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Apostolos Dasilas, Margarita Trachana

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AI-Driven Risk Mitigation in Peer-to-Peer Lending: A Systematic Literature Review and Bibliometric Analysis

Apostolos Dasilas*[1] and Margarita Trachana[2]

[1] Department of Applied Informatics, University of Macedonia
156 Egnatia str., P.O. Box 1591, 54636 Thessaloniki, Greece
Tel: +30-2310891883
E-mail: dasilas@uom.edu.gr
[2] Department of Applied Informatics, University of Macedonia
156 Egnatia str., P.O. Box 1591, 54636 Thessaloniki, Greece
Tel: +30-2310891883
E-mail: mtrachana@uom.edu.gr

Abstract

Peer-to-Peer (P2P) lending has evolved into a dynamic financial sector in recent year, attracting both investors and borrowers. This paper intends to perform a systematic literature review (SLR) to examine recent trends related to cutting-edge models, investigate the influence of artificial intelligence, comprehend market dynamics, and evaluate as well as manage the risks linked to P2P lending platforms over the last decade. Several elements can impact these risks, including the platform's design, regulatory environment, organizational structure, types of transactions, and the interrelationships among organizational components. The systematic analysis categorizes documents based on their methodological aspects and business considerations. Many proposals incorporate artificial intelligence, deep learning, or machine learning techniques; however, they often overlook the context of application, relevant variables within a business framework, explainability, and other critical factors. This study provides recommendations and outlines future research directions, emphasizing the need for further exploration in this field. The models are also applied to explore the factors that influence the success or failure of various peer-to-peer (P2P) platforms, considering both financial and information systems perspectives. Additionally, we aim to suggest strategies to mitigate the potential risks associated with P2P lending platforms.

Keywords: Risk Management, Bibliometric Analysis, Systematic Literature Review, Risk Categorization, Artificial Intelligence Methods

* (Corresponding author) Department of Applied Informatics, University of Macedonia, dasilas@uom.edu.gr

1 Introduction

Financial Technology (FinTech) has significantly revolutionized the investment sector by redefining how individuals and organizations interact with financial markets, using cutting-edge platforms that increase efficiency, accessibility, and the overall investing experience (Josyula, 2021). One key development of FinTech is peer-to-peer (P2P) lending, which allows borrowers to connect directly with lenders, bypassing traditional banks and enhancing financial inclusion, particularly in underbanked regions or for those with poor credit. Online platforms allow borrowers to access a wider range of lenders, while investors can diversify their portfolios across various loans with different risk levels (Al-Hashfi & Zusryn, 2020).

As digital innovation progresses in the financial sector, the peer-to-peer (P2P) lending industry has encountered significant challenges due to rapid platform growth, resulting in economic instability and inequalities. A significant crisis occurred in China in 2018, leading to the collapse of many platforms and causing substantial losses for both investors and borrowers (Pan & Gao, 2017; Ye & Lin, 2023). Contributing factors included regulatory failures, fraud, and lack of transparency. P2P industry rapid expansion outpaced risk management, leading to over 1,000 platform shutdowns by 2018, with losses exceeding $150 million for some, like "Wangdaizhijia." (Jing, 2019; Huang & Pontell, 2022). Despite introducing stricter regulations, many investors suffered losses, underscoring the need for better oversight and effective risk management, which varies globally due to differing regulatory environments (Wang et al., 2022).

Risk management remains central to the sustainability of P2P platforms. In particular, strong Know Your Customer (KYC) procedures are essential for preventing fraud, reducing exposure to money laundering, and ensuring compliance with regulatory standards (Kumar, 2022; Teichmann et al., 2023). However, platforms face multiple challenges, including data quality issues, technological barriers, and the need to balance security with user experience.

Due to the swift evolution of FinTech, numerous previous studies have extensively investigated the risk management in P2P lending platforms, particularly in the last decade (Giudici, 2018; Giudici et al., 2019; Bussmann et al., 2020). Although prior studies on identifying risks in P2P lending platforms have employed statistical techniques and machine learning (ML) methods, there is a need to delve deeper into the use of artificial intelligence (AI) approaches. Moreover, the interpretability of these methods is essential for P2P lending platforms, but more extensive research should be conducted to explore the current state of interpretability in existing research (Isaputra & Sumaryono, 2023). Furthermore, there is a need to investigate how advanced explainability techniques in artificial intelligence (XAI) can be utilized in the P2P lending sector to identify and explain various risks.

P2P lending platforms encounter a multitude of risks, including credit, operational, and market risks. Traditional statistical techniques often struggle to capture the complex patterns within large datasets, while AI can adeptly analyze and interpret this data (Zhang et al., 2020). Given the substantial volume and diversity of data produced by P2P lending platforms, AI technologies, particularly ML, can facilitate thorough risk analysis quickly (Smith & Jones, 2021). The financial landscape is ever-changing, and AI systems can adapt to emerging risks, providing a flexible and proactive approach to risk management (Brown, 2022). However, there remains a significant gap in the interpretability of AI algorithms, which is essential for building stakeholder trust (Lee, 2023). Addressing the underutilization of explainability techniques will be crucial for ensuring regulatory compliance, informing risk management strategies, and fostering transparency within the P2P lending ecosystem (Garcia, 2020).

The objectives of this systematic literature review paper are to pinpoint the machine learning or deep learning methods utilized for management risk in P2P lending platforms, conduct a thorough and meticulous review of the existing research on the P2P lending sector, assess the interpretability of existing research and highlight the most effective explainable artificial intelligence (XAI) techniques used in the P2P lending sector. To address these objectives, the following four research questions call for investigation:

- RQ1: How has research on AI-driven risk mitigation in P2P lending sector evolved over the last decade?
- RQ2: What key datasets, variables, and challenges (e.g, data quality, accessibility and privacy) are reported in literature?
- RQ3: Which Artificial Intelligence (AI) methods have been applied to address different risk categories (credit, fraud, operational, liquidity/systemic)?
- RQ4: What evaluation metrics are used to assess AI effectiveness, fairness, and trust in comparison to traditional approaches?
- RQ5: What research gaps and future directions can be identified to improve AI-based risk mitigation in P2P lending?

This study contributes to the P2P discourse by conducting a critical assessment of the advantages and drawbacks of diverse approaches used in the P2P lending industry over the past decade, including credit scoring models, artificial intelligence algorithms, and financial ratio analysis. The study aims to help researchers address the initial challenges arising from -FinTech, such as loan defaults, economic risks, and data inequality. Furthermore, the current literature review explores and capitalizes on the new opportunities in the P2P lending sector, making it highly relevant and engaging research. Moreover, this research highlights a significant gap in the literature on the efficacy of traditional and emerging lending approaches in real-world applications. By examining their impact on lending outcomes, we aim to clarify their strengths and weaknesses, particularly in the rapidly evolving P2P lending sector. Additionally, this paper provides new insights in the field, enriching the PRISMA framework and assisting stakeholders in making informed decisions to enhance the industry's sustainability and inclusiveness.

The subsequent structure of this paper unfolds as follows: Section 2 lays out the methodology, research questions, and research protocol; Section 3 delves into analysis; and Section 4 encapsulates main conclusions.

2 Research method

The section outlines a comprehensive approach for gathering, examining, and providing data to generate this review. Following a systematic methodology enhances the quality of the evaluation and allows the research to be reproduced. Previous studies, like the one conducted by Roy and Vasa (2024), effectively used the PRISMA methodology. The current study also employs the PRISMA approach in accordance with the study of Page et al. (2021). PRISMA, an acronym for "Preferred Reporting Items for Systematic Reviews and Meta-Analyses", is renowned for its comprehensive and transparent reporting. Its four main phases – Identification, Screening, Eligibility, and Inclusion – ensure thoroughness in the research process and foster trust and confidence in the research outcomes.

2.1 Identification

In the initial phase, our search criteria were fully immersed in the dynamic world of peer-to-peer lending for our research. We conducted a thorough search in the Scopus and Web of Science (WoS) databases in June 2025, unearthing papers that would significantly enhance our literature review. The search criteria were selected through a meticulous process aimed at exploring the dynamics of the peer-to-peer lending market, delving into modelling methods, untangling risk management intricacies, and comprehending the financial impacts of loan obligations. We focused on identifying "articles", "reviews" and "conference papers" written in English and published in the 10-year search window between 2015 and 2025, as these sources will most likely offer comprehensive and up-to-date information on our research topic. Drawing inspiration from similar studies, we carefully selected relevant keywords for the research to ensure alignment with the broader research community, fostering a sense of connection and shared understanding. The search employed the "TITLE-ABS-KEY":

(("p2p lending" OR "peer-to-peer lending" OR "p2p platform" OR "social lending" OR "p2p credit" OR "peer-to-peer credit" OR "peer-to-peer market")) AND ("machine learning" OR "deep learning" OR "artificial intelligence" OR "data mining") AND ("risk" OR "credit" OR "default" OR "fraud" OR "assessment" OR "profit*" OR "trust" OR "score*" OR "pay*").

This search resulted in 809 studies. The PRISMA methodology ensures transparency, accuracy, and reliability of the systematic review, bibliometric analysis and meta-analysis.

2.2 Screening

The screening phase plays a vital role in improving the analysis's accuracy by selecting and eliminating duplicated and irrelevant articles. The evaluation of titles, abstracts, and keywords, yielded 809 papers from journals, conferences and reviews. Moreover, the conference papers were selected and kept because they offer valuable insights into the most current trends in artificial intelligence such as deep learning and machine learning techniques. After the initial screening, 260 duplicate and irrelevant articles were excluded and, 12 studies were removed due to limited access to full-text context for our analysis. Consequently, 537 studies advanced to the eligibility stage, where a more thorough evaluation was conducted to assess the relevance for inclusion in the systematic review.

2.3 Eligibility

In this phase, the full texts of the selected studies are thoroughly reviewed to assess the eligibility for the review, applying specific inclusion and exclusion criteria for additional screening.

Inclusion Criteria:

- Studies outline the particular types of studies to be considered in the broad area of Artificial Intelligence. This includes research focusing on various aspects of risk management, as well as comparisons of various machine and deep learning techniques against statistical methods.
- Studies encompasses assessments of accuracy, efficiency, fairness, and trustworthiness, highlighting the vast potential for exploration in this field.

Exclusion Criteria

- Studies solely concentrated on statistical methods were excluded.
- Studies are imposed in order to rule out studies that are irrelevant to the risk management of P2P lending platforms. In particular, studies that do not focus on the financial aspects of P2P lending platforms were excluded. For instance, studies related to different markets, such as Uber, smart cities or banking area were removed.

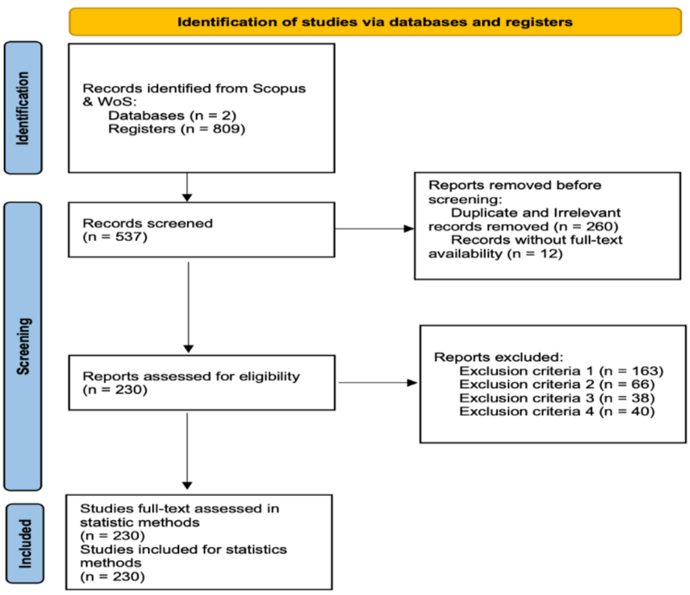
- Studies that did not have accurate information about the artificial intelligence models used were excluded. This specifically relates to a lack of comprehensive descriptions regarding the parameter tuning for each model or the methods employed for feature selection, including techniques like time series analysis, correlation, and regression.
- Studies in the form of short paper or grey literature were considered.

After a thorough examination of the remaining studies, 230 relevant studies were deemed eligible for inclusion in the systematic review. These studies were selected based on criteria focusing on machine learning, deep learning, and artificial intelligence methods within P2P lending platforms.

2.4 Inclusion

The final phase of this research requires the creation of the database for quantitative analysis. 230 empirical studies were reviewed and selected for examination. We collected from these studies such as titles, authors, publication years, journal names, keywords, artificial intelligence models, performance metrics, and validation methods. The analysis was conducted using VosViewer and R programming. PRISMA guidelines, applied on the systematic approach, aiming to provide information regarding the use of artificial intelligence techniques for risk management in P2P lending platforms, thereby enhancing the reliability, validity and trustworthiness of the finding. The flow diagram in Figure 1 shows all steps applied in this study, following the PRISMA guidelines.

Figure 1: PRISMA flow diagram. http://www.prisma-statement.org/PRISMAStatement/FlowDiagram?AspxAutomDetectCokieSupport=1



3 Results

3.1 Bibliometric Analysis

This section presents the results of the bibliometric analysis, followed by the systematic literature review.

3.1.1 Analysis of the publication year, authors, source, and countries distribution

Figure 2 shows the yearly distribution of the 230 selected publications between 2015 and 2025, revealing a strong and consistent upward trend in research on AI-driven risk mitigation in P2P lending. The number of studies increased from only 17 papers in 2015 to a peak of 109 papers in 2024, reflecting the rapid expansion of FinTech applications and the growing reliance on machine learning for credit scoring, fraud detection, and platform risk assessment. A sharp rise begins in 2018 and continues through 2020–2022, with publication volumes remaining high in 2023. The lower count observed for 2025 (56 papers) reflects partial-year data up to Q2, rather than a decline in research activity. Overall, the pattern demonstrates a tenfold growth in publications over a decade, highlighting the increasing academic and practical importance of AI in enhancing risk management across P2P lending platforms.

Figure 2: Year-wise AI methods published in P2P lending domains

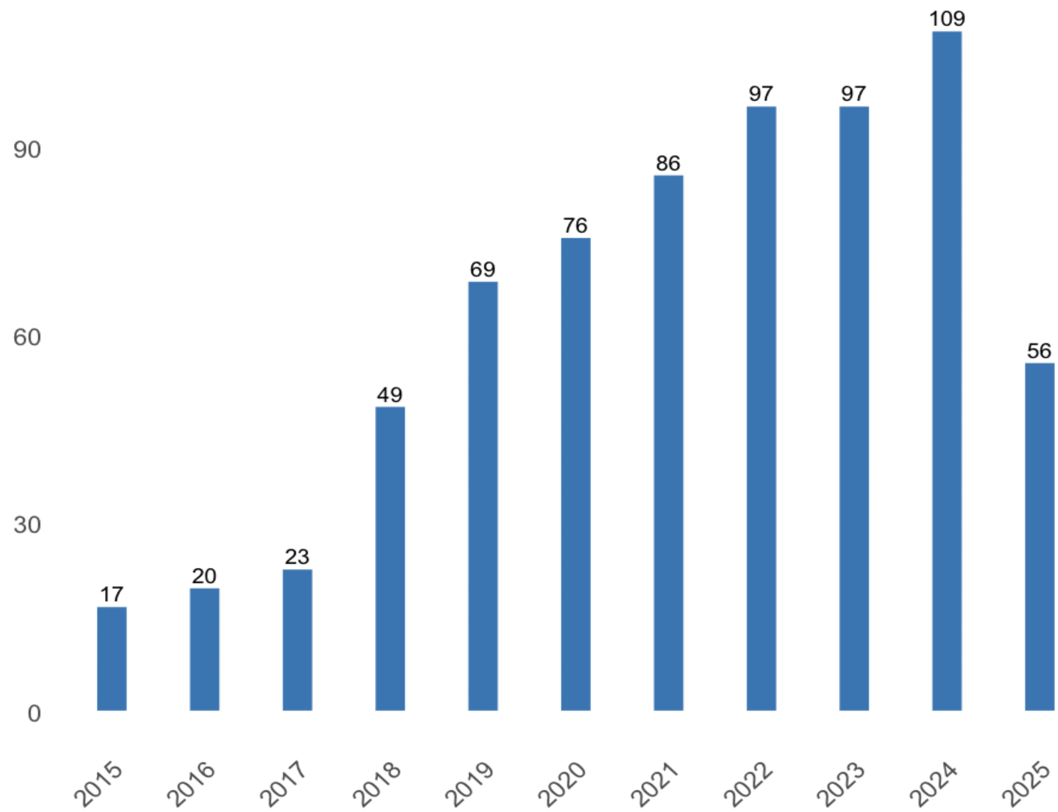


Figure 3 illustrates the international co-authorship network across the 230 selected studies. China emerges as the most active and influential contributor, forming dense collaboration links with several countries, including the United States, the United Kingdom, India, and Indonesia. The United States also plays a central connecting role, linking Asian and European research groups. Additional, though less intense, collaborations appear between China and Japan as well as China and France, indicating a concentrated but robust core of global research activity.

Beyond this core cluster, many countries—particularly in Eastern Europe, Africa, and parts of the Middle East—show minimal or no collaborative connections, highlighting an uneven global distribution of research output. These isolated nodes reflect limited international engagement and point to opportunities for expanding cross-country research partnerships. Strengthening collaboration with underrepresented regions could enrich methodological diversity, broaden dataset availability, and support more globally inclusive advancements in AI-driven P2P lending risk management.

Figure 3: Collaboration network of participating countries based on co-authorship

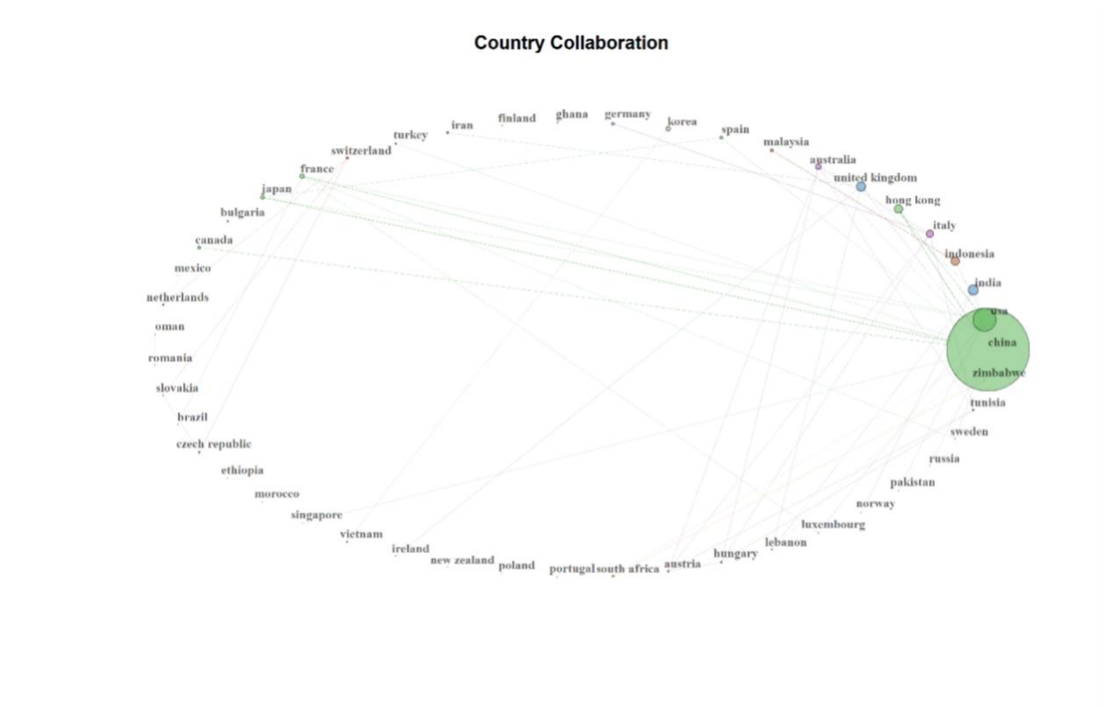


Table 1 presents the authorship statistics for the analysed studies. The results show that 13 papers were written by a single author. On average, each author contributes to around 36.6% of a paper (Documents per Author = 0.366), indicating that most publications involve multiple contributors. The average number of co-authors per document is 3.38, which reflects a strong tendency toward collaborative research. This is further supported by the collaboration index, which is close to 3 and is calculated by dividing the total number of authors in multi-authored articles by the number of those articles (Koseoglu, 2016). Therefore, collaboration is a dominant characteristic of research in the AI-driven P2P lending domain.

Table 2 summarises the publication venues of the selected studies. A total of 20 papers were published in high-ranking Q1 and Q2 journals, as defined by the Web of Science categories. The most prominent journals in the sample are *IEEE Access* and *Electronic Commerce Research and Applications*, both of which exhibit strong citation counts, highlighting their influence in the field.

The publication outlets span diverse scientific areas, including mathematics (statistics and operations research), economics (finance and electronic commerce), and computer science (artificial intelligence and information systems), as well as multidisciplinary domains. This wide distribution indicates that AI-driven risk mitigation in P2P lending is an interdisciplinary topic, attracting attention from scholars across multiple research fields.

Table 1: Dimensions of Contributions per author

Index	Value
Single-Authored Documents	13
Documents per Author	0.366
Co-Authors per Documents	3.380
International Co-Authorships	367

Table 2: Journals Classification of the P2P Lending sector

Source title	TP	TC
IEEE Access	10	429
Lecture Notes in Computer Science	10	131
Electronic Commerce Research and Applications	9	828
Expert Systems with Applications	7	708
Computational Economics	4	262
Procedia Computer Science	4	216
European Journal of Operational Research	4	158
Intelligent Systems with Applications	3	59
Information Sciences	2	164
Applied Soft Computing	2	60
International Review of Financial Analysis	2	42
Mathematics	2	35
PLOS ONE	2	29
Finance Research Letters	2	27
Intelligent Systems in Accounting, Finance and Management	2	25
Communications in Computer and Information Science	2	18
Risks	2	18
Scientific Programming	2	18
Lecture Notes in Networks and Systems	2	3

3.1.2 Citation analysis

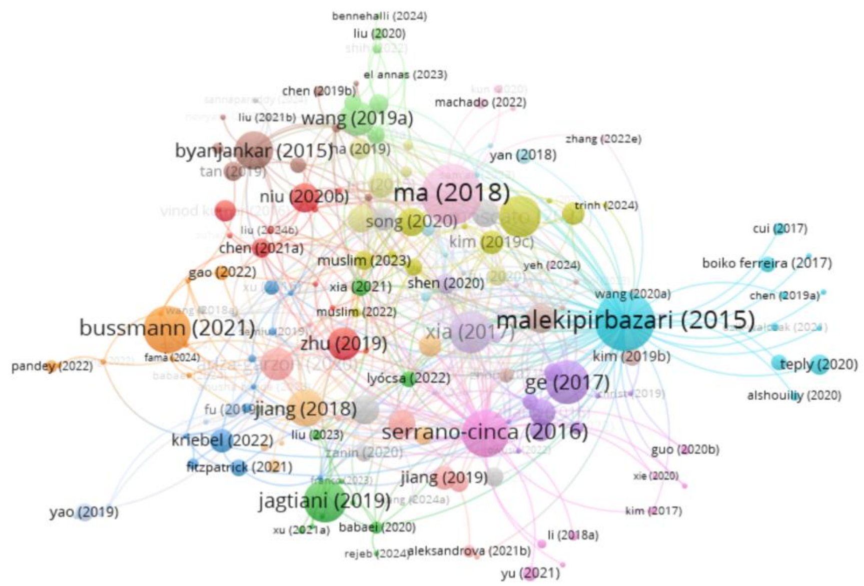
Figure 2 presents a powerful visualization of the citation network, where each circle represents a distinct paper. The size of the circles directly correlates to the number of citations each paper has received; larger circles indicate more citations. Each article is assigned a unique color. This visualization is a key tool in understanding the citation landscape and identifying the most influential documents within the scientific community. We highlight the key papers that address Research Question 1 (RQ1), providing a comprehensive view of the research field.

The most significant articles identified in Fig. 4 include the works of Malekipirbazari and Aksakalli (2015), Byanjankar et al. (2015), Serrano-Cinca and Gutiérrez-Nieto (2016), Ge et al. (2017), and Ma et al. (2018). Among these, Ma et al. (2018) is the most highly cited publication in the dataset, with **365 citations**, followed by Malekipirbazari and Aksakalli (2015) with **338 citations** and Serrano-Cinca and Gutiérrez-Nieto (2016) with **219 citations**. Ge et al. (2017) and Byanjankar et al. (2015) also appear as prominent nodes in the citation network, receiving **183** and **137** citations respectively.

It is important to interpret these citation counts in the context of publication dates, as more recent papers naturally have fewer citations simply due to their shorter presence in the academic discourse. For this reason, studies such as Serrano-Cinca and Gutiérrez-Nieto (2016) and Ma et al. (2018) are expected to maintain and potentially even increase their influence in the coming years. Both papers offer strong contributions to risk management modelling in the P2P lending sector, with a particular emphasis on practical business applications, making them highly relevant to ongoing developments in the industry.

The most frequently referenced studies focus on identifying the key elements in credit risk models for peer-to-peer (P2P) lending. These studies primarily utilize statistical and econometric approaches, including both cross-sectional and survival models. The aim of these models is to predict endogenous variables such as the approval of credit contracts, the likelihood of defaults, and performance and profitability outcomes related to credit obligations. However, the studies by Malekipirbazari and Aksakalli (2015) and Ma et al. (2018) seek to enhance the accuracy of credit risk management predictions, providing a reliable foundation for decision-making, by incorporating machine learning techniques, particularly through the application of decision tree methods.

Figure 4: Main authors' citation graph



3.1.3 Co-occurrence analysis of keywords

In this section, we examine the key themes related to risk and profit management in P2P lending literature. The analysis is based on a co-occurrence network constructed from the titles, abstracts and keywords of relevant publications. To further identify conceptual structures within the field, a hierarchical cluster analysis is also performed. VOSviewer is employed to construct both the map and the dendrogram, enabling the visual representation of terms according to their frequency, connectivity, and temporal distribution. In Figure 5, the proximity between nodes reflects the strength of the relationship among terms, while node size represents their relative frequency. Figure 6 complements this analysis by grouping terms into thematic clusters based on similarity, with lighter colors indicating more recent contributions and darker colors representing earlier work.

Insights derived from Figures 5 and 6 highlight five prominent clusters. The first major cluster, **“Business and Regulation”** (green), includes terms that capture the business-oriented modeling objectives in the P2P lending domain. Notable terms such as *default* (60 occurrences), *scoring* (32 occurrences), *investment* (25 occurrences), and *profits* (15 occurrences) exhibit high centrality, with 36, 33, 25, and 15 links respectively. Their connectivity underscores their foundational importance in risk prediction and portfolio management. Regulatory-focused terms such as *regulation*, *regulatory authority*, and *government* illustrate the growing need for governance frameworks as the sector expands. The presence of *network connectivity* within this cluster highlights an emerging research direction: the use of network-based indicators to detect latent relationships among borrowers, a trend becoming notable after 2018. Although *collateral* appears less central (7 links, 3 occurrences), its role signals an underexplored but relevant dimension in credit risk mitigation strategies.

Research indicates that effective management of risk and profits requires adherence to solid regulatory frameworks. This is evident from the presence of terms “regulation,” “regulatory authority,” and “government,” emphasizing the necessity of integrating these aspects for the sustainability and growth of the P2P lending industry. Notably, the term “network connectivity” also features within this cluster. Certain studies utilize network analysis statistics to pinpoint risk determinants, reflecting patterns observed since around 2018. These network metrics implicitly take into account latent factors arising from user relationships, potentially suggesting a contagion structure in line with regulatory perspectives. Moreover, the term “collateral” is mentioned, though it exhibits lower centrality (7 links), frequency (3 occurrences), and is the subject of fewer studies, with an average publication year of 2016. Despite these statistics, the network connectivity calls for further investigation as it plays a crucial role in hedging and risk management strategies in P2P lending industry.

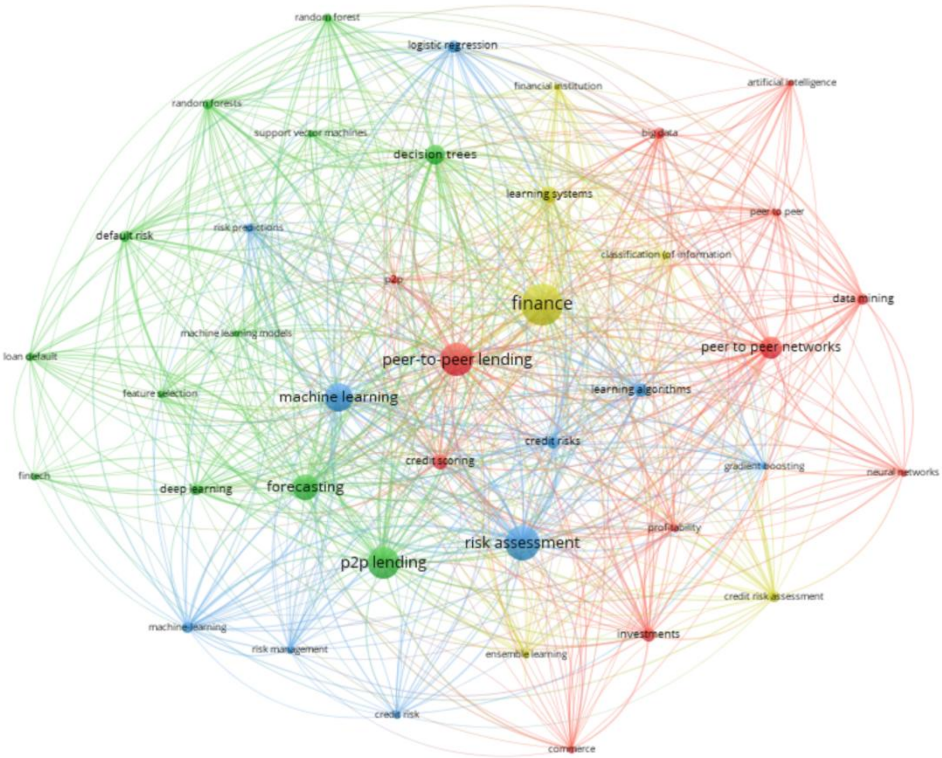
The second cluster, **“Performance Evaluation, Ensemble Models, and Soft Data”** (red), is one of the most diverse and extensive groups. It brings together concepts focused on classification tasks, such as *classifier* (26 occurrences, 33 links) and *performance* (50 occurrences, 35 links), reflecting the strong emphasis on model evaluation in the literature. Performance enhancement techniques such as *ensemble learning* (8 occurrences, 18 links) and *gradient boosting* (8 occurrences, 17 links) frequently appear, while *decision trees* (12 occurrences, 21 links) continue to serve as standard baselines. The cluster also highlights challenges like *class imbalance* and introduces emerging sources of soft information—including *NLP* (avg. year 2018), *soft information* (2019), *hard information* (2018), and *fuzzy models* (2018)—which are increasingly used to complement traditional credit scoring data.

The third cluster, **“Features and Neural Network Models”** (yellow), emphasizes feature engineering and complex data handling. Terms such as *features* (37 occurrences, 31 links), *big/complex data* (5 occurrences, 10 links), *artificial neural networks* (13 occurrences, 22 links), and *deep learning* (13 occurrences, 24 links) demonstrate the adoption of advanced architectures to model nonlinear patterns in borrower behavior. Increasing attention is also given to model evaluation strategies (6 occurrences, 13 links), essential for comparing the performance and robustness of these advanced techniques.

The fourth cluster, **“Logistic Regression and Interpretability”** (blue), focuses on classical modeling and transparency. *Logistic regression* (21 occurrences, 26 links) remains a central technique for credit risk modelling, especially due to its interpretability. Variables like *credit grade* (7 occurrences, 10 links) and *bureau score* (3 occurrences, 10 links) continue to play important roles as indicators of borrower creditworthiness. Importantly, the cluster includes *interpretability* (6 occurrences, 19 links), reflecting a validated shift toward explainable models driven by regulatory and ethical concerns.

Finally, the fifth cluster (purple) encompasses **"Traditional ML Models and Fraud-Related Topics."** This cluster (average occurrences: 4.8) groups commonly used machine-learning methods such as *random forest* and *support vector machines*, alongside terms like *fraud* (4 occurrences), which gained prominence following the collapse of the Chinese P2P market. Although *survival models* (6 occurrences, 16 links) represent more traditional approaches for estimating time-to-default, their integration with machine learning presents an opportunity for improving compliance with regulatory standards such as those set by the Basel Committee and IFRS.

Figure 5: Keyword co-occurrence graph based on authors' keyword



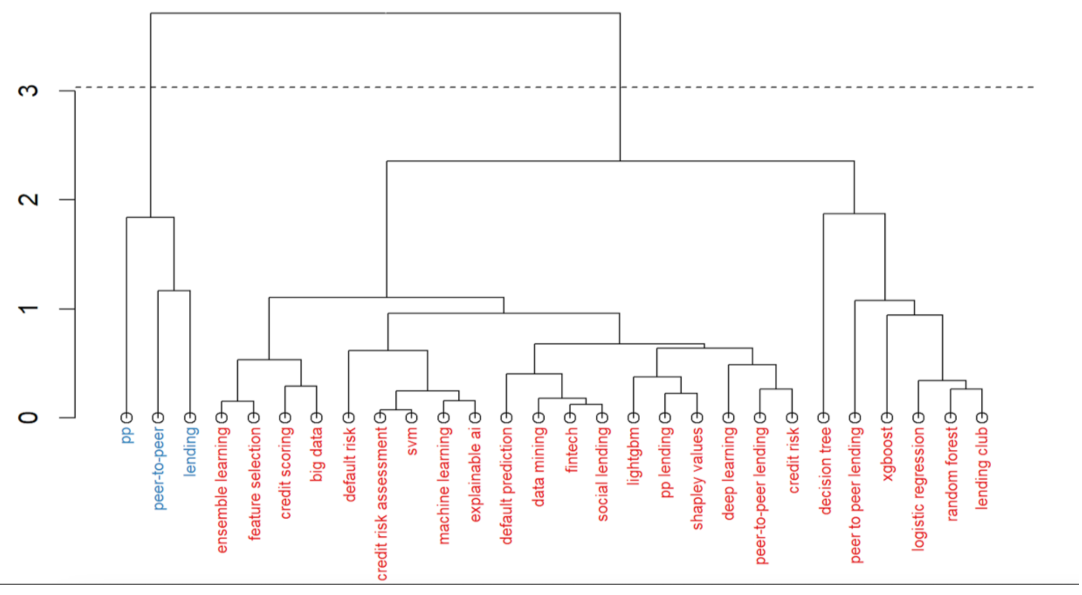
In addition to the thematic clusters, the keyword co-occurrence analysis reveals several emerging concepts within the P2P lending literature. Notably, terms such as **"microfinance"** and **"microcredit"** appear as extensions of the P2P lending domain, underscoring its role in fostering **financial inclusion** for low-income borrowers and small enterprises. Their presence in the network highlights the overlap between P2P lending and broader alternative finance ecosystems.

Temporal patterns within the network show that, beginning around **2017**, researchers increasingly adopted **cost-sensitive learning models** to integrate business considerations—such as profitability and asymmetric misclassification costs—into credit risk prediction. However, a critical modelling component, **loss given default (LGD)**, appears only infrequently in studies published around **2018**, indicating a substantial research gap in fully modeling expected losses within P2P platforms.

The evolution of machine learning techniques is also clearly visible. Early studies predominantly relied on traditional models such as **support vector machines** and **random forests** (circa 2017). Over time, the literature shifted toward more sophisticated techniques, including **gradient boosting** methods and, more recently, **deep learning** architectures. Despite this progression, **logistic regression** remains widely used as a benchmark due to its interpretability and regulatory familiarity.

Finally, the emergence of the term **"reject inference"** within the last two years signals a new and increasingly relevant research direction. As P2P platforms often observe only accepted loan applications, incorporating reject inference techniques could significantly improve model credibility and robustness by addressing selection bias in credit scoring.

Figure 6: Dednrograph based on keywords



3.2 Systematic Analysis

P2P lending platforms have emerged as a widespread alternative to traditional financial institutions, offering benefits like low entry barriers and cost-efficiency (Lyu, 2023). However, these platforms face notable risks that require careful risk management. Credit risk remains a significant concern, as borrowers may default on loans, a problem intensified by limited risk assessment capabilities and information asymmetry between borrowers and lenders (Tang et al., 2020; Nisar et al., 2020; Lyu, 2023). Legal risks also arise from regulatory uncertainties that can affect platform operations (Jing 2019; Afandi, 2023). Additionally, operational risks such as fraud and mismanagement pose threats to investors (Siaulyte & Lakstutiene, 2021). To address these challenges, P2P lending platforms employ strategies such as risk allocation, AI-based credit scoring, and guarantee funds; however, the effectiveness of these measures **remains under evaluation** (Yeo & Jun, 2020; Munmun, 2023).

The primary challenges with rule-based systems in the context of P2P lending platforms, particularly regarding the detection of suspicious loan activity, include the need for constant updates to rules to ensure their relevance and effectiveness (Whitaker, 2020). Additionally, accurately weighing the importance of different rules can be nearly impossible (Smith & Jones, 2021). A significant downside is the generation of a high volume of false positive alerts, which can reach as much as 98% (Johnson, 2019). This inundation of alerts increases the workload for compliance officers who must sort through them (Lee, 2022). When a loan is flagged as potentially suspicious, the platform is required to take action, which could involve reporting the case to regulatory bodies (Roberts, 2018). Accurately determining whether a loan is genuinely suspicious is critical; a misstep could lead to wrongly flagging a trustworthy borrower, which might trigger unwarranted investigations (Thompson, 2023). Conversely, failing to identify fraudulent loans can facilitate ongoing financial crimes and misuse of the lending system, posing risks to both the platform and its users (Adams et al., 2021).

To overcome these limitations, researchers are increasingly utilizing machine learning technologies to automatically identify suspicious transaction patterns in P2P lending platforms. This approach includes several categories of analytical **methods**, such as default loan typology detection, link analysis, behavioral modeling, risk scoring, anomaly detection, and **geolocation-based techniques**. By integrating these advanced methods, P2P lending platforms can enhance risk assessment and improve fraud detection capabilities, contributing to a more secure lending environment (Smith & Jones, 2023).

3.2.1 Datasets on P2P Lending

We begin our systematic review by examining the datasets used to assess risk and profit management strategies in peer-to-peer (P2P) lending. Table 3 summarizes the frequency of these datasets in the literature. The Lending Club (LC) dataset is the most widely used, appearing in **102 studies**, likely due to its large size, high data quality, and detailed loan-level attributes.

Platforms such as Kaggle and Mendeley also serve as secondary data repositories, providing researchers with access to various versions of Lending Club, Prosper, and other publicly shared datasets. In addition, there is extensive use of datasets originating from **China**, reflecting both the scale of the P2P lending market and the availability of platform-level data. Commonly used Chinese datasets include those from PPDai (paipaidai.com), RenRenDai (renrendai.com), and WeBank (we.com).

Figure 3 illustrates how these datasets correspond to the global distribution of P2P lending activity. The primary data sources are **China** and the United States, followed by continental Europe, the United Kingdom, Mexico, and several Southeast Asian markets.

Most studies rely on datasets involving **consumer lending**, while a smaller subset focuses on P2P business lending for small and medium-sized enterprises (SMEs). Notable contributions in this area include Giudici et al. (2020), Ahelegbey et al. (2019), and Hadji-Misheva et al. (2018), which utilize data from European External Credit Assessment Institutions (ECAIs), such as modeFinance.

Table 3: Datasets

Dataset	Country/Region	Number	Author/Year
Lending Club	United States	102	Famà et al. (2024); Babaei & Giudici (2024); Liu et al. (2024); Berhane et al. (2024); Cai & Zhang (2020); Ruyu et al. (2019); Yu & Zhang (2021); Teply & Polena (2020); Zanin (2020); Liu et al. (2020); Liang & Cai (2020); Song et al. (2020); Li & Zengyi (2020); Kim & Cho (2019); Chen et al. (2019); Zhu et al. (2019); Kim & Cho (2019); Ma et al. (2018); Wang et al. (2018); Li et al. (2021); Boiko Ferreira et al. (2017); Zhou et al. (2021); Raimundo & Bravo (2024); Addy et al. (2024); Bennehalli et al. (2024); Sannapareddy et al. (2024); Nguyen et al. (2024); Sam'an et al. (2024); Ariza-Garzon et al. (2024); Moscato & Sperlì (2023); Sharma et al. (2023); Wang et al. (2023); Zhou & Ma (2023); Han et al. (2023); Jakubik et al. (2023); Sharma et al. (2023); Agustina et al. (2023); Sam'an et al. (2023); El Annas et al. (2023); Franco et al. (2023); Muslim et al. (2023); Liu et al. (2023); Mochado & karray (2022); Amato et al. (2022); Christ et al. (2019); Lin et al. (2022); Ni et al. (2022); Zhang & Zhou (2022); Zhang & Sun (2022); Aleksandrova & Armianova (2022); Zhang et al. (2022); Mukherjee & Badr (2022); Owusu et al. (2022); Lee et al. (2021); Dzik-Walczak & Heba (2021); Sharma et al. (2021); Ariza-Garzon et al. (2020); Alshouiliy et al. (2020); Shen et al. (2020); Ma et al. (2020); Babaei & Bamdad (2020); Croux et al. (2020); Wang & Ni (2020); Turiel & Aste (2020); Caplescu et al. (2020); Costello & Lee (2019); Kim & Cho (2019); Dambanemuya & Horvát (2019); Qiu (2019); Hindistan et al. (2019); Lam & Hsiao (2019); Jagtiani & Lemieux (2019); Bastani et al. (2019); Wang et al. (2018); Namvar et al. (2018); Wei et al. (2018); Cohen et al. (2018); Kim & Cho (2017); Malekipirbazari & Aksakalli (2015); Vinod et al.(2016); Reddy & Gopalaraman (2016); Serrano-Cinca & Gutiérrez-Nieto (2016); Jin & Zhu (2015); Nguyen et al. (2019); Chang et al. (2022); Dzik-Walczak & Heba (2021)
Prosper	United States	9	Lv et al. (2019); Ding (2023); He et al. (2022); Zhang et al. (2022); Wang & Yang (2021); Liu et al. (2021); Guo et al. (2021); Li et al. (2020); Ha et al. (2019)
RenRenDai	China	10	Xu et al. (2024); Wang & Li (2019); Cao et al. (2021); Yin et al. (2023); Liu et al. (2022); Lu et al. (2022); Gao & Balyan (2022); Ma et al. (2021); Xu et al. (2021); Xia

			et al. (2019)
PPDai	China	3	Li et al. (2018); Zhang et al. (2016); Xu et al. (2015)
Bondora	Europe, Estonia, Finland and Spain	4	Liu et al. (2024); Varshney et al. (2024); Mondal et al. (2023); Byanjankar et al. (2015)
Weibo	China	2	Guo et al. (2016); Yang et al. (2022)
Undefined platforms	n/a	43	Zhong et al. (2022); Suhada & Devasia (2022); Jiang et al. (2019); Zheng et al. (2021); Wang et al. (2020); Xia et al. (2020); Xie & Chen (2020); Guo (2020); Kun et al. (2020); Wang et al. (2019); Feng et al. (2019); Niu et al. (2019); Duan (2019); Li et al. (2018); Dikmen & Burns (2022); Zhu & Chen (2021); Li et al. (2020); Dikmen & Burns (2022); Guo et al. (2025); Goh et al. (2019); Rabbani et al. (2023); Monje et al. (2025); Zhu, & Desheng (2025); Liu et al. (2024); Faturohman et al. (2024); Weidong (2019); Wang et al. (2018); Do et al. (2024); Wang et al. (2024); Nallakaruppan et al. (2024); Bone-Winkel & Reichenbach (2024); Lai (2023); Babaei & Bamdad (2023); Dasril et al. (2023); Zhu (2023); Zhao et al. (2025); Guo et al. (2025); Goh et al. (2019); Torkian et al. (2025); Lihua et al. (2025); Mezei et al. (2025); Rabbani et al. (2023); Sun & Haoxu (2025)
Kiva	China	1	Austrin & Rawal (2023)
Funding Circle	United States	1	Xu et al. (2021)
WDZJ	China	3	Yeh et al. (2024); Guo et al. (2020); Li et al. (2020)
Lending Club / Bondora	United States / China	1	Lyócsa et al. (2022)
Lending Club / We	United States / China	3	Xia et al. (2018); Xia et al. (2017); Xia et al. (2019)
Lending Club / RenRenDai	United States / China	1	Zhang et al. (2020)
Lending Club / Paipaidai	United States / China	2	Wang & Ni (2020); Zhang et al. (2020)
Lending Club / Prosper	United States	1	Chengeta & Mabika (2021)
One Undefined Institution / Lending Club	Korean / United States	1	Kim & Cho (2019)
Two Undefined Institutions / Lending Club	Australia, Germany & United States	1	Zhou et al. (2019)
MyLending	China	2	Anusha & Bhowmik (2023); Xu et al. (2016)
Wangdaizhijia	China	3	Wang et al. (2017); Fu et al. (2020); Fu et al. (2019)
Wangdaitianyan	China	1	Zhang et al. (2022)
Wangdaizhijia/Wangdaitianyan/Diyiwangdai	China	1	Cui & Liu (2022)
Web Financial Data	China	3	Ge et al. (2017); Cui et al. (2017); Cui et al. (2016)
No use dataset	-	14	Faturohmane et al. (2023); Kumari & Mohanty (2024); Owusu et al. (2023); Lv et al. (2019); Nasution et al. (2023); Ding et al. (2017); Li et al. (2024); Wang et al. (2021); Pandey & Bandhu (2022); Pan et al. (2021); Chen (2021); Li et al. (2019); Chen et al. (2019); Semiu & Gilal (2019)
Jinan Hengxin Micrp-Investment Advisory Co.,Ltd	China	2	Zhang et al. (2017); Zhang et al. (2017)
Eleon	China	1	Jiang et al. (2018)
ECAI	Europe	2	Bussmann et al. (2021); Gramespacher & Posth (2021)

Postman / WDZJ	United States / China	1	Tu & Zhong (2022)
Prosper/Paipaidai	United States / China	1	Liu et al. (2022)
Paipaidai / Lending Club / Prosper	Chine & United States	1	Niu et al. (2020)

3.2.2 Risk mitigation on P2P lending

This section outlines various risk mitigations categories related to the challenges in risk management of P2P lending platforms. It is important to note that a single study may fit into multiple categories, as it can analyze and propose solutions based on various models addressing different market aspects. The full set of risk mitigation categories is summarised in Table 5.

The classification framework builds on established research in financial, information systems, and technology risk management (Lim et al., 2011; Moeini & Rivard, 2019). It identifies twelve risk categories relevant to P2P lending: regulatory risk, operational risk, loan concentration risk, market entry risk, information security risk, credit assessment risk, users' rights risk, transparency risk, liquidity risk, default risk, information asymmetry risk, and interest rate risk. For example, regulatory risk may arise when oversight is weak, allowing platform operators to misuse funds or manipulate borrowing targets (Davis & Murphy, 2016). Several studies demonstrate this risk empirically, including Torkian et al. (2025), Lv et al. (2019), and Franco et al. (2023), who show how insufficient regulation can destabilize platforms. Bao et al. (2023) extend socio-technical risk frameworks to structure mitigation strategies for these risks.

The twelve identified risks are deeply interconnected, as illustrated in Figure 7. When regulatory oversight is weak, platforms may accept unqualified operators or borrowers, which increases loan default risk (e.g., Zhao et al., 2025; Faturohmane et al., 2023; Ni et al., 2022). Poor entry requirements and weak governance also contribute to loan liquidity risk, ultimately resulting in lender losses.

Operational risk is another key driver. Studies such as Yeh et al. (2024), Goh et al. (2019), and Xu et al. (2015) show that technical failures, weak internal controls, or poor fund allocation further heighten liquidity risk.

A lack of policies governing information disclosure can cause loan information transparency risk, as seen in Rabbani et al. (2023), which directly threatens lenders' rights, including the ability to recover funds at maturity. At the same time, poor cybersecurity practices expose P2P platforms to users' information security risk, documented by Sun & Haoxu (2025).

High regulatory risk can also influence loan interest rate risk, where platforms set unsustainably high or volatile rates. Studies such as Famà et al. (2024) and Wei et al.

(2018) demonstrate how fluctuating interest rates contribute to increased borrower defaults.

Weak platform design can produce loan credit assessment risk, as a result of inadequate borrower evaluation processes. This is the most common risk category in the literature, with 144 studies (e.g., Babaei & Giudici, 2024; Xu et al., 2024; Cai & Zhang, 2020; Kim & Cho, 2019; Ma et al., 2018). Poor credit assessments also intensify information asymmetry risk, as suggested by Zanin (2020) and Jakubik et al. (2023), by limiting lenders' access to critical borrower information.

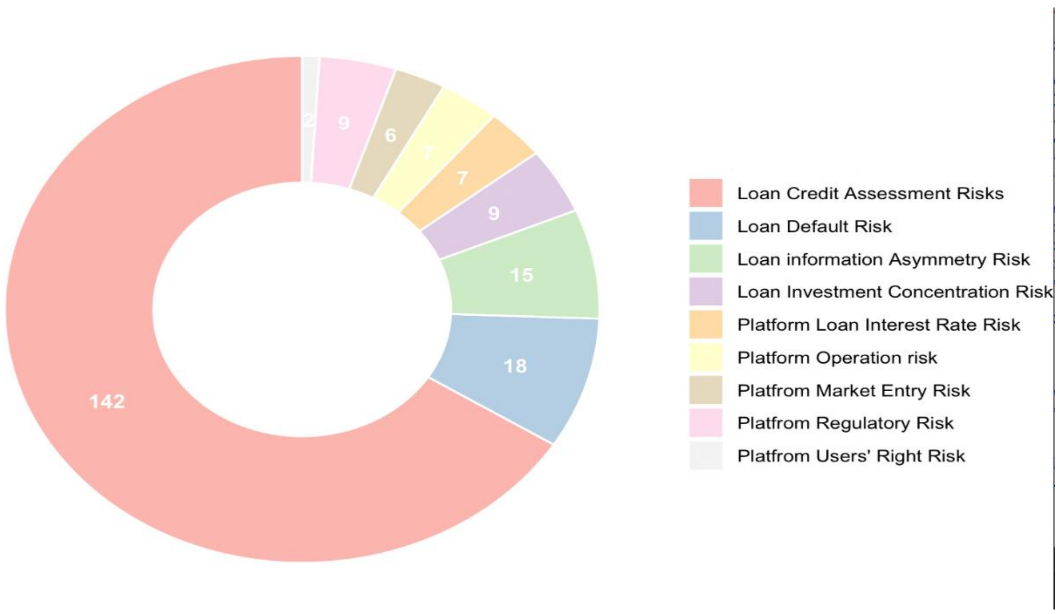
This lack of transparency may cause lenders to concentrate investments in risky loans, amplifying loan investment concentration risk, as observed in Zhong et al. (2022), Liu (2021), and Dambanemuya & Horvát (2019). Overall, inaccurate credit assessments weaken information flow and are directly linked to an increase in loan default risk.

A particularly dominant category in the literature is loan credit assessment risk, which accounts for approximately 63% of all reviewed studies. Within this category, researchers frequently introduce new modelling approaches, such as hybrid techniques, engineered features, or advanced machine learning algorithms, often reporting strong predictive accuracy. Despite these contributions, several methodological limitations remain. For instance, some studies incorporate variables such as risk grades or estimated risk levels—outputs of the risk assessment process—as model inputs, which may distort evaluation outcomes and compromise the validity of the results, as highlighted by Serrano-Cinca and Gutiérrez-Nieto (2016). Moreover, many papers do not clearly specify whether their models are intended for application scoring, behavioural scoring, or collection scoring, even though this distinction is crucial for practical deployment within lending operations. Another key inconsistency concerns the definition of default. Some studies classify default as payment delays exceeding 30 days within a one-year period, whereas others define default at the point of loan maturity. Such variability is evident in works such as Ye et al. (2018), Cho et al. (2019), Rodrigues et al. (2018), and Kim and Cho (2019), making the comparison of results across studies difficult and limiting the operational relevance of the proposed models.

Beyond credit scoring and default prediction, several studies investigate broader determinants of P2P market behaviour. Yan et al. (2016, 2017) examine the factors influencing investor participation across platforms in China, while Gao et al. (2017) analyse the determinants of past-due default rates and bad-debt ratios using both forward-looking and historical indicators. Other scholars employ alternative modelling perspectives: Li et al. (2018), for example, rely on network topology to analyse systemic risk, whereas Zhao (2015) uses neural networks to simulate expert credit assessments. Additional contributions expand the understanding of lender behaviour and borrower decision-making. Pierrakis (2019) employs principal component analysis to identify investment motivations among U.K. lenders, and Rosavina et al. (2019) use qualitative methods to explore borrowing determinants for SMEs in Indonesia, such as collateral requirements, processing time, interest rates, and associated costs. Sentiment analysis constitutes another evolving area of research. Fu et al. (2019) integrate TextCNN and LSTM models to analyse investor comments and predict daily trading volumes on Chinese P2P platforms.

Despite the substantial body of research, several important risk categories remain insufficiently explored. Fraud risk, for example, has gained prominence following the collapse of large segments of the Chinese P2P industry, yet it receives comparatively limited analytical attention. Similarly, Loss Given Default (LGD) modelling—essential for estimating expected credit losses—is rarely addressed in the P2P context. Prepayment risk, which significantly affects profitability and cash-flow planning, is also largely overlooked. These gaps reveal promising avenues for future research aimed at strengthening the sustainability and resilience of P2P lending markets.

Figure 7: Risk Categorization for selected papers



A final underexplored area concerns market knowledge and regulatory frameworks. These studies, such as Cui & Liu (2022) and Gramespacher & Posth (2021), do not depend on empirical datasets but provide essential conceptual and contextual insights into market stability, regulatory design, and investor protection. Their contributions emphasise that sustainable P2P lending markets require robust supervision, transparency standards, and clear operational guidelines.

Table 4: Risk Categorization

	Risk Mitigation	Number	Author/Year
Financial Regulatory authority - Borrower	Platform Regulatory Risk.	10	**Torkian et al. (2025); Lv et al. (2019); Franco et al. (2023); Ko et al. (2022); Babaei & Bamdad (2021); Ma et al. (2020); Fu et al. (2019); Li et al. (2019); Xu et al. (2016); Liu et al. (2023)**
Financial Regulatory Authority - Custodian	Platform market Entry Risk	6	**Liu et al. (2024); Anusha & Bhowmik (2023); Wang et al. (2021); Cui & Liu (2022); Zhang et al. (2022); Gramespacher & Posth (2021)**
Financial Regulatory Authority - Lenders	Platform Uses' Right Risk	2	**Lai (2023); Li et al. (2020)**
	Loan Information transparency Risk	1	**Rabbani et al. (2023)**
	User's Information Security Risk	1	**Sun & Haoxu (2025)**
	Loan investment concentration risk	9	**Mochado & karray (2022); Liu et al. (2022); Zhang & Zhou (2022); Zhong et al. (2022); Zhang et al. (2022); Liu (2021); Xu et al. (2021); Dambanemuya & Horvát (2019); Zhang et al. (2016)**
Borrowers - Lenders	Loan Liquidity Risk	-	-
	Loan Default Risk	18	**Zhao et al. (2025); Guo et al. (2025); Faturohmane et al. (2023); Varshney et al. (2024); Monje et al. (2025); Kumari & Mohanty (2024); Owusu et al. (2023); Kim & Cho (2019); Zhu, & Desheng (2025); Li et al. (2024); Agustina et al. (2023); Sam'an et al. (2023); Lin et al. (2022); Ni et al. (2022); Aleksandrova & Armianova (2022); Muslim et al. (2022); Liu et al. (2021); Fu et al. (2020)**
	Loan Information asymmetry Risk	15	**Zanin (2020); Addy et al. (2024); Bennehalli et al. (2024); Sannapareddy et al. (2024); Nguyen et al. (2024); Cao et al. (2021); Jakubik et al. (2023); Austrin & Rawal (2023); Amato et al. (2022); Fitzpatrick & Mues (2021); Pan et al. (2021); Alshouiliy et al. (2020); Shen et al. (2020); Croux et al. (2020); Caplescu et al. (2020)**
	Platform Operation Risk	7	**Yeh et al. (2024); Goh et al. (2019); Sam'an et al. (2024); Zhang & Sun (2022); Owusu et al. (2022); Suhada & Devasia (2022); Xu et al. (2015)**
Others	Loan Interest rate risk	7	**Famà et al. (2024); Guo et al. (2025); Torkian et al. (2025); Babaei & Bamdad (2020); Xia et al. (2020); Cohen et al. (2018); Wei et al. (2018)**
Borrowers - Lenders	Loan Credit Assessment Risks	144	**Babaei & Giudici (2024); Lihua et al. (2025); Mezei et al. (2025); Goh et al. (2019); Xu et al. (2024); Liu et al. (2024); Liu et al. (2024); Rabbani et al. (2023); Berhane et al. (2024); Cai & Zhang (2020); Ruyu et al. (2019); Yu & Zhang (2021); Teply & Polena (2020); Liu et al. (2020); Zhang et al. (2020); Liang & Cai (2020); Song et al. (2020); Niu et al.**

(2020); Li & Zengyi (2020); Kim & Cho (2019); Chen et al. (2019); Wang & Li (2019); Nasution et al. (2023); Lv et al. (2019); Setiawan & Suharjito (2019); Zhu et al. (2019); Kim & Cho (2019); Ma et al. (2018); Xia et al. (2018); Wang et al. (2018); Xia et al. (2017); Wang et al. (2017); Ding et al. (2017); Li et al. (2021); Boiko Ferreira et al. (2017); Zhou et al. (2021); Raimundo & Bravo (2024); Chang et al. (2022); Nguyen et al. (2019)

3.2.3 Methodological aspects applied on P2P Lending

3.2.3.1 Machine learning methods applied on P2P lending

The use of machine learning (ML) techniques in P2P lending has attracted considerable attention as a means of mitigating the risks inherent to these platforms (Xia et al., 2022; Nasution, 2023; Dasril et al., 2023). These methods are primarily employed to improve credit risk evaluation and default prediction, which are central issues in the P2P lending sector (Chen et al., 2021; Byanjankar et al., 2021; Munsarif et al., 2022).

Table 5 and Figure 9 summarise the distribution of ML and DL methods used in the reviewed studies. Among the traditional ML approaches, Random Forest (RF) and Logistic Regression (LR) are the most frequently adopted models, appearing in roughly 90 and 85–90 studies respectively. They are followed by Support Vector Machines (SVM) (around 70 studies), Extreme Gradient Boosting (XGBoost) **(**about 65–67 studies), Artificial Neural Networks (ANN) (around 48 studies), Decision Trees (DT) (approximately 45–52 studies), and k-Nearest Neighbours (KNN) (around 28–29 studies). These models are used both as standalone classifiers and as baselines for comparison with more advanced techniques.

In addition, ensemble learning methods such as AdaBoost and CatBoost, along with XGBoost and LightGBM, form a prominent family of models aimed at improving predictive accuracy and robustness, particularly in the presence of noisy and heterogeneous data. Many studies report that tree-based ensembles, especially RF and XGBoost, consistently outperform traditional scorecard-style logistic regression models when identifying high-risk borrowers or predicting loan defaults (e.g., Fu et al., 2019; Pan et al., 2021; Mukherjee & Badr, 2022; Varshney et al., 2024).

Researchers have also investigated how **data preprocessing** affects model performance. Techniques such as outlier detection, feature scaling, and resampling methods for class imbalance (e.g., SMOTE or cost-sensitive sampling) are shown to substantially improve prediction quality in highly unbalanced datasets typical of P2P lending, where default cases are relatively rare (Qian et al., 2021; Cheng et al., 2021; Byanjankar et al., 2020). These findings highlight that addressing data quality issues is as important as the choice of algorithm.

Beyond primary loan default modelling, ML methods are applied to other tasks, such as analysing secondary markets where loan notes are traded. For instance, Byanjankar et al. (2020) and Wang and Ni (2020) use RF, SVM, and gradient-boosting models to forecast the success of secondary market offers, providing decision support for investors considering early exit or reallocation strategies. ML-based recommender systems and credit scoring engines have also been integrated into P2P platforms to support automated loan selection and portfolio construction (Guo et al., 2020; Klimowicz & Spirzewski, 2021; Rong et al., 2023; Makokha, 2024).

Overall, the evidence indicates that ML methods substantially enhance credit risk assessment, default prediction, and investment decision-making in P2P lending. However, persistent challenges remain, including handling severe class imbalance, ensuring model robustness under changing market conditions, and providing explanations that satisfy both regulators and end users.

3.2.3.2 Deep learning applied on P2P lending

Deep learning (DL) techniques have been successfully applied across numerous domains for predictive analytics, often achieving high levels of accuracy (Huang et al., 2020). Historically, the adoption of DL was constrained by the need for large datasets and substantial computational resources, but recent advances in hardware and software have eased these limitations (Khan et al., 2021). In the context of P2P lending, DL methods are increasingly used for tasks such as fraud detection, credit scoring, sentiment analysis, and dynamic loan performance modelling (Zhang & Luo, 2022).

According to Table 5 and Figure 9, the most frequently employed DL architectures include Convolutional Neural Networks (CNNs) (19 studies), Recurrent Neural Networks (RNNs) (14 studies), Long Short-Term Memory networks (LSTMs) (18 studies), and more general Deep Neural Networks (DNNs) **(**12 studies). These architectures are often combined in hybrid pipelines. For example, Fu et al. (2019, 2020) and Austrin and Rawal (2023) use CNN or TextCNN components to extract textual features from investor comments, which are then fed into LSTM layers to capture temporal dynamics and predict trading volumes or loan performance. Other studies apply DNNs to model non-linear relationships between borrower characteristics, macroeconomic variables, and default outcomes (Owusu et al., 2022; Cheng et al., 2021; Li et al., 2018).

A particularly promising line of research involves **graph neural networks (GNNs)**, including graph convolutional neural networks (GCNNs). Although still relatively rare in the literature (7 studies in Table 5), these models are specifically designed to handle graph-structured data and are therefore well suited to P2P lending, where borrowers, lenders, and loans form complex interaction networks (Zhou et al., 2020; Qian et al., 2021; Krasanakis et al., 2022). By aggregating information from a node's neighbourhood, GNNs can capture relational patterns—such as shared lenders or co-borrowing structures—that are difficult to model with traditional feature-based approaches. Empirical results suggest that GNNs can improve the prediction of default and fraud risk compared with purely tabular models (Qian et al., 2021; Zhang et al., 2025).

Scalability is a critical consideration for deploying DL and GNN models on large P2P platforms. Techniques such as graph compression, sampling-based training, and decoupled GNN architectures have been proposed to reduce memory and computational costs while maintaining predictive performance (Weber, 2018; Kurshan et al., 2020). These approaches enable models to cope with dense and evolving transaction networks involving millions of loans and user accounts.

Interpretability remains a major challenge for DL, particularly in regulated financial environments. Recent work explores ways to make GNNs and other deep models more transparent by highlighting influential nodes, edges, or features and by integrating attention mechanisms or post-hoc explanation tools (Kurshan et al., 2020; Liu et al., 2022). Such advances are essential for aligning powerful DL models with regulatory expectations and stakeholder trust.

In summary, while deep learning methods still appear less frequently than classical ML and ensemble models in the P2P lending literature, their use is growing steadily. CNNs, RNNs, LSTMs, and GNNs are especially promising for exploiting unstructured data (such as text) and relational information (such as network links). Future research should focus on improving the scalability, interpretability, and robustness of these models, as well as integrating them with domain knowledge and regulatory constraints to support trustworthy AI-driven risk management in P2P lending.

Table 5: Machine and Deep Learning methods applied on P2P lending sector

	DL/ML Methods	Number	Author/Year
Deep Learning	CNN	19	Berhane et al. (2024); Kim & Cho (2019); Zhang et al. (2020); Kim & Cho (2019); Wang et al. (2021); Austrin & Rawal (2023); Liu et al. (2022); Lu et al. (2022); Kriebel et al. (2022); Cui & Liu (2022); Ko et al. (2022); Kim & Cho (2022); Pan et al. (2021); Chengeta & Mabika (2021); Fu et al. (2020); Kim & Cho (2019); Torkian et al. (2025); Li et al. (2020); Zhang et al. (2020)
	DNN	12	H., Sun, Haoxu (2022); Owusu et al. (2023); Owusu et al. (2022); Fu et al. (2019); Dambanemuya & Horvát (2019); Wang et al. (2024); Cheng et al. (2021); Li et al. (2020); Li et al. (2018); Xu et al. (2021); Costello & Lee (2019); Lin et al. (2022)
	RNN	14	Liu et al. (2024); Varshney et al. (2024); Anusha & Bhowmik (2023); Kriebel et al. (2022); Wang et al. (2020); Cui & Liu (2022); Xie & Chen

			(2020); Guo (2020); Wang & Ni (2020); Wang et al. (2019); Lam & Hsiao (2019); Nguyen et al. (2019); Liu et al. (2023); Chang et al. (2022)
	LSTM	18	Fu et al. (2019); Zhang et al. (2017); Zhang et al. (2017); Fu et al. (2020); Zhang et al. (2022); Wang & Ni (2020); Caplescu et al. (2020); Cui & Liu (2022); Zhang et al. (2022); Liang & Cai (2020); Zhao et al. (2025); Austrin & Rawal (2023); Mukherjee & Badr (2022); Cui et al. (2017); Liu et al. (2023); Kumari & Mohanty (2024); Liu et al. (2021); Li et al. (2020)
Machine Learning	LR	86	Caplescu et al. (2020); Ko et al. (2022); Pan et al. (2021); Berhane et al. (2024); Varshney et al. (2024); Austrin & Rawal (2023); Zhang et al. (2020); Guo (2020); Fu et al. (2019); Liu et al. (2020); Xia et al. (2018); Wang et al. (2017); Zheng et al. (2021); Ruyu et al. (2019); Niu et al. (2020); Zanin (2020); Wang et al. (2018); Boiko Ferreira et al. (2017); Bennehalli et al. (2024); Nguyen et al. (2024); Sharma et al. (2023); Mondal et al. (2023); Sam'an et al. (2023); Ding (2023); Gao & Balyan (2022); Chen (2021); Zhang et al. (2022); Li et al. (2020); Cheng et al. (2021); Shen et al. (2020); Niu et al. (2019); Chen et al. (2019); Croux et al. (2020); Li et al. (2018); Reddy & Gopalaraman (2016); Guo et al. (2016); Xu et al. (2021); Sannapareddy et al. (2024); Addy et al. (2024); Raimundo & Bravo (2024); Yeh et al. (2024); Faturohman et al. (2024); Rabbani et al. (2023); Teply & Polena (2020); Chen et al. (2019); Yin et al. (2023); Wang et al. (2023); He et al. (2022); Liu et al. (2022); Zhang & Sun (2022); Suhada & Devasia (2022); Jiang et al. (2019); Li et al. (2019); Turiel & Aste (2020); Costello & Lee (2019); Xia et al. (2019); Dzik-Walczak & Heba (2021); Guo et al. (2021); Sharma et al. (2021); Guo et al. (2020); Lyócsa et al. (2022); Ye et al. (2018); Liu (2021); Li et al. (2021); Chen et al. (2021); Zhou et al. (2019); Hindistan et al. (2019); Jagtiani & Lemieux (2019); Wang et al. (2018); Jiang et al. (2018); Namvar et al. (2018); Wei et al. (2018); Cohen et al. (2018); Zhang et al. (2016); Ge et al. (2017); Malekipirbazari & Aksakalli (2015); Byanjankar et al. (2015); Li et al. (2020); Ariza-Garzon et al. (2020); Gramespacher & Posth (2021); Moscato et al. (2021); Han et al. (2023); Amato et al. (2022); Moscato & Sperlì (2023); Famà et al. (2024); Zhang et al. (2020); Sharma et al. (2023)
	RF	88	Fu et al. (2019); Pan et al. (2021); Zhang et al. (2020); Mukherjee & Badr (2022); Ko et al. (2022); Austrin & Rawal (2023); Liu et al. (2024); Varshney et al. (2024); Liu et al. (2020); Xia et al. (2018); Franco et al. (2023); Zhu & Desheng (2025); Mochado & karray (2022); Liu et al. (2024); Ruyu et al. (2019); Weidong (2019); Song et al. (2020); Ding et al. (2017); Ding (2023); Shih et al. (2022); Chen (2021); Cheng et al. (2021); Sam'an et al. (2023); Agustina et al. (2023); Jakubik et al. (2023); Sharma et al. (2023); Nguyen et al. (2024); Sam'an et al. (2024); Boiko Ferreira et al. (2017); Mondal et al. (2023); Muslim et al. (2023); Liu et al. (2023); Byanjankar et al. (2021); Aleksandrova (2021); Xu et al. (2021); Kun et al. (2020); Ma et al. (2020); Li et al. (2020); Ha et al. (2019); Niu et al. (2019); Reddy & Gopalaraman (2016); Guo et al. (2016); Guo et al. (2021); Addy et al. (2024); Raimundo & Bravo (2024); Sannapareddy et al. (2024); Yeh et al. (2024); Rabbani et al. (2023); Goh et al. (2019); Teply & Polena (2020); Chen et al. (2019); Li & Zengyi (2020); Setiawan & Suharjito (2019); Zhu et al. (2019); Liu et al. (2022); Yin et al. (2023); Suhada & Devasia (2022); Ni et al. (2022); Jiang et al. (2019); Ye et al. (2018); Lyócsa et al. (2022); Chen et al. (2021); Li et al. (2021); Cohen et al. (2018); Namvar et al. (2018); Malekipirbazari & Aksakalli (2015); Hindistan et al. (2019); Zhou et al. (2019); Bastani et al. (2019); Jiang et al. (2018); Sharma et al. (2021); Xia et al. (2019); Guo et al. (2020); Vinod et al.(2016); Xu et al. (2016); Serrano-Cinca & Gutiérrez-Nieto (2016); Liu et al. (2023); Bone-Winkel & Reichenbach (2024); Nallakaruppan et al. (2024); Monje

		et al. (2025); Schwab et al. (2025); Moscato & Sperlì (2023); Amato et al. (2022); Han et al. (2023); Liu et al. (2021); Moscato et al. (2021); Ariza-Garzon et al. (2020); Babaei & Bamdad (2023)
KNN	28	Berhane et al. (2024); Mukherjee & Badr (2022); Pan et al. (2021); Caplescu et al. (2020); Liu et al. (2020); Zanin (2020); Niu et al. (2020); Song et al. (2020); Wang et al. (2018); Sam'an et al. (2024); Aleksandrova (2021); Li et al. (2020); Sam'an et al. (2023); Muslim et al. (2023); Ni et al. (2022); Ye et al. (2018); Sharma et al. (2021); Yu & Zhang (2021); Teply & Polena (2020); Raimundo & Bravo (2024); Malekipirbazari & Aksakalli (2015); Chang et al. (2022); Li et al. (2019); Zhou et al. (2019); Liu (2021); Pandey & Bandhu (2022); Liu et al. (2022); Han et al. (2023)
SVM	68	Wang et al. (2019); Zhang et al. (2022); Pan et al. (2021); Zhang et al. (2022); Liu et al. (2024); Varshney et al. (2024); Liang & Cai (2020); Austrin & Rawal (2023); Zhang et al. (2020); Mukherjee & Badr (2022); Xia et al. (2020); Feng et al. (2019); Lv et al. (2019); Liu et al. (2020); Kim & Cho (2019); Xia et al. (2018); Wang et al. (2017); Kim & Cho (2017); Mochado & karray (2022); Zheng et al. (2021); Shen et al. (2020); Guo et al. (2016); El Annas et al. (2023); Muslim et al. (2023); Liu et al. (2023); Tu & Zhong (2022); Fitzpatrick & Mues (2021); Gao & Balyan (2022); Ding et al. (2017); Bennehalli et al. (2024); Nguyen et al. (2024); Ruyu et al. (2019); Song et al. (2020); Lv et al. (2019); Xu et al. (2015); Zhang & Zhou (2022); Liu (2021); Ye et al. (2018); Sharma et al. (2021); Turiel & Aste (2020); Costello & Lee (2019); Yeh et al. (2024); Faturohman et al. (2024); Teply & Polena (2020); Yu & Zhang (2021); Wang & Li (2019); Raimundo & Bravo (2024); Xu et al. (2021); Zhu (2023); He et al. (2022); Liu et al. (2022); Ni et al. (2022); Xia et al. (2019); Zhou et al. (2019); Bastani et al. (2019); Jiang et al. (2018); Wang et al. (2018); Ge et al. (2017); Malekipirbazari & Aksakalli (2015); Xu et al. (2016); Serrano-Cinca & Gutiérrez-Nieto (2016); Chang et al. (2022); Liu et al. (2023); Li et al. (2020); Jin & Zhu (2015); Famà et al. (2024); Babaei & Bamdad (2023)
DT	45	Varshney et al. (2024); Anusha & Bhowmik (2023); Pan et al. (2021); Ko et al. (2022); Austrin & Rawal (2023); Caplescu et al. (2020); Feng et al. (2019); Liu et al. (2020); Mochado & karray (2022); Liu et al. (2024); Cai & Zhang (2020); Zanin (2020); Niu et al. (2020); Wang et al. (2018); Boiko Ferreira et al. (2017); Nguyen et al. (2024); Bennehalli et al. (2024); Jakubik et al. (2023); Sam'an et al. (2024); Mondal et al. (2023); Sam'an et al. (2023); Ding (2023); Yang et al. (2022); Shen et al. (2020); Tu & Zhong (2022); Xu et al. (2015); Zhang et al. (2016); Vinod et al.(2016); Liu et al. (2023); Bastani et al. (2019); Wang et al. (2018); Christ et al. (2019); Suhada & Devasia (2022); Ye et al. (2018); Jiang et al. (2019); Li et al. (2021); Semiu & Gilal (2019); Hindistan et al. (2019); Cohen et al. (2018); Addy et al. (2024); Yin et al. (2023); Pandey & Bandhu (2022); Gramespacher & Posth (2021); Nallakaruppan et al. (2024); Bone-Winkel & Reichenbach (2024); Han et al. (2023); Ariza-Garzon et al. (2020); Li et al. (2020); Alshouiliy et al. (2020); Jin & Zhu (2015); Babaei & Bamdad (2023)
ANN	47	Liu et al. (2024); Varshney et al. (2024); Ko et al. (2022); Liang & Cai (2020); Kriebel et al. (2022); Zhang et al. (2022); Babaei & Bamdad (2020); Caplescu et al. (2020); Zhang et al. (2017); Zhang et al. (2017); Cui et al. (2017); Cui et al. (2016); Liu et al. (2020); Wang et al. (2017); Torkian et al. (2025); Zhang et al. (2025); Zhu & Desheng

			(2025); Mochado & karray (2022); Zanin (2020); Wang et al. (2018); Zhang et al. (2022); Liu et al. (2023); Xu et al. (2021); Kun et al. (2020); Babaei & Bamdad (2021); Chen et al. (2021); Dzik-Walczak & Heba (2021); Guo et al. (2021); Turiel & Aste (2020); Li et al. (2019); Zhou et al. (2019); Zhang et al. (2016); Byanjankar et al. (2015); Xu et al. (2015); Chang et al. (2022); Yin et al. (2023); Zhu (2023); Ni et al. (2022); Zhang & Zhou (2022); Zhong et al. (2022); Lyócsa et al. (2022); Yeh et al. (2024); Faturohmane et al. (2023); Faturohman et al. (2024); Teply & Polena (2020); Liu (2021); Babaei & Bamdad (2023); Zhu & Chen (2021); Ma et al. (2021)
	GNN	7	Austin & Rawal (2023); Zhang et al. (2025); Zhu & Desheng (2025); Liu et al. (2024); Li et al. (2024); Lee et al. (2021); Zheng et al. (2021)
Ensemble Learning	XGBoost	65	Guo et al. (2025); Varshney et al. (2024); Anusha & Bhowmik (2023); Austrin & Rawal (2023); Chengeta & Mabika (2021); Wang et al. (2019); Austin & Rawal (2023); Nguyen et al. (2019); Torkian et al. (2025); Zhang et al. (2025); Zhu & Desheng (2025); Qiu (2019); Xu et al. (2021); Ma et al. (2020); Li et al. (2020); Kun et al. (2020); Chen et al. (2019); Duan (2019); Li et al. (2018); Reddy & Gopalaraman (2016); Guo et al. (2016); Wang & Yang (2021); Aleksandrova & Parusheva (2021); Sam'an et al. (2023); El Annas et al. (2023); Muslim et al. (2023); Liu et al. (2023); Ding (2023); Aleksandrova & Armianova (2022); Tu & Zhong (2022); Chen (2021); Cheng et al. (2021); Aleksandrova (2021); Byanjankar et al. (2021); Li et al. (2020); Li et al. (2018); Lai (2023); Zhou & Ma (2023); Cao et al. (2021); Sam'an et al. (2024); Sharma et al. (2023); Li et al. (2021); Zhou et al. (2021); Xia et al. (2017); Ruyu et al. (2019); Liu et al. (2024); Weidong (2019); Song et al. (2020); Ma et al. (2018); Ding et al. (2017); Nguyen et al. (2024); Jakubik et al. (2023); Mondal et al. (2023); Agustina et al. (2023); Yeh et al. (2024); Chang et al. (2022); Liu et al. (2023); Famà et al. (2024); Schwab et al. (2025); Monje et al. (2025); Ariza-Garzon et al. (2024); Do et al. (2024); Han et al. (2023); Bussmann et al. (2021); Ariza-Garzon et al. (2020); Zhang et al. (2020)
	Catboost	13	Chengeta & Mabika (2021); Guo et al. (2025); Zhu & Desheng (2025); Ma et al. (2018); Nasution et al. (2023); Xia et al. (2017); Zhou et al. (2021); Sam'an et al. (2024); El Annas et al. (2023); Li et al. (2021); Sam'an et al. (2023); Cheng et al. (2021); Ha et al. (2019)
	AdaBoost	15	Lv et al. (2019); Liu et al. (2024); Lv et al. (2019); Boiko Ferreira et al. (2017); Cao et al. (2021); Lai (2023); Zhou & Ma (2023); Sam'an et al. (2023); Shen et al. (2020); Ma et al. (2020); Kun et al. (2020); Sam'an et al. (2024); Yang et al. (2022); Niu et al. (2019); Xu et al. (2024)

3.2.3.3 Explainable AI applied on P2P lending

The rapid progress in computing technologies, combined with the continuous generation of large and complex datasets, has significantly expanded the use of machine learning (ML) methods over the past decade. As model development increasingly focuses on achieving higher predictive accuracy, many studies employ complex "black-box" models such as deep learning (DL), which, despite their strong performance, remain largely opaque and difficult for humans to interpret. This lack of transparency poses challenges for domains where decisions have significant human or financial consequences—such as medicine, banking, law enforcement, and legal systems—where trust, accountability, and fairness are essential (Lipton, 2016). In contrast, some areas, such as weather forecasting or targeted online advertising, do not require such levels of interpretability, as the operational need for explanation is relatively low.

In peer-to-peer (P2P) lending, however, transparency and interpretability are critical. Reliable, safe, and fair decision-making is required to maintain the trust of platform users and to comply with legal requirements (Doshi-Velez & Kim, 2017). Regulations such as the General Data Protection Regulation (GDPR) mandate the Right to Be Informed and require platforms to maintain clear Records of Processing Activities (European Parliament, 2016). Similarly, the California Consumer Privacy Act (CCPA) establishes transparency obligations for automated decision-making (California Legislative Information, 2018). As a result, AI systems used in financial compliance—including credit scoring, fraud detection, and suspicious transaction reporting in P2P lending—must be able to provide meaningful explanations.

Machine learning approaches have demonstrated substantial accuracy in detecting abnormal behaviours, identifying suspicious transactions, and uncovering patterns in P2P lending data (Kumar & Rajesh, 2021). When platforms file Suspicious Activity Reports (SARs), clear reasoning must accompany each flagged case. Yet many high-performing ML and DL models are difficult to interpret, which reduces trust and complicates their use in regulatory contexts (Lipton, 2018). This gap has driven increased interest in Explainable Artificial Intelligence (XAI).

Table 6: Explainable AI methods applied on P2P lending sector

	XAI Method	Number	Author/Year
Model Agnostic	SHAP	18	Dzik-Walczak & Heba (2021); Bussmann et al. (2021) Moscato et al. (2021); Ariza-Garzon et al. (2020); Liu et al. (2021); Moscato & Sperlì (2023); Amato et al. (2022); Nallakaruppan et al. (2024); Bone-Winkel & Reichenbach (2024); Xu et al. (2024); Monje et al. (2025); Do et al. (2024); Ariza-Garzon et al. (2024); Famà et al. (2024); Li et al. (2025); Babaei & Giudici (2024); Schwab et al. (2025); Dikmen & Burns (2022)
	LIME	14	Li et al. (2020); Moscato et al. (2021); Han et al. (2023); Amato et al. (2022); Lin et al. (2022); Dzik-Walczak & Heba (2021); Nallakaruppan et al. (2024); Bone-Winkel & Reichenbach (2024); Moscato & Sperlì (2023); Li et al. (2025); Schwab et al. (2025); Monje et al. (2025); Kumari & Mohanty (2024); Do et al. (2024)
	Anchors	6	Moscato & Sperlì (2023); Moscato et al. (2021); Amato et al. (2022); Jin & Zhu (2015); Alshouiliy et al. (2020); Zhang et al. (2020)
	BEEF	4	Amato et al. (2022); Moscato & Sperlì (2023); Moscato et al. (2021); Dzik-Walczak & Heba (2021)

Figure 8: Interpretability XAI distribution

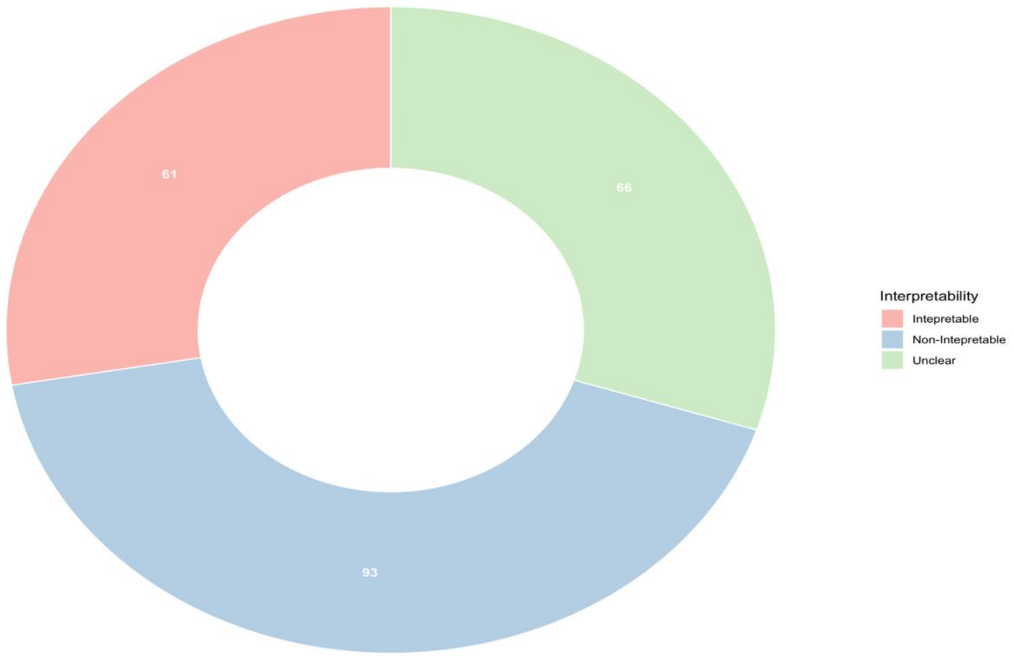


Figure 8 and Table 6 illustrate how interpretability is addressed within the reviewed literature. Out of the studies surveyed, 93 rely on non-interpretable models, 61 employ interpretable models**,** and 66 provide insufficient information to assess interpretability**.** This distribution underscores a persistent imbalance: although black-box models remain dominant, interpretability is increasingly recognised as essential for responsible AI adoption in P2P lending.

Across the reviewed studies, several model-agnostic post-hoc XAI methods have been applied to improve the interpretability of complex ML models used in P2P lending. SHAP is the most frequently used technique, appearing in 18 studies, followed by LIME with 14 studies, while Anchors (6 studies) and BEEF (4 studies) are used less often. These methods allow researchers to explain black-box models without modifying their internal structure. SHAP has been applied in works such as Dzik-Walczak and Heba (2021), Moscato et al. (2021), Amato et al. (2022), Nallakaruppan et al. (2024), Bone-Winkel and Reichenbach (2024), and Monje et al. (2025). LIME has been adopted in studies including Li et al. (2020), Lin et al. (2022), Amato et al. (2022), Han et al. (2023), and Kumari and Mohanty (2024). Anchors has been used in research by Moscato et al. (2021), Amato et al. (2022), Alshouiliy et al. (2020), and Zhang et al. (2020), while BEEF appears primarily in Amato et al. (2022), Moscato and Sperlì (2023), Moscato et al. (2021), and Dzik-Walczak and Heba (2021).

These methods provide insight into which features influence risk assessments, loan approvals, and fraud detection outcomes—thereby improving transparency, trust, and regulatory compliance.

Despite its growing prominence worldwide, the use of XAI within P2P lending remains limited, revealing an important research gap. The literature emphasises that explanations must be relevant to stakeholders' operational contexts, as lenders, borrowers, auditors, and regulators may each require different types of information. Substantial progress has been made in developing post-hoc techniques (Bussmann, 2020), and recent review articles categorise these methods, discuss their challenges, and outline emerging opportunities. However, few studies apply them directly within P2P lending frameworks.

XAI research generally distinguishes between two complementary approaches: (i) **inherently interpretable models**—such as logistic regression, decision trees, K-nearest neighbours, Bayesian models, rule-based systems, and generalized additive models—which provide transparency by design; and (ii) **post-hoc explanation techniques**, which interpret the outputs of black-box models through visualisation, feature attribution, surrogate models, or rule extraction. Figure 9 illustrates how these approaches contribute to Responsible AI in P2P lending, highlighting key principles such as fairness, transparency, privacy, and accountability.

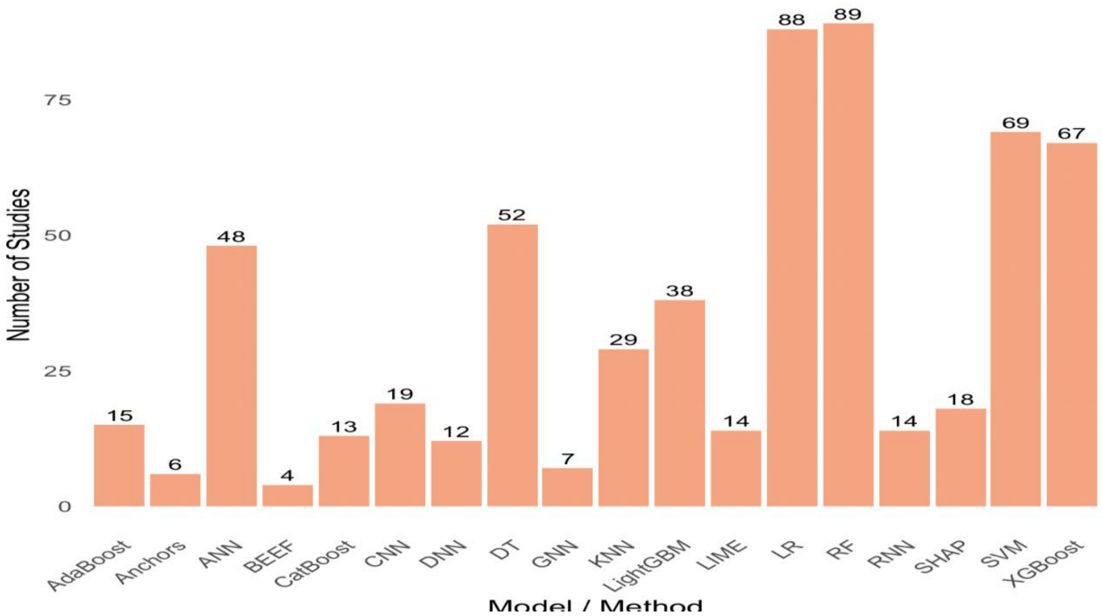
SHAP, in particular, has emerged as a powerful method for assessing feature importance and understanding complex risk assessment patterns. Empirical evidence shows that ML models such as logistic regression, random forests, and gradient boosting machines can outperform traditional credit scoring tools while also benefiting from enhanced explainability through SHAP analysis.

Integrating XAI into P2P lending platforms offers several benefits. For lenders, explanations provide better insight into risk drivers and improve investment decision-making. For borrowers, explanations clarify why loan applications are accepted or rejected, promoting fairness and reducing information asymmetry. These improvements can also support financial inclusion by making automated decisions more transparent and reducing unintended biases.

Nevertheless, several challenges remain. XAI methods must scale to large and dynamic P2P datasets, integrate smoothly into existing platform infrastructures, and present explanations through user-friendly interfaces that lenders and borrowers can easily interpret. Furthermore, XAI introduces potential concerns around privacy, proprietary business rules, and model confidentiality. Therefore, explainability must be addressed in conjunction with broader Responsible AI principles.

In summary, adopting Explainable AI in P2P lending has the potential to significantly enhance transparency, fairness, and trust in automated credit decision-making. By offering clear, meaningful explanations for complex model outputs, XAI strengthens both lender and borrower confidence, promotes responsible financial practices, and supports the development of a more equitable and sustainable P2P lending ecosystem.

Figure 9: Most frequent ML/DL and XAI methods

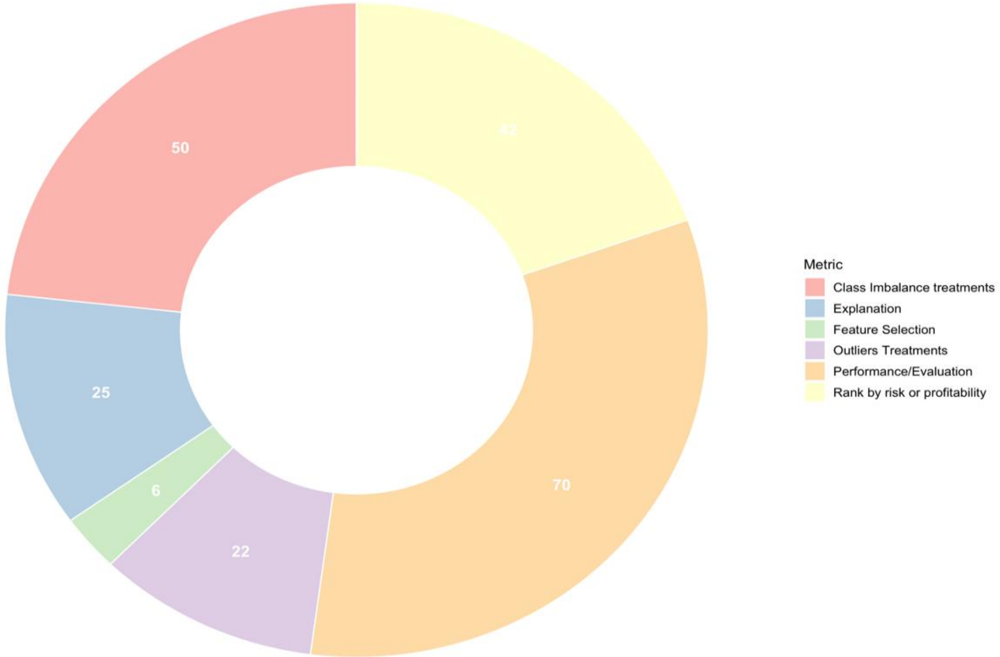


3.2.4 Metrics

This section examines the key metrics and methodological components used across P2P lending studies, particularly those focused on default prediction, fraud detection, and broader risk assessment. These elements are fundamental not only for ensuring the robustness of classification models but also for fostering trust among platform users, regulators, and financial supervisors, all of whom depend on transparent, well-validated modelling practices.

Figure 10 illustrates the distribution of the main metrics employed in the reviewed literature. A total of 70 studies relied on performance and evaluation measures, making this the most frequently used category. These studies typically focused on assessing model accuracy, AUC, precision–recall, error rates, or comparative performance across multiple classifiers. Such evaluations play a central role in determining how well proposed models capture borrower risk or detect fraudulent activities.

Figure 10: Distribution of metrics



A notable proportion of studies (50 papers) addressed class imbalance treatments**,** reflecting the persistent skew between default and non-default observations in P2P lending datasets. Common strategies included SMOTE-based oversampling, random undersampling, hybrid techniques, and cost-sensitive learning—each aimed at improving predictive stability and reducing bias toward majority-class outcomes.

The third most frequent metric category is risk ranking or profitability-based ranking**,** used in 42 studies**.** These works typically ranked loans or borrowers based on predicted returns, expected losses, or portfolio-level risk profiles, revealing the importance of linking model outputs to investment decision-making and portfolio optimization.

Explainability appears in 25 studies, indicating a growing but still limited effort to make model decisions transparent. Most explainability-related work remains tied to statistical or econometric models through coefficient interpretation or inferential tests, while only a smaller subset of machine learning papers integrate modern XAI techniques such as SHAP or LIME. Despite recent progress, the overall use of explainability tools remains comparatively low and highlights the need for more transparent ML practices in P2P lending.

Outlier treatment is addressed in 22 studies, where researchers focus on detecting and removing anomalous or extreme values that may distort model behaviour. These treatments are essential given the prevalence of noise, manipulation attempts, or unconventional borrower profiles in P2P lending environments.

Finally, only **6 studies** explicitly considered **feature selection**. Although feature selection is a crucial step for improving model efficiency, interpretability, and generalization, its limited application suggests that many studies rely on full feature sets without systematically assessing variable relevance or redundancies.

Taken together, the distribution shown in Figure 10 demonstrates that while performance evaluation and class imbalance handling are relatively mature areas in P2P lending research, other important methodological components—particularly explainability and feature selection—remain underexplored. Addressing these gaps is essential for strengthening model reliability, improving transparency, and supporting responsible and trustworthy AI adoption in P2P lending.

4 Discussion

The peer-to-peer (P2P) lending market has undergone rapid expansion over the past decade, driven by advances in digital technologies, data availability, and the proliferation of machine learning (ML) and artificial intelligence (AI) methods. These innovations have strengthened risk and profit management capabilities, enabling platforms to process vast volumes of borrower- and loan-level data and generate faster, more accurate assessments. However, they have also introduced new challenges related to supervisory oversight, regulatory compliance, and model transparency.

Our review reveals that P2P lending research is heavily influenced by data availability, particularly from the United States and China. The Lending Club dataset emerges as the most frequently used source, appearing in over one hundred studies, while Chinese datasets such as ppdai.com, renrendai.com, and we.com show increasing prominence due to the size and maturity of the Chinese P2P market. European research is comparatively more limited and focuses on systemic risk and business lending, often using data from External Credit Assessment Institutions (ECAIs).

Machine learning models dominate empirical research, especially logistic regression (86 studies), random forests (88 studies), gradient boosting techniques like XGBoost (65 studies), and SVMs (68 studies). Deep learning methods—including CNNs, RNNs, LSTMs, and DNNs—show growing adoption but remain less prevalent than classical ML approaches. Despite their predictive power, these models often suffer from opacity. As demonstrated in our analysis, more than 90 studies employ non-interpretable models, while only 61 utilise inherently interpretable approaches, and 66 do not clearly report interpretability considerations at all.

Explainability remains a significant gap in the literature. Although model-agnostic methods such as SHAP (18 studies), LIME (14 studies), Anchors (6 studies) and BEEF (4 studies) have been applied, their usage is still limited compared to the widespread deployment of black-box models. Most explainability efforts focus on coefficient interpretation in statistical models, while ML-based studies often restrict themselves to global feature importance. This hinders regulatory adoption, especially in jurisdictions governed by frameworks such as GDPR and CCPA, which require transparency and the ability to justify automated decisions.

Another important finding concerns model validation practices. Performance and evaluation metrics are widely used (70 studies), yet other critical aspects—such as feature selection (6 studies), outlier treatment (22 studies), and explanation-oriented evaluation (25 studies)—remain underutilised. Class imbalance treatment is considered in 50 studies, reflecting the sector’s highly skewed default distributions. However, hyperparameter tuning and rigorous statistical comparisons are inconsistently applied, suggesting gaps in methodological robustness.

In terms of business problem coverage, most academic work focuses on individual lending and default prediction, leaving significant areas underexplored. Fraud modelling, Loss Given Default (LGD), prepayment risk, and debt collection analytics remain insufficiently studied despite their importance for platform viability. Research rarely extends to profitability ranking (42 studies), portfolio optimisation, or the broader behavioural and macroeconomic determinants of platform performance.

Overall, while P2P lending research demonstrates rapid methodological development, it remains fragmented. High-performance models are abundant, but interpretability, responsible AI practices, and alignment with regulatory and operational needs lag behind. The sector will therefore require new frameworks that balance accuracy, fairness, transparency, and deployability—especially as platforms seek to strengthen trust, comply with regulation, and operate safely in increasingly complex financial ecosystems.

5 Conclusion

This study reviewed 220 empirical works published between 2015 and 2025 that examined risk mitigation strategies in P2P lending using machine learning (ML) and artificial intelligence (AI). Across this body of research, we identify a clear shift toward hybrid modelling approaches that combine multiple algorithms, data sources, and feature engineering techniques to enhance predictive accuracy. These hybrid models often outperform traditional credit scoring approaches, reflecting the sector’s rapid technological maturation.

Explainability has emerged as an equally important theme. Although the predictive performance of ML and deep learning models continues to improve, the sector faces persistent challenges related to model transparency. Our analysis shows that the use of explainable AI (XAI) remains limited: SHAP (18 studies) and LIME (14 studies) are the most frequently adopted techniques, while Anchors and BEEF appear rarely. Most ML studies rely solely on global feature importance rather than deeper forms of interpretability, leaving significant gaps in transparency at both the global and local level. As regulations such as GDPR and CCPA increasingly require justification of automated decisions, explainability will become indispensable for real-world adoption of advanced models in P2P lending.

The review also highlights the growing variety and complexity of data sources used in P2P credit modelling. Besides traditional financial variables, researchers are incorporating soft information, NLP-derived features, social connectivity networks, platform behavioural metrics, and other forms of big data. These inputs enhance predictive performance but also raise ethical and operational considerations. Many studies do not critically assess potential biases, fairness issues, or the legal implications of exploiting such data. Future research must ensure that the benefits of rich data do not come at the expense of equity, privacy, or regulatory alignment.

Another important finding is the uneven representation of business problems across the literature. Most studies focus on individual loan default prediction, while areas such as fraud detection, Loss Given Default (LGD), debt collection strategies, prepayment risk, and collateral mechanisms remain significantly understudied—despite their centrality to sustainable platform operations. Similarly, SME and business lending receive far less attention than individual lending, even though these segments require distinct modelling strategies and financial evaluation criteria.

Our findings underscore the need for stronger methodological practices. Although many studies report performance metrics, far fewer address class imbalance, feature selection, outlier handling, or robust statistical testing. Explainability-based metrics remain especially scarce. These gaps point to the importance of more rigorous, transparent, and reproducible modelling pipelines.

Looking ahead, future research should prioritise frameworks that integrate ethical, interpretable, and regulatory-compliant AI into P2P credit decision-making. Early efforts—such as those by Ariza-Garzon et al. (2020) and Bussmann et al. (2020)—demonstrate the feasibility of combining ML with XAI in financially regulated environments. Complementary literature on responsible AI (e.g., Carvalho et al., 2019; Barredo Arrieta et al., 2020) provides a foundation for developing models that balance accuracy with transparency, fairness, and accountability.

Finally, we highlight the importance of expanding research beyond purely technical modelling contributions. Many structural issues in P2P lending—such as regulatory deficiencies, economic vulnerabilities, political influences, and market governance—are explored mainly through qualitative studies. These should be complemented with quantitative evidence that links financial behaviour, platform dynamics, and regulatory quality to credit risk outcomes.

In conclusion, the P2P lending market presents extensive opportunities for future inquiry. As AI-driven decision systems become more deeply embedded in credit allocation, ensuring interpretability, fairness, and ethical use will be essential. Addressing these challenges will support the development of P2P lending as a transparent, inclusive, and reliable financial ecosystem for both borrowers and investors.

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