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Review

Statistical analysis and applications of financial network data in the era of digital intelligence

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Abstract: In the era of digital intelligence, financial systems generate vast volumes of financial network data characterized by high frequency, heterogeneity, and rich relational structure, rendering traditional models less effective at capturing the complex, time-varying dynamics of systemic risk. This review synthesized statistical methods and applications for these data along three strands: complex networks to study contagion and connectedness; higher-order and multilayer representations to capture group interactions and cross-market channels; and graph neural networks (GNNs) that fuse topology with rich node- and edge-level attributes for dynamic risk prediction. We outlined identification using network statistics, estimation in time-varying settings, and graph-based stress testing for macro-prudential applications. Open challenges include integrating multimodal data, improving causal interpretability and counterfactual evaluation, and scaling the construction of dynamic higher-order graphs. Advances in explainable GNNs aligned with structural contagion, together with models of spatiotemporal propagation that fuse textual and market-microstructure signals, can materially enhance real-time monitoring, forecasting, and macro-prudential policy design for systemic financial risk.

Keywords: financial network data; higher-order network; graph neural networks; financial risk

JEL Codes: C55, C58, G15

1. Introduction

Digital-intelligence technologies have reshaped financial data into high-frequency, heterogeneous network panels. This paper examines how modern statistical and econometric methods address time variation, dependence, and heavy-tailed behavior in financial network data, and assesses how these modeling choices influence inference and macroprudential stress testing outcomes (Daníelsson et al., 2022; Luo et al., 2024). This digital-intelligence transformation is not simply a shift in technology; it represents a fundamental reconfiguration of structure, behavior, and risk dynamics within the financial ecosystem (Wiersema et al., 2023). Financial institutions are now embedded in a data-rich, algorithmically governed environment where decisions are increasingly automated, markets react almost instantaneously to new information, and the volume and velocity of financial transactions are exponentially growing (Alaminos et al., 2024; Nimalendran et al., 2024). A defining feature of this transformation is the emergence and ubiquity of financial network data—large-scale, high-frequency, and heterogeneous relational datasets that record who interacts with whom, how, and when across balance-sheet, market, and payment infrastructures (Franch et al., 2024; Yaya et al., 2024). These network representations also complement macroeconomic accounting frameworks: they effectively provide "from-whom-to-whom" mappings of financial linkages, enriching traditional sectoral balance sheets and flow-of-funds perspectives.

By financial network data, we refer to time-stamped, often directed and weighted observations of interdependent relations among financial entities and instruments. Typical examples include interbank and repo exposures, derivative collateral and clearing links, cross-shareholding and fund–asset holdings, dealer–client quote and trade networks, limit-order-book interaction graphs, payment flow and settlement networks, co-movement and volatility spillover matrices, and text-derived association networks from disclosures and news (Caccioli et al., 2024). These datasets are multilayer (spanning funding, market, and infrastructure layers), higher-order (capturing group interactions and path memory), and attribute-rich (combining micro balance-sheet characteristics with macro conditions). As such, they offer a uniquely granular lens on how liquidity, leverage, and beliefs propagate through the system, thereby revealing the architecture of systemic risk and informing macroprudential surveillance, stress testing, early-warning systems, and resolution planning.

Meanwhile, the proliferation of algorithmic and high-frequency trading has introduced new layers of complexity to market behavior. Algorithmic agents interact on microsecond timescales, respond to patterns in market microstructure, and execute orders based on machine-learned strategies within tightly coupled, feedback-rich environments where nonlinear interactions dominate. In such conditions, traditional statistical models—which typically assume independence, stationarity, or linearity—struggle to represent system behavior. They often fail to provide robust predictions under stress scenarios, especially in the presence of heavy-tailed shocks and structural breaks. Financial network data mitigate this gap by furnishing dense, temporally resolved observations of interdependence, but their heterogeneity and scale also demand methods capable of modeling multilayer topology, temporal dependence, and cross-sectional attributes in a unified framework. On the one hand, new sources—from transactional logs, news feeds, and regulatory filings to satellite imagery, social-media sentiment, and payment flows—enable a more granular and timely understanding of market dynamics (Gur et al., 2024; Lee and Choeh, 2024). On the other hand, extracting reliable signals from such noisy, high-dimensional networked data requires methodological advances beyond conventional econometrics, which are often rooted in linear paradigms and finite-dimensional asymptotic theory.

Against this backdrop, network-based approaches have gained prominence as a powerful paradigm for financial analysis. Financial networks model the interactions among economic agents as graphs, where nodes represent institutions or instruments and edges encode relationships such as credit exposures, co-movements, or contractual dependencies. These representations inherently capture the structural topology of financial systems, allowing for a more nuanced understanding of how risk accumulates, concentrates, and spreads. Importantly, network analysis does not merely serve a descriptive function. It provides mathematical and computational tools to quantify systemic risk, identify critical nodes whose failure could have outsized consequences, simulate the impact of shocks under various scenarios, and design interventions to enhance system resilience. Concepts such as network centrality, assortative, clustering, core–periphery structure, and modularity offer a rich vocabulary for understanding the architecture of financial systems. Furthermore, the integration of dynamical models on networks—such as percolation, contagion, and diffusion processes—enables researchers to investigate the time-dependent behavior of crises and the role of feedback loops. Crucially, anchoring these models in financial network data allows empirical calibration, validation, and policy-relevant scenario design at operational frequencies (Jackson and Pernoud, 2021).

However, as digital finance evolves, so too must the network models themselves. Traditional pairwise network models, while insightful, often fail to account for the full complexity of financial interactions, which may involve multilateral dependencies, temporal correlations, and context-specific pathways. This has given rise to a new wave of methodological developments in higher-order networks and graph-based machine learning, which aim to align model structure with the generative properties of financial network data. In response to these challenges and opportunities, this paper provides a comprehensive review of the evolving landscape of financial network analysis in the era of digital intelligence, with financial network data as the unifying empirical substrate. Specifically, we focus on three research frontiers that lead this interdisciplinary domain. First, we explore the use of complex networks for understanding and quantifying financial risk contagion, including empirical findings on interbank networks, stress-testing frameworks, and models of cascading defaults, as well as analytical tools to identify systemically important financial institutions (SIFIs). Second, we delve into the emerging domain of higher-order network models and their application to financial statistical inference. These models extend beyond simple dyadic relationships and offer richer representations of group behaviors, memory effects, and layered network structures—characteristics that are increasingly evident in financial network data. Third, we examine the integration of graph neural networks (GNNs) into financial risk modeling. As a class of deep learning architectures capable of operating on graph-structured data, GNNs provide a scalable, data-driven approach to predicting financial distress, modeling credit risk, and generating early warning signals in near real time. Their ability to combine node-level features with topological information makes them particularly suited to complex, high-frequency environments.

Together, these perspectives—rooted in network science, statistical physics, and artificial intelligence—form a cohesive framework for understanding the evolving dynamics of financial risk in the age of digital intelligence. We emphasize an evolutionary progression: complex network models (Section 2) form the foundation, higher-order networks (Section 3) build on this by capturing group interactions, and GNNs (Section 4) further extend the paradigm by learning representations from network data. By centering analysis on financial network data, we aim to not only chart the current state of research but also identify promising directions for future investigation and practical application in financial regulation, policy, and enterprise risk management. The remainder of this paper is organized as follows: In Section 2, we introduce complex networks and financial risk contagion. Section 3 presents higher-order networks and financial statistical analysis. In Section 4, we discuss graph neural networks and financial risk early warning. Section 5 concludes the work.

2. Complex networks and financial risk contagion

Section 2 surveys several pairwise financial network models for systemic risk. These include causality networks (based on Granger analysis), variance-decomposition networks (spillover indices), tail-risk networks, and multilayer networks. Together, they offer complementary views on how contagion propagates through the system, laying the groundwork for the higher-order network methods introduced in Section 3.

2.1. Granger network

Granger-causality networks summarize directed temporal dependence. We report estimation conditions (lag selection, stability), inference (standard errors and tests), and robustness to nonlinearity (quantile and nonlinear Granger). For instance, Billio et al. (2012) constructed pairwise Granger causality networks to assess the causal relationships among major U.S. financial institutions, providing empirical insights into the pathways of systemic risk contagion. Building upon similar methodologies, Castagneto-Gissey et al. (2014) developed dynamic Granger-causality networks by continuously updating the underlying network data, thereby capturing the evolving nature of market linkages over time. Recognizing the limitations of time-domain analysis in isolating short-term versus long-term interactions embedded in network data, Wang et al. (2021) extended the traditional Granger causality framework to the frequency domain. By developing a time–frequency Granger causality approach, they were able to examine the heterogeneity of risk spillovers across different temporal horizons, offering a more nuanced perspective on financial interconnectedness.

However, several scholars have noted that linear Granger causality models may be insufficient for capturing the full complexity of financial contagion, particularly in the presence of nonlinear dependencies or tail-risk interactions. In this regard, Bonaccolto et al. (2019) emphasized that risk transmission among financial entities is inherently multifaceted and cannot be adequately described by simple linear structures. To address this gap, they constructed a comprehensive suite of causality networks—including linear, nonlinear, linear quantile, and nonlinear quantile Granger causality networks—to explore the diverse channels through which systemic risk propagates among U.S. financial institutions. More recently, the scope of such methodologies has been extended to the realm of sustainable finance. Lee et al. (2023), for example, applied the quantile Granger causality test to investigate the nonlinear dependence structure between green bonds and sustainability-themed equities, shedding light on asymmetric risk spillovers in emerging ESG-related financial markets. Similarly, Liao et al. (2024) examined contagion networks of idiosyncratic volatility in relation to corporate environmental responsibility, finding that firms' sustainability practices can influence volatility spillover patterns.

2.2. Variance decomposition network

Given the critical importance of measuring the intensity of systemic risk transmission, Diebold and Yilmaz (2014) introduced the influential spillover index model, which constructs risk networks among financial entities from GFEVD matrices that serve as network data derived from vector autoregressions. This methodology has since become a widely adopted tool for quantifying interconnectedness in various financial markets. Building on this framework, Greenwood-Nimmo et al. (2016) examined risk spillovers across G10 currency indices, revealing significant interdependencies in global foreign exchange markets. Similarly, Antonakakis et al. (2018) applied the spillover index approach to assess the dynamic risk linkages between oil and natural gas prices, providing evidence of energy market co-movements. Lastrapes and Wiesen (2021) extended the analysis to the U.S. industrial sector, highlighting the patterns of risk contagion across different industry groups. Other representative studies in this area include Kumar et al. (2022), Vidal-Llana et al. (2023), Tsuji (2024), each contributing further empirical evidence on spillover dynamics in diverse financial and commodity markets.

To better capture time-varying features present in evolving financial network data, Antonakakis et al. (2018) proposed a modified version of the spillover index model based on the time-varying parameter vector autoregression (TVP-VAR) framework. This variant demonstrates improved flexibility in detecting structural changes and evolving interconnections over time. Following this line of research, Dai et al. (2023) developed a dynamic spillover index using the TVP-VAR methodology and applied it to investigate the risk transmission channels among WTI crude oil, natural gas futures, and the Chinese stock market. Their findings underscore the value of dynamic modeling in uncovering temporal heterogeneity in cross-market spillovers. However, a notable limitation arises as the dimensionality of network data grows, making estimation increasingly costly. As the number of variables increases, the estimation process becomes increasingly complex and computationally intensive, potentially impairing the reliability of the results. In response to this challenge, recent studies—such as those by Demirer et al. (2018), Gross and Siklos (2020), and Bostanci and Yilmaz (2020)—have incorporated regularization techniques including LASSO, Group LASSO, and Elastic Net to enhance model tractability and improve estimation accuracy in high-dimensional settings. Furthermore, inference for spillover indices often relies on large-sample approximations; in practice, bootstrap methods are sometimes employed to assess the uncertainty of connectedness measures, especially when evaluating the statistical significance of spillover estimates in finite samples. Despite its broad adoption, the spillover index framework is not without theoretical constraints. As emphasized by Ando et al. (2022), the model is fundamentally based on mean-based estimations and thus primarily captures risk relationships under normal market conditions. It lacks the ability to adequately reflect tail-risk dependencies or systemic risk transmissions during periods of extreme stress, which are of particular concern to regulators and policymakers.

2.3. Tail risk network

In recent years, a growing body of research has focused on tail-risk network models constructed from tail-event network data to capture extreme dependence structures. Hautsch et al. (2015) constructed a tail risk network based on value-at-risk (VaR) metrics to examine the interconnectedness of extreme losses among major U.S. financial institutions. Building on this approach, Härdle et al. (2016) proposed the TENET framework, which employs a semiparametric quantile regression model to analyze tail risk spillovers under stress scenarios. Similarly, Wang et al. (2017) utilized the conditional autoregressive value-at-risk (CAViaR) model to quantify institution-specific tail risk and applied Granger causality networks to assess inter-institutional tail-risk dependencies within China's financial sector. Extending the tail-risk perspective to the insurance industry, Cao (2023) applied the conditional value-at-risk (CoVaR) framework to build a tail risk spillover network, providing insights into extreme risk contagion among Chinese insurance firms. Another influential line of research has been led by Ando et al. (2022), who introduced the quantile vector autoregression (QVAR) model. This method generalizes the traditional spillover index framework to the quantile domain, thereby enabling the analysis of systemic interdependencies across different market regimes and under varying distributional conditions.

For example, Chatziantoniou et al. (2021) employed quantile-based dependence analysis to investigate tail risk co-movements among major currencies, including the U.S. dollar, euro, yen, and pound sterling. Likewise, Yousaf et al. (2022) applied a similar methodology to analyze the quantile-dependent connectivity between Twitter-based sentiment indices and various financial assets. Despite their methodological advancements, most existing tail-risk network models adopt a single-layer network structure and tend to focus solely on direct linkages among financial entities. As highlighted by Wang et al. (2022a), this perspective overlooks the multi-faceted and heterogeneous nature of systemic interconnections that may exist across different channels, layers, or market conditions. Consequently, such models may fail to fully uncover the complexity of financial risk contagion in highly interconnected and digitally driven financial systems. Estimating these tail-dependent networks presents unique statistical challenges: extreme events are inherently rare, so reliably quantifying tail interconnectedness often requires techniques from extreme-value theory and large sample sizes. In practice, researchers must carefully validate tail-network models (e.g., via out-of-sample stress tests or bootstrap confidence intervals) to ensure robust inference under finite samples.

2.4. Multilayer network analysis

Recent advances emphasize multi-layer and higher-order structures in network data to capture the complexity of financial systems. For example, Wang et al. (2018) constructed both Pearson correlation networks and partial correlation networks to examine the topological features and evolutionary dynamics of global stock markets. Their comparative analysis highlighted how different types of statistical dependencies yield distinct network structures and insights. Casarin et al. (2020) introduced a network vector autoregressive (network-VAR) model to construct contemporaneous and lagged multi-layer networks, allowing them to explore how global oil prices are interconnected under various economic conditions. Similarly, Wang et al. (2021) developed a set of return-based, volatility-based, and tail-risk-based networks to systematically assess the structure and evolution of systemic risk within China's financial sector.

Furthermore, Gong et al. (2022) integrated the TENET framework with Granger causality analysis to build both sentiment networks and tail-risk networks across industries, revealing the transmission mechanisms between investor sentiment and extreme financial risks. Building on this, Ling et al. (2022) extended the network architecture by incorporating bond markets alongside equity markets, thereby constructing a two-layer inter-market network that better reflects the cross-market transmission of financial shocks. Further demonstrating the utility of multilayer network models, Foglia et al. (2023) employed a three-layer network framework to analyze spillover dynamics among sovereign risk, banking risk, and stock market risk across Eurozone countries. Their findings underscore the importance of capturing risk at multiple institutional and asset-class levels. In addition, Ouyang et al. (2024) proposed a multilayer frequency-domain network model to investigate volatility spillovers among Chinese financial institutions, providing time-scale-sensitive insights into systemic risk propagation. Together, these studies mark a methodological shift toward multilayer, frequency-aware, and semantically enriched network models, reflecting the growing recognition that financial systems are inherently multi-dimensional and that risk transmission often occurs across overlapping layers and time scales. Representative papers also include Ouyang and Zhou (2023), Zhou et al. (2024), Ouyang et al. (2025), and Zhou et al. (2025).

The practical relevance of complex network models has been demonstrated in several major crises. During the European sovereign debt crisis, network analyses of cross-border exposures and interbank linkages helped reveal contagion channels between banks and governments in the Eurozone, informing intervention strategies by central banks and regulators. Likewise, throughout the COVID-19 pandemic, dynamic connectedness indices and network measures signaled surges in systemic risk across global markets; for example, cryptocurrency markets experienced sharply increased interconnectedness as stress propagated during the 2020 outbreak (Kumar et al., 2022). International supervisory institutions have also embraced these tools: the IMF and the BIS have incorporated network-based contagion analysis into macroprudential stress tests, using interbank network simulations and derivative exposure networks to evaluate potential systemic failures under extreme scenarios. These cases underscore that the methods reviewed in Section 2 are not only theoretical but also instrumental in addressing live financial stability challenges faced by policymakers and practitioners.

3. Higher-order network and financial statistical analysis

Section 3 focuses on higher-order financial networks, which extend traditional models by allowing edges among three or more entities. We first define these structures (e.g., hypergraphs, simplicial complexes) and then show how they capture multi-entity contagion phenomena. These approaches reveal group-level risk patterns (risk “resonance”) not detectable by the pairwise networks of Section 2.

3.1. Definition of higher-order networks

Complex-network methods have become essential as they operationalize financial network data to capture and analyze risk transmission mechanisms (Glasserman and Young, 2015). Higher-order networks go beyond traditional single-layer or multilayer networks by encoding higher-order relations already present in network data. They not only account for direct pairwise links between nodes but also encode higher-order relations among nodes (Battiston et al., 2020). This perspective reveals intricate dependencies and interaction patterns among financial entities and clarifies how risks propagate across heterogeneous agents (Acemoglu et al., 2015). A higher-order network is a structure in which interactions involve three or more entities simultaneously, in contrast to models restricted to pairwise interactions. In a pairwise network, an edge represents a relationship between two nodes; in a higher-order network, a single connection can link multiple nodes (Young et al., 2021). For example, if three banks jointly hold the same asset, this can be represented by a hyperedge containing the three banks and the asset, treating them as a group (Allen et al., 2012). The key conceptual advance is moving beyond dyads by allowing links that bind multiple entities at once, thereby capturing the group-interaction complexity observed in real financial systems.

Common higher-order formalisms include hypergraphs and simplicial complexes (Iacopini et al., 2019). Hypergraphs use hyperedges to represent group relations directly; for instance, a single hyperedge can connect several banks to a common borrower, revealing multi-party contractual structures. Simplicial complexes emphasize interaction structures with hierarchical inclusion; for example, a 2-simplex (triangle) represents a triad together with all of its pairwise edges. To study structural features, scholars generalize classic network concepts to higher-order settings and propose measures such as higher-order centrality, higher-order clustering coefficients, and higher-order assortative to quantify a node's role in group interactions (Benson et al., 2016). We treat hyperedge selection as a model-selection problem. Identification is clarified via likelihood or regularization; uncertainty is quantified by resampling (graph bootstrap) or Bayesian posteriors. We report the consistency of selected motifs under sparsity and provide finite-sample intervals for higher-order centrality (Battiston et al., 2016).

3.2. Higher-order networks and financial risk resonance

Higher-order methods offer distinctive advantages when network data exhibit group interactions and synchronous co-movements, which are key to systemic financial risk. They help uncover group-interaction mechanisms that underlie financial risk resonance (Ibragimov et al., 2011). Risk resonance denotes synchronized fluctuations across multiple agents as observed in multi-entity network data under stress. This synchronization is not reducible to simple chain-like contagion. It emerges when agents share exposures or relational structures, causing co-movement under tail-risk conditions and joint responses to shocks. Pairwise network models struggle to capture this group-level, nonlinear amplification. Higher-order networks provide a powerful descriptive framework (Allen et al., 2012).

Higher-order networks provide several advantages for identifying systemic financial risk. First, they reveal key nodes and latent fragile clusters—institutions occupying central positions across many higher-order relations (Poledna et al., 2021). Traditional dyadic analysis may rate some institutions as unimportant because their degree is modest. A higher-order lens shows that these institutions participate in critical group interactions (hyperedges) and may hold "hyper-central" status. In short, such institutions lie at the core of many higher-order structures. If they falter, multiple groups may become unstable simultaneously. Evidence suggests that hypergraph-central institutions are often "hidden" systemically important nodes underestimated by traditional dyadic views (Aldasoro and Alves, 2018).

Second, higher-order methods facilitate the identification of overlapping communities and synchronous clusters. For example, higher-order community detection uncovers market segments that co-move as groups (David et al., 2024). One study modeled the global equity market as a higher-order network and showed—via community detection—that pre-pandemic communities closely matched countries' development levels. During COVID-19, this structure fractured and reorganized. Higher-order methods thus captured transitions that pairwise networks missed: when many markets face common shocks, emergent clusters no longer align with established classifications. Overall, higher-order structures offer a new window onto systemic risk. By capturing co-occurrence among three or more nodes and synchronous clustering, higher-order analysis identifies segments where vulnerabilities accumulate earlier and more accurately (Billio et al., 2012).

To operationalize higher-order networks in quantitative studies of financial risk resonance, the literature offers several representative modeling approaches. First, dynamic higher-order networks from high-frequency data (Santoro et al., 2023) extract synchronous extreme-volatility events from high-frequency trading or price series, identify assets that co-move within very short windows, and connect them via hyperedges to depict the instantaneous resonance structure. Such a method captures collective behaviors such as multi-asset "flash crashes". The second approach is the Bayesian reconstruction of higher-order connections (Young et al., 2021). When direct group-interaction data are absent, plausible hyperedges are inferred from observed pairwise relations and their statistics. The hypergraph reconstruction model of Young et al. uses maximum-likelihood estimation to infer jointly linked node sets that explain observed patterns, thereby uncovering hidden higher-order risk channels. This is valuable for regulators, who often have only fragmentary bilateral exposure data; Bayesian methods help assemble a more complete higher-order risk network. The final approach are text-driven hyperedges from social media and news (So et al., 2022). This approach incorporates sentiment or textual co-mentions into network analysis. Institutions co-mentioned in the same article or post are linked by a hyperedge to represent associations in public perception or market sentiment, capturing opinion-driven resonance. Early evidence shows that text-based hyperedges reflect linkages formed by information diffusion and improve the detection of nascent risks.

In sum, as higher-order methods mature, data sources for constructing financial higher-order networks are becoming increasingly diverse. High-frequency trading data, portfolio disclosures, news and social media feeds, and financial statements can all support such models. Integrating these sources—and complementing them with advanced statistical-inference techniques—allows regulators to reconstruct the financial system's higher-order hypernetwork more faithfully and, in turn, to identify and monitor systemic risk more effectively. Still, modeling higher-order interactions poses nontrivial statistical challenges: researchers must decide which group interactions to include (a model selection problem often addressed via Bayesian inference or regularization), and many higher-order metrics lack closed-form asymptotic distributions, complicating the task of uncertainty quantification. As a result, simulation-based validation and sensitivity analysis are often needed to ensure robust conclusions from higher-order network models.

4. Graph neural networks and financial risk early warning

Section 4 turns to graph neural networks (GNNs), which apply machine learning to financial networks. We outline the core GNN framework for graph-structured data and then survey its applications in risk forecasting and early warning. Unlike the traditional econometric models of earlier chapters, GNNs sacrifice some interpretability for greater flexibility and predictive power.

4.1. The concept of graph neural networks

The pursuit of scientific rigor and accuracy remains the central goal of financial early warning research. To address the high complexity of financial market information and the nonlinear characteristics of financial time series, analytical methods and crisis prediction techniques continue to evolve. With the rapid development of artificial intelligence and big data technologies, a growing number of researchers have begun to incorporate machine learning and deep learning models into the financial domain to enhance the precision and robustness of risk warnings. These methods not only possess strong data processing capabilities but are also able to capture complex nonlinear relationships among different targets (Bucci, 2020; Christensen and Siggaard, 2023). These models primarily include support vector machines, random forests, decision trees, XG Boost, artificial neural networks, recurrent neural networks, convolutional neural networks, long short-term memory networks, deep multilayer perceptions, restricted Boltzmann machines, deep belief networks, autoencoders, and attention mechanisms, among others (Machado and Karray, 2022; Lin et al., 2022; Niu et al., 2023; Gajamannage et al., 2023; Wu et al., 2024; Bhambu et al., 2025).

As research progresses, many scholars have recognized that individual techniques may have certain limitations. Consequently, various ensemble methods and feature selection strategies have been proposed to effectively address these issues and improve predictive accuracy (Ouyang et al., 2021; Deep et al., 2024; Ma et al., 2024; David et al., 2024; Dikmen et al., 2025). For example, Chou and Chen (2024) integrated decision trees with metaheuristic optimization algorithms to successfully construct financial market portfolios. However, financial markets are inherently network systems composed of multiple entities and complex relationships, characterized by intricate interdependencies among financial assets. Although traditional machine learning and deep learning models effectively capture nonlinearities within data, they remain limited when the inputs are full-graph financial network data with rich cross-sectional interdependencies (Wang et al., 2023). Some researchers have incorporated network topology features into early-warning indicator systems, yet these features only partially represent correlation networks and fail to fully capture their global structure. Therefore, using financial network data as direct inputs to deep learning models has emerged as a more comprehensive approach.

Graph neural networks (GNNs), as a category of deep learning architectures, extend the advantages of neural networks to graph-structured data (Cheng et al., 2022). A graph is a data structure that represents entities as nodes and their connections as edges—examples include web pages linked within the internet or social networks formed by individuals on platforms such as WeChat. GNNs are specifically designed to handle irregular graph data of varying sizes and dimensions. Their core idea lies in learning embedded representations of nodes or entire graphs from input graph-structured data, iteratively applying a message-passing mechanism to aggregate information from neighboring nodes. This approach is commonly applied to three major tasks: node-level prediction, edge-level prediction, and graph-level prediction (Huang et al., 2023; Balmaseda et al., 2023). In node-level tasks, GNNs learn representations of individual nodes, which are then fed into a classifier or regressor to make predictions. For edge-level tasks, GNNs predict relationships between nodes by leveraging node embeddings and message passing. In graph-level tasks, GNNs learn global graph features to predict properties of the entire graph. Specifically, a GNN consists of multiple graph convolutional layers, each incorporating operations such as node embedding, message passing, and pooling. During node embedding, the features of each node are transformed into low-dimensional vectors to facilitate learning and processing by neural networks. Throughout message passing, nodes receive information from their neighbors and aggregate this information to update their representations. Pooling operations then combine node representations to form a comprehensive graph-level embedding, thereby enabling graph-scale prediction tasks.

While GNNs share conceptual similarities with traditional neural networks, their ability to directly incorporate network structure offers unique advantages for financial applications. GNNs inherently process the relational configuration of financial entities, allowing them to capture complex inter-node dependencies through the learned message-passing rules. One key benefit is that GNN models can integrate both graph topology and node/edge attributes in a unified framework, extracting nonlinear patterns that would be difficult to specify a priori in an econometric model. At the same time, this data-driven flexibility comes with trade-offs. In particular, these deep models often function as black boxes; interpreting the learned relationships or assessing the statistical significance of specific inputs is challenging. Unlike a linear regression or a structural econometric model, a trained GNN does not readily yield human-interpretable parameters or standard errors. As a result, explaining GNN predictions (for instance, identifying which features or connections most influenced an output) and quantifying the uncertainty of those predictions remain active areas of research. Recent advances in explainable AI (e.g., using attention mechanisms to highlight important nodes or edges) and in developing Bayesian GNN frameworks for uncertainty quantification are promising, but integrating such techniques into financial risk pipelines is still at an early stage.

4.2. Graph neural networks and financial risk prediction

Compared to traditional neural networks such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), graph neural networks natively process financial network data and capture inter-node dependencies through message passing. GNNs have been widely applied in domains such as social networks, traffic prediction, manufacturing, and drug discovery (Liu et al., 2025; Rasool et al., 2025; Zhang et al., 2025; Lin et al., 2025). In finance, their key appeal lies in learning complex network interdependencies directly from data. The complex interconnected networks within financial systems materialize as financial network data, motivating GNN-based prediction frameworks. GNNs can be implemented in various forms, with mainstream models including graph convolutional networks (GCNs), graph autoencoders, graph generative networks, graph recurrent networks, and graph attention mechanisms. Among these, GCNs and graph attention networks (GATs) are the most widely used in financial prediction. Existing GNN-based studies on financial risk have primarily focused on stock price prediction, market risk contagion, and credit risk management.

In the domain of stock price prediction, existing research has primarily focused on forecasting stock price trends and predicting stock price crash risk. For stock price trends, Zhang et al. (2025) employed an emotion-fused dynamic attribute-driven graph attention network to address issues such as inadequate multimodal data integration and weak timeliness in existing approaches. Concurrently, the scope of research has gradually expanded beyond single industries or markets. Instead, studies increasingly leverage graph neural networks to incorporate related markets and sectors, achieving higher prediction accuracy and improved robustness (Feng et al., 2022; Ma et al., 2024; Ma and Yuan, 2024; Bukhari et al., 2025; Hu et al., 2025). Liu et al. (2024) proposed a multi-scale multimodal dynamic graph convolutional network that simultaneously captures cross-industry dynamic correlations and multimodal fusion, demonstrating superior performance over other state-of-the-art models on two real-world datasets. Similarly, research on stock price crash risk has also been approached from multi-scale and cross-market perspectives. These studies not only account for explicit relationships among firms and industries but also utilize advanced techniques to uncover latent connections. By extracting spatio-temporal features, more refined models have been developed (Han et al., 2024; Wang et al., 2025).

Research on the transmission pathways of financial systemic risk has become a prominent direction in the application of graph neural networks in finance. Compared to traditional techniques, GNNs offer significant advantages in capturing the contagion characteristics of systemic financial risk, particularly when handling networked data. They not only accurately characterize the dynamic paths of risk propagation but also integrate multi-source data fusion to provide more comprehensive information. Ali et al. (2025) constructed a cross-market hierarchical graph neural network that incorporates higher-order statistical features and dynamic time-varying correlations to model and achieve the identification and quantitative analysis of cross-market risk contagion. Gu et al. (2025) employed a graph convolutional network combined with a long short-term memory network to identify key pathways of cross-sector risk spillovers and achieve high-accuracy predictions, thereby providing a basis for decision-making by relevant financial institutions. Peng et al. (2023) addressed the limitations of traditional SRISK models in real-time interaction and dynamic relationship modeling through an external attention mechanism and relation-type-guided graph convolution, offering a highly robust tool for financial risk early warning and quantitative strategy formulation.

In the field of credit risk management, addressing the limitations of traditional credit scoring models that overlook risk correlations and dynamic risk transmission, Zandi et al. (2025) developed a dynamic multi-layer graph neural network incorporating graph attention networks and long short-term memory networks. This approach enables refined modeling of spatio-temporal risk propagation and improves prediction performance. With the advancement of information technology, smart contracts have gradually emerged, and associated security issues have become a key research focus. By integrating graph neural networks with multi-dimensional code property graphs (CPGs), methods have been developed to effectively tackle the lack of semantic information and insufficient detection accuracy in contracts, achieving high-precision, fine-grained vulnerability localization, and interpretable results (Huanliang et al., 2025). In financial fraud detection, conventional techniques are often limited by imbalanced data, irregular time series, and inadequate analysis of complex relationships, leading to biases in detection. The emergence of graph neural networks offers promising solutions to these challenges. Coupled with data augmentation techniques, GNNs can significantly enhance detection accuracy (Shih et al., 2025). When companies encounter significant fraud, they may face bankruptcy and liquidation. Graph neural networks can also contribute to joint modeling of internal firm-specific risks and contagion risks, enabling improved bankruptcy prediction for small and medium-sized enterprises (Wei et al., 2024).

Furthermore, graph neural networks are capable of effectively capturing data dynamics and handling linguistic complexity. When integrated with emerging large language models (LLMs), they enable a more comprehensive construction of knowledge graphs for financial events in Chinese (Cheng et al., 2024). In terms of time series processing, GNN-related techniques have matured considerably. They not only address lead-lag effects in univariate financial time series forecasting (Cheng et al., 2022) but also facilitate fine-grained separation and modeling of heterogeneous dependencies in multivariate time series (Ye et al., 2025), as well as efficient modeling of cross-variable dependencies and robust classification (Gui et al., 2024). However, the recursive mechanisms used in GNNs for temporal processing suffer from computational limitations. In response, some scholars have proposed a novel forecasting framework based on spatio-temporal graph neural networks (Verdone et al., 2024). Temporal graph neural networks are capable of capturing dependencies in both spatial and temporal dimensions simultaneously (Zhou et al., 2025), dynamically modeling the evolution of relationships among financial entities, thereby significantly enhancing adaptability to market dynamics. This dynamic modeling capability is particularly critical for predicting the propagation and evolution of financial risks.

Table 1. Comparative overview of modeling approaches in financial network analysis.

Aspect	Complex networks (pairwise models)	Higher-order networks (group models)	Graph neural networks (deep learning on graphs)
Interaction structure	Edges between two nodes (dyadic relationships). Can be single-layer or multilayer (multiple types of pairwise links).	Hyperedges connecting groups of 3 or more nodes simultaneously (beyond pairwise). Captures multi-entity interactions in one relational unit.	Implicitly learned graph representations combining node features and edges. Network structure and attributes encoded in learned embeddings.
Key assumptions	Often rely on specified statistical models (e.g., VAR for spillovers, linear Granger causality). Typically assume stationarity and linear or parametric forms for relationships.	More flexible, allowing nonlinear and group-wise dependencies. No fixed parametric form for hyperedges, but may require strong data richness to identify multi-node interactions.	Minimal explicit assumptions on functional form (model is data-driven). Require large training datasets; model architecture (layers, etc.) imposes structure rather than statistical distribution assumptions.
Statistical inference	Classical inference methods are applicable (e.g., hypothesis tests for Granger causality, VAR coefficient significance). Asymptotic theory available under certain conditions (large T or N).	Still developing: inference often via simulation or Bayesian methods to detect significant hyperedges or higher-order motifs. Lacks well-established asymptotic results for higher-order metrics; uncertainty quantification often needs bootstrapping.	Traditional statistical inference (p-values, confidence intervals) not directly available. Model evaluation relies on out-of-sample validation; some approaches use Monte Carlo dropout or Bayesian neural nets to gauge uncertainty.
Robustness and complexity	Can face estimation issues in high dimensions (many nodes/edges). Regularization (LASSO, etc.) or dimensionality reduction can improve stability. Model misspecification (e.g., assuming linearity) can reduce robustness under nonlinear dynamics.	Combinatorially complex as network size grows (many possible hyperedges). Risk of overfitting if data are sparse relative to possible group links. Results sensitive to missing or noisy multi-party data; requires careful validation.	Able to handle very high-dimensional, complex data (many features, nodes) via training, but susceptible to overfitting without proper regularization. Robustness depends on hyperparameter tuning and quality of training data; distribution shifts can degrade performance.
Interpretability	High interpretability: clear network measures (e.g., centrality, connectedness) and often simple model forms (linear relationships) yield intuitive insights. Results (e.g., spillover index) are directly attributable to specific linkages.	Moderate interpretability: can identify important groups or clusters (e.g., hyper-central nodes, overlapping communities), but representations are more complex to visualize. Requires new metrics (hypergraph centrality, etc.) and visualization techniques to fully explain findings.	Low out-of-the-box interpretability: model weights and learned embeddings are not easily interpretable economically. Post-hoc methods (e.g., attention weights, feature importance analysis) are needed to explain predictions; interpretability is an active research area (XAI for GNNs).
Example applications	Mapping contagion in interbank networks; calculating spillover indices for global markets. Stress-testing via network of banks' exposures; identifying key players (SIFIs) through centrality.	Analyzing overlapping portfolios (common asset holdings) to find joint default clusters. Detecting synchronous market moves (e.g., sectors moving together during COVID-19) via hyperedge modeling; uncovering hidden multi-firm risk structures.	Stock price prediction using cross-asset relational data; early warning of systemic risk via learned propagation patterns. Fraud detection by combining transaction networks with entity attributes; credit risk scoring incorporating borrower network connections.

5. Conclusions

In the context of accelerating digital transformation and the increasing penetration of artificial intelligence, big data, and unstructured information sources into financial systems, traditional approaches to financial statistical analysis are proving increasingly inadequate. This study presents a comprehensive review of financial network data and their statistical analysis and applications under the paradigm of digital intelligence. It systematically synthesizes existing research across three critical perspectives: complex networks and financial risk contagion, higher-order networks and financial statistical analysis, and graph neural networks (GNNs) for financial risk prediction and early warning.

The application of complex network theory has provided valuable insights into systemic risk transmission. Granger causality networks, spillover index models, and quantile-based dependency structures have become essential tools for uncovering contagion pathways in both normal and extreme market conditions. However, despite their significant contributions, traditional network models largely rely on pairwise interactions and are often limited in capturing the multifaceted, nonlinear, and distribution-sensitive nature of systemic interdependencies. This gap becomes more pronounced in the face of high-dimensional data and non-Gaussian risk events, both of which are increasingly characteristic of the data-rich, high-frequency digital financial landscape.

To address this, researchers have progressively adopted higher-order network models. These frameworks extend beyond dyadic links to capture multi-node interactions and latent group dynamics, providing a more refined and holistic understanding of risk co-movement and dependency structures. By incorporating tools such as hypergraphs, simplicial complexes, and higher-order motif analysis, scholars are better able to reflect the true complexity of real-world financial systems. Moreover, the use of advanced data sources—including binary time series, textual data, and high-frequency returns—has expanded the feasibility and richness of higher-order network construction. For example, the incorporation of natural language processing to extract semantic connections from financial disclosures and social media data represents a powerful frontier for constructing cognitively meaningful network representations.

Building upon both complex and higher-order network modeling, the integration of graph neural networks (GNNs) has further elevated the predictive power and flexibility of financial statistical systems. GNNs, including variants such as graph convolutional networks (GCNs) and graph attention networks (GATs), enable the embedding of both node features and network topology into dynamic predictive frameworks. These models are capable of learning from evolving graph structures, accommodating heterogeneous input sources, and capturing nonlinear dependencies across financial assets. As demonstrated by emerging empirical work, GNNs have shown significant promise in forecasting stock movements, identifying systemic risk contributors, and detecting fraudulent behavior—thus offering a new generation of tools for data-driven financial supervision and decision-making.

Looking ahead, we identify several promising directions for future research:

(1) Text-driven multilayer network data: Leveraging natural language processing techniques to extract relational signals from financial disclosures, news articles, and social media can enrich the construction of multilayer networks that integrate sentiment, policy uncertainty, and firm-level fundamentals.

(2) Multimodal data fusion in network learning: Future work could explore hybrid models that jointly process structured (e.g., returns, volatility) and unstructured (e.g., textual, visual) data for more accurate and holistic risk assessments.

(3) Cross-jurisdictional and policy-relevant modeling: As global financial systems become more integrated, understanding risk spillovers across regions, currencies, and regulatory regimes will be critical. Future models should embed geopolitical, macroeconomic, and legal considerations within financial networks.

(4) Application of graph-based simulation for stress testing: GNN-augmented simulations could serve as the next-generation infrastructure for regulatory stress testing, allowing policymakers to visualize the propagation of shocks under alternative macro-financial scenarios.

(5) Integration with macroeconomic accounting frameworks: Bridging granular financial network analysis with traditional macro-level accounts is a fruitful avenue. For instance, aligning network exposure data with sectoral balance sheets and from-whom-to-whom flow-of-funds tables could improve systemic risk monitoring by ensuring consistency between micro-level interconnections and aggregate financial constraints. Embedding network metrics into national accounting systems would enable policymakers to quantify contagion effects in the context of broader economic balance sheets and capital flow dynamics, thereby strengthening macroprudential surveillance.

In conclusion, as the digital intelligence era continues to evolve, the convergence of complex networks, higher-order network data structures, and graph-based deep learning offers a powerful, multidimensional lens through which financial systemic risk can be measured, monitored, and mitigated. Future advancements in this interdisciplinary field will not only depend on algorithmic innovation but also on the thoughtful integration of domain knowledge, policy relevance, and empirical rigor. This synthesis of data science and financial economics will be instrumental in fostering a more resilient, transparent, and adaptive global financial system.

Author contributions

The authors declare to have contributed equally to the manuscript. All authors have read and approved the final manuscript.

Use of AI tools declaration

The authors declare they have not used Artificial Intelligence (AI) tools in the creation of this article.

Conflict of interest

The authors declare no conflict of interest.

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