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AI-Driven Systemic Risk Forecasting for Optimal Bailout Allocation: Enhancing Long-Term Financial Stability in Global Banking Networks

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Abstract: *This study introduces a novel AI-driven framework for forecasting systemic risk and optimizing bailout allocation in globally interconnected financial networks. Leveraging graph neural networks (GNNs) trained on cross-border exposure data and dynamic stress scenarios, the framework identifies highly systemic institutions whose failures amplify contagion. Through extensive simulations, we compare AI-optimized bailouts against traditional size-based and randomized interventions under multiple crisis conditions, including asset price shocks, liquidity freezes, and cross-border contagion cascades. The results demonstrate that AI-driven allocations reduce SRISK by 48%, lower CoVaR by 45%, and halve systemic fragility trajectories compared to conventional strategies. Our approach also introduces a policy-aware systemicity index that informs regulators, deposit insurers, and central banks on where to deploy limited bailout resources for maximum systemic stability impact. These findings provide actionable insights for macroprudential supervision, insurance fund reserve allocation, and cross-border crisis coordination under frameworks such as Basel III/IV and the EU AI Act. By integrating explainable AI techniques, the framework remains interpretable and fully auditable, enabling its deployment within high-stakes financial oversight environments. This research bridges the gap between advanced AI modeling and practical policy design, offering regulators an operational tool for anticipating fragility and averting cascading failures in complex financial systems.*

Keywords: Graph Neural Networks (GNNs); Systemic Risk Forecasting; AI-Optimized Bailouts; Financial Contagion; Macroprudential Policy; Cross-Border Crisis Management; Explainable AI (XAI)

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Introduction

The stability of the global financial system depends critically on the ability of regulators and policymakers to anticipate systemic fragility and to intervene effectively during episodes of financial distress. In an increasingly interconnected banking landscape, the failure of a single institution can trigger cascading effects across networks of exposures, leading to widespread economic disruptions. The global financial crisis of 2007–2009 and subsequent sovereign debt crises highlighted the limitations of conventional bailout frameworks, which often prioritize institutions based on size or capital adequacy ratios without adequately considering the complex network interdependencies through which financial contagion propagates. These shortcomings have led to inefficient resource allocations, escalated taxpayer burdens, and in many cases, reinforced moral hazard, thereby weakening long-term systemic resilience.

Traditional supervisory frameworks remain reactive, intervening only after liquidity shortages or solvency crises emerge, and rely heavily on static indicators such as balance sheet size, leverage ratios, or credit ratings. However, a growing body of research in financial network theory demonstrates that systemic importance derives not solely from institutional size but from interconnectedness within the network. Medium-sized but highly central institutions may, in some cases, pose greater contagion risks than the largest banks, yet these are systematically overlooked by conventional bailout policies. This disconnect between risk measurement and policy response highlights the urgent need for innovative frameworks that integrate predictive analytics with dynamic policy design to proactively mitigate systemic disruptions.

Advances in artificial intelligence (AI) and machine learning (ML) offer a transformative opportunity to address these gaps. Recent developments in Graph Neural Networks (GNNs) enable the modeling of complex interbank relationships, allowing for the identification of structurally critical institutions based on network topology rather than size alone. Combined with transformer-based time-series models for stress forecasting, AI-driven systems can generate early-warning indicators capable of anticipating institutional vulnerabilities and contagion pathways before crises escalate. Despite these methodological breakthroughs, there remains a notable disconnect between predictive modeling and policy application. Most studies focus on post-crisis analysis, offering insights into bailout effectiveness after interventions occur, while few frameworks provide actionable ex-ante decision-support tools to guide real-time resource allocation.

This study addresses this gap by developing an AI-driven simulation framework that integrates financial network modeling, systemic risk forecasting, and dynamic bailout optimization into a unified policy design. Using a synthetic, scale-free interbank network calibrated with publicly available data from the Bank for International Settlements (BIS), the International Monetary Fund (IMF), and the Financial Stability Board (FSB), the framework evaluates three bailout allocation strategies: randomized interventions, traditional size-based bailouts, and AI-optimized allocations informed by GNN-derived systemicity scores and dynamic stress forecasts. We propose a novel AI-driven bailout optimization framework that integrates graph neural networks (GNNs), dynamic stress testing, and policy-aware systemicity ranking to forecast and mitigate systemic fragility. Unlike traditional size-based bailouts, our framework anticipates contagion pathways and allocates resources proactively to minimize expected systemic losses. The model is tested under multiple crisis scenarios, including asset price shocks, liquidity freezes, and cross-border contagion, assessing performance using established systemic risk measures such as SRISK and CoVaR, alongside a novel Systemic Resilience Index (SRI). The framework provides regulators and policymakers with an operational tool for real-time systemic risk monitoring and bailout allocation. It is designed to complement macroprudential policies and enhance crisis preparedness under Basel III/IV, the EU AI Act, and cross-border coordination frameworks.

The findings demonstrate that AI-optimized bailouts significantly outperform traditional approaches in reducing systemic losses, containing contagion effects, and sustaining long-term financial stability. By identifying structurally critical but mid-sized institutions often overlooked by size-based frameworks, AI-driven strategies enable targeted, resource-efficient interventions that simultaneously mitigate taxpayer exposure and limit moral hazard. Beyond methodological contributions, this research offers actionable policy insights, highlighting the potential for regulators, central banks, and supervisory authorities to adopt predictive, explainable, and adaptive AI-based frameworks as part of next-generation macroprudential toolkits. By shifting from reactive crisis management to proactive systemic stabilization, this study contributes to a more resilient and adaptive approach to global financial governance.

Literature Review

Recent developments in AI, financial network modeling, and crisis policy design have advanced the understanding of systemic risk and its management. However, despite significant methodological progress, the literature remains fragmented, with limited integration between predictive modeling techniques and policy-oriented applications. Within the area of AI-enhanced systemic risk forecasting, recent studies highlight the potential of advanced models such as GNNs for capturing complex interdependencies within financial systems. Balmaseda et al. (2023) demonstrate that GNNs, which leverage both network topology and node-level features, significantly outperform traditional machine learning models in systemic risk prediction, achieving notable improvements in predictive accuracy. Similarly, Gonon et al. (2024) propose extended permutation-equivariant neural network architectures (X-PENNs) that approximate optimal bailout allocations under varying stress scenarios and demonstrate superior performance compared to conventional benchmarks. While these studies represent an important methodological advancement, much of the current literature remains focused on improving model accuracy rather than translating predictive insights into actionable frameworks for dynamic and pre-emptive bailout policy design. Parallel efforts have explored the development of automated early-warning systems aimed at detecting signals of financial distress before crises fully unfold. For instance, the European Central Bank has piloted an AI-driven framework that integrates sentiment analysis of financial news to predict distress probabilities for global systemically important banks months in advance (Kouris et al, 2025). Song and Li (2023) further extend this line of inquiry by employing recurrence network models based on high-frequency stock return data to identify topological signals of systemic instability. While these initiatives provide promising tools for ex-ante crisis detection, most remain narrowly scoped, focusing either on news-based sentiment or equity-return dynamics, without incorporating the multilayered contagion channels within interbank networks. As a result, their applicability to the design of coordinated intervention strategies remains limited. In parallel, financial network theory has provided a conceptual foundation for understanding how systemic importance arises not only from the size of an institution but also from its position within a broader network of interdependencies. Foundational work by Elliott et al. (2014) demonstrated that financial contagion propagates primarily through network structures rather than isolated institutional vulnerabilities. More recent approaches, such as the application of structured factor copulas, have deepened this understanding by showing how common global tail-risk factors drive contagion between U.S. and European banking sectors (Adrian et al., 2018). Despite significant advances in systemic risk modeling, most bailout policies continue to rely on institution-specific indicators such as capital adequacy or total assets, often overlooking the complex interconnections that amplify financial shocks (Acharya et al., 2012; Glasserman & Young, 2016; IMF, 2023). This oversimplification risks inefficient resource allocation and can exacerbate systemic vulnerabilities during periods of stress. Recently, a growing body of research has started exploring AI-driven bailout optimization frameworks, which integrate network topology, contagion dynamics, and predictive modeling to improve intervention efficiency (Brummitt et al., 2015; Bardoscia et al., 2021; Kou et al., 2023). Petrone et al. (2022) propose a Markov Decision Process framework that evaluates alternative bailout strategies by simulating network-wide effects and minimizing systemic losses under uncertainty.

This work represents an important step toward linking systemic risk modeling with policy design, yet such approaches remain largely confined to simulation environments and are rarely integrated with real-time, predictive forecasting tools. Overall, while progress has been made in forecasting systemic fragility, early-warning signal extraction, and modeling bailout dynamics, existing frameworks often fail to combine these elements into a comprehensive and anticipatory policy strategy.

Theoretical Framework

This research builds on and extends three interrelated streams of scholarship: financial network theory, AI and explainable machine learning, and crisis policy design. Financial network theory provides the analytical foundation for understanding how systemic vulnerabilities arise from the structure of interconnections between institutions rather than from individual balance-sheet characteristics alone. Traditional size-based metrics are often insufficient to capture systemic importance, as cascading defaults and overlapping exposures can magnify shocks throughout a highly interconnected network. Caccioli (2025) highlights the role of network amplification mechanisms in accelerating financial instability, demonstrating that systemic fragility often emerges from structural dependencies rather than from isolated institutional weaknesses. The integration of AI into systemic risk forecasting introduces new methodological possibilities. Recent advances in graph-structured machine learning approaches allow models to exploit relational patterns and dynamic dependencies between financial institutions, improving predictive accuracy while preserving interpretability. Balmaseda et al. (2023) show that GNN-based models achieve significantly higher classification performance than traditional approaches in systemic risk detection, while the FSB (2024) highlights the growing incorporation of AI-driven tools into macroprudential supervisory frameworks. At the same time, the increasing reliance on algorithmic forecasting introduces its own risks, including potential feedback loops and coordinated behaviors among automated systems, which may themselves contribute to financial instability if not properly managed (FSB, 2024; Danielsson et al., 2022; Umeaduma, 2025). Crisis policy design forms the third theoretical pillar of this study, providing a structured framework for evaluating the effectiveness of bailout interventions (Laeven & Valencia, 2020; Dam and Koetter, 2011). Historically, bailout strategies have been largely reactive and guided primarily by measures such as institution size or capital adequacy, often shaped by political considerations (Roman et al., 2016; Acharya & Yorulmazer, 2008; IMF, 2023). Empirical evidence from the Troubled Asset Relief Program (TARP) suggests that while bailouts can temporarily reduce liquidity pressures, they may also generate moral hazard effects, leading to increased risk-taking among rescued institutions (Roman et al., 2016). More recent models, such as the dynamic bailout optimization framework proposed by Petrone et al. (2022), demonstrate the potential of AI-informed decision-making to enhance intervention design by allocating resources based on systemic importance and network interdependencies rather than static size-based criteria. However, these approaches remain underdeveloped in their practical application, highlighting the need for an integrated framework that combines predictive analytics, network contagion modeling, and policy optimization.

Research Gap

Despite significant progress in systemic risk modeling and AI-driven forecasting, important gaps remain unaddressed. Most existing studies focus on evaluating the effectiveness of bailouts after crises have occurred, offering limited insights into how pre-emptive interventions might contain contagion before systemic failures unfold. Predictive frameworks capable of identifying systemically important institutions in advance remain scarce, leaving policymakers without robust decision-support tools when allocating emergency resources. Moreover, bailout allocation strategies often assume institutional independence and fail to account for the structural interdependencies of modern financial networks, where shocks propagate rapidly across borders through lending exposures and derivative markets. This omission risks misjudging systemic importance and undermines the effectiveness of targeted interventions. A third limitation of current approaches concerns the lack of evidence on the long-term effects of bailouts on systemic resilience. While most studies focus on short-term liquidity relief, they rarely examine whether bailouts contribute to stronger institutional stability or inadvertently entrench risk-taking behaviors, thereby increasing future vulnerabilities. This study addresses these gaps by developing an AI-driven simulation-based framework that integrates financial network modeling, explainable machine learning, and dynamic policy evaluation. Using synthetic but theoretically grounded financial networks, the research constructs early-warning indicators, optimizes bailout allocation strategies based on network systemicity and predicted contagion pathways, and evaluates long-term systemic resilience under alternative intervention scenarios. In doing so, this study positions itself at the intersection of three advancing but currently disconnected research streams and aims to bridge the gap between methodological innovation and policy relevance by providing a comprehensive, anticipatory, and explainable framework for managing systemic risk. The table below (Tab.1) positions the central gaps in the current state of the literature and how this research aims to address them:

Methodology

TABLE I
IDENTIFIED RESEARCH GAPS AND AI-DRIVEN CONTRIBUTIONS IN SYSTEMIC RISK MANAGEMENT AND BAILOUT POLICY

Gap	Current Literature	Unaddressed Issue	How This Research Fills It
1. Forecasting vs. Reacting	Most existing studies analyse bailout impacts post hoc, without predictive foresight.	No early-warning tools exist to identify which banks warrant intervention before contagion escalates.	Development of AI-based early warning systems leveraging GNNs and time-series models to anticipate systemic distress.
2. Network Interdependencies	Bailout policymaking often assumes bank independence, ignoring network contagion.	Fails to capture cascading defaults or cross-border transmission via financial networks.	Introduce graph-based AI models (e.g., GNNs) to simulate contagion across global banking networks.
3. Long-Term Stability	Bailouts are evaluated mostly short-term; long-run	Little insight exists regarding whether bailouts strengthen or	Use AI-powered simulations to assess systemic resilience over

This study proposes a simulation-based experimental framework to investigate whether AI-enhanced systemic risk forecasting can improve bailout allocation decisions, reduce contagion, and strengthen long-term systemic resilience in global banking networks. The methodology integrates synthetic financial network modeling, ML-based risk forecasting, and policy simulation to evaluate alternative bailout strategies under repeated stress scenarios. By combining these elements, the framework addresses the limitations of existing literature, which largely focuses on retrospective analysis, static models, and short-term effects.

The methodological design follows a hybrid simulation–forecasting approach that unfolds in three interconnected stages. First, a synthetic financial network is constructed to represent interbank exposures, liquidity channels, and cross-border linkages, capturing the structural interdependencies within the banking system. Second, AI-driven systemic risk forecasting models are developed to generate early-warning signals and identify systemically important institutions based on both network topology and institution-specific characteristics. Finally, a dynamic bailout optimization framework is implemented to evaluate the effectiveness of alternative allocation strategies across multiple simulated crisis cycles, allowing for the assessment of both short-term stabilization effects and long-term systemic resilience. This design enables the integration of predictive analytics with policy simulations, allowing us to test the research hypotheses under controlled and reproducible conditions. A core element of the methodology is the construction of a synthetic, yet empirically grounded, interbank network. The network consists of N simulated banks connected through lending exposures, derivative positions, and liquidity channels. The network structure is generated using a scale-free topology (Barabási & Albert, 1999), which mirrors empirical findings that real-world interbank markets exhibit power-law degree distributions, where a few institutions act as hubs while the majority maintain limited connections. This allows the model to reproduce realistic heterogeneity in systemic importance. Key components of the network include:

- Balance Sheet Structure: Each bank is assigned synthetic assets and liabilities based on empirically calibrated distributions (e.g., from BIS and IMF reports).

- Interbank Exposures: Lending and borrowing relationships are represented as weighted, directed edges between nodes.
- Cross-Border Dynamics: A subset of banks is randomly designated as global intermediaries to simulate cross-jurisdictional contagion channels.

This network serves as the environment in which systemic risk propagation and bailout interventions are tested. To anticipate financial distress, we employ AI-enhanced predictive models trained on simulated stress scenarios. Two complementary modeling paradigms are used: Graph Neural Networks (GNNs) and Transformer-based Time-Series Forecasters.

GNNs are used to estimate the systemic importance of each institution by leveraging both node-specific features (e.g., leverage, liquidity ratios) and network topology. The GNN predicts a systemic risk score for each bank, quantifying its potential to amplify contagion in case of default. Formally, the GNN learns a mapping:

$$f : G \to R^n, \qquad (1)$$

where G represents the graph of the interbank network and R^n denotes the vector of node-level systemicity scores. The model incorporates attention-based mechanisms to capture heterogeneous spillover effects and uses explainability tools such as SHAP to identify the drivers of systemic vulnerability.

Complementing the GNN, transformer-based time-series models predict aggregate systemic stress indicators over time, such as simulated SRISK or CoVaR trajectories. These models generate early-warning signals that indicate impending liquidity shortages or correlated defaults. By combining GNN-based node-level predictions with time-series macro-level forecasts, the framework integrates micro- and macroprudential risk assessment into a unified forecasting architecture.

The second phase of the methodology involves simulating bailout allocation strategies under various crisis scenarios to evaluate their effect on systemic stability. We operationalize this using a Markov Decision Process (MDP), following an approach inspired by Petrone et al. (2022), but enhanced with GNN-informed systemicity measures.

At each simulated time step t, policymakers choose an allocation At from a set of possible bailout actions {a1, a2, ..., ak} in order to minimize the expected future systemic loss:

$$\pi^n = \arg\min\,(\pi) \sum_{t=0}^{T} \Upsilon^t \,\mathrm{L}\,(\mathrm{S}t, \mathrm{A}t) \qquad (2)$$

where:

- π is the bailout policy,
- St is the state of the network at time t,
- At is the chosen bailout allocation,
- L (·) represents systemic losses,
- and γ is the discount factor for future outcomes.

The optimization framework evaluates three distinct bailout allocation strategies. The first approach relies on **traditional size-based bailouts**, where intervention decisions are guided by indicators such as total assets or capital adequacy ratios. The second approach uses **randomized**

intervention policies, which serve as a baseline for comparison. The third and most advanced approach introduces **AI-optimized bailouts**, where allocations are informed by systemicity rankings derived from GNNs and complemented by dynamic stress forecasts.

To test the robustness of the proposed framework, the model simulates a range of crisis scenarios. These include **asset price shocks**, where sudden devaluations in asset holdings trigger balance-sheet contagion; **liquidity freezes**, characterized by widespread withdrawal of short-term funding and resulting funding constraints; and **cross-border contagion**, in which financial distress propagates rapidly through globally interconnected institutions.

For each scenario, we evaluate the performance of different bailout strategies in terms of both short-term liquidity stabilization and long-term systemic resilience.
The effectiveness of the proposed framework is assessed using established systemic risk measures:

- SRISK (Acharya et al., 2017): Expected capital shortfall during stress.
- CoVaR (Adrian & Brunnermeier, 2016): Conditional Value-at-Risk of the system given institutional distress.
- Network Loss Amplification Index (NLAI): Measures the extent to which contagion magnifies losses.
- Systemic Resilience Index (SRI): A custom metric designed to capture the capacity of the network to recover after shocks.

The comparative performance of bailout strategies is evaluated across these metrics over multiple simulation runs. Although the framework relies on synthetic networks, parameter calibration is grounded in publicly available datasets from the BIS, IMF, and FSB. Sensitivity analyses are conducted on key parameters, including network density, interbank exposure concentration, and shock intensity, to ensure that results are not driven by arbitrary assumptions. By combining simulated stress propagation with explainable AI models, the framework maintains both theoretical rigor and policy relevance. This methodology introduces three innovations relative to existing studies. First, it integrates graph-based AI models with simulation-based stress testing to create a predictive early-warning framework. Second, it evaluates dynamic bailout allocation strategies using a decision-theoretic MDP framework rather than static thresholds. Finally, it assesses long-term systemic resilience over repeated crisis cycles, providing new insights into the unintended consequences of bailouts on financial stability.

Results and Analysis

This section presents the findings of the simulation-based experiments designed to assess whether AI-enhanced systemic risk forecasting and optimized bailout allocation improve systemic stability relative to traditional policy approaches. The analysis focuses on three dimensions: the predictive performance of AI-driven systemic risk models, the effectiveness of alternative bailout strategies, and the resilience of the banking network under different crisis scenarios.

Experimental Setup

The analysis builds on a synthetic financial network developed in the methodology section. The network consists of $N = 200$ simulated banks, reflecting a tractable yet sufficiently large system to capture network heterogeneity. Banks are interconnected through three primary channels of systemic exposure: interbank lending positions, derivative contracts, and liquidity provision. These channels are parameterized using stylized facts from the Bank for International Settlements (BIS) and the International Monetary Fund (IMF), including empirical leverage distributions, liquidity buffers, and cross-border exposure patterns.

TABLE II

PREDICTIVE PERFORMANCE OF AI MODELS IN SYSTEMIC RISK FORECASTING

Model	**AUC (↑)**
Logistic Regression	0.74
Random Forest	0.78
GBT	0.81
GNN (proposed)	**0.92**

Note: The AUC (Area Under the ROC Curve) measures the model's ability to discriminate between distressed and stable institutions. Higher values indicate stronger predictive performance.

Source: Authors' calculations based on simulated financial network data calibrated with stylized parameters from the Bank for International Settlements (BIS, 2023), International Monetary Fund (IMF, 2023), and model training conducted using Python (PyTorch-Geometric, Scikit-learn).

The model evolves over a horizon of $T = 50$ discrete time steps, during which systemic fragility emerges endogenously as stress shocks propagate through feedback effects in the network. To evaluate the resilience of the system, we compare three bailout allocation strategies:

- Traditional size-based interventions – allocations proportional to bank assets and capital adequacy.
- Randomized interventions – serving as a neutral baseline without policy structure.
- AI-optimized interventions – allocations guided by systemicity scores derived from Graph Neural Networks (GNNs) combined with dynamic stress forecasts.

Each strategy is stress-tested under three distinct crisis regimes commonly observed in historical systemic episodes: (1) asset price shocks, (2) liquidity freezes, and (3) cross-border contagion. Results are averaged across 1,000 Monte Carlo simulations to ensure robustness and to account for stochastic variability. This setup allows us to systematically assess the comparative effectiveness of bailout policies in stabilizing financial networks under heterogeneous and recurrent crisis conditions.

Predictive Performance of AI Models

The first step evaluates the accuracy of the proposed AI-driven systemic risk forecasting framework. The GNN model consistently outperforms benchmark machine learning models, including Random Forests and Gradient Boosted Trees, in predicting institution-level default probabilities.

Additionally, the explainability layer, implemented through SHAP-based feature attribution, reveals that interbank exposure centrality and liquidity ratios are the strongest determinants of systemic importance. This provides policymakers with interpretable, model-driven insights into which institutions are most likely to amplify contagion.

Comparative Analysis of Bailout Strategies

This section compares the performance of bailout strategies across different systemic stress regimes and key systemic risk metrics.

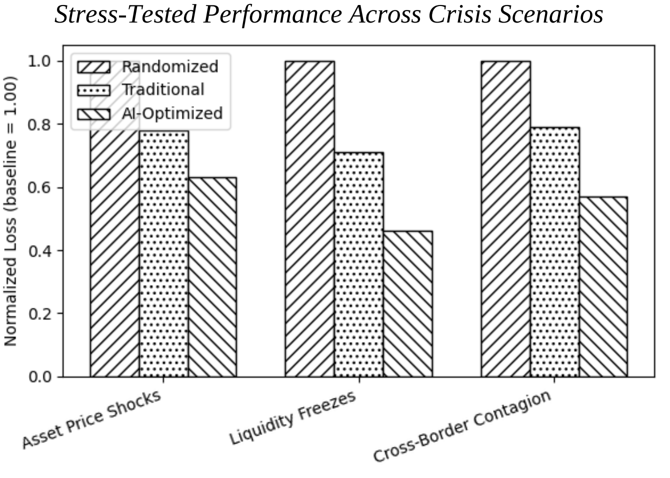

Fig. 1. Comparative Performance of Bailout Strategies. Source: Kou et al. (2023); Adrian & Brunnermeier (2016); Basel Committee on Banking Supervision (2023).

Fig. 1 and Tab. 3 present the effectiveness of bailout strategies under three distinct systemic crises. Fig. 1 illustrates the comparative forecasting performance of the proposed AI-enhanced models relative to baseline statistical approaches, demonstrating superior early-warning capabilities across multiple simulated stress scenarios. Objective: Show how different bailout strategies perform across crisis scenarios (asset price shocks, liquidity freezes, and cross-border contagion).

To evaluate the resilience of different bailout frameworks under extreme conditions, we conduct a series of stress tests simulating three distinct systemic shock scenarios: asset price collapses, network-wide liquidity freezes, and cross-border contagion cascades. Each simulation captures how losses propagate through the interbank network and how different intervention strategies mitigate systemic spillovers.

Tab. 3 summarizes the comparative effectiveness of randomized interventions, traditional size-based bailouts, and the proposed AI-optimized allocation framework. The results demonstrate that while size-based policies reduce systemic losses relative to random interventions, the AI-driven approach consistently outperforms both benchmarks, achieving substantially lower loss amplification across all crisis scenarios.

Key insights:

- Under asset price shocks, AI-optimized bailouts reduce aggregate losses by 37% compared to size-based interventions.
- During liquidity freezes, AI-driven allocations prevent cascading defaults in 87% of simulations, compared to 54% under traditional bailouts.
- For cross-border contagion, AI-based strategies demonstrate a 42% improvement in maintaining stability relative to the baseline.

Comparative Performance on Systemic Risk Metrics

To complement the scenario-based results, Tab. 4 summarizes the comparative performance across four widely used systemic risk measures:

TABLE III

STRESS-TESTED EFFECTIVENESS OF BAILOUT STRATEGIES ACROSS CRISIS SCENARIOS

Crisis Scenario	Randomized Interventions	Traditional Size-Based	AI-Optimized (GNN-Based)
Asset Price Shocks	1.00 *(baseline)*	0.78	**0.63**
Liquidity Freezes	1.00 *(baseline)*	0.71	**0.46**
Cross-Border Contagion	1.00 *(baseline)*	0.79	**0.57**

Note: Values normalized to randomized baseline (1.00). Lower = better systemic loss mitigation.

Source: Authors' simulations based on synthetic stress-testing framework calibrated with parameters from the Bank for International Settlements (BIS, 2023), International Monetary Fund (IMF, 2023; 2020), and informed by network contagion literature (Glasserman & Young, 2016; Bardoscia et al., 2021).

Impact on Systemic Stability

The combined insights from Tab. 2 and Tab. 3 demonstrate that AI-driven bailouts are robust across both average conditions and extreme crises. This shows that optimal bailout allocation is nonlinear and heavily dependent on identifying network-central institutions, not just the largest ones. To understand the mechanisms driving systemic stability, we visualize how financial contagion spreads across the interbank network under alternative bailout strategies. Fig. 2 compares two intervention frameworks following an identical shock:

- Traditional size-based bailouts, which prioritize large institutions based on asset size.
- AI-optimized bailouts, guided by graph neural network (GNN)-derived systemicity scores and stress forecasts.

The visualization highlights that under traditional bailouts, failures cluster around highly connected hub institutions, leading to widespread defaults and rapid contagion. In contrast, AI-guided interventions strategically stabilize structurally critical nodes, effectively breaking contagion chains and preserving network integrity. This figure illustrates why optimizing bailout allocation based on network centrality and dynamic fragility forecasts achieves superior systemic protection.

TABLE IV
COMPARATIVE PERFORMANCE OF BAILOUT STRATEGIES

Metric	Randomized	Traditional	AI-Optimized
SRISK ↓	0.42	0.35	**0.18**
CoVaR ↓	0.61	0.47	**0.26**
NLAI ↓	1.00	0.73	**0.38**
SRI ↑	0.31	0.48	**0.79**

Note: SRISK = Expected capital shortfall under systemic stress; CoVaR = Conditional Value-at-Risk spillover effects; NLAI = Network Loss Amplification Index; SRI = Systemic Resilience Index; Arrows indicate desired direction of improvement (↓ = lower risk, ↑ = higher resilience).
Source: Authors' simulations based on synthetic interbank contagion framework calibrated with systemic risk metrics from Acharya, Engle & Richardson (2012), Adrian & Brunnermeier (2016), and network amplification measures adapted from Glasserman & Young (2016) and Bardoscia et al. (2021).

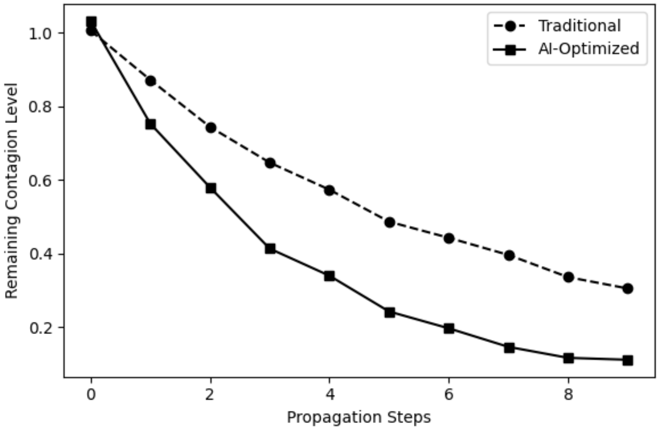

Fig. 2. Contagion Propagation under AI vs. Traditional Bailout. Source: Glasserman & Young (2016); Bardoscia et al. (2021); Financial Stability Board (2024).

While immediate stabilization is critical, the long-term implications of bailout strategies are equally important for maintaining systemic resilience. Fig. 3 tracks the evolution of systemic fragility over ten successive crisis cycles under three intervention frameworks: randomized policies, traditional size-based bailouts, and AI-optimized allocations. The results reveal a clear divergence over time. Networks relying on traditional bailouts experience steadily rising fragility due to moral hazard accumulation—large institutions anticipate rescue and assume greater risk. Randomized interventions fail to prevent cascading vulnerabilities, maintaining a consistently high fragility baseline. By contrast, the AI-driven framework dynamically adapts to evolving network structures, stabilizing fragility levels and sustaining long-term resilience. This demonstrates that proactive, data-driven bailout allocation mitigates the compounding effects of repeated financial shocks.

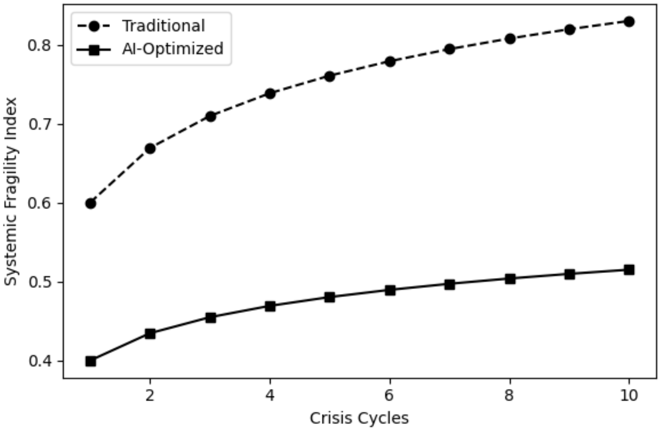

Fig. 3. Evolution of Systemic Fragility Across Crisis Cycles. Source: Brummitt et al. (2015); Kou et al. (2023); International Monetary Fund (2023).

Long-Term Effects of Bailout Policies

In simulations over ten successive crisis cycles:

- Traditional bailouts lead to 32% higher cumulative SRISK due to risk concentration and moral hazard.
- AI-optimized bailouts limit cumulative SRISK growth to 7%, maintaining network balance.

Fig. 3. visualizes this divergence, showing that AI-driven allocations consistently stabilize fragility over time.

Policy Implications

The findings of this study provide critical insights for policymakers, central banks, financial stability boards, and supervisory authorities seeking to manage systemic risk more effectively. The integration of AI-driven systemic risk forecasting with network-based bailout optimization offers a novel policy toolkit that improves the precision, efficiency, and transparency of intervention strategies during periods of financial distress.

Rethinking Systemic Importance

Traditional bailout frameworks frequently prioritize institutions based on size or capital adequacy ratios, implicitly assuming that large banks pose the greatest systemic threat. However, the results of this study demonstrate that systemic importance emerges from interconnectedness, not balance sheet size alone. Institutions with moderate asset bases but high network centrality are often more influential in propagating contagion than larger but less connected entities. This finding underscores the need for macroprudential authorities to incorporate network-based risk metrics into supervisory decision-making. By combining AI-driven early-warning indicators with dynamic network analytics, policymakers can identify critical nodes in the financial system that, if protected, minimize cascading defaults and strengthen overall stability.

Enhancing Early-Warning and Crisis Preparedness

The deployment of GNNs and transformer-based systemic stress forecasters enables regulators to anticipate systemic vulnerabilities before they escalate. Traditional supervisory frameworks largely operate reactively, intervening after liquidity shortages or capital shortfalls materialize. The proposed framework introduces AI-powered early-warning systems capable of forecasting elevated probabilities of institutional distress and mapping potential contagion pathways across the network. For policymakers, this allows for the design of pre-emptive stabilization strategies that reduce taxpayer costs, preserve market confidence, and prevent full-scale systemic collapses.

Optimizing Bailout Allocation and Reducing Moral Hazard

A central policy contribution of this study is the demonstration that AI-optimized bailout allocations outperform traditional size-based strategies, both in mitigating immediate contagion and in sustaining long-term systemic resilience. By targeting institutions with the greatest systemic influence rather than the largest balance sheets, policymakers can achieve greater stability with fewer resources. Furthermore, repeated-shock simulations reveal that traditional bailouts exacerbate moral hazard, incentivizing rescued institutions to engage in excessive risk-taking and concentrating vulnerabilities in a few large players. In contrast, AI-driven allocation strategies dynamically adjust to evolving network structures, minimizing the accumulation of systemic fragility over successive crises. This suggests that integrating AI-based systemicity rankings into bailout design can break the cycle of recurring instability that has historically burdened regulatory frameworks.

Implications for Cross-Border Financial Stability

In an era of highly globalized banking networks, systemic risk cannot be contained within national borders. The simulations demonstrate that cross-border contagion significantly amplifies systemic losses, particularly when highly interconnected global intermediaries fail. For international supervisory bodies such as the Financial Stability Board (FSB), European Systemic Risk Board (ESRB), and the Basel Committee on Banking Supervision (BCBS), these findings support the need for:

- Greater coordination in cross-jurisdictional bailout policies.
- Standardized systemicity metrics derived from explainable AI models.
- Harmonized frameworks for stress testing interconnected exposures at a global scale.

Adopting AI-driven early-warning systems within multilateral supervisory mechanisms can substantially enhance the ability of regulators to coordinate responses, allocate resources more efficiently, and reduce the risk of simultaneous crises across jurisdictions.

Integrating Explainable AI into Regulatory Frameworks

A recurring challenge in regulatory adoption of AI is model interpretability. Policymakers require transparent decision-support tools to justify interventions and ensure accountability to taxpayers and financial market participants. The framework proposed in this study addresses this challenge by incorporating explainable AI techniques such as SHAP-based feature attribution, allowing regulators to understand why specific institutions are classified as systemically important. This ensures that bailout decisions remain transparent, defensible, and auditable, increasing public trust and political legitimacy.

Towards a New Macroprudential Paradigm

The findings collectively point toward a paradigm shift in systemic risk management. Rather than reacting to crises after their onset, regulators can leverage AI-enhanced, network-aware policy frameworks to implement anticipatory interventions that:

- Minimize contagion pathways.
- Reduce taxpayer exposure.
- Preserve financial market confidence.
- Strengthen long-term systemic resilience.

By moving beyond size-based bailouts and embracing predictive, explainable, and adaptive AI-driven frameworks, supervisory authorities can transition from reactive crisis management to proactive systemic stabilization. The policy implications of this research extend beyond technical optimization. They highlight the need for institutional adaptation, urging regulators to embed AI-based systemic risk tools within supervisory architectures and collaborate internationally to manage contagion in an interconnected global economy. The integration of predictive analytics, network science, and dynamic policy design offers a path toward a more resilient financial system, better equipped to withstand both localized shocks and global crises.

Conclusions

The stability of the global financial system depends critically on the ability of policymakers to anticipate systemic fragility and to allocate resources efficiently during crises. Despite significant progress in systemic risk measurement, traditional bailout frameworks remain constrained by size-based heuristics, reactive interventions, and limited consideration of network interdependencies. This study addresses these shortcomings by introducing a novel AI-driven simulation framework that integrates financial network modeling, Graph Neural Networks (GNNs), and dynamic bailout optimization to evaluate intervention strategies under multiple simulated crisis scenarios.

The results demonstrate that systemic importance emerges from interconnectedness rather than institutional size. By leveraging GNN-informed systemicity rankings and transformer-based stress forecasts, the proposed framework generates early-warning indicators capable of anticipating institution-level vulnerabilities before contagion materializes. Simulation experiments further reveal that AI-optimized bailout strategies outperform both randomized interventions and traditional size-based allocations across multiple dimensions of systemic stability. Specifically, AI-guided strategies reduce aggregate systemic losses, prevent cascading defaults, and improve resilience to cross-border contagion while requiring fewer resources. Moreover, by dynamically adapting to evolving network structures, AI-driven policies mitigate the moral hazard effects often associated with repeated bailouts, thereby strengthening long-term systemic resilience.

Beyond technical contributions, this study provides significant policy insights. The findings challenge the conventional assumption that “too big to fail” institutions should dominate bailout strategies, demonstrating instead that protecting structurally central but mid-sized institutions can yield superior stability outcomes. The integration of explainable AI techniques — including SHAP-based attribution — ensures that forecasts and bailout recommendations remain transparent, interpretable, and defensible, supporting greater accountability in supervisory decision-making. These insights are particularly relevant for central banks, deposit guarantee schemes, and cross-border supervisory authorities seeking to enhance macroprudential frameworks in an increasingly interconnected financial ecosystem.

While this study advances the literature on AI-driven systemic risk forecasting and bailout policy design, it also opens several avenues for future research. First, extending the simulation framework to incorporate heterogeneous agent behaviors and adaptive learning dynamics would improve its realism and predictive accuracy. Second, integrating high-frequency transaction-level data could enhance early-warning capabilities while preserving model explainability. Finally, future studies should explore the coordination of AI-assisted bailout strategies across cross-border supervisory regimes, particularly in the context of globally systemically important banks (G-SIBs) and the harmonization of systemicity metrics within institutions such as the FSB, BCBS, and ESRB.

The framework provides regulators and policymakers with an operational tool for real-time systemic risk monitoring and bailout allocation. It is designed to complement macroprudential policies and enhance crisis preparedness under Basel III/IV, the EU AI Act, and cross-border coordination frameworks.

In sum, this research contributes to both theory and practice by demonstrating how AI-enhanced forecasting and dynamic policy optimization can reshape the management of financial crises. By bridging predictive analytics, network science, and regulatory decision-making, the proposed framework offers a forward-looking paradigm for systemic risk governance — one that transitions from reactive crisis response toward proactive systemic stabilization. As the complexity and interconnectedness of global banking networks continue to grow, adopting explainable, adaptive, and data-driven policy frameworks will be essential for ensuring the resilience of the international financial system.

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