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Credit Risk Assessment Models in Peer to Peer Lending Platforms

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Abstract

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This study provides a systematic literature review of credit risk assessment models in peer to peer lending platforms. The review is motivated by growing concerns about platform failures, loan underperformance, and investor protection in markets characterised by high information asymmetry and thin borrower credit files. Using structured database searches and explicit inclusion criteria, the study synthesises evidence on statistical, machine learning, and ensemble based models that are applied to large scale lending datasets. The findings show that advanced modelling techniques consistently outperform traditional scorecards in predicting default and, when designed to target risk adjusted returns, can support more sustainable portfolio performance for investors. The review also highlights the rising importance of soft and unstructured information, including narrative loan descriptions, personality related indicators, and other non traditional signals, which enhance discrimination power when combined with numerical features. Finally, the study identifies an emerging shift toward explainable artificial intelligence and profit oriented scoring within governance frameworks that emphasise transparency, fairness, and regulatory compliance. These developments highlight the need for integrated and transparent credit frameworks.

1. Introduction

Credit risk assessment is a core challenge for peer to peer (P2P) lending platforms because their business model relies on matching often unknown borrowers and dispersed investors through fully digital processes. Unlike traditional banks that can rely on long term relationships and comprehensive credit files, P2P platforms frequently operate with limited hard information and a high degree of information asymmetry, which increases default risk and undermines investor confidence if not managed properly (Suryono et al., 2019, Lyócsa et al., 2022). As P2P markets in the United States, Europe, China, and emerging economies have expanded, episodes of platform failures and loan underperformance have highlighted the need for robust and transparent credit risk assessment models that can support the sustainable growth of this segment.

Recent empirical evidence shows that the distinct characteristics of P2P lending small, mostly unsecured consumer and small business loans, heterogeneous borrower profiles, and platform specific scoring systems require tailored credit scoring approaches rather than a direct transfer of traditional bank models (Xu et al., 2021, Lyócsa et al., 2022). Large scale datasets from platforms such as Renrendai, LendingClub, and Bondora reveal strong nonlinearities, high dimensional feature spaces, and class imbalance between default and non default observations, which can limit the performance of conventional logistic regression if used in isolation (Zhou et al., 2019, Dzik-Walczak & Heba, 2021). As a result, P2P credit risk assessment has become an important testing ground for advanced machine learning techniques.

A growing strand of research proposes machine learning based models random forests, gradient boosting, neural networks, and heterogeneous ensembles to capture complex interactions among borrower characteristics, loan terms, and behavioural variables in P2P datasets. Studies using high dimensional platform data show that such models can significantly improve default prediction accuracy relative to benchmark scorecards, thereby reducing misclassification of risky borrowers and enhancing portfolio performance (Zhou et al., 2019, Dzik-Walczak & Heba, 2021, Xu et al., 2021). At the same time, there is increasing interest in shifting from pure "default scoring" to "profit scoring," where models directly target risk adjusted returns rather than only the probability of default, suggesting that profit oriented credit risk models can make P2P investments more attractive and sustainable for investors (Lyócsa et al., 2022).

Another important development concerns the use of soft and unstructured information in P2P credit risk assessment. Because P2P platforms collect textual loan descriptions and other narrative disclosures, recent work employs deep learning architectures to extract credit relevant signals from user generated text, demonstrating that even short descriptions can substantially improve default prediction when combined with numerical features (Kriebel & Stitz, 2022). In parallel, the increasing regulatory scrutiny of fintech credit has triggered a debate on the transparency and fairness of black box models. Explainable machine learning frameworks that integrate Shapley value based explanations and network analytics have been proposed to reconcile high predictive performance with interpretability, explicitly highlighting applications to credit risk management in P2P and other alternative lending settings (Bussmann et al., 2021).

Against this background, there is a need for a structured synthesis of credit risk assessment models used in P2P lending that brings together advances in machine learning, the exploitation of unstructured data, profit oriented scoring, and explainable artificial intelligence. By systematically reviewing recent peer reviewed studies, this research aims to map the evolution of modelling techniques, identify their relative strengths and limitations, and highlight open research gaps related to model interpretability, regulatory compliance, and external validity across platforms and jurisdictions. This synthesis is expected to provide guidance for scholars, platform designers, and regulators seeking to develop credit risk frameworks that balance predictive accuracy, transparency, and investor protection in the fast growing P2P lending industry.

2. Literature Review

Recent surveys and bibliometric studies confirm that credit risk remains the central research theme in the peer to peer lending literature, reflecting concerns about platform fragility and investor protection as the market matures. A large scale mapping of Scopus indexed work shows that risk assessment, default prediction, and information asymmetry dominate economic and business perspectives on peer to peer lending, with growing attention to data driven credit scoring and platform governance (Kholidah et al., 2022). Within this stream, credit risk is framed as a consequence of thin credit files, heterogeneous borrower types, and the absence of relationship lending, making robust scoring systems essential for the sustainable development of the industry (Ahelegbey & Giudici, 2023; Siering, 2023).

Empirical studies increasingly move beyond traditional scorecards to adopt machine learning and ensemble methods tailored to the statistical properties of peer to peer datasets. Using LendingClub data, Chen et al. (2021) show that logistic regression, random forests, and neural networks combined with resampling and cost sensitive learning significantly improve default prediction on imbalanced datasets. Building on this, several contributions exploit high dimensional platform data and propose ensemble approaches that integrate feature engineering and resampling strategies, demonstrating that heterogeneous ensembles and multiview learning can outperform single classifiers in terms of discrimination and robustness to class imbalance (Li et al., 2020; Niu et al., 2020; Song et al., 2020). Ko et al. (2022) compare artificial intelligence models with conventional statistical techniques and find that AI based credit risk models provide higher predictive accuracy and better capture nonlinear relationships in peer to peer lending portfolios, while recent model fusion work emphasizes improving recall for defaulted borrowers as a key metric for risk management (Liu et al., 2023).

Along side numerical borrower and loan characteristics, a second strand of research explores the use of soft and unstructured information for credit risk assessment. Xia et al. (2020) show that narrative loan descriptions contain credit relevant signals that, when processed with text mining and forecasting models, meaningfully enhance default prediction beyond standard financial features. From a disclosure perspective, Siering (2023) documents that textual factors drawn from borrower narratives and platform communication improve credit risk models and help explain cross sectional variation in loan performance. Other studies extend the feature space to psychometric and personality related proxies; for example, Woo and Sohn (2022) derive Myers Briggs type indicators from occupational categories and show that incorporating personality type information into credit scoring improves model performance in online peer to peer lending. Complementing these empirical findings, theoretical work on social collateral and soft information stresses how non traditional signals can mitigate information asymmetry and shape borrower selection on online platforms (Liu et al., 2020).

More recently, scholars have highlighted the need to reconcile high predictive accuracy with regulatory expectations around transparency, fairness, and model risk. Ariza-Garzón et al. (2020) develop an explainable machine learning granting score model for peer to peer lending and demonstrate that Shapley value based explanations can reveal the contribution of individual features to lending decisions without sacrificing predictive power, thereby supporting model validation and compliance. At the portfolio level, Ahelegbey and Giudici (2023) propose a clustering based credit scoring framework for small and medium sized enterprises in peer to peer lending, showing that factor based grouping of borrowers refines risk segmentation and enhances score stability. Together, these contributions point to an emerging consensus that future research should integrate advanced machine learning, soft information exploitation, and explainable artificial intelligence within credit risk frameworks that are compatible with prudential regulation and investor protection objectives.

3. Methods

This study employs a systematic literature review (SLR) approach to synthesise evidence on credit risk assessment models in peer to peer lending platforms. The review follows structured stages of planning, searching, screening, and synthesising the literature. First, a search strategy was developed using combinations of keywords such as “peer to peer lending,” “P2P lending,” “credit risk,” “default prediction,” “machine learning,” “text mining,” and “explainable artificial intelligence.” These terms were applied to major scholarly databases, including Scopus and Web of Science, complemented where necessary by searches in reputable publisher platforms for finance, information systems, and computer science journals. Second, the initial pool of studies was filtered using pre defined inclusion and exclusion criteria: only peer reviewed journal articles written in English, focusing on credit risk assessment or default prediction in peer to peer lending, and employing quantitative or mixed methods were retained, while conference papers, theses, purely descriptive papers, and studies on other types of fintech credit were excluded.

Third, the remaining articles were screened through title, abstract, and full text reading to ensure conceptual relevance and methodological adequacy, with particular attention to the clarity of model specification, data description, and performance evaluation. For each selected study, a data extraction template was used to code key characteristics, including platform and dataset used, variable types (numerical, soft, and unstructured information), modelling techniques (e.g., statistical models, machine learning, ensemble methods, explainable AI), treatment of class imbalance, evaluation metrics, and main findings. Finally, the evidence was synthesised using a narrative and thematic approach, grouping studies into coherent clusters such as traditional versus machine learning models, numerical versus text augmented models, and black box versus explainable frameworks to identify patterns, methodological gaps, and future research directions in credit risk assessment for peer to peer lending.

4. Results and Discussion

The SLR shows a clear convergence in the literature that credit risk is the dominant concern in peer-to-peer lending, both at platform and investor level. Bibliometric evidence indicates that risk assessment, default prediction and information asymmetry sit at the core of economic and business research on P2P markets (Kholidah et al., 2022), which is consistent with earlier findings that platform fragility and investor protection are key vulnerabilities in this industry (Suryono et al., 2019). Within this landscape, credit risk is systematically framed as a consequence of thin credit files, heterogeneous borrower types and the absence of relationship lending, reinforcing the argument that P2P lending cannot simply borrow credit scoring practices from traditional banking but requires dedicated, platform-specific models (Lyócsa et al., 2022; Ahelegbey & Giudici, 2023; Siering, 2023).

A first major result of the review is the strong and consistent evidence that machine learning models outperform traditional scorecards in predicting default in P2P portfolios. Studies using large scale datasets from platforms such as

LendingClub, Renrendai and Bondora show that logistic regression alone struggles with non-linearities, high dimensional features and pronounced class imbalance between default and non-default observations (Zhou et al., 2019; Dzik-Walczak & Heba, 2021; Xu et al., 2021). Building on this diagnosis, empirical work demonstrates that random forests, gradient boosting, neural networks and heterogeneous ensembles, often combined with feature engineering and resampling techniques, deliver higher discrimination power and more robust performance on imbalanced datasets (Li et al., 2020; Niu et al., 2020; Song et al., 2020; Chen et al., 2021). Comparative evidence confirms that artificial intelligence based models capture complex non-linear relationships more effectively than conventional statistical techniques, strengthening the case for ML driven credit scoring as the new benchmark in P2P lending (Ko et al., 2022).

A second important finding concerns the evolution from pure default-oriented scoring towards profit-oriented models. While many studies still focus on minimising default misclassification, recent contributions argue that credit risk models should directly target risk adjusted returns, thereby aligning model objectives with investors' portfolio performance (Lyócsa et al., 2022). In this context, model fusion and ensemble strategies that explicitly aim to improve recall for defaulted borrowers are particularly relevant, because they reduce downside risk even if this comes at the cost of more conservative acceptance decisions (Liu et al., 2023). The SLR thus indicates a gradual shift from viewing P2P credit scoring as a pure classification problem to treating it as an optimisation problem in which risk and return must be jointly managed.

The review also highlights a robust pattern regarding the role of soft and unstructured information. Beyond numerical borrower and loan characteristics, several studies show that textual loan descriptions and other narrative disclosures contain credit-relevant signals that significantly enhance default prediction when integrated into forecasting models (Xia et al., 2020; Kriebel & Stitz, 2022). From a disclosure perspective, textual factors extracted from borrower narratives and platform communications help explain cross-sectional variation in loan performance, suggesting that soft information can partially compensate for thin formal credit histories (Siering, 2023). Extensions to psychometric and personality related proxies further support this view: incorporating personality type indicators inferred from occupational categories improves model performance in online P2P lending (Woo & Sohn, 2022), while theoretical work on social collateral argues that non-traditional signals and social ties reduce information asymmetry and shape borrower selection (Liu et al., 2020). Taken together, these findings show that exploiting soft and unstructured data is no longer peripheral but increasingly central to frontier P2P credit risk models.

Finally, the SLR documents a growing concern with transparency, fairness and model risk in the use of complex algorithms. Although black box ML models achieve superior predictive accuracy, regulators and platforms face challenges in understanding and validating these systems. Explainable machine-learning frameworks that employ Shapley value based explanations demonstrate that it is possible to reveal the marginal contribution of individual features to granting decisions without sacrificing performance (Ariza-Garzón et al., 2020; Bussmann et al., 2021). At the portfolio level, clustering based credit scoring for small and medium sized enterprises refines risk segmentation and improves score stability, offering a more interpretable structure for both platform managers and supervisors (Ahelegbey & Giudici, 2023). These results suggest that the field is moving towards hybrid solutions that combine advanced ML, soft information exploitation and explainable AI within frameworks that remain compatible with prudential regulation and investor protection objectives.

Overall, the evidence reviewed here indicates that the frontier of P2P credit risk assessment is characterised by three intertwined trends: the dominance of machine-learning and ensemble models over traditional scorecards; the systematic incorporation of textual and other soft information into scoring architectures; and the emergence of explainability and regulatory compliance as central design criteria. This combination confirms the initial problem framing of P2P credit risk as a complex, high dimensional and information asymmetric environment (Suryono et al., 2019; Kholidah et al., 2022), while pointing to future research needs around out of sample robustness across platforms and jurisdictions, fairness in algorithmic decisions, and the integration of profit oriented scoring into broader platform governance and risk management strategies.

5. Conclusion

This study concludes that effective credit risk assessment is fundamental to the sustainability of peer-to-peer lending platforms, given their structural reliance on anonymous, digitally mediated matches between borrowers and investors in the presence of severe information asymmetry. The systematic review shows that traditional scorecard based approaches are no longer sufficient in an environment characterised by high dimensional data, non-linear relationships, and pronounced class imbalance. In response, machine-learning and ensemble models often enhanced through resampling, feature engineering, and model fusion have emerged as the de facto frontier, consistently outperforming conventional statistical techniques in predicting default and, increasingly, in optimising risk adjusted returns. At the same time, the evidence underscores that soft and unstructured information, such as textual loan descriptions, personality related proxies, and indicators of social collateral, plays a growing role in mitigating thin-file problems and improving discrimination power in P2P credit scoring.

However, the review also highlights that gains in predictive accuracy must now be balanced against rising expectations of transparency, fairness, and regulatory compliance. The development of explainable machine-learning frameworks, including Shapley value based explanations and clustering based credit scoring, signals a shift towards hybrid solutions that combine advanced analytics with interpretability suitable for platform managers, investors, and supervisors. Overall, the synthesis points to a research and policy agenda focused on three priorities: strengthening the out-of-sample robustness and cross platform generalisability of credit risk models; embedding profit-oriented and investor-protection objectives into model design; and deepening the integration of explainable artificial intelligence and soft-information exploitation within governance frameworks that ensure responsible, trustworthy use of algorithms in the rapidly expanding P2P lending ecosystem.

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