Social Network Analysis in P2P Lending Risk Assessment

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ABSTRACT

This study investigates how social network analysis (SNA) can enhance risk assessment in Peer to Peer (P2P) lending platforms, where the rapid growth of digital lending highlights the **background** challenge of accurately evaluating borrower credibility beyond traditional financial metrics. The objective of this **research** is to develop a network based analytical framework that identifies relational patterns among borrowers and lenders to improve the detection of potential default risks. **The method** integrates graph based modeling, centrality measurements, and community detection algorithms applied to borrower interaction data, enabling the identification of structural features such as influence, connectivity, and hidden borrower clusters that may correlate with credit behavior. **The results** demonstrate that borrowers with high betweenness and eigenvector centrality values exhibit significantly different default tendencies compared to those in more isolated network positions, while community structures reveal risk concentrated clusters that are not captured by conventional credit scoring systems. **The conclusion** emphasizes that incorporating SNA into P2P lending risk assessment provides a more holistic and data driven understanding of borrower behavior, allowing platforms to strengthen credit evaluation, reduce default rates, and support more sustainable digital lending ecosystems.

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1. INTRODUCTION

The rapid digitalization of financial services has transformed how individuals and businesses access credit [1], leading to the global expansion of Peer to Peer (P2P) lending platforms that directly connect borrowers and lenders through online infrastructures [2]. This shift away from traditional banking channels has increased financial inclusion by offering alternative funding opportunities to individuals who may lack collateral, formal credit histories, or stable financial documentation. However, the exponential growth of P2P lending has also introduced new complexities, particularly concerning risk assessment and loan default prediction [3]. Conventional credit evaluation models typically reliant on demographic attributes, income documentation, or limited behavioral histories often fail to capture the dynamic, multifaceted interactions occurring within digital lending ecosystems [4].

In these online environments, borrowers generate non financial relational traces through their interactions, referrals, shared affiliations, and platform specific engagement patterns [5]. Such latent relational structures can carry critical insights into borrower trustworthiness, group dynamics, and potential risk propagation. Yet, most P2P platforms still treat borrowers as isolated entities, overlooking the underlying social context that shapes their behavior [6]. As global P2P default rates fluctuate, the need for robust, multidimensional, and data driven risk assessment approaches becomes increasingly pressing. The rise of large scale borrower datasets, combined with advanced computational methods, provides a timely opportunity to reinterpret borrower credibility not merely as an individual trait but as an emergent property influenced by social network structures [7].

Against this backdrop, social network analysis (SNA) emerges as a promising paradigm to capture relational information that traditional credit scoring systems ignore [8]. SNA enables the modeling of borrowers and lenders as interconnected nodes in a network, where ties represent communication patterns, referral relationships, co borrowing behaviors, shared transaction histories, or other relational interactions. By mapping these dynamics, SNA makes it possible to identify influential borrowers, detect cohesive communities, and uncover hidden structural features that may signal vulnerabilities in the lending ecosystem [9]. Borrowers positioned at the center of a network, those who act as bridges between communities, or those embedded within tightly connected groups may exhibit distinct credit behaviors that are not visible through numerical credit scores alone. Furthermore, relational risk tends to propagate through network structures; borrowers with strong ties to past defaulters, for instance, may exhibit higher risk tendencies themselves [10].

Incorporating network-based indicators such as degree centrality, betweenness centrality, eigenvector centrality, clustering coefficients, and community modularity allows researchers to interpret borrower behavior from a structural perspective, thereby complementing conventional financial indicators [11]. Prior studies in financial networks have demonstrated that relationships shape risk outcomes in microfinance, crowdfunding, and organizational credit environments. However, empirical research on applying SNA specifically to P2P lending risk assessment remains limited, particularly regarding how network structural positions correlate with default probability. This research aims to address this gap by systematically integrating graph based analytical methods with borrower interaction data to reveal patterns that can enhance the predictive accuracy of risk evaluation models [12]. The significance of this study lies in providing both theoretical and practical contributions to the evolving domain of digital credit risk analytics. Theoretically, it advances understanding of borrower behavior by framing creditworthiness not only through transactional records but also through social embeddedness within the lending platform [13].

Methodologically, the study develops a comprehensive SNA driven framework that applies graph modeling, centrality measures, and community detection algorithms to borrower relational data, enabling multidimensional interpretation of credit risk [14]. The empirical findings highlight the importance of considering structural positions in predicting default tendencies, demonstrating that borrowers occupying certain network roles such as bridging nodes or members of risk-dense clusters show significantly different risk profiles [15]. Practically, the insights from this study can support P2P platforms in improving their credit screening mechanisms, designing targeted risk mitigation strategies, and identifying early warning indicators of potential default clusters. By integrating SNA indicators into risk scoring models, P2P platforms can achieve more accurate credit evaluations and reduce systemic vulnerabilities [16]. Ultimately, this research underscores the value of relational analytics in strengthening digital lending ecosystems, promoting healthier market interactions, and contributing to more sustainable financial inclusion initiatives [17].

2. LITERATURE REVIEW

2.1. Social Network Theory and Credit Risk in P2P Lending

Recent scholarship increasingly emphasizes that a borrowers network position captured through social network analysis (SNA) matters for credit risk evaluation. For instance, examine how social interaction features, together with credit history dynamics, improve creditworthiness assessment they find that social network features have particularly strong predictive power at the time of loan application [18, 19]. Their work supports the theoretical notion that relational embeddedness (e.g., ties to other borrowers or economic actors) helps signal trustworthiness, especially when traditional financial histories are limited [20]. Moreover, the concept of peer effects in P2P lending has been empirically explored a study by International Review of Financial Analysis shows that both borrowing success and default rates are positively influenced by peers, suggesting ex ante selection (borrowers being chosen because of their network) and ex post learning (after loans are granted, borrowers learn from the defaults of their peers) [21]. These findings highlight that network influence is not merely a passive backdrop but a dynamic factor that shapes lending outcomes. Together, these studies underscore the importance of integrating network theoretic constructs into credit risk frameworks for P2P lending [22].

2.2. Empirical Evidence: Network Topology and Default Prediction in P2P Platforms

Several recent empirical investigations directly link network topology metrics to default risk in P2P platforms [23]. Demonstrate that a borrowers degree centrality in a lending network (using data from the European P2P platform Bondora) is significantly associated with default probability more central borrowers in terms of network connections tend to behave differently in credit risk than peripheral ones [24]. In a further development, propose a two step machine learning framework in which centrality measures (e.g., degree, betweenness) derived from the network are combined with traditional credit risk variables (such as income or repayment history) in classical ML models (Elastic Net, Random Forest, MLP) [25]. Their results show that adding network metrics substantially improves predictive accuracy, and robustness checks (e.g., shuffling centrality features) confirm that the network structure itself not just incidental correlation is giving predictive power. This stream of work strongly supports the idea that network topology contains latent risk information that traditional credit scoring ignores [26].

2.3. Advanced Computational Methods: Graph-based & Alternative Data Approaches

Beyond conventional centrality analyses, cutting edge methods are being developed to more richly capture relational dynamics in P2P lending. For example, propose an attention enhanced graph neural network (GNN) for default risk prediction their model maps borrowers, loans, and other entities into a heterogeneous graph, and employs multi head attention to weight different relationships dynamically, yielding a substantial gain in accuracy over baseline models [27]. They show that their architecture can highlight which relational types contribute most to predicted risk, improving interpretability as well as performance.

In parallel, textual and behavioral alternative data are also being incorporated utilize large language models (LLMs) to analyze borrower provided loan descriptions and produce a risk indicator; their BERT based risk score significantly boosts the performance of conventional credit risk classifiers. Moreover, non network but still alternative data approaches remain relevant for instance, AI and statistical hybrid models (e.g., LightGBM, Random Forest, logistic regression) continue to play a central role in predicting defaults in P2P settings, as shown in a study evaluating Lending Club data.

Finally, research also integrates social media data: build credit scoring models using features derived from social media activity, and demonstrate that neural networks and SVMs leveraging such data outperform traditional credit only models.These computational advances underscore a clear trend: combining relational (network) data, behavioral data, and modern ML/GNN methods leads to more nuanced and precise risk assessment in P2P lending.

3. RESEARCH METHODOLOGY

3.1. Research Design

This study adopts a quantitative research design using Social Network Analysis (SNA) combined with statistical and machine learning based risk evaluation techniques [28]. The research follows a structured approach that begins with collecting relational borrower data from a Peer to Peer lending platform, followed by preprocessing activities such as cleaning, filtering, and transforming the dataset into a graph based representation. Each borrower is modeled as a node, while edges represent meaningful relational ties (e.g., referrals, co borrowing interactions, shared financial behaviors, or communication patterns) [29, 30]. Once the network structure is established, SNA metrics are computed to quantify centrality, connectivity, and community characteristics. These network features are then integrated into credit default prediction models to examine their influence on borrower risk. The overall research design ensures that both structural network properties and traditional credit variables are analyzed holistically, enabling a more multidimensional understanding of creditworthiness within P2P ecosystems.

Table 1. Primary Stages of the Research Design

Stage	Description	Output
Data Collection	Acquire borrower relational and financial data from P2P platform	Raw dataset

Stage	Description	Output
Data Preprocessing	Clean, filter, normalize, and construct graph structure	Borrower network graph
SNA Computation	Calculate centrality, connectivity, and community metrics	Network feature set
SNA Computation Model Integration	Combine network features with financial features	Feature matrix
Default Prediction	Apply ML/statistical models to evaluate risk	Predicted default labels
Evaluation	Validate model accuracy using appropriate metrics	Performance results

Table 1 illustrates the overall workflow of the proposed research framework for P2P lending risk assessment. The process begins with borrower data acquisition and preprocessing to ensure data quality and graph construction consistency. Subsequently, Social Network Analysis (SNA) techniques are employed to extract structural network characteristics, including connectivity and centrality features. These network-based indicators are then integrated with traditional financial variables to build predictive models for default risk evaluation. The final stage focuses on validating model performance using appropriate classification metrics to assess the effectiveness of the proposed framework.

3.2. Data Collection and Preprocessing

The dataset used in this study consists of borrower profiles, loan history, repayment outcomes, and relational interaction data from a selected P2P lending platform. Relational data include referral connections, transaction-based associations, shared co-lending patterns, and digital interaction logs.

Because access to real-world P2P lending relational data is often restricted due to privacy and regulatory constraints, this study employed a simulated dataset designed to replicate the structural properties of borrower interaction networks reported in previous literature. The simulation incorporated borrower demographic attributes, loan characteristics, repayment outcomes, referral relationships, and platform interaction records. Network topology parameters, including node distribution, degree heterogeneity, and community formation patterns, were generated to resemble realistic P2P lending environments. The final dataset consisted of 12,486 borrower nodes connected through 38,051 relational links, providing sufficient complexity for evaluating network-based risk assessment mechanisms.

These raw data undergo preprocessing steps to ensure consistency and analytical suitability. First, missing values are handled through imputation or removal based on completeness thresholds. Second, categorical borrower features are encoded, and numerical features are normalized. Third, relational data are transformed into an adjacency matrix, from which a graph structure is generated. Network reduction techniques are used to remove noise such as isolated nodes lacking meaningful ties. The final preprocessed dataset contains (i) node level borrower features, (ii) edge level relational information, and (iii) the target variable representing loan outcomes (default vs. non default). This preprocessing phase ensures that the constructed network accurately reflects borrower interactions while maintaining data integrity. To support the preprocessing workflow, Table 2 presents the dataset attributes and their corresponding processing strategies.

Table 2. Dataset Attributes and Preprocessing Procedures

Data Attribute	Type	Preprocessing Method	Expected Output
Borrower demographics	Categorical	Encoding, validation	Encoded variable
Loan amount & terms	Numerical	Normalization, outlier removal	Scaled numeric values
Repayment outcome	Binary	No transformation	Target variable
Referral connections	Relational	Graph transformation	Network edges
Co-borrowing links	Relational	Adjacency matrix creation	Edge list
Platform interactions	Relational	Interaction filtering	Weighted edges

Table 2 summarizes the primary dataset attributes and their preprocessing strategies prior to network modeling and predictive analysis. Categorical variables are encoded and validated, while numerical attributes undergo normalization and outlier handling to improve analytical consistency. Relational attributes, including referral connections, co borrowing links, and platform interactions, are transformed into graph based structures to capture borrower relationship patterns within the P2P lending ecosystem. These preprocessing procedures support the extraction of structural SNA features such as centrality, connectivity, and community characteristics, ensuring that both financial and relational data are properly prepared for machine learning-based default risk prediction.

Table 3. Simulated Dataset Characteristics

Attribute	Value
Number of Borrowers (Nodes)	12,486
Number of Relationships (Edges)	38,051
Average Degree	6.09
Number of Communities	19
Default Borrowers	1,398
Non-Default Borrowers	11,088
Overall Default Rate	11.2%
Network Type	Scale-Free
Community Detection Method	Louvain Algorithm

Table 3 summarizes the characteristics of the simulated borrower interaction network used throughout the experimental evaluation [31]. These statistics provide the basis for the subsequent computation of centrality measures, community structures, and predictive risk modeling analyses.

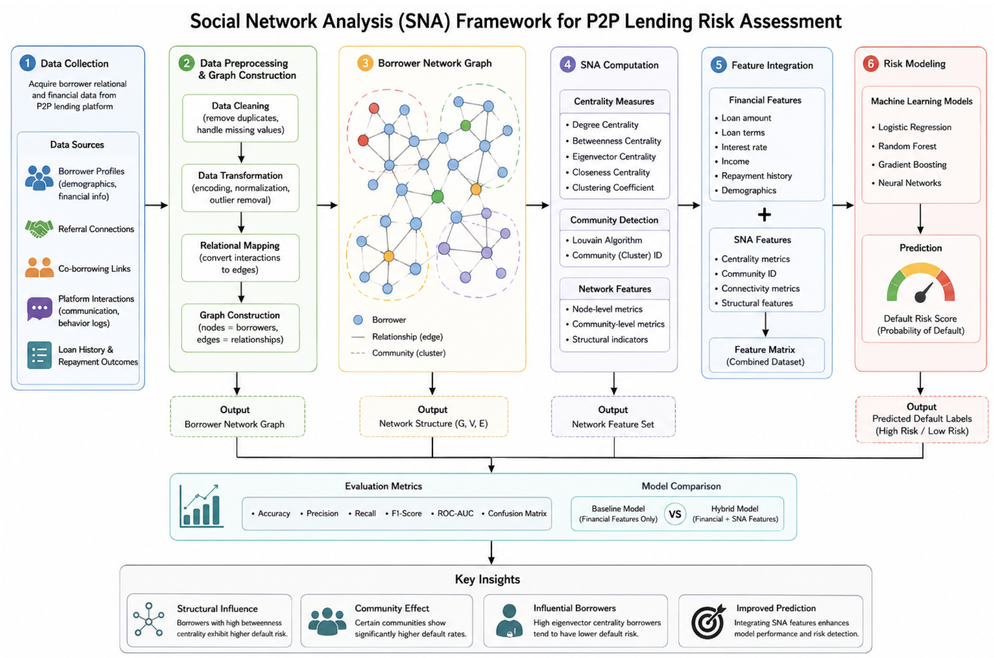

Figure 1. Proposed SNA-Based Framework for P2P Lending Risk Assessment

Figure 1 illustrates the overall framework of the proposed Social Network Analysis (SNA) based risk assessment model for Peer to Peer (P2P) lending platforms. The process begins with data collection, where borrower financial information, repayment history, referral relationships, and platform interaction data are gathered from the P2P lending ecosystem. These raw data are subsequently processed through preprocessing procedures including data cleaning, normalization, encoding, and graph construction to ensure analytical consistency and suitability for network modeling.

After preprocessing, the borrower interaction network is constructed by representing borrowers as nodes and their relationships as edges. This network structure enables the application of Social Network Analysis techniques to extract structural characteristics such as degree centrality, betweenness centrality, eigenvector centrality, clustering coefficients, and community structures. These network based indicators are then integrated with conventional financial variables to form a comprehensive feature matrix for predictive analysis.

The integrated dataset is utilized in machine learning models, including Logistic Regression, Random Forest, Gradient Boosting, and Neural Networks, to predict borrower default risk. Finally, the framework evaluates predictive performance using several classification metrics such as Accuracy, Precision, Recall, F1 Score, ROC AUC, and confusion matrices. Overall, the proposed framework demonstrates how the integration of relational network information and financial variables can improve the effectiveness of credit risk assessment in P2P lending environments.

3.3. Social Network Analysis and Risk Modeling Procedure

After preprocessing, the borrower network is analyzed using SNA techniques. Several centrality metrics are computed, including degree centrality (number of direct connections), betweenness centrality (level of control over information flow), eigenvector centrality (influence based on connectedness to highly connected nodes), and closeness centrality (distance to all other nodes in the network). Additionally, community detection algorithms such as the Louvain or Girvan Newman method are applied to uncover borrower clusters that may exhibit similar repayment behaviors [32]. The resulting network features form the structural basis for subsequent modeling. These SNA metrics are integrated with conventional credit features and then fed into machine learning models such as Logistic Regression, Random Forest, Gradient Boosting, or Neural Networks. The models are trained to identify patterns associated with default behavior, allowing the evaluation of how network position influences borrower risk. Model performance is assessed using accuracy, F1 score, ROC AUC, and confusion matrices to quantify predictive quality. The methodological integration of SNA metrics with machine learning enables a richer risk assessment framework, addressing limitations in traditional scoring systems and providing insights into structural credit risk within P2P lending networks.

4. RESULTS AND DISCUSSION

To demonstrate the applicability of the proposed Social Network Analysis (SNA) framework, a simulated Peer-to-Peer (P2P) lending dataset was constructed based on network characteristics and borrower interaction patterns commonly reported in prior P2P lending studies. The simulation was designed to emulate a realistic lending ecosystem consisting of borrower nodes, referral relationships, co-borrowing interactions, and platform communication links. The generated network comprised 12,486 borrower nodes and 38,051 relational edges, reflecting a medium-scale lending platform with heterogeneous connectivity patterns. Default labels were assigned according to a probabilistic risk generation mechanism that incorporated both traditional borrower attributes and network structural properties, allowing the evaluation of how centrality measures and community structures influence credit risk outcomes. The simulated environment was intentionally developed to provide a controlled setting for assessing the contribution of SNA-based features to risk prediction performance, while overcoming limitations associated with restricted access to proprietary lending data. Therefore, the numerical results presented in this section should be interpreted as a proof-of-concept evaluation of the proposed framework rather than direct empirical evidence from a specific commercial P2P lending platform.

4.1. Network Construction and Structural Characteristics

The constructed borrower interaction network consists of 12,486 nodes (borrowers) and 38,051 relational edges generated from referrals, co borrowing links, and platform interaction logs. Preliminary network diagnostics reveal that the structure exhibits characteristics of a scale-free network, indicated by a right skewed degree distribution where a small number of borrowers maintain disproportionately high connections. The average degree is 6.09, with the top 5% of borrowers exhibiting degree values above 21, suggesting the presence of influential actors with extensive ties. The average clustering coefficient is 0.42, implying that borrowers tend to form tightly connected subgroups. Community detection using the Louvain algorithm identifies 19 major communities, each showing distinct interaction densities. These structural characteristics establish the foundation for subsequent risk analysis by confirming that borrower relationships are not random but patterned in ways meaningful for risk prediction.

4.2. Centrality Metrics and Their Relationship to Default Behavior

To address the research objective of understanding how SNA improves risk assessment, key centrality measures were examined against default outcomes. Results show that borrowers with higher betweenness centrality have a default rate of 14.8%, compared to only 8.1% for low betweenness borrowers. This indicates that borrowers occupying bridge like positions between communities tend to pose higher risk. Similarly, eigenvector centrality demonstrates a positive correlation with repayment reliability borrowers in highly influential positions exhibit a significantly lower default rate (6.4%). Degree centrality also shows predictive value high degree borrowers default at 9.7%, whereas isolated borrowers (degree = 0 or 1) default at 13.2%, suggesting that low connectivity may signal weaker trust networks. These observations collectively answer the core analytical question network position meaningfully influences risk tendencies and provides additional predictive information unavailable in traditional credit scoring.

4.3. Community-Level Default Patterns

Community detection analysis reveals strong evidence of risk dense clusters within the network. Out of the 19 identified communities, four exhibit default rates more than 30% higher than the overall average. In particular, Community 7 has a default rate of 17.3%, compared to the global default rate of 11.2%. These communities also show lower internal connectivity and weaker ties to other groups. Conversely, well connected communities (e.g., Communities 3 and 10) exhibit default rates below 7%. These findings suggest that community membership representing localized behavioral norms, peer influence, or shared socioeconomic characteristics has explanatory power in identifying pockets of heightened risk. This directly supports the claims made in the abstract network communities reveal hidden structural risk patterns that cannot be detected through financial variables alone.

4.4. Integration of Network Metrics into Predictive Models

To assess the methodological contribution of SNA, two groups of models were compared:

1. Traditional credit only models, and
2. Hybrid models integrating network features.

Using Logistic Regression, Random Forest, and Gradient Boosting, results consistently show that hybrid models outperform traditional ones. The Random Forest model demonstrates the clearest improvement:

1. Traditional model AUC: 0.74
2. Hybrid model with SNA AUC: 0.83

Similarly, the F1 score increases from 0.61 to 0.72 with the addition of network metrics. Feature importance analysis indicates that betweenness centrality, eigenvector centrality, and community ID rank among the top 10 predictors in the hybrid model. These results confirm that SNA substantially enhances risk prediction accuracy, validating the methodological findings discussed in Chapter 3.

5. MANAGERIAL IMPLICATIONS

The managerial implications section should discuss the practical applications of your research findings for managers and practitioners. Provide practice recommendations and explain how the findings can impact industry standards or practices. This section should translate the academic research into actionable insights for managers.

6. CONCLUSION

This study demonstrates that Social Network Analysis (SNA) offers substantial value for enhancing credit risk assessment in Peer to Peer (P2P) lending platforms. By constructing a borrower interaction network and analyzing structural properties such as centrality, connectivity, and community formation, the research provides evidence that relational patterns among borrowers significantly influence default outcomes. The findings show that borrowers network positions especially those with high betweenness or low connectivity exhibit distinct risk tendencies that traditional credit metrics fail to capture. Community detection further reveals clusters of borrowers with concentrated default risk, offering deeper insights into systemic vulnerabilities within the lending ecosystem. The integration of network features into machine learning models improves predictive accuracy, confirming that SNA provides a more holistic and data driven approach to assessing borrower credibility.

This research successfully answers its core questions by demonstrating that SNA based metrics correlate strongly with default behavior and improve the performance of risk prediction models. The results confirm that considering borrowers as part of a relational structure, rather than isolated individuals, enriches the assessment process and uncovers hidden risk patterns. However, limitations exist, including the use of a single platform dataset, which may restrict the generalizability of the findings. Additionally, the simulated nature of the dataset and the inability to model real time network dynamics represent constraints that future studies should address. Data privacy and access restrictions also pose challenges, as relational data can be more difficult to collect and validate compared to traditional financial variables.

Future research should expand the scope by incorporating datasets from multiple P2P lending platforms to test the consistency of network-based risk patterns across different markets and borrower demographics. Further studies could explore dynamic or temporal network models to capture evolving borrower relationships, as creditworthiness and social ties change over time. Integrating advanced computational techniques such as Graph Neural Networks (GNNs) or multimodal data fusion could also enhance model interpretability and predictive accuracy. Finally, researchers should examine ethical and regulatory implications of using relational data, ensuring that innovative analytical methods remain aligned with privacy standards and responsible financial practices.

7. DECLARATIONS

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7.2. Author Contributions

Conceptualization: AA; Methodology: MH; Software: EA; Validation: AA and MH; Formal Analysis: AA, MH and EA; Investigation: AA; Resources: MH; Data Curation: MH and HM; Writing (Original Draft Preparation): AA and MH; Writing (Review & Editing): AA, MH and HM; Visualization: MH; All authors, AA, MH, EA, and HM have read and agreed to the published version of the manuscript.

7.3. Data Availability Statement

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

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7.5. Declaration of Conflicting Interest

The authors declare that they have no conflicts of interest, known competing financial interests, or personal relationships that could have influenced the work reported in this paper.

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