ISSN:3049-0952
www.jsetms.com

A REVIEW OF FINTECH INNOVATIONS IN PEER-TO-PEER LENDING AND CREDIT RISK ASSESSMENT TECHNIQUES

Sandeep Shivam
Independent Researcher, IEEE
McKinney, Texas, USA
Sandeep.shivam@ieee.org

To Cite this Article
Sandeep Shivam, "A Review of FinTech Innovations in Peer-to-Peer Lending and Credit Risk Assessment Techniques", Journal of Science Engineering Technology and Management Science, Vol. 03, Issue 05, May 2026, pp: 55-62, DOI: http://doi.org/10.64771/jsetms.2026.v03.i05.pp55-62
Submitted: 23-03-2026 *Accepted: 28-04-2026* *Published: 05-05-2026*

***Abstract*—Peer-to-peer (P2P) lending is another important financial technology (FinTech) innovation, which has helped to connect the two parties (borrowers and lenders) using online platforms without an intermediary between them, a financial institution. This is because such platforms enable unsecured lending, as borrowers can take loans and investors can finance them based on their risk and return preferences. P2P lending has been experiencing a blistering evolution due to the digital transformation phenomenon, the need to seek alternative funding, and the adoption of new and effective technologies, including artificial intelligence (AI), machine learning (ML), and blockchain. Nevertheless, efficient credit risk analysis is one of the biggest issues associated with the sustainability of platforms and assists in decreasing the loan default rate. Older credit scoring models are often based on a very thin financial history and do not capture dynamic borrower behaviour, and are therefore not believed to be applicable to the new digital borrowing markets. FinTech solutions address such limitations with alternative data, predictive analytics and automated decision-making systems. The AI-based methods to optimize credit assessment, fraud detection, and dynamic risk profiling include random forests, gradient boosting, neural networks, and natural language processing. Another way these technologies drive financial inclusion is by empowering underserved individuals and small enterprises to access credit via digital lending ecosystems.**

Keywords—Peer-to-Peer (P2P) Lending, FinTech, Credit Risk Assessment, Artificial Intelligence, Machine Learning, Financial Inclusion.

I. Introduction

FinTech or financial technology is the name that is used to refer to the application of sophisticated digital technologies to the automation and support of financial services. FinTech has proven to be among the game-changing innovations in the financial sector that presented new solutions to financial processes, which made them more efficient, accessible, and transparent[1]. The technologies of AI, big data analytics, blockchain, and mobile computing have made it possible to create new financial models, which disrupt the traditional banking systems [2][3]. P2P lending, crowdfunding, online wallets, internet-based payments, and other digital financial services that supply financial services more quickly and conveniently than conventional banking processes have been made possible by these developments.

P2P lending has emerged as one of the most notable FinTech innovations in digital lending. The conventional finance intermediaries are eliminated, allowing borrowers and financiers to communicate directly through online channels [4]. Through the digital platform, P2P lending ensures that the cost of operation is minimized and transparency is enhanced and alternative sources of financing are offered to individuals and small businesses who might have problems accessing loans through mainstream banks [5][6][7]. The development of internet connectivity and information technology has also contributed to growth of P2P lending sites as it has allowed efficient data gathering and a better matching mechanism between the borrowers and the lenders.

The most significant issues in P2P lending systems are the proper evaluation of the borrower's creditworthiness as well as the management of credit risk [8][9]. The conventional credit-scoring models tend to use few financial factors and past credit information which may not entirely depict the financial behaviour of most borrowers especially those with limited or no credit history [10]. In order to overcome these shortcomings, the latest FinTech solutions are also actively introducing innovative technologies like AI, ML, and big data analytics to improve credit-risk assessment [11]. Through these technologies, lenders can offer a more accurate and dynamic analysis of borrower risk through the analysis of vast quantities of both structured and unstructured data, consisting of behavioral patterns, transactional history, and other financial indicators. Digital lending platforms have become much more efficient and trustworthy due to recent advances in AI-based credit scoring systems, natural language processing, blockchain-based fintech, and real-time data analytics[12]. These innovations facilitate automated processing of loans, fraud detection and dynamic risk profiling besides increasing financial inclusion by empowering underserved groups to get credit by using alternative data assessment.

A. Organization of the Paper

This paper is organized as follows for the remainder: The loan process and operational procedures of P2P lending platforms in FinTech are covered in Section II. Credit risk assessment in P2P lending and shortcomings of conventional credit rating systems are described in Section III. FinTech developments in credit risk assessment leveraging blockchain, AI, ML, and NLP are presented in Section IV. Section V examines recent research on appraisal of credit risk in P2P lending using AI and FinTech. Finally, Section VI summarises the paper's key conclusions and makes recommendations for more study.

II. PEER-TO-PEER (P2P) LENDING PLATFORMS IN FINTECH

The method of obtaining funds from the internet community via digital platforms that act as intermediaries between those with funds and those who need them is known as peer-to-peer lending. It may be characterized as the delivery of unsecured loans via the use of an internet platform that links lenders and borrowers. A borrower might be a person or a business that needs a loan [13]. Interest rates for loans might be determined by the platform or agreed upon by lenders and borrowers. There is an origination charge for borrowers, an administrative fee, and any extra fees for lenders that use the platform for additional services. Services such as assessing borrowers' creditworthiness and collecting on loans are provided by the platforms.

A. Working Mechanism of P2P Lending

There are various ways in which the P2P lending platforms work, based on their operating purpose and organization. In general, these operating processes may be separated into two types, which are represented by Prosper Marketplace and Kiva. These sites depict two different strategies of linking borrowers and lenders under internet lending circumstances [14][15]. The general steps used in the operational process consist of registration of the borrower, credit assessment, listing of loans, investment by investors and management of the repayment. Under this system, online platforms take the role of mediators that promote safe financial dealings alongside the regulation of risk assessment and lending policies [16][17]. As shown in Figure 1, process of P2P lending involves borrowers requesting loans via what is known as a lending platform that conducts credit checks and provides them to lenders who finance the loans under regulatory oversight.

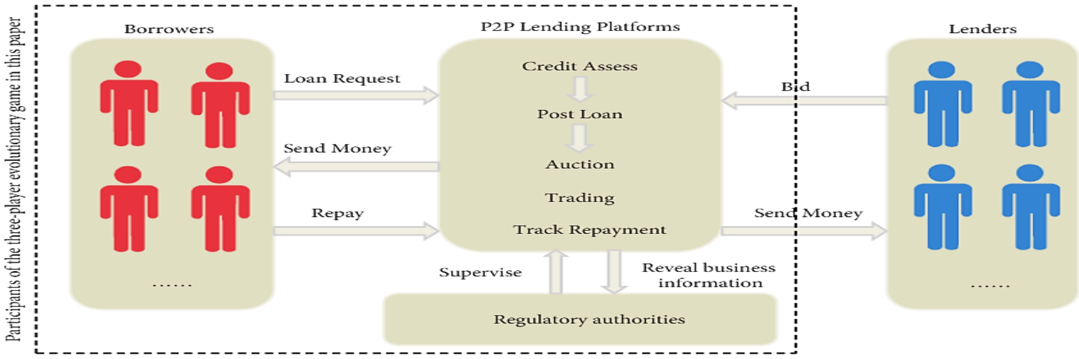

Fig. 1. The Working Mechanism Of P2P Lending

1) Borrowers

Borrowers are patients or companies that require financial assistance using P2P lending facilities. In most business websites, including Prosper Marketplace, borrowers are required to create an account, complete the personal information and financial data, and submit a loan application that includes the purpose of the loan and a reasonable interest rate [18]. The site then assesses the creditworthiness of the borrower and posts the loan request on which investors can fund. However, in networks like Kiva, borrowers typically do not use the site directly but via local partner organizations.

2) Lenders

In P2P lending platforms, lenders, or investors, or donors, as they call them depending on the platform model, lend money to the borrowers. During commercial operations such as those found in Prosper Marketplace, lenders tend to invest in loans according to the investment criteria and risk preferences of their choice and anticipated returns [19][20]. They can finance some of the various loans so as to diversify their investment portfolio. In non-profit microcredit organizations, like Kiva, social impact is an incentive instead of monetary gains to lenders.

3) Field Partners

In other P2P lending structures, notably those employed by Kiva, field partners are local organizations that are significant. These organizations are microfinance institutions, non-governmental organizations (NGOs), and social enterprises that serve as the middlemen between the borrowers and the online platform. Field partners examine loan applications, check the information about loan applicants, post loan requests on the platform, and administer loan disbursements and loan repayments.

4) Groups and Teams in Lending Communities

Certain P2P platforms imply some form of community to enhance trust and cooperation among the participants. On websites such as Prosper Marketplace, members can create groups of borrowers and lenders, with shared interests or other affinities [21]. Such groups are normally controlled by a group leader who promotes participation and assists in keeping the platforms alive. The credibility of loans can be enhanced by group endorsements, which will result in a greater access to funds. These are teams that combine resources to finance loans and work towards improving the social impact of lending processes.

B. Global Growth and Market Trends of P2P Lending

The global P2P lending market has been growing significantly as financial technology is rapidly growing, and more people demand alternative lending solutions. Most of the FinTech businesses are embracing the emerging innovative technologies like AI, Big Data Analytics, and blockchain to improve credit risk measurement and the efficiency of their platforms[22]. P2P lending has been receiving widespread international coverage, especially in Western markets, where it has become an alternative financial paradigm involving borrowing and lending under the auspices of digital platforms. P2P lending in India is a comparatively new phenomenon that has enjoyed consistent expansion as a number of FinTech firms providing online lending services emerge [23][24]. These websites provide internet-based marketplaces that let individuals lend and borrow money without the involvement of conventional financial institutions.

In India, a number of websites like Faircent and Len Den Club have been significant in the marketing of the P2P lending services [25]. These sites set interest rates and repayment conditions depending on the type of loan and a profile of borrower and the credit risk rating. Interest rate models tend to be different among platforms and can take various approaches such as fixed interests as provided by the platform, dynamic interests depending on the cost-plus models or the contract between lenders and borrowers, which involves the operational costs of the platform, commissions of the platform, and returns of the lenders.

The following Table I summarizes some of leading P2P lending platforms operating in India along with their key characteristics.

TABLE I. SUMMARY OF LEADING PEER-TO-PEER (P2P) LENDING PLATFORMS IN INDIA

Platform	Location / Year of Commencement	Minimum Loan Amount	Maximum Loan Amount	Average Interest Rate	Borrower Evaluation Criteria
Faircent	Gurgaon / 2014	₹30,000	₹5,00,000	22–23%	Credit score, salary details, and bank account data
Lendbox	Delhi / 2015	₹10,000	₹5,00,000	12–36%	Big data analytics and advanced data intelligence
i-Lend	Hyderabad / 2013	₹25,000	₹5,00,000	16–23%	Social network data and borrower profile analysis
LenDenClub	Mumbai / 2015	₹5,000	No upper limit	12.5–35%	Credit score, salary information, and other financial factors
Rupaiya Exchange	Delhi / 2015	₹5,000 (Personal) / ₹50,000 (Business)	₹5,00,000 – ₹70,00,000	15–36%	Credit underwriting process and screening based on financial eligibility

C. Pros and Cons of P2p Lending

P2P lending has a number of advantages and issues for both lenders and borrowers. The main pros and cons of P2P lending based on views of borrowers and investors are summarized in Table II.

TABLE II. ADVANTAGES AND DISADVANTAGES OF PEER-TO-PEER (P2P) LENDING FOR BORROWERS AND LENDERS

Participants	Advantages (Pros)	Disadvantages (Cons)
Borrowers	• Lower interest rates and usually no collateral requirement. • Online and paperless loan application process. • Fixed monthly repayment installments. Credit eligibility requirements may be less strict than traditional banks. • No prepayment penalties in many cases.Higher possibility of funding innovative business ideas compared to traditional banks.	• Loan amounts may be lower compared to bank loans. • Missed or delayed payments can negatively affect the borrower's credit score. • Security and protection may be lower than traditional banking systems. • Lack of standardized lending requirements across different platforms. • Sometimes there are more borrowers than available lenders, which may delay funding.
Lenders (Investors)	• Potentially greater returns than mutual funds or conventional savings accounts. • Regular monthly repayments with interest income. • Potential to diversify investment in several loans to limit the risk exposure.	• Risks associated with default by loan borrowers (on loan repayment). Poor liquidity as compared to bonds or stocks because of the extended investment periods. • Limited regulatory protection and possibility of fraud or borrower default.

III. CREDIT RISK ASSESSMENT IN P2P LENDING

The significance of risk management and traditional credit rating system used in the financial systems. It also highlights the limitations of old credit scoring techniques in the dynamism of FinTech world, and the need to develop more advanced and broad-based assessment techniques.

A. Risk Management in Peer-to-Peer Lending

Risk management is important in identifying risk of loan default in the evaluation of credit risks in P2P lending sites. The credit scoring models are also quite widespread in the evaluation of credit worthiness of borrowers, the estimates of default and decision-making in loan approvals[26][27]. The conventional credit risk assessment techniques primarily depend on the statistical models and historical finance information, such as demographics, income level, employment status, credit history, and the behaviour of borrower repayment[28]. These have assisted the lending platforms in putting the right interest rates and controlling possible financial risks. Moreover, credit appraisal and evaluation are often supported by credit rating agencies and financial records to enhance the precision of lending decisions [29]. As P2P lending and FinTech technologies evolve, recent risk management strategies now use more information sources and analytics to drive credit risk.

The P2P lending sites employ various structural assurance methods to assess credibility of borrowers and reduce the loan risks. Table III shows some P2P lending platforms and types of borrower assessment that they use to evaluate credit risk

TABLE III. P2P LENDING PLATFORMS AND BORROWER EVALUATION STRATEGIES

P2P Lending Platform	**Borrower Evaluation Strategy (Structural Assurance Mechanism)**
Fair cent	• In addition to loan records and credit ratings, borrowers are assessed using over 120 factors spanning around 400 datapoints, including their financial, professional, social, and educational backgrounds. • Physical verification of office and residential addresses is conducted, along with income statement validation and assessment of repayment capacity and past financial behavior.
Lend box	• Performs monetary, social, professional, and personal background checks using cutting-edge tech, ML algorithms, and big data analytics. • Evaluates thousands of data points such as salary details, spending patterns, location, education, utility bills, credit card usage, asset holdings, and investment behavior to determine creditworthiness.
i2iFunding	• Utilizes a proprietary credit scoring model based on more than 20parameters in addition to traditional credit scores. • Assigns borrowers a RiskCategory ranging from A to F based on credit profile strength. • Social network data is also analyzed, and investor protection plans with legal recovery support are provided.
LenDenClub	• Employs a five-point credit evaluation system including PersonalDetails, ProfessionalBackground, FinancialInformation, CreditHistory, and PhysicalVerification. • Credit scores are calculated using more than 100 verified borrower data points to determine risk levels.
Rupaiya Exchange	• Financial data, societal characteristics, and behavioral patterns are used to determine payback capabilities in borrower verification and credit rating.

B. *Traditional Credit Scoring in the FinTech Era*

Historical credit records and traditional credit measures, which are the basis of traditional credit scoring systems, do not accurately reflect the dynamic nature of the financial patterns of current borrowers [30]. As it is pointed out in Table IV, there are significant weaknesses in these systems and how they may affect borrowers.

TABLE IV. KEY LIMITATIONS OF TRADITIONAL CREDIT SCORING SYSTEMS

Limitation Category	**Specific Issues**	**Impact on Borrowers**
Inadequacies for Non-Traditional Borrowers	Heavy reliance on established credit histories	Excludes “credit-invisible” individuals who lack formal credit records
	Nuance is lacking in the representation of dynamic financial realities.	Disproportionately penalizes borrowers for past financial difficulties
	High weight on factors such as age of credit accounts	Disadvantages individuals new to credit or with limited credit history
Challenges in Microfinance and FinTech Contexts	Continued dependence on traditional credit bureau scores	Conflicts with FinTech goals of expanding financial inclusion
	Application of conventional metrics in alternative lending	Leads to higher RejectionRates among underserved populations
	Inadequate evaluation for borrowers lacking collateral	Limits effectiveness for microfinance and small-scale borrowers
Data Gaps and Potential Biases	Partial and static view of financial life	Fails to capture important indicators such as income stability and cash flow
	InformationAsymmetry	Reduces accuracy in assessing repayment capacity and financial risk
	Correlation with demographic factors	May create or strengthen prejudices against certain demographic groups.

IV. FINTECH INNOVATIONS IN CREDIT RISK ASSESSMENT

Financial technology (FinTech) has led to an innovation in the traditional credit risk assessment by incorporating innovative data-focused technologies into credit assessment, including AI, ML, and blockchain, to enhance the effectiveness, transparency, and precision of credit assessment. These innovations empower lenders to process large amounts of data, both structured and unstructured, to automate lending processes and to increase financial inclusion by evaluating borrowers with thin credit histories.

A. *Key Innovations Driving Fintech Lending*

Some of the main Innovations Driving Fintech Lending are outlined below:

1) *Natural Language Processing (NLP) for Enhanced Customer Interactions*

Natural Language Processing (NLP) can be used to automatically engage with clients and deliver efficient services, it has also enhanced customer communication in FinTech lending platforms[31]. Chatbots and other virtual assistants based on NLP can assist their users during the loan application process, answer their questions and other inquiries and provide real-time help, which enhances their experience and accessibility [32]. Information extraction and validation of information in financial statements, tax records and identification proofs are also automated by these systems in documentation and compliance systems. Consequently, NLP would decrease manual work, increase the speed of loan processing, and guarantee regulation in the digital lending systems.

2) *Real-Time Loan Processing and Approval*

FinTech lending has made it possible to process loans in real-time and underwrite them automatically with help of AI and ML technologies. AI algorithms process data of borrowers, including credit scores, income trends, and expenditure and financial history, to assess creditworthiness and estimate risk of default. ML models are continually trained over historical data about lending to make better decisions and detect anomalies as odds of fraud or financial instability[33]. The automation seriously affects the time taken to issue a loan approval, as the lenders are able to provide lending approvals instantly and improve the efficiency and satisfaction of the customers.

3) Blockchain and Smart Contracts in Lending

Transparency, security, and efficiency in lending of FinTech are encouraged by the blockchain technology based on the decentralized and immutable registry wherein financial transactions are stored. The lending transactions are well encrypted and time-stamped, limiting the possibility of fraud and manipulation of data. Smart contracts are also used to automate the lending process by carrying out predefined agreements such as loan repayment and loan disbursement schedules without the involvement of middlemen. These technologies reduce the operation cost, establish a higher degree of trust between borrowers and lenders and provide more efficient and transparent peer-to-peer lending systems.

B. AI/ML Techniques

The process of the FinTech industry development, as a reaction to the limitations of traditional credit scoring system, has increasingly been characterized by the use of sophisticated AI and ML algorithms.

- **Decision Trees and Random Forests:** DT offer a rule-based method of categorization that is simple to comprehend. RF extends this by adding additional decision trees that are trained on a new set of data and attributes, and combining their predictions[34]. It is this combination technique that makes Random Forests a great choice in credit scoring due to the fact that it generally enhances strength, decreases over-fitting as well as enlarging the predictive power. Experiments show that RF algorithms are effective in binary classification problems, such as default prediction.
- **Gradient Boosting Machines (GBM):** It has powerful ensemble algorithms like XGBoost and AdaBoost. GBMs construct models one after another, with the emphasis on the errors of the earlier models. They are also known to attain state-of-the-art performance on a broad spectrum of classification tasks, such as loan default prediction and are often very accurate despite the different or sparse data types. XGBoost performance and speed have been acclaimed.
- **Support Vector Machines (SVM):** SVMs are advanced classification algorithms, classifying in a high-dimensional feature space with the optimal hyperplane. Non-linear interactions can be managed by the use of the kernel functions; this can be of great use when dealing with complex datasets, which have more than two features.
- **Neural Networks (NNs) and Deep Learning:** NNs have the ability to identify complex and non-linear patterns and interactions on large datasets, particularly those in a DL architecture with many layers[15]. The hierarchical nature of their feature representations enables them to analyze a wide variety of data types, and this is why even unstructured data can be very predictive.
- **Logistic Regression:** Despite the fact that it is regarded as a traditional statistical tool, logistic regression is an often-used standard in credit scoring because of its effectiveness and easy interpretation. The model is a logistic form of a linear combination of predictor variables that have been through a logistic function to determine probability of a binary outcome (default/no default).

C. AI-Powered Risk Assessment and Credit Accessibility

AI enhances the measurement of credit risk and availability of credit through the enhancement of credit scoring systems, fraud detection, dynamic profiling of risks, and inclusive digital lending solutions.

1) AI-Powered Risk Assessment

- **AI-Based Credit Scoring Models:** AI use has significantly improved credit scoring through the introduction of predictive analytics and behavioral analysis [35]. Unlike the traditional models where the main source of data used is historical credit reports, the AI-based models are based on other and real-time sources of data to provide more accurate, dynamic, and comprehensive evaluations of borrower risk.
- **Fraud Detection and Prevention:** The AI and ML technologies are also helpful to enhance the financial security as there is an opportunity to detect fraudulent transactions with the help of anomaly detection, transaction pattern analysis, and real-time monitoring[20]. These systems improve the identification of suspicious transactions and reduce the losses incurred as a result of fraud, although the challenges are false positives and transparency.
- **Dynamic Risk Profiling:** AI could offer dynamic risk profiling of the behaviour of the borrowers, as well as the financial spending of the borrowers as they are constantly tracked. Such advanced methods as reinforcement learning can also be used by such lending systems to dynamically revise the risk judgments so as to enhance the quality of the decisions made, besides proactively managing risks at the financial institutions.

2) Transforming Credit Accessibility

- **AI-Driven Personalized Lending:** The creation of credit scoring made possible by AI has considered additional data, such as social media presence of a borrower, utility payments and history of transactions to create a more comprehensive and more precise decision regarding their creditworthiness.
- **Expansion of Financial Inclusion:** AI-powered FinTechs can be used to provide small businesses and disadvantaged populations with digital lending, digital microloans with alternative repayment procedures, and reach the unbanked areas[36].
- **Overcoming Accessibility Barriers:** The access to credit is improved with the aid of AI lending systems, in particular, mobile and cloud-based systems because they automate the processing process and offer real-time risk evaluation, scale to digital platforms, but the problem of data privacy, algorithm bias, and governmental control cannot be overlooked.

V. Literature Review

A literature overview of FinTech innovations, credit scoring and digital lending activity in modern financial systems is summarized in Table V. The summary provides the focus of the research, methods, important conclusions, and the problematic issues concerning AI-based credit assessment, P2P lending, and FinTech-based financial services.

S. Yadav (2025) explores how fintech NBFCs can be used to modernize credit lending processes for unqualified or unestablished borrowers in India. To obtain information on this research through secondary sources, the researcher analyzed the data published by SIDBI, as well as the Fintech Association of Consumer Empowerment (FACE). The research is conducted over the years 201819 up to 202324 and analyzes the personal credit information of finTech NBFCs in India. The paper juxtaposes finTech NBFCs with more traditional NBFCs and banks regarding the personal lending practices of both, including such aspects as loan acceptance rates and bad debt. Despite the fact that the traditional bank clients are of higher market value because of their premium credit products and a few requests for personal loans, the fintech NBFCs are mostly targeted at such consumers[37].

A. Alamsyah et al. (2025) provide a new vision of assessing the creditworthiness of people without collateral or traditional credit histories through social media analytics and advanced ML-based systems. The conventional credit rating models tend to incorporate information supplied by the central banks and especially the information that relates to the traditional collateral items such as real estate or savings accounts. Based on LinkedIn profile information as demographics, psychology, psycholinguistics, and social networks, generate a forecast model of a comprehensive financial reliability test. Our credit scoring techniques apply both expert judgment thresholds to categorize potential borrowers, in particular the youth with no collateral or established credit record, as good or bad credit risks, and scoring models to generate continuous credit scores[38].

S. K, M. Chendragiri, and B. V. Reddy (2024) explore how the shifting financial landscape is transforming the traditional financing model and peer-to-peer (P2P) lending in the context of digital transformation. The general objective of the study is to predict the future of finance by examining how innovative technologies such as blockchain, AI, and sophisticated algorithms influence different financial sectors. The objective of descriptive research is to provide a detailed account of a population or phenomenon by means of non-interventionist methodologies, such as surveys or observational studies. Structured surveys or questionnaires with closed-ended questions, which may be distributed via a variety of in-person and online means, are often used in data collecting. Non-probability sampling methods, such convenience sampling, are often used in the research [39].

J. K. Roy and L. Vasa (2024) explore the relationship between digitalization, credit scoring, and financial technology, AI, ML, and blockchain as it pertains to the credit services industry. Three primary research questions were covered in this study: Population, intervention, comparison, results, and setting were all part of the study's thorough methodology, which helped guarantee that the data obtained were relevant to the study's aims. The development of the research questions was based on the PICOS framework, and the systematic review and selection of the studies were done with the PRISMA method. The papers that were reviewed had a wide range of datasets and methods[40].

B. E. Abikoye et.al. (2024) Standard for the integration of fintech and conventional banking operations and risk management procedures. The goal of the framework is to guarantee that the financial industry uses sophisticated technologies like ML and AI to conduct risk assessments consistently and effectively. The primary reason why the financial services industry is rapidly innovating is the use of fintech businesses, which offer a variety of services that enhance efficiency, accessibility, and customer satisfaction. However, there are serious risks connected to fintech growth, including operational flaws, data privacy concerns, cyberthreats, and challenges with regulatory compliance [41].

B. Sanga and M. Aziakpono (2023) perform a systematic literature review on the financing of SMEs and fintech from 2008 to 2022. This subject has been the subject of unstructured and independent publications thus far. Consequently, it is imperative to consolidate the empirical research and its conclusions regarding the efficacy of FinTech in addressing the financing requirements of SMEs. The results of the bibliometric analysis show that empirical research on the topic of FinTech and funding for SMEs are few. A decade after FinTech 3.0 began in 2008, an avalanche of empirical research sprang out, most of which relied on quantitative methodologies grounded on survey data and FinTech platforms. Additionally, more empirical research has been done on developing alternative digital finance for SMEs than on FinTech and bank lending to SMEs [42]

TABLE V. SUMMARY OF LITERATURE ON FINTECH INNOVATIONS AND CREDIT RISK ASSESSMENT IN DIGITAL LENDING SYSTEMS

Authors (Year)	Study On	Approaches	Key Findings	Challenges	Research Summary
S. Yadav (2025)	Modernization of credit lending practices through FinTech NBFCs in India	Secondary data analysis using reports from FACE and SIDBI; comparison of FinTech NBFCs with traditional NBFCs and banks (2018–2024 data)	FinTech NBFCs focus on low-volume but high-value personal loans, while traditional banks dominate in market value and premium credit offerings	Limited market penetration and dependency on personal credit data	The study focuses on the rising role of FinTech NBFCs in improving loan availability for underprivileged borrowers in India.
A. Alamsyah et al. (2025)	Alternative credit scoring using social media analytics	Machine learning models using LinkedIn data (demographics, personality traits, psycholinguistics, social network analysis)	Social media-based models can effectively predict creditworthiness for individuals without traditional credit history	Data privacy concerns and reliability of social media information	The research proposes innovative ML-based credit scoring models for assessing borrowers lacking collateral or formal credit history.
S. K, M. Chendragiri, and B. V. Reddy (2024)	Digital transformation in funding and Peer-to-Peer (P2P) lending	Descriptive research using structured surveys and questionnaires with convenience sampling	Technologies such as AI, blockchain, and advanced algorithms are transforming	Sampling limitations and evolving	The study explains how digital technologies are reshaping traditional lending models and

 ISSN:3049-0952
www.jsetms.com

			financial lending ecosystems	regulatory environment	enabling alternative financial platforms like P2P lending.
J. K. Roy and L. Vasa (2024)	FinTech, AI, ML, and blockchain applications in credit scoring and lending	Systematic literature review using PRISMA model and PICOS framework	Integration of advanced technologies improves credit risk assessment and lending efficiency	Lack of standardized datasets and integration complexity	The review consolidates research on AI-driven financial technologies and their role in improving credit services and lending systems.
B. E. Abikoye et.al. (2024)	Risk management framework for collaboration between FinTech firms and traditional financial institutions	AI and ML-based risk assessment framework	Integrating cutting-edge technology can enhance financial risk management and operational effectiveness	Data privacy concerns, cybersecurity risks, and difficulties with regulatory compliance	The study proposes a framework for integrating FinTech innovation with traditional banking systems to enhance secure and efficient financial services.
B. Sanga and M. Aziakpono (2023)	FinTech and SME financing	Bibliometric analysis and a systematic evaluation of the literature (2008–2022)	FinTech platforms significantly improve access to financing for SMEs, especially through digital lending platforms	Limited empirical studies and fragmented research in the field	The study summarizes global research trends in FinTech-based SME financing and highlights the need for more empirical investigations.

VI. Conclusion and Future Work

P2P lending has become a significant part of the FinTech ecosystem as it allows direct contact between the borrowers and lenders via digital platforms. It has a number of benefits like quicker processing of loans, lessening the reliance on conventional banking institutions and increased access to credit between individuals and small businesses. Good credit risk evaluation and good risk management tools are, however, critical to the viability of P2P lending platforms. Conventional ways of credit scoring usually do not reflect the dynamic financial nature of the new generation borrowers, and there is a necessity to adopt more sophisticated and data-driven methods. The accuracy, transparency, and efficiency of credit evaluation have greatly increased with the use of cutting-edge technologies like blockchain, AI, ML, and NLP. The technologies are also helpful in detection of fraud, dynamic risk profiling, and increased financial inclusion. Altogether, credit assessment practices based on FinTech contribute to the improvement of the reliability and sustainability of P2P lending systems.

The next generation of AI-based credit scoring can consider development of better interpretable and ethical P2P lending credit scoring models. Through incorporation of real-time alternative data sources and better regulatory frameworks, it could be further ensured that digital lending ecosystems are more transparent, fair, and secure.

References

[1] J. A. Jafri, S. I. Mohd Amin, and A. Abdul Rahman, "Financial technology (Fintech) research trend: a bibliometric analysis," *Discov. Sustain.*, vol. 6, no. 1, p. 513, Jun. 2025, doi: 10.1007/s43621-025-01225-6.

[2] H. A. Davey, "Impact of Financial Technology on Traditional Banking," *Shanlax Int. J. Manag.*, vol. 11, no. S1-Mar, pp. 208–216, Mar. 2024, doi: 10.34293/management.v11iS1-Mar.8044.

[3] S. B. Shah, "Advanced Framework for Loan Approval Predictions Using Artificial Intelligence-Powered Financial Inclusion Models," in *2025 IEEE Integrated STEM Education Conference (ISEC)*, 2025, pp. 1–10. doi: 10.1109/ISEC64801.2025.11147327.

[4] Y. Liu, K. Fujiwara, and T. Jinushi, "Peer-to-peer lending for individual and MSME finance: Evidence from an original survey in China," *Int. Rev. Econ. Financ.*, vol. 93, pp. 38–51, Jun. 2024, doi: 10.1016/j.iref.2024.02.038.

[5] L. T. P. Nguyen, S. Muthaiyah, M. O. Sy, and W. Kalabeke, "P2P Lending platforms in Malaysia: the awareness among Malaysian adults," *F1000Research*, vol. 10, p. 1096, Sep. 2023, doi: 10.12688/f1000research.73401.3.

[6] P. Badri, A. Nerella, R. Murugesan, and K. Sundravadivelu, "Deep Learning–Based Multivariate Models for Bankruptcy and Litigation Risk Prediction," *Adv. Consum. Res.*, vol. 2, no. 4, pp. 4442–4450, 2025.

[7] T. K. Shah, "Cloud-Based Data Warehousing for Marketing Agility: Lessons from FinTech Migrations to Snowflake and AWS," *Int. J. Adv. Res. Sci. Commun. Technol.*, vol. 4, no. 4, pp. 642–652, Mar. 2024, doi: 10.48175/IJARSCT-16000B.

[8] S. B. Shah, "Evaluating the Effectiveness of Machine Learning in Forecasting Financial Market Trends: A Fintech Perspective," in *2025 3rd International Conference on Integrated Circuits and Communication Systems (ICICACS)*, IEEE, Feb. 2025, pp. 1–6. doi: 10.1109/ICICACS65178.2025.10968297.

[9] D. Patel, "Explainable Risk Decision Systems Using Artificial Intelligence Models for Payment Fraud Identification with Mitigation," in *2026 14th International Symposium on Digital Forensics and Security (ISDFS)*, IEEE, Mar. 2026, pp. 01–06. doi: 10.1109/ISDFS69419.2026.11459006.

[10] F. Wu, X. Su, Y. S. Ock, and Z. Wang, "Personal Credit Risk Evaluation Model of P2P Online Lending Based on AHP," *Symmetry (Basel).*, vol. 13, no. 1, p. 83, Jan. 2021, doi: 10.3390/sym13010083.

[11] T. K. Abiola, "AI-powered credit risk assessment and algorithmic fairness in digital lending: A comprehensive analysis of the United States digital finance landscape," *World J. Adv. Res. Rev.*, vol. 26, no. 3, pp. 1446–1460, Jun. 2025, doi: 10.30574/wjarr. 2025.26.3.2291.

[12] N. Prajapati, "The Role of Machine Learning in Big Data Analytics: Tools, Techniques, and Applications," *ESP J. Eng. Technol. Adv.*, vol. 5, no. 2, 2025, doi: 10.56472/25832646/JETA-V5I2P103.

[13] V. Sikarwar, "AI-Powered Process Mining for Intelligent, Personalized Customer Experience in the Insurance Sector," *Int. J. Res. Publ. Eng. Technol. Manag.*, vol. 8, no. 4, 2025, doi: 10.15662/IJRPETM.2025.0804007.

[14] H. Zhao, Y. Ge, Q. Liu, G. Wang, E. Chen, and H. Zhang, "P2P Lending Survey: Platforms, Recent Advances and Prospects," *ACM Trans. Intell. Syst. Technol.*, vol. 8, no. 6, pp. 1–28, Nov. 2017, doi: 10.1145/3078848.

[15] S. A. Pushkala, "Financial Fraud Identification Using Graph Neural Network And LSTM With Autoencoder-Based Data Refinement," *J. Int. Cris. Risk Commun. Res.*, vol. 9, no. 1, 2026, doi: 10.63278/jicrcr.vi.3615.

[16] R. M. Shettar, "An Overview Study on P2P Lending," *Int. Bus. Manag.*, vol. 7, no. 2, pp. 14–18, 2019.

[17] P. Chandrashekar, "Data-Driven Loan Default Prediction: Enhancing Business Process Workflows with Machine Learning," *Int. J. Emerg. Res. Eng. Technol.*, vol. 6, no. 4, pp. 18–26, 2025, doi: 10.63282/3050-922X.IJERET-V6I4P103.

[18] T. Shah, "The Role of Customer Data Platforms (CDPs) in Driving Hyper-Personalization in FinTech," *Int. Res. J. Eng. Technol.*, vol. 12, no. 04, p. 10, 2025.

[19] G. You, H. Guo, A. A. Dagestani, and S. Deng, "Evolutionary Game Analysis of Three Players on Behavioral Strategy of P2P Lending Participants: A Sustainable Operations Perspective," *Complexity*, vol. 2021, no. 1, Jan. 2021, doi: 10.1155/2021/7795016.

[20] A. Nerella, P. Badri, K. Sundravadivelu, and R. Murugesan, "Navigating Regulatory Hurdles in AI-Driven Credit Card Approvals: Balancing Innovation and Compliance," *J. Inf. Syst. Eng. Manag.*, vol. 8, no. 4, pp. 1–9, 2023.

[21] C. Patel, "Generative AI for Personalized Marketing and Customer Experience in E-Commerce," *Int. J. Emerg. Res. Eng. Technol.*, vol. 7, no. 1, pp. 12–19, 2026, doi: 10.63282/3050-922X.IJERET-V7I1P103.

[22] S. Shivam, "Efficient Machine Learning-Based Classification Model for Credit Risk Scoring in Lending Systems," in *2025 International Conference on Artificial Intelligence, Blockchain, Cloud Computing, and Data Analytics (ICoABCD)*, IEEE, Dec. 2025, pp. 1–8. doi: 10.1109/ICoABCD67551.2025.11470933.

[23] H. Kumar and B. Johnson, "P2p Lending in India: A Comparative Analysis of Trust, Product and Price of Select Platforms," *Int. J. Bus. Manag. Invent. ISSN*, vol. 8, no. 01, pp. 31–37, 2019.

[24] H. Kohli, R. Rajamani, M. R. Reddy Deva, and S. A. Pahune, "Improving Prediction of Credit Risks Based on Advanced Machine Learning and Feature Engineering Techniques in Banking Sector," in *2025 5th International Conference on Artificial Intelligence and Signal Processing (AISP)*, IEEE, Nov. 2025, pp. 1–5. doi: 10.1109/AISP68263.2025.11396116.

[25] H. P. Kapadia and K. C. Chittoor, "AI Chatbots for Financial Customer Service: Challenges & Solutions," *J. Adv. Futur. Res.*, vol. 2, no. 2, p. 7, 2024.

[26] M. Siering, "Peer-To-Peer (P2P) Lending Risk Management: Assessing Credit Risk on Social Lending Platforms Using Textual Factors," *ACM Trans. Manag. Inf. Syst.*, vol. 14, no. 3, 2023, doi: 10.1145/3589003.

[27] S. Tarakampet, S. Begam, and S. B. S. Ali, "Integrating Custom Enterprise Applications with Legacy Systems for Risk Management: A Modern Enterprise Approach," *Int. J. Trend Sci. Res. Dev.*, vol. 10, no. 1, 2026.

[28] S. Shivam, V. Nutalapati, T. P. Patel, A. K. Padhy, M. Kumari, and R. Purushothaman, "Transformer-Based Framework for Imbalanced Transaction Fraud Detection in FinTech Systems," in *2026 14th International Symposium on Digital Forensics and Security (ISDFS)*, IEEE, Mar. 2026, pp. 1–6. doi: 10.1109/ISDFS69419.2026.11459102.

[29] S. Kakkar, "Advancing Credit Risk Modeling Through Generative Artificial Intelligence: Methods, Applications, And Challenges," *Int. J. Financ. DATA Sci.*, vol. 3, no. 2, pp. 30–48, Sep. 2025, doi: 10.34218/IJFDS_03_02_003.

[30] S. Muthaiyah, L. T. P. Nguyen, Y. V. Choong, and T. O. K. Zaw, "Risk Ordering Relation and Risk Control for P2P Lending Platforms: A Multi-Agent Systems (MAS) Approach," *Emerg. Sci. J.*, vol. 8, no. 4, pp. 1655–1665, Aug. 2024, doi: 10.28991/ESJ-2024-08-04-024.

[31] G. T. Adewale, J. U. Umavezi, and O. Olukoya, "Innovations in Lending-Focused FinTech: Leveraging AI to Transform Credit Accessibility and Risk Assessment," *Int. J. Comput. Appl. Technol. Res.*, vol. 14, no. 01, Jan. 2025, doi: 10.7753/IJCATR1401.1004.

[32] S. B. Karri, S. Gawali, S. Rayankula, and P. Vankadara, "AI Chatbots in Banking: Transforming Customer Service and Operational Efficiency," in *Advancements in Smart Innovations, Intelligent Systems, and Technologies*, 2025, pp. 61–81. doi: 10.3233/FAIA251498.

[33] A. Katangoori, "The Role of Big Data in Advancing Artificial Intelligence: Methods and Case Studies," *Int. J. Artif. Intell. Mach. Learn.*, vol. 6, no. 1, pp. 37–54, Jan. 2026, doi: 10.51483/IJAIML.6.1.2026.37-54.

[34] V. R. Duvalla, "AI-Powered Credit Risk Assessment: Transforming Lending in FinTech," *Eur. J. Comput. Sci. Inf. Technol.*, vol. 13, no. 23, pp. 115–131, Apr. 2025, doi: 10.37745/ejcsit. 2013/vol13n23115131.

[35] Y. He and W. Fan, "FinTech, bank risk-taking, and credit allocation," *Humanit. Soc. Sci. Commun.*, vol. 12, no. 1, p. 1670, Nov. 2025, doi: 10.1057/s41599-025-05931-4.

[36] S. Singamsetty, "Efficacy of Data Governance a Cutting Edge Approach to Ensuring Data Quality in Machine Learning for Banking Industry," in *2024 2nd International Conference on Signal Processing, Communication, Power and Embedded System (SCOPES)*, IEEE, Dec. 2024, pp. 1–7. doi: 10.1109/SCOPES64467.2024.10991944.

[37] S. Yadav, "The Rise of Digital Credit: An Analysis of Fintech NBFCs in India's Personal Credit Market," *Int. Res. J. Mod. Eng. Technol. Sci.*, vol. 07, no. 04, pp. 1661–1672, May 2025, doi: 10.56726/IRJMETS72100.

[38] A. Alamsyah, A. A. Hafidh, and A. D. Mulya, "Innovative Credit Risk Assessment: Leveraging Social Media Data for Inclusive Credit Scoring in Indonesia's Fintech Sector," *J. Risk Financ. Manag.*, vol. 18, no. 2, p. 74, Feb. 2025, doi: 10.3390/jrfm18020074.

[39] S. K, M. Chendragiri, and B. V. Reddy, "Delve into Innovations in Peer-to-Peer Lending and Conventional Funding," *Empir. Econ. Lett.*, vol. 23, no. 3, 2024, doi: 10.5281/zenodo. 14253184.

[40] J. K. Roy and L. Vasa, "Machine Learning and Artificial Intelligence Method for FinTech Credit Scoring and Risk Management," *Int. J. Bus. Anal.*, vol. 11, no. 1, pp. 1–23, Jul. 2024, doi: 10.4018/IJBAN.347504.

[41] B. E. Abikoye, W. Adelusi, S. C. Umeorah, A. O. Adelaja, and C. Agorbia-Atta, "Integrating Risk Management in Fintech and Traditional Financial Institutions through AI and Machine Learning," *J. Econ. Manag. Trade*, vol. 30, no. 8, pp. 90–102, Aug. 2024, doi: 10.9734/jemt/2024/v30i81236.

[42] B. Sanga and M. Aziakpono, "FinTech and SMEs financing: A systematic literature review and bibliometric analysis," *Digit. Bus.*, vol. 3, no. 2, p. 100067, Dec. 2023, doi: 10.1016/j.digbus.2023.100067.