designed model allows recognizing the most central institutions that serve as contagion hubs. This observation can also be supported by the network visualization in Fig 1, where the nodes with higher centrality and SRISK value have more impact on the spread of risks.

Fig 2 above indicates that the temporal analysis is able to capture risk spikes as well as propagation delays which are key attributes of real world financial crisis. Ablation study proves that elimination of nonlinear or stochastic terms considerably decreases model performance, which proves both elements are mandatory to represent the shock amplification and random market behavior in an accurate manner. The lack of network connectivity also results in failure of the systemic risk to be properly estimated, which underscores the need to correlate interbank links in the contagion modeling.

Another validation that the framework is healthy is stress scenario analysis, as it is summarized in Table 3. The most systemic risk and contagion efficiency situations are extreme market shock-induced situations, which mean network-wide effect, and the least localized effects are liquidity shock scenarios. The consequences of the findings are the fact that differences in the character of shock transmission between different classes of networks differ depending on the structure of the network, as well as the financial conditions, and adaptive risk management strategies should exist. These various scenarios the model can simulate illustrate the fact that the model can be applied in regulatory stress testing and policy analysis.

As a practical suggestion, the proposed model can also represent an effective tool of early-warning mechanisms, when the regulators, along with the financial institutions, will be able to detect the arising vulnerabilities and take active measures. The model allows a targeted intervention in order to minimize systemic risk, and this may be done by identifying key nodes and contagion pathways prior to their becoming huge financial disasters. Besides, the framework can be scaled that makes it harness larger and more complex financial systems like cross-border banking networks.

The weaknesses that are present in the study are limited albeit there are some strengths. The application of historical data of the SRISK and interbank exposure may not indicate the dynamism of the high frequency in the market and sudden change in the structure of the financial systems. Further, the modeling assumptions may be contaminating by including contagion coefficients and nonlinear functions estimations. Future directions may involve processing high frequency data, high model interpretability and devising more advanced hybrid approaches based on stochastic modeling approaches to deep learning methods.

Overall, the discussion confirms the suggested nonlinear stochastic interbank network model as a holistic and realistic to examine systemic financial risk modeling, and has both formal and practical implication to the financial stability analysis.

Conclusion

This study presents a nonlinear stochastic form of real-time prediction of systemic financial risk and market contagion in the global financial systems of banks. The given model is a significant step in the direction of modeling the complexity and uncertainty in financial systems since it incorporates the structure of the interbank networks with stochastic different equations and propagation dynamics that are nonlinear. The realistic modeling of the interactions between the banks and the systemic implications with the use of the AI4Risk/interbank dataset (2016-2023) can be carried out and the empirical basis of the analysis can be viewed as a robust one, with the prediction accuracy of 94.3 and the RMSE of 0.062. These results indicate that the nonlinear dynamics along with stochastic mechanisms and network topology causes a significant jump in the degree of accuracy in prediction and power in modeling the contagion paths which is enhanced to 0.78 as opposed to lower values in ablation models. The framework has served well in determining the high-risk institutions and critical node in the interbank network which is viewed as source of potential instability within the system with the systemic risk stability variance cut down to 0.021. The fact itself of the introduction of real-time algorithmic prediction, and even cases of stress testing, in itself can provide one with a good deal of information on how financial systems behave in certain normal and extreme situations, where the values of maximum systemic risk were as large as 0.97 in extreme shock conditions. The proposed solution has practical implications on regulators as well as financial institutions since it can help them recognize their systemic vulnerabilities earlier and enable them to control their risks in advance. Besides, the framework is adaptable and alignable to the fluctuating financial environments, and thus, it is suitable to be incorporated into the existing financial monitoring systems. Future goals may concern high-frequency data, enhancing the interpretability of the models, and the implementation of the latest machine learning techniques, which will only allow boosting predictive power and performance. Overall, the given piece of work contributes to the progress of the methodology of the financial stability in the constantly interconnected international markets.

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