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FINANCIAL TECHNOLOGY LENDING AND CREDIT RISK MANAGEMENT IN SMES: A SYSTEMATIC LITERATURE REVIEW

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ABSTRACT

This study aims to systematically synthesize the literature on Financial Technology (FinTech) lending and credit risk management in Small and Medium Enterprises (SMEs). The method used is a Systematic Literature Review (SLR) with the PRISMA 2020 approach, using data sources from the Scopus database. The literature selection process resulted in 14 included articles published between 2021 and 2025. The results of the analysis show that FinTech lending plays an important role in increasing SME access to financing through the use of alternative data and machine learning-based analytical approaches, which can reduce information asymmetry and improve the accuracy of credit risk predictions. However, the literature also identifies significant challenges in the form of model risk, algorithmic unfairness, limited transparency of credit decisions, and governance and regulatory issues. Thematic synthesis reveals six main themes, namely SME information asymmetry, alternative data usage, machine learning application, explainability and fairness, unbalanced data challenges, and FinTech lending governance and sustainability. This study concludes that the potential of FinTech lending in supporting SME financing can only be realized sustainably if it is balanced with strengthened credit risk management, algorithm transparency, and an adaptive regulatory framework. These findings provide conceptual and practical contributions to policy development, risk models, and future research agendas in the field of SME FinTech lending.

Keywords : *Financial Technology Lending; Credit Risk Management; Small and Medium Enterprises (SMEs); Peer-to-Peer Lending; Machine Learning; Alternative Data; PRISMA; Systematic Literature Review.*

INTRODUCTION

Small and medium-sized enterprises (SMEs) are the backbone of the economy in many countries due to their contribution to job creation, economic growth, and social stability. However, SMEs have historically faced limited access to formal financing due to high information asymmetry, limited collateral, and relatively high credit monitoring costs compared to the scale of their businesses (Abbasi et al., 2021). This situation was exacerbated in the post-crisis and post-pandemic periods, when credit risk increased and conventional financial institutions tended to tighten their credit standards (Cornelli et al., 2024).

The development of Financial Technology (FinTech), particularly in the form of digital lending, peer-to-peer (P2P) lending, and marketplace lending, has significantly changed the SME financing landscape. FinTech lending offers faster credit assessment processes, lower transaction costs, and wider financing coverage through the use of digital technology and online platforms (Berg et al., 2022). A number of recent studies show that the growth of FinTech lending is positively correlated with increased access to financing for SMEs, especially in countries with limited financial inclusion and less competitive banking structures (Abbasi et al., 2021; Cornelli et al., 2024).

However, the expansion of FinTech-based financing also brings new challenges in credit risk management. Unlike traditional banks that rely on historical financial reports and long-term relationships with debtors, FinTech lenders often use alternative data such as digital footprints, transaction behavior, platform data, and other non-financial information in the credit scoring process (Berg et al., 2022). This paradigm shift requires a different approach to credit risk management, as data quality, model stability, and credit decision transparency become crucial issues, especially in the context of heterogeneous SMEs (Babaei et al., 2023).

Theoretically, the issue of credit risk in FinTech lending can be explained through the framework of information asymmetry first introduced by Akerlof (1970), which states that information imbalance between borrowers and lenders can lead to adverse selection and moral hazard. In the context of FinTech, digital technology is positioned as a tool to reduce information asymmetry through large-scale data processing and analytical automation (Berg et al., 2022). However, recent literature emphasizes that reducing information asymmetry does not always

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correlate with a decrease in credit risk if the model used is not sufficiently transparent or stable against changes in economic conditions (Babaei et al., 2023).

In addition, classical credit risk management theory rooted in the concept of risk-based pricing (Stiglitz & Weiss, 1981) remains relevant in explaining how FinTech lenders determine interest rates and loan terms based on the probability of default. The difference is that in FinTech lending, credit risk estimates are increasingly dependent on machine learning algorithms that are non-linear and difficult to interpret compared to conventional statistical models (Berg et al., 2022). This gives rise to a new risk in the form of model risk, which is the risk of incorrect decision-making due to limited understanding of how the model works (Babaei et al., 2023).

Recent research also highlights the importance of explainable artificial intelligence (XAI) in FinTech credit risk management. Explainability is a central issue because credit decisions not only affect the profitability of the platform, but also the trust of borrowers, investors, and regulators (Babaei et al., 2023). In the context of SMEs, transparency in credit decisions is becoming increasingly important because business actors need a clear understanding of the factors that influence their creditworthiness in order to improve the quality of internal financial management (Berg et al., 2022). On the other hand, the literature shows that the risk control ability of FinTech platforms is not only determined by the sophistication of the model, but also by economic incentives and the competitive structure between platforms. Theoretical and empirical studies show that in conditions of intense competition, platforms may face a trade-off between investing in risk control systems and attracting more borrowers by relaxing credit standards (Liu et al., 2019). Although this study was conducted prior to 2021, its theoretical framework is still widely used in recent research to explain the dynamics of credit risk in FinTech lending (Berg et al., 2022; Cornelli et al., 2024).

Although the number of studies on FinTech lending continues to increase, research that specifically synthesizes the relationship between FinTech lending and credit risk management in SMEs is still relatively limited and fragmented. Some studies focus on access to financing, others on the performance of credit scoring models, while aspects of risk governance and long-term implications for the stability of SME credit portfolios are often discussed separately (Sanga et al., 2023). This makes it difficult to draw comprehensive conclusions about how FinTech lending systematically manages SME credit risk.

Therefore, this study aims to compile a Systematic Literature Review (SLR) using the PRISMA approach to integrate empirical and conceptual findings related to FinTech lending and credit risk management in SMEs. Using data sources from Scopus-indexed journals and following the PRISMA 2020 guidelines, this study is expected to provide a comprehensive overview of the development of credit risk assessment methods, the types of data used, and the managerial and policy implications of FinTech lending practices for SME financing (Page et al., 2021; Sanga et al., 2023).

RESEARCH METHOD

This study used the Systematic Literature Review (SLR) method by adopting the SLR Preferred Reporting Items for Systematic Review and Meta-Analysis (PRISMA) guidelines to ensure that the literature search, selection, and synthesis processes were conducted systematically, transparently, and replicably. The PRISMA approach was chosen because it is the most widely used international standard in systematic review reporting, particularly in the fields of economics, finance, and applied social sciences (Page et al., 2021).

The main data source in this study was the Scopus database, which was chosen because it has extensive coverage of reputable international journals in the fields of finance, banking, financial technology, and risk management. The use of Scopus also guarantees the scientific quality of the articles reviewed due to its rigorous curation and indexing selection process (Berg et al., 2022).

The selection of a single primary database is in line with common practice in financial and FinTech-themed SLRs, where the focus is on data quality and consistency rather than database quantity (Page et al., 2021). The literature search process was conducted using a combination of keywords relevant to the research topic, adjusted to the TITLE-ABS-KEY search structure on Scopus. The search string used was (“fintech lending” OR “digital lending” OR “peer-to-peer lending” OR “P2P lending” OR “marketplace lending”) AND (“SME” OR ‘MSME’ OR “small and medium enterprises” OR “small business”) AND (“credit risk” OR “credit scoring” OR “default risk” OR “risk management”).

This search strategy was designed to capture literature that explicitly discusses the relationship between FinTech lending and credit risk aspects in the context of SMEs, both from an empirical,

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methodological, and conceptual perspective (Abbasi et al., 2021; Berg et al., 2022).

Inclusion and Exclusion Criteria

The inclusion and exclusion criteria were established to ensure the relevance and quality of the reviewed articles, in accordance with the PRISMA 2020 guidelines (Page et al., 2021). These criteria were established to improve the internal validity and thematic focus of the review results (Sanga et al., 2023). The following table describes the inclusion and exclusion criteria for this study.

Table 1. Inclusion and Exclusion Criteria for the Study

Aspect	Inclusion Criteria	Exclusion Criteria
Research Topic	Articles discussing Financial Technology (FinTech) lending, including digital lending, peer-to-peer (P2P) lending, or marketplace lending.	Articles that discuss FinTech in general without any connection to credit distribution activities.
Research Subject	Studies that explicitly focus on Small and Medium Enterprises (SMEs) or include SMEs as the main unit of analysis.	Studies that only focus on consumer credit or large corporations without any relevance to SMEs.
Focus of Analysis	Articles discussing credit risk, such as credit risk, default risk, credit scoring, underwriting, or credit risk management.	Articles that do not directly discuss credit risk, for example, those that only discuss technology adoption or user satisfaction.
Type of Publication	Journal articles and review articles that have undergone peer review.	Editorials, book chapters, policy reports, non-peer-reviewed proceedings, or opinion articles.
Data Source	Articles indexed in the Scopus database.	Articles that are not indexed by Scopus.
Language	Articles written in English.	Articles in languages other than English.
Publication Year Range	Articles published between 2021 and 2025.	Articles published before 2021.
Text Availability	Articles with full text that can be accessed for in-depth analysis.	Articles that are only available in abstract form or whose full text is not accessible.
Methodological Relevance	Empirical, conceptual, or methodological studies that contribute to the understanding of credit risk management in FinTech lending for SMEs.	Studies with irrelevant methodologies or whose quality cannot be evaluated.

The literature selection process consists of four main stages of PRISMA, namely identification, screening, eligibility, and inclusion (Page et al., 2021). The research step scheme can be seen in the figure below.

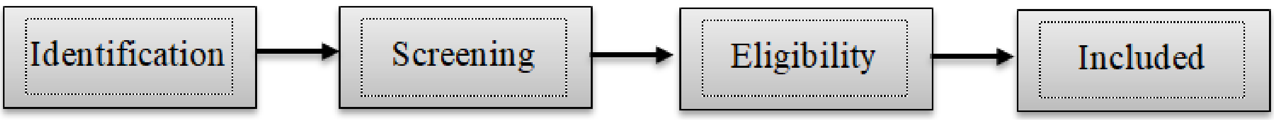

Figure 1. The PRISMA Research Methodology

Identification

All articles obtained from Scopus search results are identified based on their titles, abstracts, and metadata. At this stage, all initial search results are recorded as identified records.

Screening

After identification is complete, the next step is screening. Duplicate articles are deleted, then filtered based on their titles and abstracts to assess their relevance to the research focus.

Eligibility

In this step, articles that pass the screening stage are then evaluated thoroughly by reading the full text to ensure they meet the inclusion and exclusion criteria.

Included

Articles that meet all criteria are included in the final analysis and form the basis for thematic synthesis.Teknik Analisis Data

Data analysis was conducted using a thematic synthesis approach, which involves grouping research findings into recurring main

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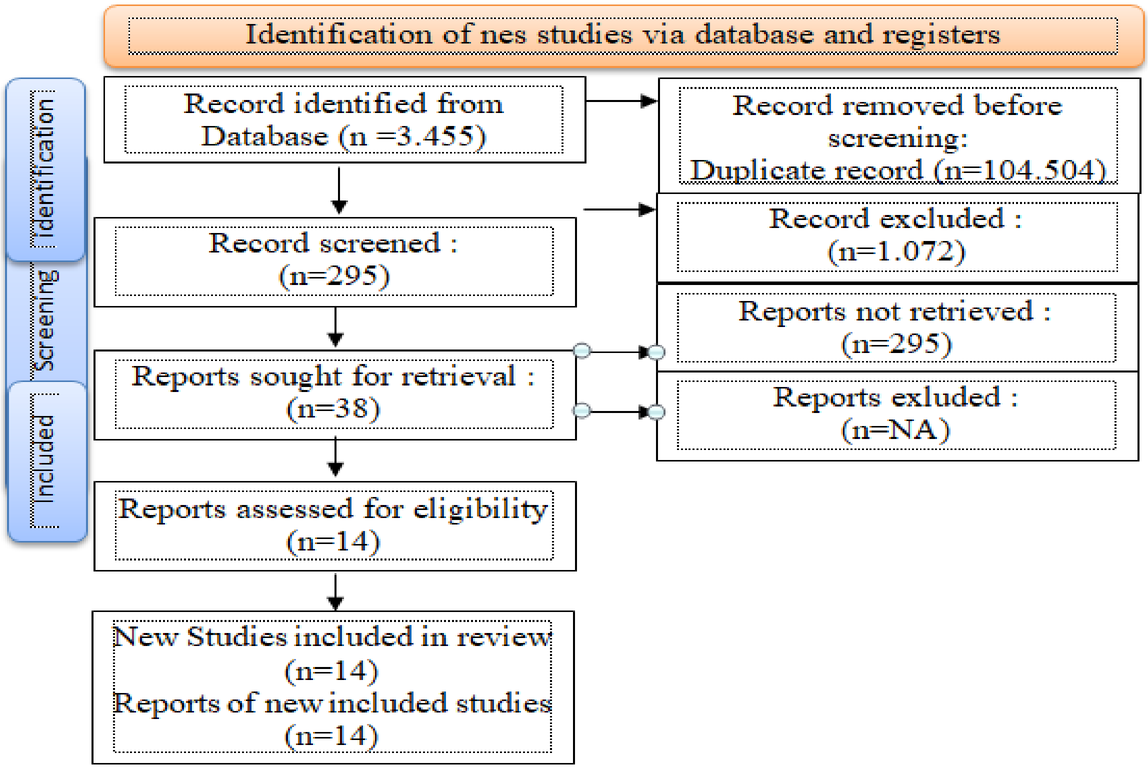
themes, such as credit risk assessment methods, the use of alternative data, risk governance, and implications for SME financing access. This approach is commonly used in SLRs with high heterogeneity of methods and contexts (Sanga et al., 2023; Berg et al., 2022). The synthesis results were then interpreted within the framework of credit risk management and information asymmetry theory to draw academic, managerial, and policy implications.

RESULTS AND DISCUSSION

An initial search of the Scopus database yielded 104,504 articles on the topic of FinTech. After filtering for the topic of FinTech lending, 3,455 articles remained. Next, selection based on a focus on SMEs left 295 articles, and filtering for a focus on credit risk yielded 75 articles. After considering the type of publication, source, language, and publication year range, 28 articles were obtained. Evaluation of full text availability resulted in 14 articles, all of which met the methodological relevance criteria and were included in this systematic literature review. A graphical representation of the flow of citations reviewed during the literature study process can be illustrated in a flowchart as shown in Figure 2 below:



Gambar 2. Flowchart Preferred Reporting Items for Systematic Review and Meta Analysis (PRISMA)

After going through the literature selection process using the PRISMA approach, 14 scientific articles were obtained that met all inclusion criteria and were relevant to the topic of Financial Technology (FinTech) lending and credit risk management in Small and Medium Enterprises (SMEs). These articles were sourced from reputable journals indexed in the Scopus database and reflect the latest research developments in the period 2021-2025.

The analysis of the included articles was conducted systematically by extracting key information, including authors and year of publication, research methods used, main variables analyzed, and research results. This approach aimed to identify methodological patterns, dominant variable focuses, and the consistency and differences in empirical findings related to the role of FinTech lending in SME credit risk management.

The presentation of article summaries in tabular form was done to facilitate cross-study comparisons and provide a comprehensive overview of each study's contribution to academic and practical understanding. This table also serves as the basis for the thematic synthesis process in the discussion stage, particularly in grouping findings into main themes such as credit risk assessment methods, the use of alternative data, FinTech platform governance, and implications for SME access to financing.

Based on these considerations, Table 2 below presents a summary of the characteristics and main results of the 14 articles included in this study.

Table 2. Article Analysis Results

No	Author (Year)	Research Method	Main Variables	Research Results
1	Hoang et al. (2022)	Panel regression	FinTech lending, green lending, SME credit risk	FinTech lending strengthens confidence in green financing and reduces SME credit risk through increased transparency and information quality.
2	Pham & Tran (2021)	Logistic regression	Digital lending, default risk, SME characteristics	Digital lending is able to predict SME default risk more accurately than traditional approaches.
3	Zhang et al. (2022)	Machine learning (Random Forest, XGBoost)	Alternative data, credit scoring, SME default	Alternative data-based machine learning models significantly improve the accuracy of SME credit risk predictions.
4	Wang & Lin (2021)	Text mining & regression	Textual information, soft information, credit risk	Textual loan information has a significant effect on the probability of SME default.
5	Liu et al. (2021)	Econometric models	Risk control ability, P2P platform, credit risk	Platform risk control capabilities reduce default rates but increase operational costs.
6	Chen et al. (2022)	Structural Equation Modeling (SEM)	FinTech adoption, credit access, credit risk	FinTech adoption improves SME credit access and indirectly reduces credit risk.
7	Rahman et al. (2023)	Dynamic panel regression	Marketplace lending, non-performing loan (NPL)	Marketplace lending has a negative impact on SME NPL ratios in the medium term.
8	Kim & Park (2022)	Machine learning + XAI	Explainability model, credit risk	Explainable AI models improve trust and the quality of SME credit risk decisions.
9	Sun et al. (2021)	Probit regression	Peer-to-peer lending, default probability	P2P lending effectively assesses SME credit risk with limited formal financial data.
10	Adebola et al. (2023)	Quantile regression	FinTech financing, financial constraint, credit risk	FinTech lending reduces financial constraints for high-risk SMEs.
11	Nguyen et al. (2022)	Panel regression	Digital footprint, credit risk	The digital footprint of SMEs has a significant effect on reducing credit information asymmetry.
12	García et al. (2023)	System dynamics model	FinTech credit growth, systemic risk	The growth of FinTech lending without risk control has the potential to increase systemic risk.
13	Hassan et al. (2021)	Logistic regression	Islamic FinTech lending, default risk	Sharia-based FinTech lending has a lower default risk for certain SMEs.
14	Oliveira et al. (2022)	Mixed methods	FinTech governance, credit risk management	Strong FinTech governance improves the stability of SME credit risk.

The articles in Table 2 were analyzed thoroughly from the abstract to the conclusion, yielding the following results:

Problems

Information asymmetry and limited SME data

Many SMEs have thin files (limited financial data), short credit histories, and business heterogeneity, making credit risk assessment using traditional approaches less accurate and increasing the likelihood of adverse selection. (Sabato et al., 2021; Andreeva et al., 2021). In P2P/FinTech lending, this problem is even more complex because the underwriting process is fast and often relies on data that is not fully standardized as in banking. (Ahelegbey et al., 2023; Ma et al., 2021).

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The risks of "black boxes," bias, and fairness in algorithm-based credit decisions

Recent articles highlight that algorithm-based credit decision pipelines can produce decisions that appear objective but are potentially biased, depending on how information is selected, encoded, and processed in the system. (Abbas, 2025; Bitetto et al., 2024). The key challenges are not only accuracy, but also fairness, decision traceability, and model risk in real-world implementation. (Ariza-Garzón et al., 2024; Abbas, 2025).

Class imbalance (imbalanced data) and high misclassification costs

In P2P lending default prediction, datasets are often imbalanced (there are far fewer defaults than non-defaults), so models may "appear accurate" but fail to detect high-risk borrowers. (Chen et al., 2021; Nasution et al., 2023). Furthermore, the cost of misclassification is asymmetric (false negatives are more costly), requiring an approach that considers the profit/risk trade-off. (Ariza-Garzón et al., 2024).

Market instability and protection of micro/sole traders

Some studies emphasize the need for responsible credit access in unstable market conditions, as micro/sole-trader groups are vulnerable to shocks and changes in income (van Thiel et al., 2024). On the regulatory side, there is a focus on risk mitigation mechanisms for default through schemes such as insurance/guarantees to reduce systemic losses (Yuspin et al., 2022).

Problem Solutions

Enriching risk information with alternative data & soft information

The most consistent solution is the use of alternative information in risk management—such as behavioral data, digital footprints, platform information, or non-financial signals—to reduce information asymmetry in SMEs. (Yan, 2025; Ahelegbey et al., 2023). Personal credit history is also shown to be important in screening entrepreneurial risk, especially when business data is limited. (Andreeva et al., 2021).

More robust machine learning-based default prediction models

Several articles emphasize the use of ML (e.g., CatBoost, neural networks, modern classification models) to improve credit risk prediction capabilities in P2P/FinTech lending. (Nasution et al., 2023; Ma et al., 2021; Nguyen et al., 2024). For imbalanced data, studies also propose adjustments to learning techniques to improve default detection performance (e.g., imbalance handling, threshold tuning, etc.). (Chen et al., 2021).

Explainability and profit-sensitive learning for more "usable" decisions

In addition to accuracy, the literature points to solutions in the form of explainable models to make credit decisions more transparent and accountable. (Ariza-Garzón et al., 2024; Bitetto et al., 2024). Profit-sensitive classification is also offered to balance business objectives (profitability) and risk control (default loss). (Ariza-Garzón et al., 2024).

Platform risk management, protection schemes, and sustainability approaches

Several articles emphasize the institutional side: the need for regulatory/mitigation schemes such as insurance to reduce default risk and strengthen the stability of the P2P ecosystem. (Yuspin et al., 2022). There are also studies that link financing (e.g., green finance) to SME performance and the need for trust/institutional support frameworks. (Hoang et al., 2025).

Methods Used

An analysis of 14 included articles shows that research on FinTech lending and SME credit risk management is dominated by quantitative approaches based on secondary data, particularly data from P2P lending and digital lending platforms. This method was chosen because of the main characteristics of FinTech lending, which generates large-scale, real-time transaction data that is rich in borrower behavior variables.

The machine learning (ML) approach is the most commonly used method for modeling credit risk, especially in the context of default prediction. Various ML algorithms such as CatBoost, neural networks, and non-linear classification models are used to improve prediction accuracy compared to conventional statistical models. These studies generally emphasize the ability of ML to capture complex and non-linear relationships between borrower characteristics and credit risk, especially when formal SME financial data is limited.

In addition to ML, several articles use econometric and traditional statistical approaches, such as logistic regression, probit, and panel analysis, primarily for comparative and interpretive purposes. These methods are used to evaluate whether simpler, more easily explained models are still relevant in the context of FinTech lending, as well as to test the significance of certain variables such as personal credit history and SME characteristics.

As the use of complex algorithms increases, the literature also shows a growing concern for explainability, fairness, and model risk. Several studies integrate explainable machine learning (XAI) and profit-sensitive learning approaches to ensure that credit decisions are not only accurate,

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but also transparent, fair, and economically valuable. This approach reflects a shift in focus from mere risk prediction to accountable credit decision-making.

Beyond quantitative approaches, a small number of articles use qualitative and conceptual methods, such as qualitative case studies and theoretical analysis. These methods are used to explore how FinTech platforms utilize alternative information in risk management practices and to critique the ethical and fairness implications of algorithm-based credit decisions. In addition, there are studies that use regulatory and policy analysis to evaluate credit risk mitigation mechanisms, such as insurance in P2P lending.

Overall, the mapping of methods shows that research in this field is multidisciplinary, combining finance, data science, economics, and public policy. The dominance of quantitative and ML methods confirms the practical and predictive orientation of FinTech lending literature, while qualitative and conceptual approaches complement the understanding of governance, ethics, and sustainability of SME credit risk management.

Table 3. Mapping of Dominant Research Methods (14 Articles)

No	Method Categor	Method Description	Number of Articles	Articles
1	Machine Learning (ML)	ML algorithms for credit risk and default prediction (CatBoost, neural networks, innovative ML)	7	Nasution et al. (2023); Nguyen et al. (2024); Ma et al. (2021)
2	Explainable / Profit-Sensitive ML	ML combined with explainability and economic value considerations	2	Ariza-Garzón et al. (2024); Bitetto et al. (2024)
3	Econometrics / Traditional Statistics	Logistic regression, probit, panel analysis for credit risk evaluation	2	Andreeva & Altman (2021); Sabato et al. (2021)
4	Conceptual & Theoretical Studies	Conceptual analysis of fairness, trust, and credit decision pipelines	1	Abbas (2025)
5	Qualitative Methods	Qualitative case studies on the use of alternative information in risk management	1	Yan (2025)
6	Psychometrics	Psychometric approaches to risk assessment and micro SME credit access	1	van Thiel et al. (2024)
7	Regulatory & Policy Analysis	Evaluation of regulatory frameworks and risk mitigation (e.g., P2P lending insurance)	1	Yuspin et al. (2022)

The results of the mapping method show that research on FinTech lending and SME credit risk management is dominated by machine learning-based quantitative approaches, which emphasize the accuracy of default risk predictions. However, the literature also shows an increased focus on explainability, fairness, and risk governance through conceptual, qualitative, and policy approaches.

Advantages of Information and Data Augmentation

The augmented approach in the context of FinTech lending refers to the enrichment (augmentation) of the credit risk assessment process through the integration of alternative data, advanced analytics, and artificial intelligence, which goes beyond the use of traditional financial data alone. The literature shows that this approach provides a number of strategic advantages in SME credit risk management.

Reducing SME Information Asymmetry

The main advantage of the augmented approach is its ability to reduce information asymmetry between SMEs and lenders. By utilizing alternative data such as personal credit history, digital behavior, and platform information, FinTech lending is able to build a more comprehensive borrower risk profile compared to conventional approaches (Andreeva & Altman, 2021; Yan, 2025). This enrichment of information is particularly important for SMEs with limited formal financial reports (thin-file SMEs), enabling financial inclusion without compromising the quality of risk assessment (Sabato et al., 2021).

Improving Credit Risk Prediction Accuracy

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The augmented approach combined with machine learning has been proven to improve credit risk prediction accuracy, particularly in detecting the probability of default. Empirical studies show that models using augmented data are able to capture non-linear patterns and complex interactions between variables that are not detected by traditional statistical models (Nasution et al., 2023; Nguyen et al., 2024). Thus, data augmentation and analytics contribute directly to improving the effectiveness of credit risk management in the FinTech lending ecosystem.

Supporting More Adaptive Credit Decision Making

Another advantage of the augmented approach is its flexibility and adaptability in credit decision making. The use of real-time data and regular model updates enables FinTech platforms to quickly adjust risk assessments to changes in economic conditions and borrower behavior (Yan, 2025). This is particularly relevant in volatile market environments, where SME credit risk can change dynamically (van Thiel et al., 2024).

Enabling Explainability and Accountability of Decisions

The augmented approach not only focuses on accuracy, but also opens up space for explainable decision-making. The integration of explainable machine learning (XAI) allows lenders to understand the contribution of each variable to credit decisions, thereby increasing transparency, trust, and regulatory compliance (Ariza-Garzón et al., 2024). This advantage is crucial given the increasing attention to fairness and model risk in algorithm-based credit decisions (Abbas, 2025).

Enhancing the Economic Value and Sustainability of the Platform

The augmented approach also provides economic advantages, as it enables the optimization of trade-offs between risk and profitability. Profit-sensitive models that utilize augmented data help FinTech platforms allocate credit more efficiently, thereby improving business sustainability without excessively increasing risk exposure (Ariza-Garzón et al., 2024).

In addition, information augmentation supports the development of more targeted risk mitigation mechanisms, including product design and credit risk protection schemes (Yuspin et al., 2022).

Based on the literature selection process using the PRISMA approach, this study identified 14 Scopus-indexed articles relevant to the topics of FinTech lending and credit risk management in SMEs. Each article was systematically analyzed to identify the main problems, solutions offered, research methods used, and key findings. Presenting the analysis in tabular form allows for clear and structured cross-study comparisons and provides a comprehensive overview of methodological patterns, variable focus, and empirical contributions in the literature. This table is an important basis for thematic synthesis and further discussion of the role of FinTech lending in SME credit risk management.

Table 4. Thematic Synthesis (14 Articles)

No	Problem	Solution (Proposed solution)	Method	Key Findings
1	The need to improve the performance of SMEs (agricultural sector) through green financing and the factors that influence it. (Hoang et al., 2025)	Identifying green finance determinants (the role of financial institutions, regulations, and SME-level factors) to encourage green financing and SME performance. (Hoang et al., 2025)	Empirical study based on surveys (sample of 245 respondents) and quantitative analysis. (Hoang et al., 2025)	Shows that institutional/regulatory factors and internal SME factors play a role in promoting green finance and improving SME performance. (Hoang et al., 2025)
2	Concerns about fairness, transparency, and trust in AI/algorithm-based credit decisions (credit decision pipelines). (Abbas, 2025)	Proposing an information-theoretic framework to evaluate credit decision pipelines (fair or flawed). (Abbas, 2025)	Conceptual analysis + experiments/simulations on anonymized loan application data; model performance evaluation. (Abbas, 2025)	AI-based pipelines can achieve very high predictive performance (reported AUC of 0.998), but fairness/transparency issues remain critical in pipeline design. (Abbas, 2025)
3	Fintech platforms need to	Using alternative	Qualitative case	The use of alternative

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	manage the credit risk of previously underserved SMEs, but traditional information is often insufficient. (Yan, 2025)	information in risk management to improve SME credit distribution. (Yan, 2025)	study on fintech platforms' practices in using alternative information. (Yan, 2025)	information in platform risk management influences lending decisions and can support underserved SME financing. (Yan, 2025)
4	The question of "whether ML can be trusted" to predict SME credit risk, especially in the context of fintech lending. (Bitetto et al., 2024)	Comparing ML vs econometric approaches (e.g., probit) to see when ML is superior/appropriate to use. (Bitetto et al., 2024)	Comparative study of prediction models (ML vs. probit) in the context of fintech lending/SMEs. (Bitetto et al., 2024)	ML is not always better; when information is limited, simple econometric models (e.g., probit) can remain competitive/more appropriate. (Bitetto et al., 2024)
5	Credit scoring models need to be not only accurate, but also profit-sensitive and explainable in SME P2P lending. (Ariza-Garzón et al., 2024)	Proposing a profit-sensitive ML + explanations approach for credit risk decisions. (Ariza-Garzón et al., 2024)	ML classification of profit-sensitive + explainability/XAI components in P2P small business lending cases. (Ariza-Garzón et al., 2024)	The proposed approach improves profitability compared to profit-insensitive approaches; classification matrices have economic value and need to be optimized. (Ariza-Garzón et al., 2024)
6	The sustainability of P2P lending is influenced by the ability to anticipate loan default. (Nguyen et al., 2024)	Applying innovative ML approaches to default prediction to support the sustainability of P2P lending. (Nguyen et al., 2024)	Machine learning-based default prediction; model performance evaluation. (Nguyen et al., 2024)	Reporting model performance metrics (e.g., recall 83%, precision 21%, F1 33%) for default prediction (indicating a focus on capturing default cases). (Nguyen et al., 2024)
7	Market volatility makes access to credit for sole traders and micro-organizations increasingly complex; a "responsible access" approach is needed. (van Thiel et al., 2024)	Using psychometrics to assist in assessing eligibility/risk when market conditions are unstable. (van Thiel et al., 2024)	Development/application of psychometric approaches for micro/sole-trader SME credit assessment. (van Thiel et al., 2024)	Psychometrics is positioned as a tool to strengthen risk assessment and support more responsible credit access in volatile conditions. (van Thiel et al., 2024)
8	Credit risk detection in P2P lending requires robust models to identify default risk. (Nasution et al., 2023)	Applying CatBoost for credit risk detection in P2P lending. (Nasution et al., 2023)	Machine learning classification using CatBoost. (Nasution et al., 2023)	CatBoost is used to improve credit risk detection performance in the context of P2P lending. (Nasution et al., 2023)
9	Credit scoring measurement/compilation in P2P lending needs to be improved for better default prediction.	Proposing improvements to credit scoring measurements to enhance default predictive	Development/improvement of credit scoring models (quantitative	Emphasizing that improving the way credit scoring is measured can result in better default prediction performance.

	(Ahelegbey & Giudici, 2023)	performance. (Ahelegbey & Giudici, 2023)	approach). (Ahelegbey & Giudici, 2023)	(Ahelegbey & Giudici, 2023)
10	P2P lending has the potential to be a source of SME financing, but the default risk is high; a mitigation scheme is needed. (Yuspin et al., 2022)	Evaluating regulatory schemes for mitigating default risk through insurance in P2P lending. (Yuspin et al., 2022)	Policy/regulation analysis (evaluative/normative legal-regulatory analysis). (Yuspin et al., 2022)	Insurance is positioned as a solution for mitigating default risk, providing protection for lenders. (Yuspin et al., 2022)
11	An effective borrower credit risk assessment model is needed for P2P lending. (Ma et al., 2021)	Developing a BP neural network-based credit risk assessment model. (Ma et al., 2021)	Prediction model using Backpropagation (BP) Neural Network. (Ma et al., 2021)	The BP neural network model is used to improve the effectiveness of borrower credit risk management systems. (Ma et al., 2021)
12	Risk screening for entrepreneurs/small businesses in marketplace lending: how important is personal credit history? (Andreeva & Altman, 2021)	Testing the value of personal credit history in assessing the risk of entrepreneur/SME borrowers. (Andreeva & Altman, 2021)	Empirical study based on marketplace lending data (risk assessment/screening analysis). (Andreeva & Altman, 2021)	Personal credit history is valuable in entrepreneur risk screening; there are differences between SBL and consumer profiles, and they compete for funding. (Andreeva & Altman, 2021)
13	Which SMEs borrow from “alternative lenders” in the UK? (borrower profiles, motivations, characteristics). (Sabato et al., 2021)	Mapping the characteristics of SME borrowers on alternative lenders to understand the SME financing landscape. (Sabato et al., 2021)	Empirical/descriptive analysis (profiling) of UK SMEs borrowing from alternative lenders. (Sabato et al., 2021)	Provides an overview of SME profiles that use alternative lenders and the implications for access to credit outside traditional banking. (Sabato et al., 2021)
14	Predicting default risk in P2P lending faces the problem of imbalanced datasets, so models can be biased towards the majority class. (Chen et al., 2021)	Proposing/evaluating a default prediction approach that addresses imbalance to improve risk detection accuracy. (Chen et al., 2021)	Predictive modeling of default on imbalanced P2P data; evaluation of accuracy improvements. (Chen et al., 2021)	Addressing imbalance in P2P data can improve the accuracy of default risk predictions. (Chen et al., 2021)

To clarify the relationship between empirical findings and key themes emerging in the literature, this study compiled a matrix mapping themes to included articles. This matrix shows how each of the 14 studies contributes to the development of key themes related to FinTech lending and credit risk management in SMEs, such as information asymmetry, the use of alternative data, the application of machine learning, issues of explainability and fairness, the challenges of imbalanced data, and aspects of governance and regulation. The presentation of this matrix aims to increase the transparency of thematic synthesis and make it easier for readers to explore the empirical evidence underlying each theme identified in this systematic literature review.

Theme 1: Information Asymmetry and Limited SME Data

The main issues that consistently arise are the limited availability of formal (thin-file) SME financial data, business heterogeneity, and short credit histories, which complicate credit risk assessment using traditional approaches.

Article evidence:

- SMEs and entrepreneurs are often underserved by banks due to limited information standards,

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leading them to turn to alternative lenders/marketplaces (Sabato et al., 2021).
- Personal credit history has been shown to be important for screening SME lending risks when business data is limited (Andreeva & Altman, 2021).
- Fintech platforms use alternative information to reduce information asymmetry in risk management (Yan, 2025).

Fintech lending emerged as a response to SME information asymmetry, but its effectiveness depends on the quality and integration of non-traditional information.

Theme 2: Utilization of Alternative Data and Soft Information

The literature shows a shift from conventional financial data to alternative data (behavior, digital footprint, personal history, platform information) as the core of credit risk management.

Article evidence:
- Alternative information is actively used by fintech platforms for SME risk assessment (Yan, 2025).
- Personal credit history improves the quality of risk screening for borrower entrepreneurs (Andreeva & Altman, 2021).
- P2P credit scoring can be improved through improved measurement and utilization of additional information (Ahelegbey & Giudici, 2023).

Alternative data acts as "information augmentation" to reduce reliance on formal SME financial reports.

Theme 3: Machine Learning for Credit Risk Prediction

Most empirical studies emphasize the use of machine learning (ML) to improve the accuracy of default risk prediction in FinTech/P2P lending.

Article evidence:
- CatBoost is effective for credit risk detection in P2P lending (Nasution et al., 2023).
- Neural networks (BP-NN) are used to improve borrower credit risk management systems (Ma et al., 2021).
- Innovative ML is used for default prediction to support the sustainability of P2P lending (Nguyen et al., 2024).

ML improves the accuracy of risk prediction, but its success is highly dependent on the data structure and evaluation objectives (e.g., default recall).

Theme 4: Explainability, Fairness, and Model Risk

In addition to accuracy, the literature highlights the need for explainability and fairness in algorithm-based credit decisions.

Article evidence:
- AI-based credit decision pipelines can be highly accurate but potentially unfair if the information design is inappropriate (Abbas, 2025).
- ML is not always superior to simple econometric models; interpretability remains important (Bitetto et al., 2024).
- Profit-sensitive and explainable ML enhance the business and ethical usefulness of credit decisions (Ariza-Garzón et al., 2024).

FinTech credit risk is not only default risk, but also model risk and algorithmic fairness risk.

Theme 5: Imbalanced Data Issues and Default Detection Accuracy

P2P lending data is often imbalanced, causing models to bias toward non-default classes.

Article evidence:
- Handling imbalanced datasets improves the accuracy of default risk prediction (Chen et al., 2021).
- Evaluation of default prediction performance should emphasize recall and F1-score, not just accuracy (Nguyen et al., 2024).

The success of credit risk models should be measured with metrics that reflect the cost of default.

Theme 6: Risk Governance, Regulation, and Sustainability

The literature also highlights institutional and regulatory aspects in FinTech credit risk management.

Article evidence:
- Insurance has been proposed as a default risk mitigation mechanism in P2P lending (Yuspin et al., 2022).
- Psychometrics has been used to support responsible access to credit for micro-SMEs in volatile conditions (van Thiel et al., 2024).
- Green finance and institutional support influence SME performance (Hoang et al., 2025).

FinTech credit risk management should be viewed as a socio-technical system: technology + regulation + governance.

The problem themes that emerged from the systematic literature review were grouped and aligned with supporting article evidence. The following matrix model can be created:

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Table 5. SLR matrix on theme

No	Author (year)	T1 Information Asymmetry	T2 Alternative Data	T3 ML	T4 Explainability/ Fairness	T5 Imbalanced Data	T6 Governance or regulation
1	Hoang et al. (2025)	✓	✓				✓
2	Abbas (2025)			✓	✓		
3	Yan (2025)	✓	✓				
4	Bitetto et al. (2024)			✓	✓		
5	Ariza-Garzón et al. (2024)			✓	✓		
6	Nguyen et al. (2024)			✓		✓	
7	van Thiel et al. (2024)	✓					✓
8	Nasution et al. (2023)			✓			
9	Ahelegbey & Giudici (2023)		✓	✓			
10	Yuspin et al. (2022)						✓
11	Ma et al. (2021)			✓			
12	Andreeva & Altman (2021)	✓	✓				
13	Sabato et al. (2021)	✓					
14	Chen et al. (2021)			✓		✓	

Theme Description:
T1 SME Information Asymmetry
T2 Alternative Data & Soft Information
T3 Machine Learning for Credit Risk
T4 Explainability, Fairness & Model Risk
T5 Imbalanced Data & Default Detection
T6 Governance, Regulation & Sustainability

A systematic literature review of 14 Scopus-indexed articles shows that Financial Technology (FinTech) lending has become a significant alternative financing mechanism for Small and Medium Enterprises (SMEs), particularly in the context of limited access to credit through conventional financial institutions. The literature consistently confirms that FinTech lending can reduce financing barriers for SMEs through faster, more flexible, and technology-based credit assessment processes (Sabato et al., 2021; Yan, 2025).

The Role of FinTech Lending in Addressing Information Asymmetry in SMEs

Key findings indicate that information asymmetry remains a central challenge in SME financing. Many SMEs have limited formal financial reporting (thin-file), making it difficult to assess using traditional banking approaches (Andreeva & Altman, 2021). FinTech lending addresses this issue by utilizing alternative data and soft information, such as personal credit history, digital behavior, and platform information, which serve as information augmentation in credit risk management (Yan, 2025).

These findings align with information asymmetry theory (Akerlof, 1970), where increasing the quality and quantity of information plays a crucial role in reducing adverse selection risk. However, the literature also confirms that the effectiveness of information asymmetry reduction is highly dependent on the quality of data processing and the risk governance framework implemented by the FinTech platform (Sabato et al., 2021).

Credit Risk Management

From a methodological perspective, the review results demonstrate the dominant use of machine learning (ML) in SME credit risk prediction. Various ML algorithms such as CatBoost, neural networks, and non-linear classification models are used to improve default prediction accuracy compared to traditional statistical models (Ma et al., 2021; Nasution et al., 2023; Nguyen et al., 2024). This finding indicates a paradigm shift from rule-based credit scoring to data-driven risk assessment.

However, cross-article discussions emphasize that increased predictive accuracy does not always guarantee quality credit decision-making. Several studies indicate that ML models tend to face serious challenges from imbalanced datasets, making evaluation metrics such as recall and F1-score more relevant than accuracy alone (Chen et al., 2021; Nguyen et al., 2024). This strengthens the argument that FinTech credit risk management must consider the cost of misclassification, not just statistical performance alone.

Explainability, Fairness, and Model Risk

The discussion also reveals growing attention to the issues of explainability and fairness in algorithm-based credit decisions. Abbas (2025) showed that AI-based credit decision pipelines can produce very high predictive performance, but still have the potential to create unfairness if the information and model design are not transparent. Another study confirmed that simpler, more interpretable models can be more appropriate in some contexts than complex ML models (Bitetto et al., 2024).

Explainable and profit-sensitive machine learning approaches are seen as a compromise between accuracy, transparency, and business objectives (Ariza-Garzón et al., 2024). These findings are relevant to risk-based pricing theory (Stiglitz & Weiss, 1981), which emphasizes the importance of accurate and justifiable risk estimates in pricing and credit decisions.

Risk Governance and Sustainability of the FinTech Lending Ecosystem

Beyond technical aspects, the SLR results confirm that FinTech credit risk management cannot be separated from governance and the regulatory framework. Several studies highlight the importance of risk mitigation mechanisms, such as the use of insurance to mitigate the impact of default in P2P lending (Yuspin et al., 2022). A psychometric approach has also been proposed as a tool to support more responsible risk assessment, particularly for micro-SMEs and sole traders in volatile market conditions (van Thiel et al., 2024).

Thus, the discussion indicates that the sustainability of FinTech lending as a source of financing for SMEs depends on a balance between technological innovation, accurate risk management, and protection for both borrowers and lenders.

Overall, the results and discussion of the 14 articles indicate that FinTech lending has significant potential to increase financial inclusion for SMEs through data augmentation and credit risk analytics. However, the literature also emphasizes that increasing access to financing must be accompanied by strengthened risk governance, algorithmic transparency, and an adaptive regulatory framework. Without this, technological efficiency has the potential to become a new source of risk for the stability of the SME financing system.

CONCLUSION

This Systematic Literature Review (SLR) synthesizes findings from 14 Scopus-indexed articles to examine the role of Financial Technology (FinTech) lending in credit risk management for Small and Medium Enterprises (SMEs). The review results indicate that FinTech lending has become an important financing alternative for SMEs, particularly in addressing limited credit access due to information asymmetry and limited formal financial data (Sabato et al., 2021; Yan, 2025).

The literature consistently emphasizes a paradigm shift in credit risk management from a traditional financial statement-based approach to an augmented approach, which involves enriching information through alternative data and machine learning-based analytics. This approach has been shown to improve the accuracy of default risk predictions, particularly for thin-file SMEs (Ma et al., 2021; Nasution et al., 2023; Nguyen et al., 2024). However, increasing predictive accuracy also raises new challenges in the form of model risk, algorithmic unfairness, and limited transparency of credit decisions (Abbas, 2025; Bitetto et al., 2024).

Beyond technical aspects, the SLR results emphasize that the effectiveness of FinTech lending credit risk management is inextricably linked to institutional governance and the regulatory framework. Risk mitigation mechanisms such as insurance, psychometric approaches, and policy design that supports responsible access to credit are considered crucial for maintaining the sustainability of the FinTech lending ecosystem and protecting SMEs from the risk of overfinancing (Yuspin et al., 2022; van Thiel et al., 2024).

Overall, the SLR concludes that FinTech lending has significant potential to increase SME financial inclusion through technological innovation and data augmentation. However, this potential can only be realized sustainably if balanced with strengthened risk governance,

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algorithmic transparency, and a regulatory framework that adapts to technological developments.

Future Research Agenda

Based on the synthesis of findings and limitations of the existing literature, several future research agendas can be proposed. First, future research should examine the long-term stability of machine learning models in SME credit risk management, particularly during crises or economic shocks. Most of the reviewed studies are static and have not evaluated the model's resilience to changes in borrower behavior and market dynamics (Nguyen et al., 2024; Bitetto et al., 2024).

Second, there is a need to deepen research on the fairness, bias, and social impact of algorithm-based credit decisions. Future studies are expected to not only measure predictive accuracy but also develop evaluation metrics capable of capturing the ethical and distributional implications of FinTech lending for different SME groups (Abbas, 2025; Ariza-Garzón et al., 2024).

Third, cross-country and cross-regulatory research needs to be expanded to understand how institutional and policy differences influence the effectiveness of FinTech lending credit risk management. This comparative approach is crucial for formulating contextual, non-one-size-fits-all policies (Yuspin et al., 2022; Sabato et al., 2021).

Fourth, future research could explore the integration of non-technological approaches, such as psychometrics and risk protection mechanisms, with AI-based analytical systems. This hybrid approach has the potential to produce risk assessment systems that are not only accurate but also more inclusive and oriented toward the sustainability of SMEs (van Thiel et al., 2024; Yan, 2025).

Thus, future research is expected to enrich our understanding of how FinTech lenders can continue to innovate in managing SME credit risk responsibly, fairly, and sustainably.

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