A Systematic Literature Review on Graph-Based Models in Credit Risk Assessment

Abstract

This review provides a comprehensive analysis of graph-based models in credit risk assessment within the financial industry. It systematically categorizes and evaluates various models, including factorial network models, Graphical Gaussian Models (GGMs), Graph Neural Networks (GNNs), network centrality measures, community detection methods, dynamic multi-layer networks, and advanced techniques like graph attention networks and hypergraphs. The analysis highlights the comparative advantages of graph-based models over traditional approaches in capturing complex relationships and contagion within financial networks. Factorial network models and GGMs excel in understanding latent factors and systemic risks, while GNNs and network centrality measures enhance predictive accuracy and explainability. Community detection and dynamic multi-layer networks offer insights into risk transmission and systemic risk. Advanced techniques such as graph attention networks, hypergraphs, and knowledge graph models integrate diverse data sources for holistic credit risk assessment. Additionally, the review underscores the potential of graph-based models in handling imbalanced data, improving credit scoring for thin-file borrowers, and mitigating financial contagion. The findings emphasize the need for future research to integrate early warning systems into customer segmentation frameworks and extend the utility of graph-based models to identify positive financial behaviors and lending opportunities.

Keywords: Graph-Based Models; Credit Risk Assessment; Network Analysis; Financial Networks; Machine Learning (ML); Systemic Risk; P2P Lending
JEL classification: G00, G1, G12, G14, G02, G4

1. Introduction

This study builds upon the increased interest in the application of graph-based models within the financial industry, particularly focusing on their role in credit risk assessment. By systematically examining the integration of network analysis and traditional credit scoring, this literature review aims to unveil the potential of graph-based techniques in enhancing predictive accuracy and risk management.

With the rise of advanced analytical techniques and the proliferation of Big Data the financial industry has undergone a significant evolution, offering novel opportunities for enhanced credit risk assessment and management. Among the innovative approaches emerging in this domain, graph-based models have gained significant attention for their ability to capture complex interdependencies and network effects within financial interactions. The term of a graph-based model is hereby defined as a Graph-Based Modeling System (GBMS) to develop a sophisticated modeling environment for problems that can be represented by an attributed graph [Jones, 1990]. This literature review systematically examines the role of graph-based models in credit default prediction, providing a comprehensive overview of different models and their applications in credit risk assessment.

In recent years, the financial sector has increasingly relied on sophisticated data-driven methods to improve risk management practices and enhance decision-making processes [Kou et al., 2014]. Traditional credit scoring models, predominantly based on individual borrower characteristics and static financial ratios, often fall short in capturing the intricate web of relationships and interactions that influence credit risk. Graph-based models, which leverage the structural properties of networks, offer a promising alternative by incorporating relational data into risk assessment frameworks.

The literature on graph-based models is diverse with many model applications but it can be broadly categorized into several main types: network centrality measures [Liu et al., 2024a,b, Long et al., 2022], community detection algorithms [Ahelegbey et al., 2019b, Leng et al., 2017, Anagnostou et al., 2018, Kanno, 2022, Tonzer, 2015], graphical gaussian models (GGMs) [Cerchiello and Giudici, 2016], and graph neural networks (GNNs) [Cheng et al., 2022, Lee et al., 2021, Mitra et al., 2024, Liu et al., 2022, Muñoz-Cancino et al., 2023a,b, Shumovskaia et al., 2021, Song et al., 2024, Wei et al., 2024, Wu et al., 2023]. Each of these models provides unique insights into the structural and dynamic aspects of financial networks. Network centrality measures, such as degree centrality, betweenness, and closeness, are found to identify the most influential nodes within a network, offering valuable information on systemic risk and potential points of failure. In contrast, community detection algorithms partition the network into cohesive subgroups, facilitating the identification of clusters with similar risk profiles. Graph neural networks, as an advanced machine learning approach, act as an overarching technique and integrate both node features and topological information, thereby enabling more accurate and robust credit risk predictions.

The application of graph-based models in credit risk assessment has demonstrated significant improvements in predictive performance and risk mitigation. By capturing the interconnectedness of borrowers and financial institutions, these models provide a more holistic view of credit risk, accounting for contagion effects and systemic vulnerabilities. Empirical studies have shown that incorporating network features into credit scoring models enhances their accuracy and reliability, particularly in the context of peer-to-peer (P2P) lending platforms and complex financial networks.

Comparative analyses between graph-based and traditional models highlight the advantages of the former in addressing the limitations of conventional approaches. Traditional models often assume independence among borrowers, neglecting the impact of network effects and interdependencies. In contrast, graph-based models explicitly account for these factors, leading to more accurate risk assessments and better-informed decision-making. Studies have demonstrated that graph-based models outperform traditional models in various settings, including default prediction, systemic risk analysis, and portfolio management.

1.1. Research questions

The premise of this study is to analyze and compare the various graph-based models used in credit risk assessment or other related domains to determine their relative effectiveness and scope of applications. To achieve this goal, we seek to answer the following primary research question: 'How do different graph-based models compare in enhancing credit risk assessment?' This general question is divided into the following sub-questions:

- What types of graph-based models are most commonly used in credit risk assessment?
- What are their specific applications?
- What areas will further spur the use of graph-based models in the context of credit risk assessment?

Hence, we structure our study as follows: Section 2 outlines the methodology employed for the review process. Section 3 provides an overview of different graph-based models, while Section 4 discusses their applications in credit risk assessment. Section 5 presents a comparative analysis of graph-based and traditional models. Finally, Section 6 offers conclusions and future research directions.

2. Methodology

In this literature review we follow the premise of a structured approach to ensure a consistent and unbiased outcome of the review process. Building on the methodological framework established by Varsha P S et al. [2024], our review is structured into eight key steps, which define the scope and direction of our study. Initially, we identify the research questions by formulating specific research questions. Next, we develop and validate a detailed review methodology to guide our data search and analysis. The third step involves an extensive examination and analysis of relevant literature to ensure a thorough exploration of the topic. Following this, we apply specific criteria to carefully select studies for inclusion, ensuring their relevance and quality. In the fifth phase, we conduct a detailed assessment of the quality of each selected study. We then proceed to systematically extract pertinent information from each study. The seventh phase involves analyzing and synthesizing the collected data to integrate findings and generate significant insights. Finally, we compile our results into comprehensive reports, presenting our findings in a clear and organized manner. This methodological approach ensures the rigor and reliability of our literature review, providing valuable insights into the subject matter.

Both Scopus[1] and Web of Science[2] are selected as research databases to draw upon the relevant literature data analysed for this study. Scopus covers a wide range of scientific disciplines, providing comprehensive research materials. It also offers powerful search and filtering capabilities[Burnham, 2006]. Web of Science has an extensive range of article repositories [Mongeon and Paul-Hus, 2016] and robust search features [Chadegani et al., 2013]. The advanced search function of both databases is used to customize a unique search query that includes keywords such as: 'graph', 'network', 'network models', 'network-based models', 'graph models', 'network-based modeling', 'graph-based modeling', 'credit risk', 'financial risk', 'banking risk', 'loan risk', 'credit scoring', 'risk assessment', 'financial', 'banking', 'loan', 'P2P', 'Peer-to-Peer', 'networks', and 'graphs'.These keywords were subsequently combined with the Boolean operators 'AND' and 'OR'. After several trials, we find the search results to include papers applying graph-based models in analyzing disease transmission, which do not match the research scope of this study. Thus, we further modify the research query to exclude keywords "COVID-19", "epidemic", "infection", "disease" and "virus". Subsequently, we retrieve our first two article resources:

- Source A: Use the following search query string to search in Scopus:

  TITLE-ABS-KEY(("graph" OR "network" OR "graphs" OR "networks" OR "network models" OR "network-based models" OR "graph models" OR "network-based modeling" OR "graph-based modeling") AND ("credit risk" OR "financial risk" OR "banking risk" OR "loan risk" OR "credit scoring" OR "risk assessment") AND ("financial" OR "banking" OR "loan" OR "P2P" OR "Peer-to-Peer"))
  AND PUBYEAR > 1993
  AND DOCTYPE(ar) NOT TITLE-ABS-KEY("COVID-19" OR "epidemic" OR "infection" OR "disease" OR "virus")

[1] https://www.scopus.com/home.uri
[2] https://www.webofscience.com/wos/woscc/basic-search

- Source B: Use the following search query string to search in Web of Science:

  (TS=("graph" OR "network" OR "graphs" OR "networks" OR "network models" OR "network-based models" OR "graph models" OR "network-based modeling" OR "graph-based modeling") AND TS=("credit risk" OR "financial risk" OR "banking risk" OR "loan risk" OR "credit scoring" OR "risk assessment")
  AND TS=("financial" OR "banking" OR "loan" OR "P2P" OR "Peer-to-Peer") AND TS=("network" OR "graph" OR "network models" OR "graph models" OR "network-based modeling" OR "graph-based modeling"))
  NOT TS=("COVID-19" OR "epidemic" OR "infection" OR "disease" OR "virus")

  After applying the search queries, the retrieved papers are further filtered according to a set of exclusion criteria outlined in Table 1.

Table 1: Summary of article selection criteria.

Criteria	**Decision**
Inclusion of pre-defined keywords in title, abstract, or keyword list	Inclusion
Article publication in a scientific journal	Inclusion
Article written in English	Inclusion
Article published before 1993	Exclusion
Duplicates of an original article	Exclusion
Relevance of abstract, title, and content to research objective	Exclusion
Unavailability of the article online for free	Exclusion
Publisher is MDPI or Hindawi	Exclusion

We manually check the papers returned by Scopus and explore that, according to Scopus' definition of the search query, some studies researching the influence of COVID-19 to financial market by applying graph-based models are also included. These studies remain suitable for our research question and were thus included in the sampling process though they contain disease-relevant keywords.

To align the systematic sampling approach of the literature returned by the two databases, we adjust the search query for Web of Science and check the additional publications returned. This forms the third source of this review:

- Source C: Use the following search query string to search in Web of Science:

  (TS=("graph" OR "network" OR "graphs" OR "networks" OR "network models" OR "network-based models" OR "graph models" OR "network-based modeling" OR "graph-based modeling") AND TS=("credit risk" OR "financial risk" OR "banking risk" OR "loan risk" OR

"credit scoring" OR "risk assessment")
AND TS=("financial" OR "banking" OR "loan" OR "P2P" OR "Peer-to-Peer") AND TS=("network" OR "graph" OR "network models" OR "graph models" OR "network-based modeling" OR "graph-based modeling"))

After applying these search queries, the retrieved articles already included in Source B are removed. The remaining 69 studies comprise Source C.

For publications from all three sources, we combine them and conduct further checks, which are explained in Fig 1.

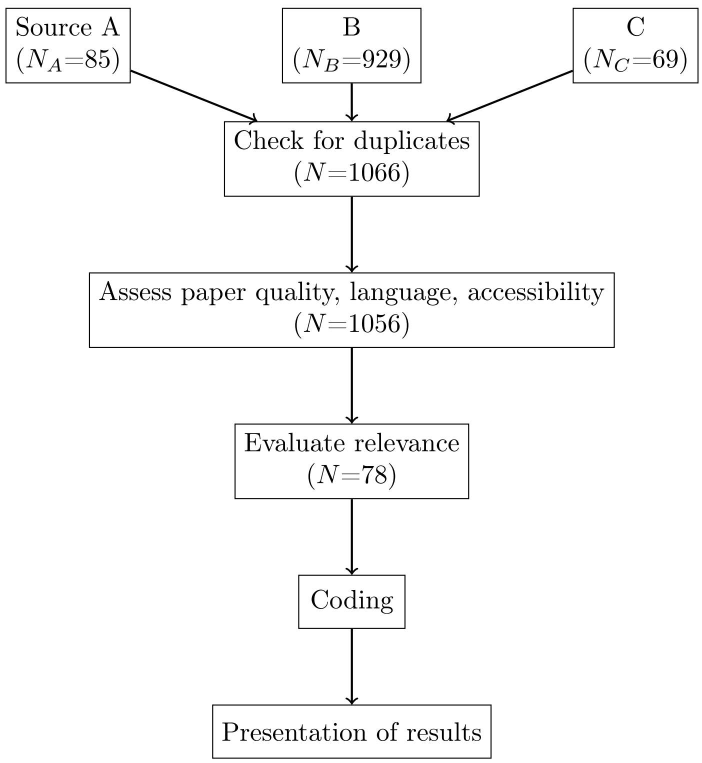

Figure 1: Flowchart of the Literature Review Process

During the "Coding" step, we focus on the following eight aspects of the included research studies:

- Type of graph: Which type of graph is applied to model the data, directed or undirected, weighted or unweighted, multi-graph, or other types?
- Application situation: The application situation that the graph-based model is applied to.

- Research question
- Methodology
- Data source
- Task type: What is the task type for the model?
- Performance metrics: What metrics are applied to measure the performance of the model?
- Validation and testing methods

These aspects of the literature will be presented in the following sections.

3. Deconstructing the research landscape

In this section, we will analyze the research landscape by examining three key aspects. First, we will look at the temporal distribution of literature to understand trends and changes over time. Next, we will explore the distribution of journals and topics to identify dominant areas of focus. Finally, we will analyze the frequency of keywords to gain insights into the recurring themes and emerging trends in the field.

3.1. Temporal distribution of literature

The temporal distribution of literature is plotted in Fig 2. The first study on this topic was published by Hu et al. in 2012 [Hu et al., 2012]. This paper applies an undirected weighted graph to model systemic risk in banking systems. It shows a significant increase in publications starting from 2018, with a noticeable peak in 2024. The data indicate that the research interest in this field has grown considerably over the years, particularly in recent times, suggesting a more central interest network-based credit risk modeling.

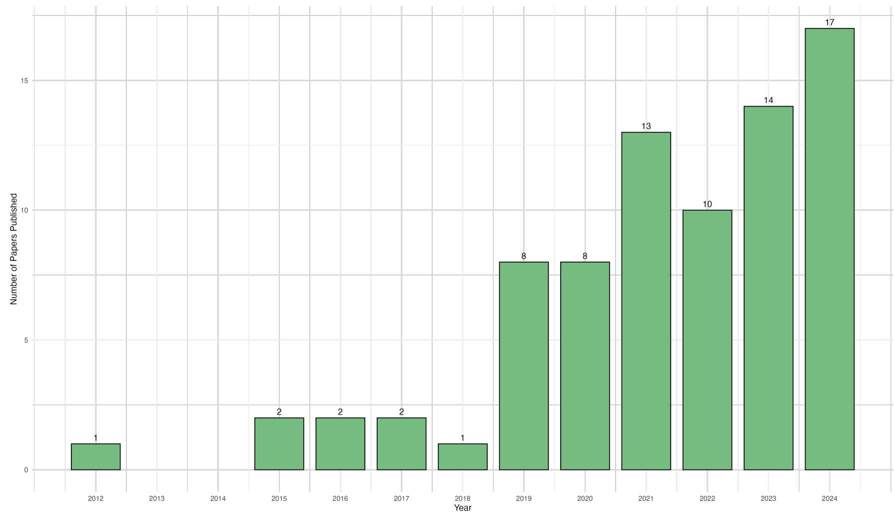

Figure 2: Temporal Distribution of Literature

3.2. Journal and topic distribution

This section presents an analysis of the journals and their primary topics where the top 20 most cited papers were published (Table 2). The journals represented in this list span a range of disciplines, reflecting the interdisciplinary nature of the research. The majority of the journals focus on Business & Economics (e.g., Journal of Financial Stability, International Review of Financial Analysis), indicating a strong emphasis on economic stability and financial analysis. The field of Computer Science also features prominently, particularly through journals like MIS Quarterly and Expert Systems with Applications. Additionally, there is a significant presence of journals related to Engineering and Operations Research & Management Science, such as Quality Engineering and European Journal of Operational Research, pointing to the applied nature of the research in optimizing processes and systems. Other areas such as Physics and Mathematics are represented by journals like Physical A and Journal of Systems Science & Complexity.

Table 2: Top 20 Cited Papers in the Field

	Authors	Source Title	Cited by	Topics
1	Poledna, S; Molina-Borboa, JL; Martínez-Jaramillo, S; van der Leij, M; Thurner, S	Journal of Financial Stability	189	Business & Economics
2	Tonzer, L	Journal of Financial Stability	90	Business & Economics
3	Hu, DN; Zhao, JL; Hua, ZM; Wong, MCS	Mis Quarterly	66	Computer Science; Information Science & Library Science; Business & Economics
4	Rao, CJ; Liu, M; Goh, M; Wen, JH	Applied Soft Computing	62	Computer Science
5	Giudici, P; Hadji-Misheva, B; Spelta, A	Quality Engineering	56	Engineering; Mathematics
6	Liu, JM; Zhang, SC; Fan, HY	Expert Systems with Applications	40	Computer Science; Engineering; Operations Research & Management Science
7	Wang, L; Li, SW; Chen, TQ	Chaos Solitons Fractals	35	
8	Ahelegbey, DF; Giudici, P; Hadji-Misheva, B	Physica a-Statistical Mechanics and Its Applications	33	Physics
9	Yildirim, M; Okay, FY; Özdemir, S	Expert Systems with Applications	33	Computer Science; Engineering; Operations Research & Management Science
10	Lee, JW; Lee, WK; Sohn, SY	Expert Systems with Applications	31	Computer Science; Engineering; Operations Research & Management Science

Table 2: Top 20 Cited Papers in the Field

	Authors	Source Title	Cited by	Topics
11	Fayyaz, MR; Rasouli, MR; Amiri, B	Industrial Management & Data Systems	28	Computer Science; Engineering
12	Giudici, P; Hadji-Misheva, B; Spelta, A	Frontiers in Artificial Intelligence	26	Computer Science
13	Oskarsdóttir, M; Bravo, C	Omega-International Journal of Management Science	22	Business & Economics; Operations Research & Management Science
14	Bhattacharya, M; Inekwe, JN; Valenzuela, MR	International Review of Financial Analysis	21	Business & Economics
15	Cerchiello, P; Giudici, P	Expert Systems with Applications	20	Computer Science; Engineering; Operations Research & Management Science
16	Kriebel, J; Stitz, L	European Journal of Operational Research	19	Business & Economics; Operations Research & Management Science
17	Durango-Gutiérrez, MP; Lara-Rubio, J; Navarro-Galera, A	Int. J. Financ. Econ.	16	
18	Leng, AL; Xing, GY; Fan, WG	Journal of Systems Science & Complexity	15	Mathematics
19	Kang, YZ; Jia, N; Cui, RB; Deng, J	Applied Soft Computing	14	Computer Science
20	Brownlees, C; Hans, C; Nualart, E	Journal of Monetary Economics	14	Business & Economics

3.3. Distribution based on keywords

The word cloud (Fig 3) generated from the keywords of the collected literature provides a visual representation of the most prominent topics and areas of research within the review sample. The most frequently occurring keywords include "credit risk," "credit scoring," and "peer-to-peer lending," highlighting the central focus on financial risk assessment and the mechanisms of credit evaluation. Other significant terms such as "machine learning," "deep learning," and "graph neural network" indicate that various models and methodologies are being employed in this research area. Additionally, keywords like "covid-19 pandemic" and "financial stability" suggest a recent interest in understanding the impacts of global crises on financial systems. The diverse array of keywords reflects the interdisciplinary nature of the research, encompassing fields such as economics, finance, computer science, and network theory, with a particular emphasis on risk management, network models, and the application of artificial intelligence in financial contexts.

Figure 3: Word Cloud of Ketwords

4. The role of graph-based models in credit default prediction

4.1. Overview of Different Graph-Based Models

Graph-based models have emerged as powerful tools for analyzing and predicting credit risk, leveraging the complex relationships inherent in financial networks. We find various types of graph-based models that are employed in the literature to capture the multifaceted nature of credit risk.

One of the primary models is the *factorial network model*, which improves credit risk management by segmenting heterogeneous populations into clusters based on the comovement of latent factors. This segmentation allows for the construction of more accurate credit score models, as demonstrated by Ahelegbey et al. [2019a]. Similarly, the latent factor model classifies firms into major network communities to estimate efficient logistic models for P2P credit scoring, showing enhanced predictive performance compared to traditional methods [Ahelegbey et al., 2019b].

Graphical Gaussian models or (GGMs) are another vital approach, particularly useful for systemic risk estimation. These models leverage financial network structures to enhance the understanding of interconnectedness and systemic risks, providing a more detailed depiction of risk propagation through financial systems [Cerchiello and Giudici, 2016].

Contrarily, *Graph neural networks* (GNNs) have gained prominence for their ability to incorporate both node features and graph structures into credit risk prediction. For instance, Giudici et al. [2019] and Liu et al. [2022] propose using GNNs to integrate alternative data, such as centrality measures derived from similarity networks, significantly improving predictive accuracy and model explainability. Additionally, Cheng et al. [2022] utilize deep graph learning to quantify systemic risk in networked-loans, showcasing its effectiveness in detecting and isolating contagion risk. Congruently, the application of GNNs extends further, as Muñoz-Cancino et al. [2023a] and Song et al. [2024] demonstrate their potential in combining multiple graph representation learning methods to enhance credit scoring for thin-file borrowers and enterprise credit risk assessment, respectively. This highlights the versatility of GNNs in various financial contexts but also points to their intricate implementation. Consequently, Shumovskaia et al. [2021] discuss using GNNs for predicting new interactions in the network of bank clients and improving credit scoring, indicating their potential in enhancing customer relationship management in the banking sector. In the context of fraud detection, Shi and Zhao [2023] explore the use of hierarchical graph attention networks (HGAT) for integrating local and extensive structural information, significantly improving the detection of financial fraud. Shi et al. [2024] present a hybrid model using GNNs for credit risk prediction by integrating graph representation learning and k-nearest neighbors (kNN) methods, which shows to improve the predictive performance. Moreover, Wu et al. [2023] introduce a novel credit scoring approach called CDGAT, which uses GNNs to predict potential credit card defaulters by considering customer interactions, further demonstrating the utility of GNNs in credit scoring applications. Wei et al. [2024] discuss using GNNs to predict enterprise bankruptcy by combining intra-risk and contagion risk, providing a comprehensive approach to risk assessment. In turn, Song et al. [2024] propose a multi-structure cascaded graph neural network framework for enhancing enterprise credit risk assessment, underscoring the advanced capabilities of GNNs in handling complex financial datasets.

However, other approaches such as, *modeling systems with network centrality measures* remain a pivotal role in assessing credit risk. Liu et al. [2024b] demonstrate that a borrower's position within a P2P network, indicated by their degree centrality, is crucial in predicting loan default probabilities. This approach is further validated by Lu et al. [2022], who employ multi-layer and parallel-connected graph convolutional networks to detect default risk in P2P lending by considering a debtor-creditor relationship network. The importance of centrality measures is further emphasized in studies by Bhattacharya et al. [2020], Brownlees et al. [2021], and Long et al. [2022], indicating their effective application in credit risk modeling. In addition, Ahelegbey et al. [2022] investigate the impact of the COVID-19 pandemic on the economic relationships among top 50 S&P companies by leveraging network analysis models that combine market and textual data. This study highlights how centrality measures can also reveal the shifts in economic relations during a global crisis. Similarly, Ben Amor et al. [2022] apply the Financial Risk Meter (FRM) to capture systemic risk behavior in emerging markets, incorporating centrality measures to inform portfolio allocation decisions. Further research by Giudici et al. [2019] proposes enhancing credit risk accuracy by leveraging topological information embedded into similarity networks, employing topological coefficients such as centrality measures. This methodology is supported by Giudici et al. [2020], who suggest augmenting traditional credit scoring methods with centrality measures derived from similarity networks among borrowers to improve predictive accuracy and model explainability. Liu et al. [2024b] further underscore these findings by emphasising the significance of a borrower's position and connectivity within the P2P lending network for accurate credit risk assessment.

These studies collectively underscore the critical role of network centrality measures in diverse risk analysis settings, from assessing systemic risk during crisis to improving credit risk management in peer-to-peer lending platforms.

Another immanent strand in the family of graph-based models, namely *community detection methods* are utilized to identify clusters of financially interconnected firms, aiding in the understanding of risk transmission mechanisms. Anagnostou et al. [2018] propose augmenting systematic risk factors with a contagious default mechanism, constructing credit stress propagation networks to calibrate contagion parameters for infectious defaults. This methodology is supported by the work of Rao et al. [2020], who implemented a 2-stage modified random forest model for credit risk assessment in P2P lending. Ahelegbey et al. [2019b] present a latent factor-based classification technique to divide the population into major network communities, enhancing the predictive performance of P2P scoring models. Ahelegbey et al. [2022] analyze the impact of the COVID-19 pandemic by combining market and textual data to highlight intercompany connections using community detection algorithms. Bhattacharya et al. [2020] investigate financial connectivity using community detection in syndicated loan networks to relate financial integration and credit risk of banks. Studies by Cerchiello and Giudici [2016], Cheng et al. [2022], and Chen et al. [2020] further employ deep graphical models with community detection techniques to enhance systemic risk estimation in markets such as interbank lending and regulate contagion risk within the networked loans. Lee et al.

[2021] incorporate a community detection technique into a graph convolutional network to enhance the credit default prediction process. Similarly, Óskarsdóttir and Bravo [2021] apply multi-layer network analysis with community detection to improve credit risk prediction. Congruently, Poledna et al. [2015] expand this study context to explore the multi-layer nature of systemic risk in financial networks using community detection methods, and Tonzer [2015] consider cross-border interbank networks to understand banking risk and contagion through the use of community structures.

Building on this approach *Dynamic multi-layer network models* have been employed to capture the interactions across different layers of financial networks. Jin et al. [2024] and Poledna et al. [2015] illustrate the application of these models in understanding the propagation of systemic risk in interconnected financial systems. At the micro level, Lu et al. [2022] utilize multi-layer and parallel-connected graph convolutional networks for detecting debt default in P2P networks, while Song et al. [2024] enhance enterprise credit risk assessment with cascaded multi-level graph representation learning. Óskarsdóttir and Bravo [2021] and Lin et al. [2022] further explore the implications of multilayer networks in financial risk prediction and information diffusion, respectively.

Further advanced techniques such as *graph attention networks* (GATs) and *hypergraphs* are also found to be utilized to enhance the credit risk assessment process. Shi and Zhao [2023] and Song et al. [2024] illustrate the use of hierarchical GATs and multi-structure cascaded GNNs, respectively, to capture complex inter-entity relationships and high-order relationships among enterprises. Their resulting approaches lead to superior performance in financial fraud detection and enterprise credit risk assessment.

As another graph representation concept, *knowledge graph models* have been utilized to account for the integration of relational data into credit risk models. Mitra et al. [2024] and Zhang et al. [2024] demonstrate the effectiveness of these models in improving credit risk assessments for Micro, Small, and Medium-sized Enterprises (MSMEs) by leveraging enterprise association data. Furthermore, Song et al. [2024] also showcase the enhancement of enterprise credit risk assessment using a knowledge graph embedded network implementation. This approach allows for a more nuanced understanding of the relationships and dependencies between different enterprise entities by learning relation-specific representations. Similarly, Shi et al. [2024] illustrate the benefits of an integrated graph representation learning approach with graph transformation, which yields improved credit risk prediction over a conventional credit scoring approach. Scholarly work by Lee et al. [2021] further emphasizes the utilization of graph convolutional networks, highlighting the importance of virtual distances among borrowers in credit default prediction. These studies collectively underscore the pivotal role of advanced graph-based models in refining credit risk assessments and underscore the growing importance of incorporating complex relational data into financial risk modeling.

Further model types such as *Graph-based semi-supervised learning models* and *graph pattern mining models* have also been explored in credit risk contexts. Kang et al. [2021] applied a semi-supervised reject inference framework for consumer credit scoring, while Ribeiro et al. [2019] employed graph pattern mining to identify financial risk patterns.

These diverse graph-based model applications point towards collectively enhancing the predictive power and interpretability of credit risk assessments, offering nuanced insights into the dynamics of financial networks and providing robust tools for risk management in the financial sector.

4.2. Applications of graph-based models in credit risk assessment

Graph-based models have found extensive applications in credit risk assessment, leveraging the inherent interconnectedness within financial networks to enhance predictive accuracy and risk management strategies. These models offer significant advantages in capturing the complex relationships and contagion effects that traditional models often overlook.

One prominent application is the improvement of credit scoring models for personal- and corporate loans in Peer-to-Peer (P2P) lending platforms. Ahelegbey et al. [2019b] introduced a latent factor-based method that constructs a network of Small- and Medium sized Enterprises (SMEs) based on latent factor co-movements, allowing for the development of more accurate credit score models for different clusters, outperforming conventional logistic regression models. Similarly, Giudici et al. [2019] demonstrated that incorporating topological information from borrowers' financial data into credit scoring models significantly enhances their predictive performance. The effectiveness of these approaches is further corroborated by studies highlighting the roles of network topology and network centrality in credit risk assessment for personal P2P lending [Liu et al., 2024a,b]. Additionally, the use of multilayer and parallel-connected graph convolutional networks for detecting debt default in P2P networks [Lu et al., 2022], factorial network models for improving P2P credit risk management [Ahelegbey et al., 2019a], and network-based scoring models to enhance credit risk management in P2P lending platforms [Giudici et al., 2019] have shown promising results. Moreover, FCM-based P2P network lending platforms for dynamic credit risk assessment [Han et al., 2020], graph convolutional networks for credit default prediction [Lee et al., 2021], and evaluating borrowers' default risk with a spatial probit model [Lee and Sohn, 2021] further exemplify the utility of graph-based models. Furthermore, the impact of network-derived interfirm financial transactions and user-generated text on credit risk in P2P lending is found to enhance the prediction accuracy of scoring models [Vinciotti et al., 2019, Kriebel and Stitz, 2022].

In the context of SME credit risk, Long et al. [2022] proposed a framework that incorporates both intrinsic risk and relational risk derived from neighboring firms' risk events. This approach, which combines relational risk scores with traditional financial and demographic features, significantly improves the discrimination and granting performance of SME credit risk evaluations. Vinciotti et al. [2019] further highlighted the impact of interfirm financial transactions on the credit risk of SMEs, showing that incorporating transaction network information enhances the predictive power of credit risk models. Rishehchi Fayyaz et al. [2020] applied network-aware approaches to credit risk prediction in supply chain finance, thereby considering the importance of social network structures in managing financial stability. These findings are echoed in Muñoz-Cancino et al. [2023b], who among others [Long et al., 2022, Vinciotti et al., 2019] discusses the dynamic nature of creditworthiness influenced by social interaction features.

Subsequently, Muñoz-Cancino et al. [2023a] developed a framework that integrates multiple methods of graph representation learning with social network information to assess the creditworthiness of thin-file borrowers. By combining feature engineering, graph embeddings, and GNNs, this approach significantly improves credit scoring performance for individuals and companies with limited credit histories. Yıldırım et al. [2021] also demonstrated the effectiveness of incorporating graph theory into big data analytics for default prediction, showing substantial improvements in predictive accuracy. These advanced techniques are further explored by Han et al. [2020] and Shumovskaia et al. [2021], who among other scholars apply graph-based models to dynamic credit risk assessment scenarios [Muñoz-Cancino et al., 2023a, Yıldırım et al., 2021, Han et al., 2020, Shumovskaia et al., 2021].

Overall, the applications of graph-based models in credit risk assessment illustrate their ability to capture complex relationships and contagion effects within financial networks. By leveraging the structural properties of these networks, graph-based models provide deeper insights into risk propagation and interdependencies. In the following section, we further detail the work that has exclusively focused on analyzing bank lending and systemic credit risk assessment.

4.3. Applications of Graph-Based Models in Analyzing Bank Lending and Systemic Credit Risk

Within the literature the analysis of systemic risk within financial systems, particularly through the lens of bank lending networks, has garnered substantial academic attention. Systemic risk pertains to the risk of collapse of an entire financial system or entire market, due to the potential domino effect of the failure of a single entity or cluster of entities, which can result in a severe economic downturn. Graph-based models have emerged as powerful tools to study such interconnected financial networks, offering insights into how risks propagate and how the structure of these networks can influence systemic stability. Thus, the application of graph-based models in understanding credit risk contagion within interbank markets is another critical area. Chen et al. [2021] developed a network model to study credit risk contagion in the supply chain finance context under COVID-19, considering factors like disruptions and financial stress propagation. Their findings revealed how credit risk contagion accumulates and spreads, highlighting the nonlinear evolution of risk contagion within the financial system. Zhao et al. [2023] further explored cross-border credit networks, and found how international banking linkages facilitate risk contagion, thereby identifying the centrality of certain banking sectors in propagating systemic risk. This is supported by Hu et al. [2012], who analyzed the systemic risk within banking systems by utilizing a BI algorithm that incorporates both network- and financial principles to reveal intricate contagion pathways in interbank relationships. Cerchiello and Giudici [2016] utilize conditional graphical models to estimate systemic risk in a European interbank network, thereby underlining that the transmission of systemic risk underlies a strong country effect induced by the economic strength of an individual nation.

From these insights it becomes evident that graph-based models may represent an effective tool for assessing systemic risk when analyzing banking networks. Several studies [Steinbacher et al., 2016, Tonzer, 2015, Chen et al., 2020, Cheng et al., 2022, Lin et al., 2022, Poledna et al., 2015, Jin et al., 2024] have focused on the robustness and vulnerability of banking networks to systemic shocks. For instance, Steinbacher et al. [2016] propose a network-based structural model to illustrate the propagation of idiosyncratic and systemic shocks across banking systems. Their findings suggest that while idiosyncratic shocks have limited impact, systemic shocks can cause extensive damage due to their contagious potential. Tonzer [2015] accounted for this in their objective to analyze how interconnectedness in cross-border interbank networks can contribute to financial contagion and systemic risk. It is found that cross-border linkages among banking systems of different countries are related to systemic credit risk transmissions and interconnections between banks appear to propagate shocks within the network. This finding suggests that network topological properties of a network contain valid information about the risk contagion between node instances. Congruently, Chen et al. [2020] construct a network model of credit risk contagion in the interbank lending market, considering the impact of bank runs and fire sales of external assets, and reveals how these factors exacerbate the spread of financial distress. In turn, Cheng et al. [2022] proposed a deep graph learning approach to mitigate contagion risk in networked-loans, showing that banks' centrality within the network significantly influences their susceptibility to systemic risk. These results confirm the importance of understanding the network component in form of interconnectedness among banks to manage systemic risk effectively [Poledna et al., 2015, Steinbacher et al., 2016]. Building on this foundation Lin et al. [2022] investigated the co-evolution of financial information diffusion and risk spreading on two-layer networks, finding that optimal information diffusion can significantly suppress financial risk. This highlights the potential of graph-based models in designing strategies to control risk contagion. Additionally, Poledna et al. [2015] emphasize the multi-layer nature of systemic risk, arguing that systemic risk can be differentiated into separate layers of financial networks (e.g., interbank, derivatives, and payment networks) that each contribute to the overall systemic risk. Their findings suggest that understanding the interconnectedness across these layers is crucial for effective risk management.Jin et al. [2024] further develop a dynamic multi-layer financial network model to study risk contagion between banks and firms. Their model incorporates both traditional bank-firm lending relationships and dynamic short-term loans, showing how these interactions influence systemic stability.

5. The relationship between network analysis and credit risk assessment

This section explores the intricate relationship between network analysis and credit risk assessment, highlighting two discovered research streams from our review of the literature that aims to investigate how these two areas intersect and inform each other. Despite research efforts in both fields, the literature exemplifies a limited amount of studies that explicitly address their integration. This analysis aims to identify patterns and potential synergies, thereby providing a foundation for future research in this domain. From this systematic review of the literature it is found that the two predominant research streams that consider the integration of network analysis and credit risk are found in the field of P2P lending and corporate bankruptcy prediction. The employed research methods are primarily linked to supervised ML approaches that vary from simple linear models to complex neural networks and tree-based models.

5.1. The interplay between network analysis and credit risk in P2P lending

Network analysis has emerged as a pivotal tool in understanding the interconnected nature of financial entities, loan pools, and the propagation of risks through these connections. Traditional credit risk assessment models often fail to capture the complexity of these interconnections, focusing instead on isolated financial metrics. Consequently, the integration of network analysis is found to address this shortcoming by providing a more holistic view through an enhanced data representation that can yield latent information that otherwise remains hidden in the data structure. For instance, Ahelegbey et al. [2019a] and Liu et al. [2024a] highlight how network models can improve credit risk assessment in P2P lending by identifying latent factors and community structures within financial loan networks. These studies demonstrate that incorporating network-derived variables can significantly enhance the predictive accuracy of credit risk models. These insights coincide with other studies [Giudici et al., 2019, 2020, Chen et al., 2022, Ahelegbey et al., 2019a,b, Han et al., 2020] that find retrieved network-induced information to significantly improve the prediction accuracy of various scoring models. Nevertheless, it becomes evident that the application of network theory in credit risk assessment for P2P lending is primarily dominated by generalised linear models (GLS). Giudici et al. [2019] discuss the use of network-based scoring models represented through a logistic regression classifier to better capture the risk profiles of borrowers in peer-to-peer lending platforms via the computation of network effects measured through centrality measures. It is found that the inclusion of the centrality features in the credit modelling process contains relevant information for forecasting borrower default [Giudici et al., 2019]. This finding is corroborated by the results of Giudici et al. [2020], Chen et al. [2022], and Ahelegbey et al. [2019b], which showcase for the model family of GLS, the ability of topological features to to convey latent information that benefits the prediction of the credit default likelihood. Other studies such as Ahelegbey et al. [2019a] and Han et al. [2020] reveal that further advanced graph representations such as fuzzy recognition maps and factor network-based segmentation inhere beneficial information for the default prediction process in the context of P2P lending. In light of these findings it becomes crucial to intensify research efforts in the domain of complex network analysis to retrieve more empirical evidence on the effectiveness of graph-based credit risk modeling in P2P lending.

5.2. Network analysis and corporate default prediction

Within the area of credit risk assessment at the corporate level, scholarly efforts have been intensified to integrate network analysis with existing ML methods for predicting firm bankruptcy prediction in the context of SMEs. Several studies [Kou et al., 2021, Yıldırım et al., 2021, Sukharev et al., 2020, Zhou et al., 2023, Shi et al., 2024, Mitra et al., 2024] have proven the effectiveness of graph-based models in predicting firm default over conventional modeling approaches. Kou et al. [2021] leverage network data extracted from payment networks of SMEs, where firms are represented as nodes and shared payment transactions as edges, to forecast corporate defaults. The resulting topological insights demonstrate that incorporating transactional data enhances the prediction accuracy of SME bankruptcies. Building on this approach, Yıldırım et al. [2021] introduce graph centrality metrics and conduct a comparative analysis of statistical and tree-based credit scoring models using a dataset of Turkish firms. Their results indicate consistent improvement across all graph-augmented model ROC curves compared to traditional methods. Similarly, Sukharev et al. [2020] corroborate these findings, showing that transactional information derived from graphs substantially boosts the accuracy of neural networks in predicting loan defaults among bank clients. On the other hand, research focused on consumer credit default prediction also supports the value of graph-topological data in credit risk modeling. Zhou et al. [2023] utilize graph-attention-based networks to capture the complex interrelationships among users of credit providers, leading to superior predictive performance for the graph-based model compared to conventional machine learning techniques. Shi et al. [2024] employ a hybrid approach that combines graph neural networks (GNNs) with k-nearest-neighbor (KNN) to perform unsupervised graph transformations, thereby enhancing the prediction of loan defaults. Their model's higher classification accuracy relative to standard machine learning models highlights the advantage of establishing connections between observed instances before modeling to better exploit latent information in credit data. Conversely, Mitra et al. [2024] propose a novel credit risk assessment model for MSMEs that integrates a Relational Graph Convolutional Network (RGCN) with a Random Forest (RF) classifier. This approach leverages the strengths of knowledge graphs to capture complex relationships between entities such as borrowers, lenders, and their transactions. By embedding these relationships and combining them with traditional financial metrics, the RGCN-RF model delivers superior performance over conventional models in identifying credit risk.

5.3. Challenges and future directions

While the integration of network analysis and credit risk assessment holds great promise, we identify several challenges that remain to be solved. One obstacle is rooted in the data availability and quality of model training sets that can impose constraints, as highlighted by Muñoz-Cancino et al. [2023a]. Ensuring the robustness of network models in the face of incomplete or noisy data is crucial for their effective application [Hu et al., 2012] and thus a major concern for future research efforts. Furthermore, the computational complexity of network-based methods necessitates advanced techniques for scalability and efficiency. Studies such as Yıldırım et al. [2021] and Wu et al. [2023] underscore the importance of leveraging big data analytics and scalable machine learning frameworks to handle the vast amounts of financial data involved. In addition, the development of further advanced distributed ledger technologies (DLTs) and decentralized finance might grant further opportunities to assess credit risk in financial transactions specifically bound to these applications. Currently, scholarly efforts concentrated on providing an understanding to the structural properties of blockchains networks and their financial implications [Treiblmaier and Beck, 2019]. Hence, future research could explore how graph-based models can be adapted to assess credit risk within these decentralized networks. For example, the unique transactional patterns on blockchain could be modeled using graph structures to identify potential risks in smart contracts or lending pools. Additionally, the integration of peer-to-peer lending platforms with DeFi protocols could benefit from graph-based models to predict default risks more accurately. Another evolving area with future potential for the effective integration of network analysis in the context of credit risk modeling refers to real-time credit scoring. Given that many ML-driven credit scoring models operate on static data sources [Dastile et al., 2020], real-time monitoring systems can continuously assess credit risk as new data becomes available. In volatile credit markets that react in stronger magnitudes to sudden changes in economic conditions, these models can enhance the scoring accuracy and thus the credit risk assessment within these markets. Graph-based models may offer suitable characteristics for such tasks as the given network structure could allow for monitoring multiple inputs such as transactions, market movements, and changes in borrower behaviour simultaneously. First study approaches by Steinbacher et al. [2016] on the robustness of banking networks to systemic shocks underline the need for a timely response of credit providers in times of market stress. Studies particularly on multi-layer networks such as in Lin et al. [2022], Lu et al. [2022], and Song et al. [2024] can pinpoint to new approaches that could foster the application of graph-based models in this area. Overall, the relationship between network analysis and credit risk assessment is multifaceted and presents further applicable fields for exploration. By bridging these fields, we aim to direct researchers to develop more robust and network-based predictive models that better capture the complexities of modern credit systems.

6. Conclusion

In this study we conducted a comprehensive systematic literature review on the novel application of graph-based models in credit risk assessment. We explored a sample of 78 scholarly articles related to the research premise to uncover key themes and use cases in the field of graph-based credit risk modeling. The review aimed to provide a detailed understanding of how graph-based techniques enhance credit risk assessment and to identify emerging trends and future research directions in this field.

This structured approach allowed us to address the primary research questions posed at the beginning of the review:

- **Main techniques used for graph-based credit risk assessment and their validation:** The literature reveals a significant surge in interest in graph-based models for credit risk assessment, particularly over the past decade. The research landscape is characterized by a diversity of methodologies, including GNNs, network centrality measures, and community detection algorithms, which are frequently applied across various financial contexts related to credit issuance such as P2P lending as well as banking- and SME lending. These techniques are found to employ robust predictive capabilities and offer new dimensions in understanding systemic risks and financial contagion. The keyword analysis highlights the growing importance of terms like 'graph-based models', 'credit risk', and 'network analysis', reflecting the increasing recognition of these models' potential.

- **Relationship between network analysis and credit risk assessment:** The intersection of network analysis and credit risk assessment has been increasingly researched, revealing how graph-based models can capture the complex interdependencies and systemic risks within financial networks more effectively than traditional models. The review underscores that while network analysis has made significant strides in enhancing credit risk assessment, the integration of these techniques into traditional credit risk frameworks remains an area for further exploration. This gap suggests substantial opportunities for future research to build more holistic and integrated credit risk models.

Overall, the analysis of graph-based models in credit risk assessment uncovers distinct patterns of research focus and highlights areas with significant potential for further development. The methodologies reviewed range from simple graph-based indicators to complex, multi-layered network models, each contributing uniquely to the predictive power and interpretability of credit risk assessments. This diverse landscape points to the need for continued scientific innovation, particularly in integrating graph-based techniques with conventional credit risk models to enhance their applicability and effectiveness across different financial settings.

6.1. Implications of the study

This study has significant implications for both academic research and practical applications within the field of credit risk assessment. By examining the current landscape of graph-based models, we not only consolidates existing knowledge but also shed light on areas where further development is needed. The implications of these findings are immanent and can be categorized into research implications and practical implications.

- **Research Implications:** The results indicate that graph-based models have demonstrated considerable promise in enhancing the accuracy and robustness of credit risk assessment. These models, particularly Graph Neural Networks (GNNs), network centrality measures, and community detection methods, have been shown to provide deeper insights into the systemic risks and interconnectedness inherent in financial networks. However, the study also highlights several gaps in the existing literature that warrant further exploration. For instance, while graph-based models have been effectively applied in various contexts such as peer-to-peer lending and banking networks, there is a noticeable scarcity of research on their integration with traditional credit risk models. This gap presents an opportunity for future research to develop hybrid frameworks that combine the strengths of both graph-based and conventional models, potentially leading to more comprehensive and accurate risk assessment tools. Additionally, the review identifies a need for more empirical studies that test the effectiveness of graph-based models across different financial contexts and market conditions. Such studies could provide valuable evidence to support the broader adoption of these models in practice.

- **Practical Implications:** For practitioners, the findings of this review offer valuable insights into the potential applications of graph-based models in real-world settings. The ability of these models to capture complex relationships and predict systemic risks more accurately than traditional models could further evolve credit risk management. By adopting graph-based techniques, financial institutions could enhance their ability to identify high-risk borrowers, detect early warning signs of financial distress, and manage systemic risks more effectively. Moreover, the review suggests that graph-based models could be particularly useful in contexts where traditional models struggle, such as in assessing the creditworthiness of thin-file borrowers or in dynamic environments such as volatile as peer-to-peer credit markets. Implementing these models could lead to more informed lending decisions, reduced default rates, and improved overall financial stability. Furthermore, the study highlights the importance of continuous evaluation and adaptation of these models to ensure they remain effective in the face of evolving financial landscapes and emerging risks.

6.2. Limitations and future recommendations

While this systematic literature review offered valuable insights into the domain of network-based credit risk assessment, it is critical to recognize the inherent limitations that may have influenced our findings. These limitations should be considered when interpreting the results of this study:

- **Reliance on specific citation databases and search terms:** The review's scope was narrowed down by exclusively using the Web of Science and Scopus databases and specific search queries to gather the literature. While this approach streamlined the literature collection process, it inevitably resulted in the omission of potentially relevant studies that were either not available in these database or categorized under different keywords.

- **Application of distinct search filters:** The use of search engine filters pertaining to article type, interest area, language, and publication year may have inadvertently prevented the inclusion of additional relevant studies.

- **Subjectivity in further selection:** Despite using specific keywords and queries to retrieve a comprehensive literature list, the subjective evaluation led to the exclusion of numerous articles that were not wholly aligned with the research objective.

- **Limited available literature:** The review encountered limitations imposed by the literature itself, as network-based credit risk models have only recently begun to receive wider attention in the academic community, therefore limiting the breadth of available research.

Taking into account these limitations and building on the study results, we ought to express several recommendations that can be made to guide future research and potential implementations:

- **Exploring the integration of network models within traditional credit risk frameworks:** As the review indicated, few articles explored the incorporation of network analysis within traditional credit risk models. Future studies could bridge this literature gap by developing systems that allow to blend these methodologies to build theoretically enhanced prediction models.

- **Expanding the functionality of network-based models:** Traditionally, these models are designed to detect and track risk early through their topological features. However, a further advanced approach could involve monitoring specific indicators of borrowers' financial health and growth through parametric adaptations, thus identifying promising lending opportunities and expanding the utility of network-based models beyond risk mitigation.

Hence, the scope for innovation and expansion within the fields of network-based credit risk assessment is immanent. By exploring underrepresented applications and adopting novel approaches to existing technologies, future research can continue to enhance our understanding of advanced topological systems, ultimately contributing to more effective and comprehensive financial decision-making processes.

References

Ahelegbey, D. F., P. Cerchiello, and R. Scaramozzino (2022, May). Network based evidence of the financial impact of Covid-19 pandemic. *International Review of Financial Analysis 81*, 102101.

Ahelegbey, D. F., P. Giudici, and B. Hadji-Misheva (2019a, June). Factorial Network Models to Improve P2P Credit Risk Management. *Frontiers in Artificial Intelligence 2*, 8.

Ahelegbey, D. F., P. Giudici, and B. Hadji-Misheva (2019b, May). Latent factor models for credit scoring in P2P systems. *Physica A: Statistical Mechanics and its Applications 522*, 112–121.

Anagnostou, I., S. Sourabh, and D. Kandhai (2018). Incorporating Contagion in Portfolio Credit Risk Models Using Network Theory. *Complexity 2018*, 1–15.

Ağca, S., J. R. Birge, Z. Wang, and J. Wu (2023, December). The impact of COVID-19 on supply chain credit risk. *Production and Operations Management 32*(12), 4088–4113.

Behbehani, D., N. Komninos, K. Al-Begain, and M. Rajarajan (2023, May). Cloud Enterprise Dynamic Risk Assessment (CEDRA): a dynamic risk assessment using dynamic Bayesian networks for cloud environment. *Journal of Cloud Computing 12*(1), 79.

Ben Amor, S., M. Althof, and W. K. Härdle (2022, April). Financial Risk Meter for emerging markets. *Research in International Business and Finance 60*, 101594.

Bhattacharya, M., J. N. Inekwe, and M. R. Valenzuela (2020, November). Credit risk and financial integration: An application of network analysis. *International Review of Financial Analysis 72*, 101588.

Brownlees, C., C. Hans, and E. Nualart (2021, January). Bank credit risk networks: Evidence from the Eurozone. *Journal of Monetary Economics 117*, 585–599.

Burnham, J. F. (2006, March). Scopus database: a review. *Biomedical Digital Libraries 3*, 1.

Cerchiello, P. and P. Giudici (2016, January). Conditional graphical models for systemic risk estimation. *Expert Systems with Applications 43*, 165–174.

Chadegani, A. A., H. Salehi, M. M. Yunus, H. Farhadi, M. Fooladi, M. Farhadi, and N. A. Ebrahim (2013, April). A Comparison between Two Main Academic Literature Collections: Web of Science and Scopus Databases. *Asian Social Science 9*(5), p18.

Chen, C., L. Zhou, C. Sun, and Y. Lin (2024, June). Does oil future increase the network systemic risk of financial institutions in China? *Applied Energy 364*, 123176.

Chen, T., Y. Wang, Q. Zeng, and J. Luo (2020, March). Network model of credit risk contagion in the interbank market by considering bank runs and the fire sale of external assets. *Physica A: Statistical Mechanics and its Applications 542*, 123006.

Chen, W., Z. Li, and Z. Xiao (2021, September). On Credit Risk Contagion of Supply Chain Finance under COVID-19. *Journal of Mathematics 2021*, 1–13.

Chen, X., Z. Chong, P. Giudici, and B. Huang (2022, August). Network centrality effects in peer to peer lending. *Physica A: Statistical Mechanics and its Applications 600*, 127546.

Cheng, D., Z. Niu, J. Li, and C. Jiang (2022). Regulating systemic crises: Stemming the contagion risk in networked-loans through deep graph learning. *IEEE Transactions on Knowledge and Data Engineering*, 1–1.

Cinicioglu, E. N., G. Huyugüzel Kışla, A. O. Onder, and Y. G. Muradoğlu (2024, March). The Changing Behavior of the European Credit Default Swap Spreads During the Covid-19 Pandemic: A Bayesian Network Analysis. *Computational Economics 63*(3), 1213–1254.

d'Ambrosio, N., G. Perrone, and S. P. Romano (2023, October). Including insider threats into risk management through Bayesian threat graph networks. *Computers & Security 133*, 103410.

Dastile, X., T. Celik, and M. Potsane (2020, June). Statistical and machine learning models in credit scoring: A systematic literature survey. *Applied Soft Computing 91*, 106263.

D'Innocenzo, E., A. Lucas, A. Opschoor, and X. Zhang (2023, December). Heterogeneity and dynamics in network models. *Journal of Applied Econometrics*, jae.3013.

Durango-Gutiérrez, M. P., J. Lara-Rubio, and A. Navarro-Galera (2023, April). Analysis of default risk in microfinance institutions under the Basel III framework. *International Journal of Finance & Economics 28*(2), 1261–1278.

Giudici, P., B. Hadji-Misheva, and A. Spelta (2019, May). Network Based Scoring Models to Improve Credit Risk Management in Peer to Peer Lending Platforms. *Frontiers in Artificial Intelligence 2*, 3.

Giudici, P., B. Hadji-Misheva, and A. Spelta (2020, April). Network based credit risk models. *Quality Engineering 32*(2), 199–211.

Gu, Y., S. Zhu, Z. Yang, and Y. Zhao (2019, July). Research on banking systemic risk contagion based on network dynamic time-variant contagion kinetics model. *Journal of Intelligent & Fuzzy Systems 37*(1), 381–395.

Han, H., Y. Yang, R. Zhang, and B. Brekhna (2020). FCM-Based P2P Network Lending Platform Credit Risk Dynamic Assessment. *IEEE Access 8*, 195664–195674.

Hu, Zhao, Hua, and Wong (2012). Network-Based Modeling and Analysis of Systemic Risk in Banking Systems. *MIS Quarterly 36*(4), 1269.

Hurd, T. R., J. P. Gleeson, and S. Melnik (2017, February). A framework for analyzing contagion in assortative banking networks. *PLOS ONE 12*(2), e0170579.

Jin, L. (2021). Risks' cross-contagion between shadow banks based on complex network theory: evidence from China. *Kybernetes. The International Journal of Cybernetics, Systems and Management Sciences 50*(6), 1900–1918.

Jin, Q., L. Sun, Y. Chen, and Z.-L. Hu (2024, March). Financial risk contagion based on dynamic multi-layer network between banks and firms. *Physica A: Statistical Mechanics and its Applications 638*, 129624.

Jones, C. V. (1990, January). An Introduction to Graph-Based Modeling Systems, Part I: Overview. *ORSA Journal on Computing Vol. 2*(Issue 2), 136–151.

Jović, Z. and M. L. Đaković (2022, September). Interbank Network as a Channel of Credit Contagion in Banks: Is Moral Hazard Transferable? *Journal of Central Banking Theory and Practice 11*(3), 117–135.

Kang, Y., N. Jia, R. Cui, and J. Deng (2021, July). A graph-based semi-supervised reject inference framework considering imbalanced data distribution for consumer credit scoring. *Applied Soft Computing 105*, 107259.

Kanno, M. (2022, October). Exploring risks in syndicated loan networks: Evidence from real estate investment trusts. *Economic Modelling 115*, 105953.

Kanno, M. (2024, January). Assessing the impact of the COVID-19 crisis on sovereign default risk. *Research in International Business and Finance 68*, 102198.

Kou, G., Y. Peng, and G. Wang (2014, August). Evaluation of clustering algorithms for financial risk analysis using MCDM methods. *Information Sciences 275*, 1–12.

Kou, G., Y. Xu, Y. Peng, F. Shen, Y. Chen, K. Chang, and S. Kou (2021, January). Bankruptcy prediction for SMEs using transactional data and two-stage multiobjective feature selection. *Decision Support Systems 140*, 113429.

Kriebel, J. and L. Stitz (2022, October). Credit default prediction from user-generated text in peer-to-peer lending using deep learning. *European Journal of Operational Research 302*(1), 309–323.

Lee, J. W., W. K. Lee, and S. Y. Sohn (2021, April). Graph convolutional network-based credit default prediction utilizing three types of virtual distances among borrowers. *Expert Systems with Applications 168*, 114411.

Lee, J. W. and S. Y. Sohn (2021, December). Evaluating borrowers' default risk with a spatial probit model reflecting the distance in their relational network. *PLOS ONE 16*(12), e0261737.

Leng, A., G. Xing, and W. Fan (2017, October). Credit risk transfer in SME loan guarantee networks. *Journal of Systems Science and Complexity 30*(5), 1084–1096.

Lin, M., L. Duan, Y. Li, and Q. Xiao (2022, May). The Roles of Information Diffusion on Financial Risk Spreading on Two-Layer Networks. *Frontiers in Physics 10*, 905205.

Liu, G., K. Zhou, and X. Sun (2024, February). The influence mechanism of real estate enterprises' status on debt default risk. *Journal of Property Investment & Finance 42*(1), 28–49.

Liu, J., S. Zhang, and H. Fan (2022, June). A two-stage hybrid credit risk prediction model based on XGBoost and graph-based deep neural network. *Expert Systems with Applications 195*, 116624.

Liu, Y., L. J. Baals, J. Osterrieder, and B. Hadji-Misheva (2024a, October). Leveraging network topology for credit risk assessment in P2P lending: A comparative study under the lens of machine learning. *Expert Systems with Applications 252*, 124100.

Liu, Y., L. J. Baals, J. Osterrieder, and B. Hadji-Misheva (2024b, May). Network centrality and credit risk: A comprehensive analysis of peer-to-peer lending dynamics. *Finance Research Letters 63*, 105308.

Long, J., C. Jiang, S. Dimitrov, and Z. Wang (2022, October). Clues from networks: quantifying relational risk for credit risk evaluation of SMEs. *Financial Innovation 8*(1), 91.

Lu, S., Y. Wang, X. Liu, and C. Jiang (2022, May). Multi-layer and Parallel-connected Graph Convolutional Networks for Detecting Debt Default in P2P Networks. *Emerging Markets Finance and Trade 58*(6), 1688–1701.

Maghyereh, A. and H. Abdoh (2024, August). Tail risk connectedness among GCC banks episodes from the Global Financial Crisis to COVID-19 pandemic. *The Quarterly Review of Economics and Finance 96*, 101869.

Mitra, R., A. Dongre, P. Dangare, A. Goswami, and M. K. Tiwari (2024, June). Knowledge graph driven credit risk assessment for micro, small and medium-sized enterprises. *International Journal of Production Research 62*(12), 4273–4289.

Mongeon, P. and A. Paul-Hus (2016, January). The journal coverage of Web of Science and Scopus: a comparative analysis. *Scientometrics 106*(1), 213–228.

Mou, J., J. Christopher Westland, T. Q. Phan, and T. Tan (2020, March). Microlending on mobile social credit platforms: an exploratory study using Philippine loan contracts. *Electronic Commerce Research 20*(1), 173–196.

Muñoz-Cancino, R., C. Bravo, S. A. Ríos, and M. Graña (2023a, March). On the combination of graph data for assessing thin-file borrowers' creditworthiness. *Expert Systems with Applications 213*, 118809.

Muñoz-Cancino, R., C. Bravo, S. A. Ríos, and M. Graña (2023b, May). On the dynamics of credit history and social interaction features, and their impact on creditworthiness assessment performance. *Expert Systems with Applications 218*, 119599.

Naeem, M. A., A. Senthilkumar, N. Arfaoui, and R. Mohnot (2024, June). Mapping fear in financial markets: Insights from dynamic networks and centrality measures. *Pacific-Basin Finance Journal 85*, 102368.

Ouyang, Z.-S., Y. Huang, Y. Jia, and C.-Q. Luo (2020, May). Measuring Systemic Risk Contagion Effect of the Banking Industry in China: A Directed Network Approach. *Emerging Markets Finance and Trade 56*(6), 1312–1335.

Paraíso, P., S. Ruiz, P. Gomes, L. Rodrigues, and J. Gama (2021, August). Using network features for credit scoring in microfinance. *International Journal of Data Science and Analytics 12*(2), 121–134.

Poledna, S., J. L. Molina-Borboa, S. Martínez-Jaramillo, M. Van Der Leij, and S. Thurner (2015, October). The multi-layer network nature of systemic risk and its implications for the costs of financial crises. *Journal of Financial Stability 20*, 70–81.

Qian, Q., X. Chao, and H. Feng (2023, May). Internal or external control? How to respond to credit risk contagion in complex enterprises network. *International Review of Financial Analysis 87*, 102604.

Rao, C., M. Liu, M. Goh, and J. Wen (2020, October). 2-stage modified random forest model for credit risk assessment of P2P network lending to "Three Rurals" borrowers. *Applied Soft Computing 95*, 106570.

Ribeiro, B., N. Chen, and A. Kovacec (2019, January). Shaping graph pattern mining for financial risk. *Neurocomputing 326-327*, 123–131.

Rishehchi Fayyaz, M., M. R. Rasouli, and B. Amiri (2020, July). A data-driven and network-aware approach for credit risk prediction in supply chain finance. *Industrial Management & Data Systems 121*(4), 785–808.

Shi, F. and C. Zhao (2023, December). Enhancing financial fraud detection with hierarchical graph attention networks: A study on integrating local and extensive structural information. *Finance Research Letters 58*, 104458.

Shi, Y., Y. Qu, Z. Chen, Y. Mi, and Y. Wang (2024, June). Improved credit risk prediction based on an integrated graph representation learning approach with graph transformation. *European Journal of Operational Research 315*(2), 786–801.

Shumovskaia, V., K. Fedyanin, I. Sukharev, D. Berestnev, and M. Panov (2021, August). Linking bank clients using graph neural networks powered by rich transactional data. *International Journal of Data Science and Analytics 12*(2), 135–145.

Song, L., H. Li, Y. Tan, Z. Li, and X. Shang (2024, January). Enhancing Enterprise Credit Risk Assessment with Cascaded Multi-level Graph Representation Learning. *Neural Networks 169*, 475–484.

Steinbacher, M., M. Steinbacher, and M. Steinbacher (2016, April). Robustness of banking networks to idiosyncratic and systemic shocks: a network-based approach. *Journal of Economic Interaction and Coordination 11*(1), 95–117.

Stolbov, M. and D. Parfenov (2023, September). Credit risk linkages in the international banking network, 2000–2019. *Risk Management 25*(3), 21.

Sukharev, I., V. Shumovskaia, K. Fedyanin, M. Panov, and D. Berestnev (2020, November). EWS-GCN: Edge Weight-Shared Graph Convolutional Network for Transactional Banking Data. In *2020 IEEE International Conference on Data Mining (ICDM)*, Sorrento, Italy, pp. 1268–1273. IEEE.

Tonzer, L. (2015, June). Cross-border interbank networks, banking risk and contagion. *Journal of Financial Stability 18*, 19–32.

Treiblmaier, H. and R. Beck (Eds.) (2019). *Business Transformation through Blockchain: Volume I*. Cham: Springer International Publishing.

Varsha P S, A. Chakraborty, and A. K. Kar (2024, April). How to Undertake an Impactful Literature Review: Understanding Review Approaches and Guidelines for High-impact Systematic Literature Reviews. *South Asian Journal of Business and Management Cases 13*(1), 18–35.

Vinciotti, V., E. Tosetti, F. Moscone, and M. Lycett (2019, October). The Effect of Interfirm Financial Transactions on the Credit Risk of Small and Medium-Sized Enterprises. *Journal of the Royal Statistical Society Series A: Statistics in Society 182*(4), 1205–1226.

Wang, C., F. Yu, Z. Zhang, and J. Zhang (2021, February). Multiview Graph Learning for Small- and Medium-Sized Enterprises' Credit Risk Assessment in Supply Chain Finance. *Complexity 2021*, 1–13.

Wang, L., S. Li, and T. Chen (2019, February). Investor behavior, information disclosure strategy and counterparty credit risk contagion. *Chaos, Solitons & Fractals 119*, 37–49.

Wang, Y., Z. Wu, J. Gao, C. Liu, and F. Guo (2024, February). A multi-level classification based ensemble and feature extractor for credit risk assessment. *PeerJ Computer Science 10*, e1915.

Wei, S., J. Lv, Y. Guo, Q. Yang, X. Chen, Y. Zhao, Q. Li, F. Zhuang, and G. Kou (2024, February). Combining intra-risk and contagion risk for enterprise bankruptcy prediction using graph neural networks. *Information Sciences 659*, 120081.

Wu, J., X. Zhao, H. Yuan, and Y.-W. Si (2023, May). CDGAT: a graph attention network method for credit card defaulters prediction. *Applied Intelligence 53*(10), 11538–11552.

Yıldırım, M., F. Y. Okay, and S. Özdemir (2021, August). Big data analytics for default prediction using graph theory. *Expert Systems with Applications 176*, 114840.

Zhang, L., Q. Song, M. Fan, and X. Yao (2024, April). Credit strategy research based on Markov random field and enterprise association knowledge graph. *International Journal of Systems Science 55*(5), 844–857.

Zhang, Y. and X. Nan (2023, March). Debt default, financial risk transmission and governance from the perspective of supply chain network. *Heliyon 9*(3), e14224.

Zhao, H., Y. Li, Q. Sai, and Y. Ren (2023, May). Cross-border credit networks, banking risk contagion and suppression effects. *Social Networks 73*, 130–141.

Zhou, B., J. Jin, H. Zhou, X. Zhou, L. Shi, J. Ma, and Z. Zheng (2023, November). Forecasting credit default risk with graph attention networks. *Electronic Commerce Research and Applications 62*, 101332.

Zhu, A., W. Chen, J. Zhang, X. Zong, W. Zhao, and Y. Xie (2019). Investor immunization to Ponzi scheme diffusion in social networks and financial risk analysis. *INTERNATIONAL JOURNAL OF MODERN PHYSICS B 33*(11), 1950104.

Óskarsdóttir, M. and C. Bravo (2021, December). Multilayer network analysis for improved credit risk prediction. *Omega 105*, 102520.

7. Appendix

	Citation Key	Type of graph	Data Source	Task type
1	Liu et al. [2024a]	Undirected, Weighted	Bondora platform data, covering loan information from June 2009 to April 2022	Credit risk assessment and loan default prediction
2	Liu et al. [2024b]	Undirected, Weighted	Bondora platform data, covering loan information from June 2009 to April 2022	Credit risk assessment and loan default prediction
3	Giudici et al. [2020]	Undirected, Weighted	ModeFinance data on financial ratios from balance sheets of 9981 SMEs, mostly based in Southern Europe	Credit risk assessment and loan default prediction
4	Giudici et al. [2019]	Undirected, Weighted	European External Credit Assessment Institution (ECAI) data on financial ratios from 4514 Italian SMEs	Credit risk assessment and prediction of loan defaults
5	Lu et al. [2022]	Directed, Weighted	Renrendai platform transaction data from January 1, 2015, to March 31, 2015, including 1,115,855 transactions	Default risk detection in P2P lending platforms
6	Ahelegbey et al. [2019a]	Undirected, Weighted	European External Credit Assessment Institution (ECAI) data on 15,045 SMEs engaged in P2P lending across Southern Europe	Credit risk assessment and loan default prediction

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	Citation Key	Type of graph	Data Source	Task type
7	Ahelegbey et al. [2019b]	Undirected, Weighted	European External Credit Assessment Institution (ECAI) data on 813 SMEs, mostly based in Southern Europe, for the year 2015	Credit risk assessment and loan default prediction
8	Shumovskaia et al. [2021]	Directed, Weighted	Large European bank's transaction data over several years, anonymized and depersonalized	Link prediction and credit scoring
9	Han et al. [2020]	Directed, Weighted	Nine indicators derived from transaction data, user product data, and overdue compensation data from the Lu Jinfu platform and two other platforms	Platform risk assessment, Credit risk evaluation
10	Lee et al. [2021]	Undirected, Weighted	Lending Club data, including 2,260,688 loan records with 145 attributes collected until December 2018	Credit risk assessment and default prediction
11	Wu et al. [2023]	Directed, Weighted	Transaction data from Industrial and Commercial Bank of China (Macau) Limited (ICBC Macau) from January 1, 2015, to December 31, 2019	Credit risk assessment and prediction of credit card defaulters
12	Song et al. [2024]	Directed, Weighted	Real-world enterprise data from 5195 companies in China, collected from Datayes and CSMAR databases, including 18 financial indicators	Credit risk assessment

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	Citation Key	Type of graph	Data Source	Task type
13	**?**	Undirected, Weighted	Publicly available datasets including Lending Club, Home Credit, and PPD datasets from 2013 to 2015, and additional datasets specific to default detection	Default risk detection in P2P lending
14	Lee and Sohn [2021]	Undirected, Weighted	Lending Club dataset from June 2007 to December 2018, focusing on loans issued in 2012 for which default records were known	Default risk prediction
15	Rao et al. [2020]	Directed, Weighted	Loan data from the Pterosaur Loan platform, focusing on "Three Rurals" borrowers	Credit risk evaluation
16	Muñoz-Cancino et al. [2023a]	Undirected, Weighted	Multi-source dataset from a large Latin American country, characterizing relationships, interactions, and credit history for the entire population, including both individuals and companies	Credit risk assessment and creditworthiness prediction
17	Wang et al. [2024]	Undirected, Weighted	Internal electronic credit data of a commercial bank from 2015 to 2017, desensitized to contain feature information on loan and personal data	Credit risk assessment and multi-classification

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	Citation Key	Type of graph	Data Source	Task type
18	Steinbacher et al. [2016]	Directed, Weighted	Balance sheet data from 40 real banks, including Tier 1 capital and total assets, extracted from 2011 Annual Reports	Shock propagation analysis in banking networks
19	Vinciotti et al. [2019]	Undirected, Weighted	Financial transaction data between SMEs in the UK	SME credit risk assessment
20	Mitra et al. [2024]	Directed, Weighted	Indian MSMEs database from CMIE, including financial statements and relational data spanning six years (2016-2021)	Credit risk assessment and prediction of enterprise defaults
21	Muñoz-Cancino et al. [2023b]	Undirected, Weighted	Dataset of 97,000 individuals and companies from a Latin American bank, including social interaction data and financial data	Creditworthiness assessment
22	Ribeiro et al. [2019]	Undirected, Weighted	Two datasets: a qualitative bankruptcy data benchmark and a real-world French database of corporate companies	Financial risk prediction
23	Hu et al. [2012]	Undirected, Weighted	Federal Deposit Insurance Corporation (FDIC) data from 7,822 banks, spanning from 2001 to 2010	Systemic risk analysis and prediction of contagious bank failures
24	Stolbov and Parfenov [2023]	Directed, Undirected, Weighted	Aggregate probability of default (PD) data from the Credit Research Initiative covering 46 countries from January 2000 to December 2019	Credit risk propagation analysis

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	Citation Key	Type of graph	Data Source	Task type
25	Kriebel and Stitz [2022]	Undirected, Weighted	Lending Club dataset from 2007 to 2014, including 40,229 funded loans with user-generated text descriptions	Credit risk assessment and default prediction
26	Shi et al. [2024]	Undirected, Weighted	Benchmark credit datasets including Australian Credit Data, German Credit Data, Default of Credit Card Clients Data Set, and South German Credit Data	Credit risk assessment and prediction
27	Zhao et al. [2023]	Undirected, Weighted	Credit risk assessment	Z-score, Nonperforming loan ratio
28	Cheng et al. [2022]	Directed, Weighted	Comprehensive loan dataset from commercial banks across two of China's main mega city clusters (Yangtze River and Pearl River Delta), covering 0.83 million guarantee relationships and 0.57 million SMEs from January 2004 to December 2015	Systemic risk assessment and contagion risk prediction
29	Cerchiello and Giudici [2016]	Undirected, Weighted	Financial and market data for the largest European banks from 2001 to 2010, sourced from FDIC	Systemic risk estimation and contagion risk prediction
30	Bhattacharya et al. [2020]	Directed, Weighted	Syndicated loan data from Loan Pricing Corporation DealScan Dataset, covering 39 countries from 1988 to 2014	Credit risk assessment and financial integration analysis

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	Citation Key	Type of graph	Data Source	Task type
31	Wang et al. [2021]	Undirected, Weighted	Financial data from 104 quoted SMEs in China's mobile manufacturing supply chain, covering the period from 2011 to 2019	Credit risk assessment and prediction of risky vs. non-risky SMEs
32	Leng et al. [2017]	Directed, Weighted	Data from a real SME loan guarantee network in Hangzhou, Zhejiang province, China, involving 13 SMEs	SME credit risk assessment, systemic risk analysis
33	Kang et al. [2021]	Undirected, Weighted	Financial data provided by a leading Chinese fintech company, covering 30,112 loan applicants from March 1, 2015, to March 31, 2017	Credit risk assessment and reject inference
34	Shi and Zhao [2023]	Directed, Weighted	Publicly available financial report dataset demonstrating fraud and non-fraud cases from multiple sectors	Financial fraud detection
35	Jin et al. [2024]	Directed, Weighted	Data from banks and firms in China, covering interbank loans, firm-bank loans, and cross-shareholding relationships	Risk contagion analysis, Systemic risk management

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	Citation Key	Type of graph	Data Source	Task type
36	Tonzer [2015]	Directed, Weighted	Annual data for banking systems of 15 European countries, Canada, Japan, and the United States from 1994 to 2012, including bilateral cross-border asset and liability positions from BIS and country-specific banking sector data from Bankscope and World Bank	Banks' risk assessment, financial stability analysis
37	Liu et al. [2022]	Undirected, Weighted	Lending Club dataset from 2007 to 2016, including personal and demographic information of applicants	Credit risk assessment and default prediction
38	Lin et al. [2022]	Directed, Weighted	Data from various financial institutions and CEO interactions, simulated data for model validation	Financial risk spreading, Systemic risk management
39	Ouyang et al. [2020]	Directed, Weighted	Weekly stock market closing price data from 16 listed Chinese banks, Baidu search index, and various macroeconomic indicators from January 2014 to September 2018	Systemic risk measurement and contagion risk analysis
40	Brownlees et al. [2021]	Directed, Weighted	Markit, providing daily CDS spreads for one-year to ten-year contracts for Eurozone banks and sovereigns from January 2006 to December 2013	Credit risk assessment and network analysis

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	Citation Key	Type of graph	Data Source	Task type
41	Poledna et al. [2015]	Directed, Weighted	Data from Banco de México, covering daily exposures between major Mexican financial intermediaries from 2007 to 2013 across four markets: derivatives, securities, foreign exchange, and deposits & loans	Systemic risk assessment, Quantification of financial crises costs
42	Zhang et al. [2024]	Undirected, Weighted	Transaction data between enterprises in China, including sales and input invoice data for 123 MSMEs from an enterprise credit assessment platform	Credit risk assessment, Credit strategy development
43	Óskarsdóttir and Bravo [2021]	Multilayer Network, Directed, Weighted	Agricultural lending dataset from a Latin American country, covering loans between 1998-2013, including loan information, sociodemographic data, and past financial behavior.	Credit risk assessment and loan default prediction
44	Kanno [2022]	Directed, Weighted	Data from Refinitiv LPC's DealScan database, covering syndicated loan deals for J-REITs from FY2013 to FY2021, including information on lenders, borrowers, loan amounts, and maturity periods	Risk contagion analysis, Credit risk assessment

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	Citation Key	Type of graph	Data Source	Task type
45	Long et al. [2022]	Undirected, Weighted	Data from a Chinese regional commercial bank and Qichacha (an enterprise information inquiry website) covering manufacturing SMEs and NEEQ SMEs in China from 2016 to 2020	Credit risk assessment, Relational risk quantification
46	Paraíso et al. [2021]	Directed, Weighted	Dataset from a microfinance institution in Sub-Saharan Africa, including smartphone data for 11,486 loans from 2016 to 2020	Credit scoring, Loan classification
47	Chen et al. [2020]	Directed, Weighted	Balance sheet data from banks in the interbank lending market, including interbank assets, liabilities, and external assets	Credit risk contagion analysis, Systemic risk management
48	Rishehchi Fayyaz et al. [2020]	Directed, Weighted	SCF data from an automotive industry in Iran, including financial transactions and organizational attributes of 500 actors in the SCF network	Credit risk assessment and prediction of actor defaults
49	Wei et al. [2024]	Directed, Weighted	Real-world multi-source data on SMEs in China, covering enterprise business information and litigation events from 2014 to 2021	Bankruptcy prediction for SMEs

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	Citation Key	Type of graph	Data Source	Task type
50	Anagnostou et al. [2018]	Directed, Weighted	CDS data for synthetic test portfolios, calibrated with real data from sovereign and corporate bonds in various countries	Portfolio credit risk estimation and extreme loss prediction
51	Yıldırım et al. [2021]	Undirected, Weighted	Financial data for over one million companies in Turkey from 2010 to 2018, including balance sheet, credit, and invoice datasets	Default prediction
52	Hurd et al. [2017]	Directed, Weighted	Theoretical Model	Modeling and Simulation
53	Behbehani et al. [2023]	Directed, Dynamic Bayesian Network	Case study based on the Capital One breach, synthetic dataset generated using vulnerabilities from NVD, exploit-db.com, and AlienVault OTX Pulse.	Dynamic Risk Assessment
54	d'Ambrosio et al. [2023]	Directed, Bayesian Threat Graph (BTG)	Theoretical model based on existing literature and empirical data, including vulnerability databases and global security incident trends.	Risk Management and Cybersecurity
55	Mou et al. [2020]	Directed, Weighted	Proprietary dataset from a financial firm in Manila, Philippines, including 784 loan contracts and 4,142,474 individual SMS and voice communications.	Risk Assessment

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	Citation Key	Type of graph	Data Source	Task type
56	Chen et al. [2021]	Undirected, Weighted, Scale-free Network (BA model)	Theoretical model based on empirical studies and simulation data representing the supply chain finance network and the impact of COVID-19.	Credit Risk Contagion Analysis
57	Cinicioglu et al. [2024]	Directed, Bayesian Network	Daily CDS values from 17 EU countries, obtained from Refinitiv Datastream database.	Systemic Risk Assessment
58	Ağca et al. [2023]	Undirected, Network-based (Complex Network Analysis)	Theoretical model based on empirical data from financial statements and supply chain information of firms. Specific data details are not provided in the summary but would typically include financial ratios, credit ratings, and inter-firm transaction data.	Credit Risk Contagion Analysis
59	Liu et al. [2024]			
60	Durango-Gutiérrez et al. [2023]	Not specified	Data from two microcredit portfolios in Bolivia and Colombia, containing 4,758 entries for Bolivia and 2,627 entries for Colombia.	Credit Risk Assessment

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	Citation Key	Type of graph	Data Source	Task type
61	Kanno [2024]	Correlation-based Network	Sovereign CDS spreads, sovereign bond yields, and recovery rates from Refinitiv Datastream for G7+5 countries. Macroeconomic and COVID-19-related data from various sources, including Datastream, Eikon, and government statements.	Sovereign Default Risk Assessment
62	Zhang and Nan [2023]	Directed, Weighted, Dynamic Network	Daily closing price data of 31 associated enterprises in Evergrande's supply chain from January 2, 2020, to December 27, 2021, obtained from the Choice database.	Financial Risk Spillover and Contagion Analysis
63	Chen et al. [2024]	Directed, Weighted Network	Sovereign CDS spreads, stock market data, bond yields, and exchange rates from various financial institutions in China from 2011 to 2021.	Systemic Risk Assessment
64	Ben Amor et al. [2022]	Directed, Weighted	Bloomberg, market indices, macroeconomic data from Adrian and Brunnermeier (2016)	Risk Assessment, Portfolio Optimization
65	D'Innocenzo et al. [2023]	Dynamic Diagonal Spatial Model	Weekly changes of 5-year government yield spreads from Datastream and Bloomberg (2009-2022)	Risk assessment, Empirical modeling

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	Citation Key	Type of graph	Data Source	Task type
66	Jović and Đaković [2022]	Undirected Network	Bank non-performing loans (NPL) data, macroeconomic variables from the National Bank of Serbia and the Statistical Office of the Republic of Serbia	Risk assessment, Analysis of credit contagion
67	Qian et al. [2023]	Undirected, Unweighted Network	Financial data from interconnected enterprises (supply chain relationships, credit reports)	Risk assessment, Strategy evaluation
68	Wang et al. [2019]	Undirected, Weighted Network	Financial data from credit asset markets, behavioral finance data	Risk assessment, Contagion analysis
69	Zhu et al. [2019]			
70	Naeem et al. [2024]	Directed, Weighted Networks	Proprietary datasets from financial institutions detailing bilateral exposures and balance sheet information	Risk Assessment
71	Ahelegbey et al. [2022]	Multilayer, directed, weighted, time-varying graph	Interbank market transaction data, balance sheet data, public financial statements	Network analysis, risk propagation, stability assessment
72	Gu et al. [2019]	Dynamic, Directed, Weighted Network	Banking data including interbank lending, balance sheets, financial statements	Risk assessment, Systemic risk analysis
73	Jin [2021]			
74	Maghyereh and Abdoh [2024]	Directed, Weighted, and Unweighted Graphs	Financial Data from Enterprises, Simulated Data	Credit Risk Contagion Control
75	Chen et al. [2022]	Directed; Weighted	Chinese lending platform	Predictive analysis
76	Kou et al. [2021]	Directed; Weighted	SME data	Predictive analysis

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	Citation Key	Type of graph	Data Source	Task type
77	Sukharev et al. [2020]	Directed; Weighted	Bank transactional data	Credit scoring
78	Zhou et al. [2023]	Directed; Weighted	Credit default datasets	Risk prediction