Modelling green credit scores for Retail Clients and SMEs

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Abstract. Forecasting credit risk for small and medium-sized enterprises (SMEs) presents significant challenges for financial institutions. Accurately assessing the creditworthiness of SMEs is crucial for reducing financial risk and ensuring the stability of lending practices. While traditional credit risk models focus on financial metrics, the integration of sustainability-related features into these models remains underexplored. Incorporating sustainable practices can enhance the robustness and relevance of credit risk assessments, offering a more comprehensive evaluation of an SME's overall risk profile. This research investigates the application of machine learning models and techniques in forecasting credit risk for SMEs. A systematic literature review and analysis were conducted to identify the current applications of machine learning in credit risk forecasting and to examine sustainable-related features. The study addresses environmental factors, aiming to integrate these aspects into credit scoring practices to improve model robustness and sustainability. The analysis revealed that while several machine learning models are effective in predicting SME credit risk, incorporating sustainable-related features can significantly enhance model accuracy and reliability. The study provides a detailed understanding of the effectiveness and challenges of existing models and offers insights into potential improvements. By integrating environmental factors, the research contributes to the development of more sustainable and comprehensive credit scoring practices.

Additional Key Words and Phrases: Green Credit Score, Sustainability, Credit Risk Assessment, Machine Learning Models, SMEs, Systematic Literature Review

1 INTRODUCTION

The financial sector is undergoing a transformative shift towards integrating environmental, social, and governance (ESG) criteria into financial decision-making processes. This shift aligns with global efforts to combat climate change and promote sustainable development, such as the United Nations Sustainable Development Goals[1] and the Paris Agreement[2]. One significant development in this context is the concept of sustainable finance, which aims to foster economic growth while ensuring long-term environmental protection, social well-being, and good governance. Sustainable finance integrates ESG factors into financial activities to promote investments that contribute to a more sustainable and inclusive economy (European Commission, 2021). Sustainable finance has the potential to redirect capital flows towards more sustainable projects and businesses, thus contributing to a greener economy [Dovbiy 2022].

Credit scores are numerical representations of a borrower's creditworthiness, traditionally based on factors such as repayment history, debt levels, and credit utilization (Equifax,2022)[3]. These scores help financial institutions assess the risk associated with lending to individuals or businesses. Green credit scores have emerged as a crucial tool within the sustainable finance framework. These scores provide a quantifiable measure of a borrower's environmental performance, helping financial institutions evaluate the sustainability of their lending practices [Sachs et al. 2019] . By assessing the environmental impact of borrowers, green credit scores encourage businesses, particularly Small and Medium-sized Enterprises (SMEs), to adopt more sustainable practices [Zhu et al. 2019a]. SMEs play a vital role in the economy, but they often face challenges in accessing finance due to perceived higher risks. For instance, SMEs may be seen as having less financial stability, limited credit history, or insufficient collateral compared to larger companies. Green credit scores can potentially mitigate these challenges by providing a clearer picture of an SME's sustainability efforts, thereby facilitating access to capital [Petrenko 2021].

This study conducts a systematic literature review to consolidate existing methodologies and data sources related to the development and deployment of green credit score models. The review aims to identify and analyze the machine learning (ML) models and techniques used, as well as the types of data commonly utilized in these models to assess SME credit risk in sustainable settings.

The motivation for this research stems from the urgent need to refine and enhance credit risk assessment models to incorporate sustainability metrics in a manner that accurately reflects the environmental and social impact of borrowers, improves predictive accuracy, and provides actionable insights for financial institutions. For instance, financial institutions can better support the transition to a low-carbon economy. This research is guided by two primary questions:

RQ1: What machine learning models and techniques have been employed to develop and deploy green credit score models for assessing SME credit risk in sustainable settings?

RQ2: What types of data (e.g., financial, environmental, social, network-based) are commonly utilized by machine learning models for evaluating the credit risk of SMEs in the context of sustainable settings?

To answer these research questions, a systematic literature review is conducted. A systematic literature review is a methodical and reproducible process for identifying, evaluating, and synthesizing existing research on a specific topic [Wijnhoven and Machado 2024]. This approach will involve a comprehensive search of academic databases and relevant publications to identify studies that have developed and employed machine learning models for green credit scoring and SME credit risk assessment. The review will focus on identifying the machine learning techniques used, the types of data integrated into these models, and how network analysis has been incorporated to enhance credit risk assessment.

The growing interest in sustainable finance has led to increased availability and quality of data related to ESG criteria. Financial institutions and stakeholders can now access a wealth of unstructured data, including environmental metrics, social indicators, and

[1] https://sdgs.un.org/goals
[2] https://unfccc.int/process-and-meetings/the-paris-agreement/the-paris-agreement
[3] https://www.equifax.com/

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network data. This data is crucial for developing sophisticated credit risk models that can accurately assess the sustainability and financial health of borrowers [Escrig-Olmedo et al. 2019]. The integration of ML techniques into these models allows for more precise and dynamic assessments, leveraging large datasets to identify patterns and trends that traditional models might overlook [Ziolo et al. 2019]. This thesis contributes to the field by proposing enhanced credit risk models that incorporate these diverse data sources and advanced ML methods, aiming to improve the accuracy and reliability of credit assessments in the context of sustainable finance. By addressing both environmental and network-based factors, this research seeks to pave the way for more robust and sustainable credit scoring practices.

The systematic literature review will follow a structured process, including the definition of search criteria, selection of relevant studies, and critical evaluation of the methodologies and findings of these studies. This approach ensures that the review is thorough, transparent, and replicable, providing a solid foundation for understanding the current state of research in green credit score models.

The structure of this thesis is organized as follows: Section Methodology discusses the methodology, detailing the systematic literature review process and the selection criteria for the studies included. Section Findings presents the findings of the literature review, highlighting key insights and trends in the application of machine learning to green credit scoring. Section Discussion offers a discussion on the practical implications of these findings and proposes a research agenda for future studies. Finally, Section Conclusion concludes the thesis, summarizing the main contributions and suggesting directions for future research.

2 METHODOLOGY

A systematic literature review methodology has been adopted for this study to consolidate existing methodologies and data sources related to the development and deployment of green credit score models [Gupta et al. 2018]. The primary databases used for this review were Consensus[4] and Scopus[5], which provide comprehensive coverage of literature in finance, machine learning, and sustainability.

For RQ1 we had the query (“machine learning" AND "green credit score”) OR ("SMEs" AND "credit risk"). In the first phase, the initial search on Scopus yielded 285 research papers. In the second phase, the analysis was restricted to peer-reviewed journal articles and reviews, reducing the number of research papers to 196. In the third phase, the focus was narrowed to research within the domains of finance, sustainability, credit scoring, and ML, further reducing the number of research papers to 38. In the fourth phase, a date range was applied to find documents between 2015 and 2024, which led to 28 research papers. In the fifth phase, titles, keywords, and abstracts of the selected papers were screened to exclude inappropriate papers, ensuring that the remaining papers were relevant to the objectives of the systematic review process. Finally, we obtained 20 research papers that were entirely appropriate for studying green credit score models within the specified domains and time frame.

[4]https://consensus.app/search/
[5]https://www.scopus.com/home.uri

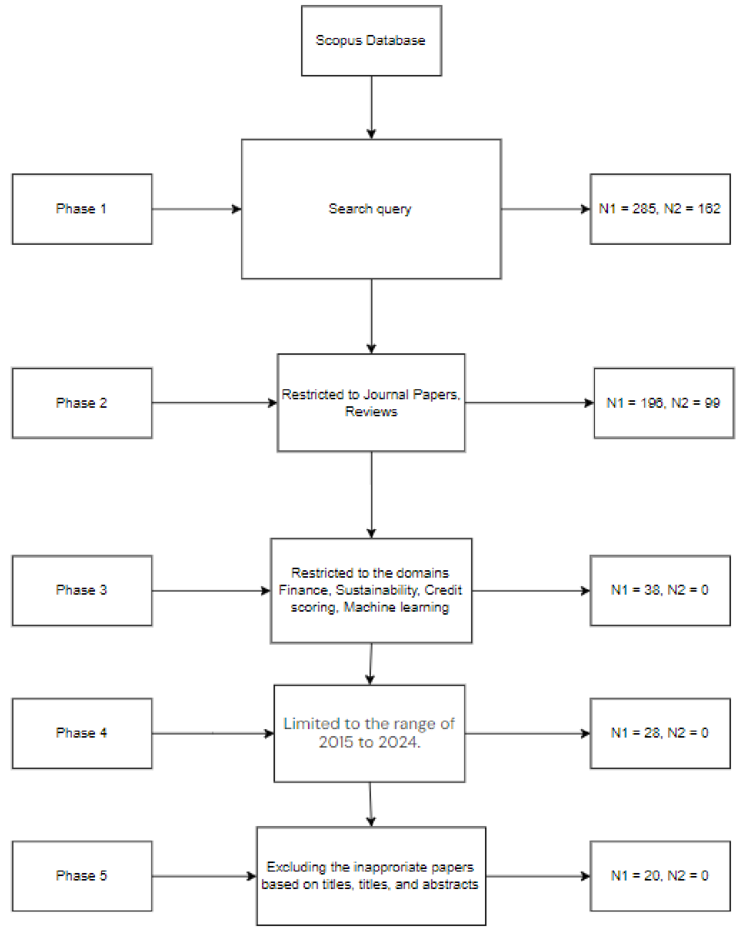

Fig. 1. Stages of the study selection process for the literature review from Scopus

For RQ2 we had the query (“data types" AND "machine learning models"). Initially, the search on Scopus yielded 162 documents. In the next step, the analysis was limited to peer-reviewed journal articles and reviews, reducing the number of documents to 99. Further narrowing the focus to research within the domains of finance, sustainability, credit scoring, and machine learning led to 0 documents. Finally, applying a date range to locate documents published between 2015 and 2024 also resulted in 0 relevant documents. Therefore, the refined search for the second research question did not yield any documents meeting the criteria after applying all filters.

Fig 1 illustrates the systematic literature review process, from the Scopus database, used in the study, specifically for addressing two research questions (N1 and N2). Here’s a detailed explanation of each phase shown in the flowchart:

- **Phase 1 Seach Query(Scopus Database):** The process begins with a search query conducted in the Scopus database.Two sets of initial results were obtained for the two research questions: N1 = 285 (for Research Question 1) and N2 = 162 (for Research Question 2).

- **Phase 2 Restriction to Journal papers, Reviews:** This phase involves applying initial filters to the search results. The search results are restricted to include only journal papers and reviews. This reduces the number of results to N1 = 198 and N2 = 99.
- **Phase 3 Restriction to specific domains:** The results are further restricted to specific domains: Finance, Sustainability, Credit Scoring, and Machine Learning. This additional filtering narrows down the results to N1 = 38 and N2 = 0.
- **Phase 4 Date range limitation:** The results are limited to a specific date range, from 2015 to 2024. This time-based filtering further refines the results to N1 = 28 and N2 = 0.
- **Phase 5 Excluding the inappropriate papers:** In the final phase, inappropriate papers are excluded based on titles, keywords, and abstracts. After this exclusion process, the final number of relevant papers is N1 = 20 and N2 = 0.

During the systematic literature review process conducted on the Scopus database for RQ2, the final results after applying all filtering criteria were zero. This means that no relevant articles were identified that directly addressed the specific aspects of RQ2. As a result, there are no findings or analysis available from Scopus for this particular research question. To address this gap, we have used another search engine called Consensus. Consensus[6] is designed to aggregate and provide access to scientific literature, offering a different set of resources and potentially uncovering relevant studies that were not indexed or found in Scopus. By utilizing Consensus, we aim to find additional articles that can contribute to the analysis and findings for RQ2. Moreover, we have also used Consensus for find relevant journals for RQ1. Here, we have prompted the whole sentences of the research questions to find the papers.

Figure 2 illustrated the almost the same literature review process, due to the filter limitations of the Consensus search engine. One more limitation to address is that this search engine does not tell me how many in total relevant articles it has, but gives me the 20 most relevant ones. Here's a detailed explanation of each phase shown in the flowchart:

- **Phase 1 Search query(Consensus database):** The process begins with a search query conducted in the Consensus database. Two sets of initial results were obtained for the two research questions: N1 = 20 (for Research Question 1) and N2 = 20 (for Research Question 2).
- **Phase 2 Restriction to Journal papers, Reviews:** This phase involves applying initial filters to the search results. The search results are restricted to include only journal papers and reviews. This reduces the number of results to N1 = 18 and N2 = 12.
- **Phase 3 Restriction to specific domains:** The results are further restricted to specific domains: Finance, Sustainability, Credit Scoring, and Machine Learning. This additional filtering narrows down the results to N1 = 15 and N2 = 9.
- **Phase 4 Restriction to high quality:** The results are further restricted to high quality publication based on journal rankings Q1. It narrows down the results to N1 = 12 and N2 = 6.

[6]https://consensus.app/search/

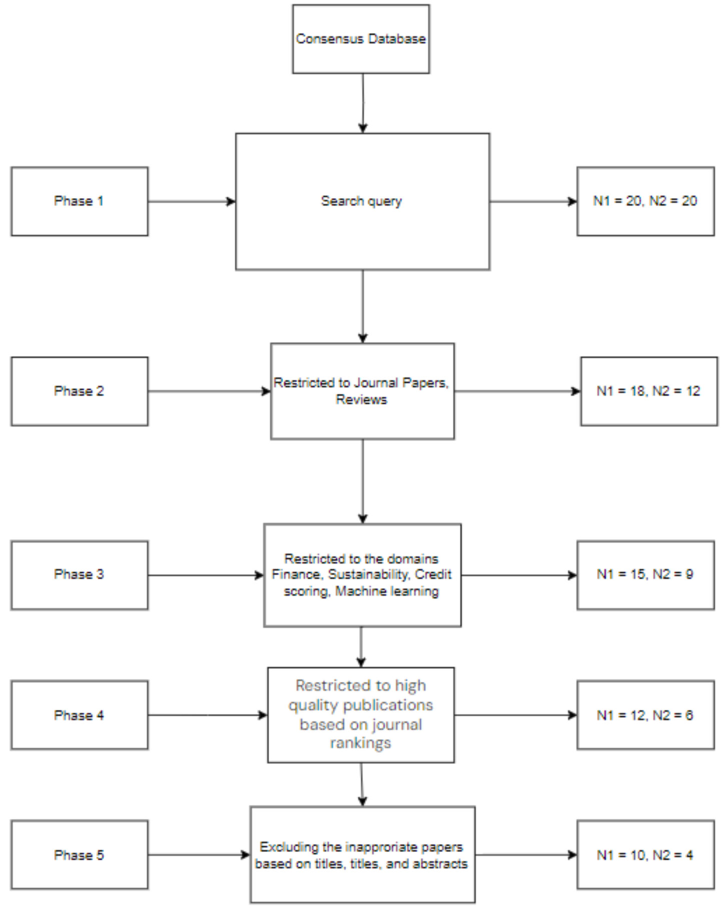

Fig. 2. Stages of the study selection process for the literature review from Consensus

- **Phase 5 Excluding the inappropriate papers:** In the final phase, inappropriate papers are excluded based on titles, keywords, and abstracts. After this exclusion process, the final number of relevant papers is N1 = 10 and N2 = 6.

3 FINDINGS

The findings extracted from the search engine Scopus[7] will be discussed in two parts with three subsections, for each research questions. In the first section a year-wise distribution graph will be discussed. Thereafter, a pie chart showing distribution of documents by subject area will be discussed. Lastly, an overview table of the found papers.

3.1 Year-wise distribution

Figure 3 demonstrates the year-wise distribution of the publications included in the review. The graph shows a significant increase in

[7]https://www.scopus.com/home.uri

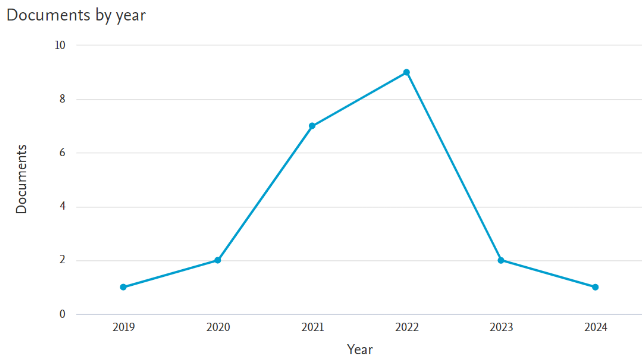

Fig. 3. Year wise distribution of research articles as obtained May 30, 2024.

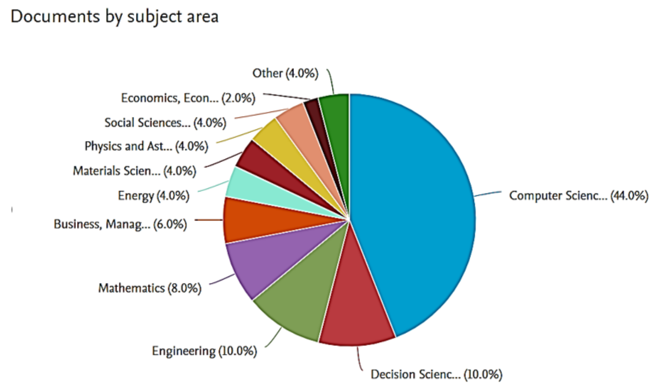

Fig. 4. Subject area distribution of research articles

the number of documents from 2019 to 2022, peaking in 2022 with nine documents. After 2022, there is a noticeable decline, with two documents published in both 2023 and 2024. This trend indicates growing interest in the topic during the early 2020s.

The initial surge in publications likely reflects increased exploration and foundational work in the field, as researchers sought to establish key methodologies and frameworks. The peak in 2022 suggests a culmination of these efforts, with many studies contributing to a deeper understanding of the subject.

The subsequent decline may be attributed to several factors. Researchers might have shifted focus towards more specialized areas within the broader topic, exploring emerging challenges and new applications. Additionally, changes in funding priorities or shifts in industry focus could have influenced the number of studies. The decline does not necessarily indicate saturation but rather a transition to more targeted research efforts.

Global events, such as economic shifts or the impacts of the COVID-19 pandemic, may have also affected research activities, contributing to the reduction in new studies. As the field evolves, ongoing interest and future publications are likely to focus on addressing complex issues and refining existing models, ensuring continued advancement in this dynamic area.

3.2 Subject-area distribution

Figure 4 provides a pie chart showing the distribution of the documents by subject area. The largest proportion of the documents (44%) falls under Computer Science, indicating a strong emphasis on the technological aspects of green credit scoring models. Decision Sciences and Engineering each account for 10% of the documents, reflecting the interdisciplinary nature of the research. Other significant subject areas include Mathematics (8%), Business, Management and Accounting (6%), and several others, each contributing 4% or less, such as Energy, Materials Science, Physics and Astronomy, Social Sciences, and Economics.

3.3 Overview tables

Various studies have been analyzed to understand the application of machine learning models and techniques in developing green credit score models for assessing SME credit risk in sustainable settings. The findings are summarized in the corresponding tables in Appendix A and Appendix B, which provide a comprehensive overview of the machine learning models employed, their key findings, and the specific techniques utilized in each study. Appendix A contains the table for Scopus, while Appendix B contains the table for Consensus.

The tables include the following key information:

- **Study:** This column lists the citations of the research papers reviewed.
- **ML models:** This column provides the machine learning models used in the papers.
- **SMEs:** This column indicates whether the study is linked to SMEs.
- **Key Findings:** This column summarizes the major findings from each study. The findings reveal insights into the effectiveness of different machine learning models in predicting and assessing credit risk, the factors influencing SME creditworthiness, and innovative approaches to risk assessment.

3.3.1 Key Highlights

. Logistic regression is frequently used, demonstrating its effectiveness in analyzing default risk in supply chains and predicting default probabilities [Liu et al. 2021]. Deep neural networks have shown considerable success in reducing financial transaction risks [Subramanian and Thangarasu 2023]. Ensemble learning approaches, particularly for technology-based SMEs, have significantly improved the accuracy of credit risk assessments [Wu et al. 2022]. Support Vector Machines (SVM) and decision trees have proven effective in predicting SME credit risk and optimizing loan strategies (Zhao, Yang, Peng, & Li, 2022). Artificial Neural Networks (ANN) combined with Genetic Algorithms (GA) have enhanced the accuracy of credit risk models (Huang et al., 2022). Temporal knowledge graphs have further refined credit risk assessment accuracy (Hong et al., 2022). Survival analysis has been effectively utilized to assess credit risk over time, providing valuable insights into the temporal dynamics of financial risk (Chen, Wang, & De Leone, 2022). The Random Subspace-Real AdaBoost (RS-RAB) method has been particularly effective in predicting SME credit risk in supply chain finance (Zhu, Xie, Wang, & Yan, 2016). ANN models, when combined with logistic regression, have consistently outperformed traditional methods in credit risk estimation (Boguslauskas & Mileris, 2009). The RS-MultiBoosting approach has improved the accuracy of forecasting SMEs' credit risk (Zhu, Zhou, Xie, Wang, & Nguyen, 2019). Support Vector Machines (SVM) and decision trees have also provided optimal loan strategies for SMEs (Cui, Ye, Huang, & Yang, 2021). Gradient boosted trees and deep neural networks have outperformed traditional models in credit assessment, showcasing advancements in machine learning methodologies (Munkhdalai et al., 2019). Lastly, extreme learning machines (ELM) models have outperformed traditional credit scoring techniques, underscoring their potential in revolutionizing credit risk assessment processes (Bequé & Lessmann, 2017). Across various methodologies, ML models consistently demonstrate superior performance in credit risk assessment compared to traditional methods such as logistic regression and decision trees. For instance, deep neural networks and ensemble methods like Random Subspace-Real AdaBoost (RS-RAB) have shown considerable success in reducing financial transaction risks and enhancing prediction accuracy. The superiority of these models is evident through their higher prediction accuracy, optimized loan strategies, and real-time risk assessment capabilities, which are not as effectively achieved by traditional models. These advancements underscore the transformative potential of machine learning in financial risk management. Specific examples of environmental data utilized in these models include carbon emissions, energy consumption, waste management practices, and resource usage metrics. Such data points are crucial for evaluating the environmental sustainability of SMEs and integrating green credit scoring into financial risk assessments, further encouraging innovation and integration in the financial sector.

4 DISCUSSION

This review of literature provides a summarized view of the existing studies that have utilized machine learning models to develop green credit score models for assessing SME credit risk in sustainable settings. A systematic literature review was conducted to identify relevant articles, and a synthesis of the literature has been developed to summarize the findings from these studies. It is divided into two parts for each research question, respectively:

4.1 Machine Learning Approaches

4.1.1 Practical Implications

. The practical applications of machine learning models in SME credit risk assessment are vast, providing significant improvements in risk prediction, loan allocation, and overall financial stability. The following are key practical implications derived from the reviewed studies:

- **Improved Credit Risk Prediction**: The application of advanced machine learning models such as deep neural networks and ensemble methods significantly enhances the accuracy of credit risk predictions. This improvement supports more reliable loan decisions, thereby reducing the likelihood of defaults .
- **Dynamic and Real-Time Risk Assessment**: The integration of temporal models, such as those using temporal knowledge graphs, allows for dynamic risk assessment that adapts to real-time financial data. This capability is crucial for SMEs operating in volatile markets where financial conditions can change rapidly .
- **Explainability and Transparency**: Ensuring the explainability of machine learning models is critical for their adoption in financial institutions. Studies like Huang et al. (2022) focused on enhancing the interpretability of models, making them more transparent and trustworthy for stakeholders. This transparency is essential for regulatory compliance and gaining stakeholder confidence .
- **Optimized Loan Allocation**: Machine learning models such as those using logistic regression and random forests optimize loan allocation by accurately predicting the probability of default. This approach ensures that credit is extended to the most reliable borrowers, improving overall loan portfolio performance .
- **Sector-Specific Insights**: Different sectors require tailored approaches to credit risk assessment. For example, the use of evolutionary game models in technological SMEs by Wang et al. (2022) highlighted the dynamic nature of risk in tech-focused industries, providing insights into optimal risk management strategies .

*4.1.2 **Research Agenda***

. Future research should address several key areas to further enhance the application of machine learning in SME credit risk assessment:

- **Real-Time Data Integration**: Developing models that leverage real-time financial transaction data will improve the responsiveness and accuracy of credit risk assessments. This real-time integration is vital for SMEs operating in dynamic economic environments.
- **Enhanced Model Explainability**: Continued efforts to improve the explainability and transparency of machine learning models will facilitate their broader adoption. Research should focus on developing techniques that make complex models more interpretable without sacrificing predictive accuracy.
- **Sector-Specific Applications**: Expanding research to include sector-specific applications of machine learning models will help identify unique risk factors and mitigation strategies. This focus will provide tailored risk assessment tools for various industries.
- **Combination of Different Data Types**: Future studies should explore the combination of different data types, including text data, images, and videos, to enhance the robustness of credit risk models. Multi-modal data integration could

provide a more comprehensive view of an SME's financial health.

4.2 Data types used

4.2.1 Synthesis of Literature

. The synthesis of these studies reveals several important trends and insights regarding the types of data utilized.

(1) **Financial Data**: Financial data, including transaction histories, balance sheets, and profit and loss statements, is the most commonly utilized type of data. For example, Xie and Li (2022) used financial data to analyze default risk in supply chains using logistic regression and PCA. Similarly, Subramanian and Thangarasu (2023) leveraged financial transaction data to reduce risks using deep neural networks.
(2) **Environmental Data**: Environmental data, although less frequently used, is integrated into some models to assess the impact of environmental factors on credit risk. Wu et al. (2023) incorporated environmental performance indicators into their ensemble learning model to evaluate technology-based SMEs.
(3) **Social Data**: Social data, including customer reviews, social media interactions, and sentiment analysis, is used to gauge the reputational risk and customer perception of SMEs. Zhao et al. (2022) used social media analysis to predict SME credit risk, highlighting the importance of customer feedback in risk assessment.
(4) **Network-Based Data**: Network-based data, which includes relationships with suppliers, customers, and financial institutions, is crucial for understanding interconnected risks. Studies such as those by Cheng et al. (2020) employed network-based data to model the contagion risk in networked-guarantee loans using RNN and Temporal Inter-chain Attention Networks.
(5) **Combined Data Types**: Some studies combined multiple data types to improve the robustness of their models. For instance, Zhang, Li, and Liu (2023) utilized a mix of financial and network-based data to predict credit risk factors using grey artificial neural networks. This approach helped in capturing the multifaceted nature of credit risk in SMEs.

The synthesis highlights that while financial data remains the cornerstone of credit risk assessment, integrating environmental, social, and network-based data can provide a more holistic view of an SME's risk profile.

5 CONCLUSIONS

5.1 ANSWER RESEARCH QUESTION 1

The research identifies a variety of machine learning models used to develop green credit score models for assessing SME credit risk in sustainable settings. Logistic Regression combined with PCA is frequently employed for its simplicity and effectiveness in dimensionality reduction, enhancing the interpretability of credit risk factors. Deep Neural Networks excel at identifying complex patterns within financial transactions, significantly reducing transaction risks for SMEs. Ensemble Learning methods, such as bagging and boosting, are particularly effective in improving credit risk assessment accuracy, especially for technology-based SMEs, by integrating multiple predictive algorithms. Grey Artificial Neural Networks handle uncertain and imprecise data effectively, providing accurate predictions of credit risk factors in SME environments. Support Vector Machines and Decision Trees offer robust frameworks for credit risk prediction and loan optimization, demonstrating high applicability in various financial contexts. Overall, these models provide a comprehensive approach to assessing credit risk, reflecting the growing integration of sustainability considerations in financial decision-making.

5.2 ANSWER RESEARCH QUESTION 2

The types of data used in machine learning models for evaluating SME credit risk in sustainable and circular economies encompass financial, environmental, social, and network-based data. Financial data, including transaction histories and balance sheets, remains foundational, providing crucial insights into an SME's financial health. Environmental data, such as sustainability performance indicators, assesses the impact of sustainable practices on credit risk, aligning financial assessments with broader environmental goals. Social data, derived from customer reviews and social media interactions, evaluates reputational risks and public perception. Network-based data captures the interconnected risks between SMEs and their suppliers, customers, and financial institutions, enhancing the robustness of credit risk models. The integration of these diverse data types allows for a more holistic evaluation of credit risk, supporting responsible lending practices and the transition towards sustainable finance.

5.3 Further work

Future research should focus on:

- **Real-Time Data Integration**: Developing models that leverage real-time financial transaction data for dynamic risk assessment, enhancing the timeliness and accuracy of credit evaluations.
- **Enhanced Model Explainability**: Improving the transparency and interpretability of complex machine learning models to facilitate broader adoption and trust among stakeholders.
- **Sector-Specific Applications**: Expanding research to include sector-specific applications to identify unique risk factors and tailored mitigation strategies for different industries.
- **Comprehensive Data Integration**: Exploring the integration of various data types, including text, images, and videos, to provide a more holistic view of an SME's financial health and risk profile.

5.4 Limitations

While a broad range of literature was reviewed, some relevant studies may not have been accessible, potentially limiting the synthesis of existing research findings. The use of the Consensus search engine posed challenges due to its fewer filtering options compared to Scopus.

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6 APPENDICES

6.1 Appendix A - ML Models for Green Credit Score Models from Scopus

Study	ML Method	SMEs	Data Used	Key Findings
([Li and Fu 2022])	Logistic Regression, PCA	Yes	Supply chain financial data	Logistic regression effectively analyzes default risk in supply chains.
([Subramanian and Thangarasu 2023])	Deep Neural Networks	Yes	SME transaction data	Reduces financial transaction risk effectively.
([Wenjuan Feng and Chen 2023])	Ensemble Learning	Yes	Tech SME financial data	Improves credit risk assessment accuracy.
([Zhang et al. 2022], 2023)	Grey Artificial Neural Network	Yes	SME credit data	Helps in understanding and predicting credit risk factors.
([Wu and Pan 2021])	Random Forest	No	Financial institution data	Improves credit scoring accuracy.
([Chen et al. 2022])	Survival Analysis	Yes	SME data	Effectively assesses credit risk over time.
([Zhao et al. 2022])	SVM, Decision Trees	Yes	Supply chain data	Effective in predicting SME credit risk.
([Huang et al. 2024])	ANN, GA	Yes	SME credit data	Enhances accuracy of credit risk models.

([Tian et al. 2022])	Rule-based methods, Logistic Regression, SVM	No	Credit data	Improves classification of customer and enterprise defaults.
([Wang et al. 2022]	Evolutionary Game Model	Yes	Tech SME data	Dynamic equilibrium of bank-enterprise cooperation.
([Anglekar et al. 2021])	SVM, Decision Tree, Linear Optimization	Yes	Loan data	Assesses credit risk, especially under unexpected scenarios like COVID-19.
([Hong et al. 2021])	Temporal Knowledge Graphs	Yes	Temporal financial data	Improves credit risk assessment accuracy.
([Zheng and Chen 2022])	Logistic Regression	Yes	Financial ratios data	Effectively assesses credit risk.
([Cui et al. 2021])	SVM, Decision Tree, Linear Optimization	Yes	SME financial data	Provides optimal loan strategies.
([Jiang 2022])	AI-based models	Yes	Business indicators and profitability trends	Efficient credit risk assessment.
([Malakauskas and Lakstutiene 2021])	AI Tools	Yes	Creditworthiness data	Enhances accuracy and reliability of models.
([Fu et al. 2022])	IG-GA-SVM	No	Supply chain finance data	Optimizes feature selection, improving prediction accuracy.
([Zhang et al. 2021])	Proportional Hazards Model	No	Automobile supply chain data	Predicts credit risk with 72 p accuracy.
([Cheng et al. 2020])	RNN, Temporal Inter-chain Attention Network	No	Networked-guarantee loans data	Improves risk rating, enabling better monitoring.
([Ye 2021])	DEMATEL-CRITIC	Yes	Agricultural supply chain data	Evaluates risk factors effectively, aiding in risk prevention and control.

6.2 Appendix B - ML Models for Green Credit Score Models from Consensus

Study	ML Method	SMEs	Data Used	Key Findings
([Zhu et al. 2016])	RS-RAB (Random Subspace-Real AdaBoost)	Yes	Financial data from listed SMEs	Effectively predicts SME credit risk in supply chain finance.
([Boguslauskas and Mileris 2009])	Artificial Neural Networks, Logistic Regression	Yes	Financial data	ANN models outperform traditional methods in credit risk estimation.
([Cui et al. 2021]))	SVM, Decision Tree	Yes	Financial data, reputational metrics	Provides optimal loan strategies for SMEs.
([Alagöz and Çanakoğlu 2021]))	Logistic Regression, Random Forest, Artificial Neural Networks	Yes	Loan samples with financial variables	Logistic Regression provides better results for credit risk analysis.
([García et al. 2019]))	Ensemble methods (Bagging, AdaBoost, Random Subspace)	Yes	Financial datasets with various features	Enhances performance of classifiers for credit risk prediction.
([Munkhdalai et al. 2019]))	Logistic Regression, Support Vector Machines, Gradient Boosted Trees, Deep Neural Networks	Yes	Financial data, consumer finance data	ML methods outperform traditional models in credit assessment.
([Khandani et al. 2010]))	Various machine learning models	Yes	Customer transactions, credit bureau data	ML models improve classification rates of credit-cardholder defaults.
([Alam et al. 2020]))	Gradient Boosted Decision Trees, K-means SMOTE oversampling	Yes	Credit card data	Significantly improves prediction accuracy for credit card defaults.
([Turkson et al. 2016]))	Various machine learning algorithms, Random Forest	Yes	Bank credit data with 23 features	Enhances accuracy in predicting bank credit worthiness.
([Bequé and Lessmann 2017]))	Extreme Learning Machines (ELM)	Yes	Financial data	ELM models outperform traditional credit scoring techniques.
([Sabeti et al. 2020]))	Various classification models	Yes	Financial data	State machines enhance credit score modeling.
([Varun et al. 2023]))	Novel classification methodology, binary classifiers	Yes	Private datasets	New classification methods improve credit score analysis.
([Breeden 2020])	Various machine learning methods	Yes	Financial data	Survey highlights the breadth of ML methods in credit risk.
([Araz et al. 2020]))	RS-RAB (Random Subspace-Real AdaBoost)	Yes	Financial data from listed SMEs	Effectively predicts SME credit risk in supply chain finance.
([Zhu et al. 2019b]))	RS-MultiBoosting	Yes	Financial ratios, trade goods features, core enterprise profit margins	Improves accuracy in forecasting SMEs' credit risk.