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The Emergence of Artificial Intelligence in Credit Ratings: A Systematic Review

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ABSTRACT

Purpose: This paper analyzes systematic literature focused on technological innovation in credit rating and credit rating agencies (CRAs), particularly emphasizing developments in artificial intelligence (AI), innovative models, and machine learning (ML) models. Credit ratings play a vital role in financial markets by evaluating the creditworthiness of various entities, which in turn influences investor decisions.

Methods: The research methodology employs a systematic analysis of the literature, utilizing the Web of Science database, from which pertinent literature was extracted, refined, and analyzed using Biblioshiny in R Studio. Key research inquiries encompass publication trends, prominent authors, and institutional affiliations that contribute to the domain of technological innovation in CRAs.

Findings: This study examines the evolution of AI applications in credit rating, exploring models such as ANNs, SVMs, and ensemble methods. Key research inquiries also encompass publication trends, prominent authors, and institutional affiliations that contribute to the domain of technological innovation in CRAs.

Implications: The integration of AI-based models by CRAs has led to enhanced efficiency and greater predictive accuracy, outpacing traditional techniques such as logistic regression and discriminant analysis.

Originality: The present systematic review provides a comprehensive understanding of how artificial intelligence is redefining the landscape of credit rating systems, marking a decisive shift from traditional, analyst-driven assessments toward data-intensive, automated, and highly accurate predictive frameworks.

1. Introduction

Credit rating is a significant factor in determining the creditworthiness of borrowers, individuals, companies, and governments. It serves as an indicator of the chances that a borrower has of meeting their financial obligations, hence playing a crucial role in offering vital information to investors, who are consequently in a position to make informed financial decisions. Credit Rating Agencies (CRAs) play a very crucial role in this regard, offering credit ratings after a comprehensive assessment of various factors, which include the financial history of the borrower, their current financial position, and the prevailing economic conditions. With the growth of the financial markets in India, there has been a growing need for unbiased assessments of credit risk. These agencies play a crucial role in offering unbiased assessments that are vital in maintaining the confidence of investors, especially in today's complex financial instruments. There have been concerns about the credibility of their ratings, especially in relation to complex financial instruments. There have been concerns about the conflict of interest that is inherent in the "issuer-pays" system and the lack of competition in the sector (Yu *et al.*, 2020). With the growing importance of credit risk assessment, financial institutions are increasingly turning to CRAs for the assessment of borrowers' capacity to fulfil their financial obligations. New techniques, such as the use of artificial intelligence models like fuzzy support vector machines (FSVM), have been developed to enhance credit risk predictions, providing greater accuracy than existing techniques. Furthermore, the rating of Initial Public Offerings (IPOs) has emerged as a key mechanism for improving market efficiency by reducing information asymmetry between investors. With the increasing focus on sustainable practices, the incorporation of Environmental, Social, and Governance (ESG) considerations into credit rating assessments is gaining popularity, indicating a move towards more comprehensive assessments.

1.1. History of Credit Ratings

The regulatory history of credit rating agencies in India has been developing in a progressive manner under the guidance of the Securities and Exchange Board of India, which introduced the Credit Rating Agencies Regulations, 1999, to regulate the registration, functioning, transparency, and code of conduct for CRAs. The initial regulations primarily focused on basic eligibility criteria, disclosure requirements, and the absence of conflict of interest. However, following the global financial crisis of 2008, which exposed the vulnerabilities of rating agencies across the globe, SEBI has been tightening the regulations through periodic amendments, which include stricter disclosure requirements, improved rating surveillance, detailed press releases, and enhanced governance standards. The 2010 amendments primarily focused on transparency, timely dissemination of rating announcements, rating rationale accountability, and improved governance standards. From 2020 onwards, the amendments have increasingly focused on technological changes, cross-regulatory actions, investor protection, and tightened timelines for complaints (Farahani *et al*., 2025). The recent amendments between 2023 and 2026 indicate a contemporary approach to regulation, which seeks to enhance eligible CRA business activities, streamline processes, tighten disclosure segregation in the context of rating financial instruments regulated by different authorities, and solidify risk monitoring obligations. In sum, the regulatory path of SEBI indicates a transition from foundational regulation to a holistic, disclosure-driven, and globally consistent framework that seeks to improve the credibility, reliability, and investor confidence in credit ratings.

A favourable credit rating not only attracts investors and reduces interest rates but also indicates a lower risk of default in the future. Although machine learning models have been found to outperform traditional models, they have been criticized for their lack of interpretability, which remains an important factor in the financial industry (Wang & Ku, 2021). Although significant improvements have been made in terms of accuracy, the interpretability of these "black-box" models remains a challenge in credit rating prediction.

1.2 Need for AI in Credit Ratings

Existing literature shows that artificial intelligence has been increasingly influencing financial decision-making systems, especially in the area of credit scoring, where responsible AI research has become a major focus. Previous systematic evidence shows that research in this area primarily focuses on technological developments, ethical and fairness issues, practical limitations, and potential uses (Farahani *et al*., 2025). However, these studies primarily focus on AI in banking credit scoring systems rather than credit rating systems, which creates a significant research gap in understanding how AI is influencing credit rating methods, transparency, and reliability. In view of the increasing use of automated assessment tools in the financial market, there is a need for comprehensive research synthesis on artificial intelligence in credit rating research to integrate scattered research findings, assess methodological shifts, and provide future research perspectives (Mathen & Paul, 2025). This research aims to fill this research gap by conducting a systematic review of the existing literature on the development and implications of AI in credit rating practices.

2. Objectives of the Study

- To identify key research trends, influential studies, and emerging themes in AI-driven credit risk assessment in this domain.
- To examine the impact of artificial intelligence and machine learning on improving the accuracy and transparency of credit rating systems by reviewing existing literature.

3. Research Methodology

A systematic review of all the literature on the topic of Artificial Intelligence, Credit Rating Agencies, and their ratings has been conducted. The analysis of the literature used the following search string:

"Technology" OR "Innovation" OR "Machine Learning" OR "Neural Network" OR "AI" OR "Artificial Intelligence" OR "Model" AND "Credit Rating Agencies" OR "CRA" OR "Indian Credit Rating Agencies" OR "Credit Rating" OR "Credit Rating Agency"

On 1/11/2025, 77 articles were retrieved. After the final extraction of the documents from the Web of Science database, the extracted 26 documents were exported in a BibTeX file to Biblioshiny in R Studio software. Biblioshiny is a visualization application of R Studio that helps in analyzing the bibliometric data extracted from the databases for the bibliometric analysis of the concerned subject or field. As shown in the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) Framework.

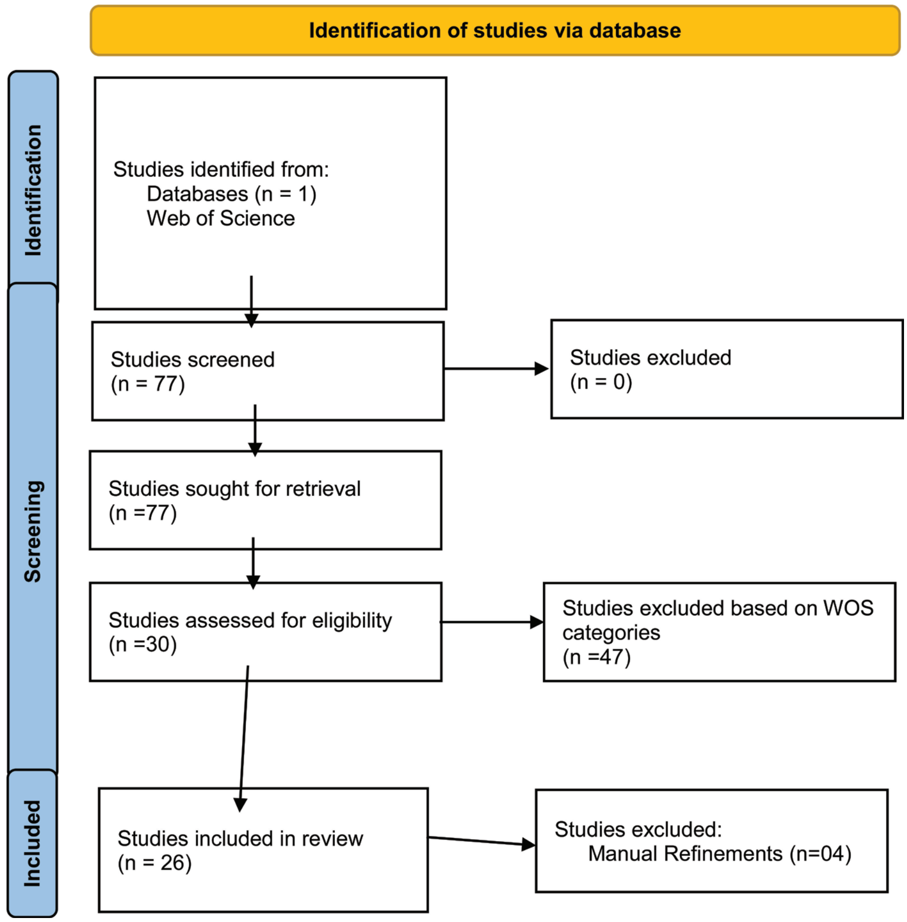

Figure 1: PRISMA Framework

Source: (Page *et al.*, 2021)

4. Result

4.1. Main Information

In Table 1, the bibliometric summary shows a moderately growing research field over the period 2005–2025, with 26 documents published across 24 sources and an annual growth rate of 10.96%, reflecting increasing scholarly attention. The average document age of 4.15 years suggests that the literature is relatively recent, while a strong average of 22.23 citations per document and 1,125 references points to good academic impact and theoretical grounding. The area is marked by a strong level of research collaboration, with 78 authors, only 4 single-authored papers, an average of 3.08 co-authors per paper, and a significant 30.77% international co-authorship, signifying global knowledge sharing. In terms of content diversity, the presence of 119 author keywords and 74 Keywords Plus signifies diverse topics, whereas the dominance of 23 journal articles and three early access articles signifies the area's strong focus on peer-reviewed and up-to-date research sharing.

Table 1: Main Bibliometric Information of the Dataset (2005-2025)

Description	**Results**
Main Information About Data	
Timespan	2005:2025
Sources (Journals, Books, Etc.)	24
Documents	26
Annual Growth Rate %	10.96
Document Average Age	4.15
Average Citations Per Doc	22.23
References	1125
Document Contents	
Keywords Plus (ID)	74
Author's Keywords (DE)	119
Authors	
Authors	78
Authors Of Single-Authored Docs	4

Authors Collaboration	
Single-Authored Docs	4
Co-Authors Per Doc	3.08
International Co-Authorships %	30.77
Document Types	
Article	23
Article; Early Access	3

Source: Biblioshiny in R

Table 2: Country Scientific Production

Country	Articles	Years
China	44	2005, 2010, 2011, 2014, 2018, 2019, 2021, 2022, 2023, 2024, 2025
South Korea	7	2005, 2010, 2011, 2014, 2018, 2019, 2021, 2022, 2023, 2024, 2025
Canada	6	2018, 2019, 2021, 2022, 2023, 2024, 2025
Spain	6	2022, 2023, 2024, 2025
Italy	4	2025
Nigeria	4	2023, 2024, 2025

Source: Biblioshiny in R

Table 2, Countries' Scientific Production, shows the comparative scientific production of different countries. China overwhelmingly leads, with almost 45 publications, leaving all other countries far behind. The next higher contributors are South Korea, Canada, and Spain, with each country making a modest number of publications, approximately 5 to 7. In the table, the preeminent position of China in scientific production compared to other countries is evident, with the latter countries showing a substantially lower level of scientific production.

4.2. Collaboration among Countries

The literature shows that China acts as the central hub of international collaboration, maintaining the highest number of linkages with multiple countries, such as Canada, Iran, Korea, Lebanon, Nigeria, Singapore, the United Kingdom, and the USA, indicating its strong global research connectivity. The China–USA collaboration appears relatively stronger, with a higher frequency, suggesting a more consistent partnership compared to other bilateral ties. In contrast, collaboration involving Canada–Nigeria and Korea–Lebanon and the Netherlands is limited and occurs only once, reflecting weaker or more occasional interactions. Overall, the collaboration highlights an asymmetric structure dominated by China, while other countries exhibit sparse and peripheral collaboration patterns, suggesting scope for broader and more balanced international research cooperation.

4.3. Thematic Map

Figure 2 illustrates a thematic map that presents the conceptual framework of research themes in terms of relevance, which represents the centrality of the topic, and development, which represents density. The upper-right quadrant, titled Motor Themes, illustrates well-developed and highly relevant topics that are driving the field. Here, "credit rating," "machine learning," and "feature selection" are dominant, signifying their central and mature status in current research. The upper-left quadrant examines Niche Themes that include specialized yet less central topics, such as "green innovation," "impact," "performance," "learning models," and "optimization," signifying specialized areas of research with high internal development. The lower-right quadrant examines Basic Themes that include "algorithms," "artificial intelligence," "innovation," and "financial constraints," which are basic and generally relevant yet less developed. Finally, the lower-left quadrant examines Emerging or Declining Themes that include underdeveloped or declining topics, such as "model," "scoring model," and "selection," signifying low current research interest or declining status. In summary, the thematic map illustrates machine learning and credit rating as the central, dynamic forces in the research field.

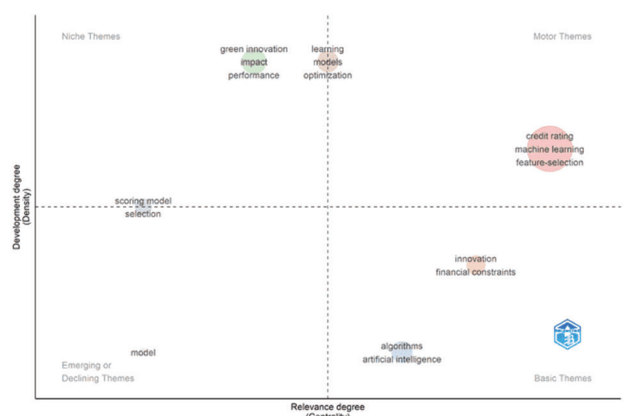

Figure 2: Themes related to the research
Source: Biblioshiny in R

4.4. Word Cloud

The word cloud in Figure 3 shows the most frequently used keywords in the research field, signifying prominent topics and emerging areas of focus. The most common terms, such as "credit rating," "machine learning," "algorithms," and "prediction," show their key role and prominence in the literature. Related concepts such as "support vector machines," "feature selection," "classification," and "neural networks" indicate the strong use of artificial intelligence and data-driven methods in credit rating research. Overall, the word cloud illustrates that current research is heavily centered on using machine learning and AI algorithms to improve credit rating accuracy, risk assessment, and financial innovation. Support Vector Machines and green innovation are good variables to use.

4.5. Most Cited Articles

Table 3: Citation based Analysis of AI and Machine Learning Research in Credit Rating

Paper	**DOI**	**Total Citations**
Li & Sun (2021). *Neural Computing and Applications*	https://doi.org/10.1007/s00521-020-04958-9	160
Tsai & Chen (2010). *Applied Soft Computing*	https://doi.org/10.1016/j.asoc.2009.08.003	117
Wang *et al.* (2005). *International Journal of Machine Tools and Manufacture*	https://doi.org/10.1016/j.ijmachtools.2004.09.015	87
Wu *et al.* (2022). *Production and Operations Management*	https://doi.org/10.1111/poms.13634	56
Helleiner & Wang (2018). *Review of International Political Economy*	https://doi.org/10.1080/09692290.2018.1490330	34
Wang *et al.* (2024). *Journal of Environmental Management*	https://doi.org/10.1016/j.jenvman.2024.121212	19
Wu *et al.* (2014). *Kybernetes*	https://doi.org/10.1108/K-10-2013-0218	16
Wang *et al.* (2023). *Frontiers in Environmental Science*	https://doi.org/10.3389/fenvs.2023.1126692	16
Moon *et al.* (2011). *Journal of the Operational Research Society*	https://doi.org/10.1057/jors.2010.15	15
Yang *et al.* (2023). *Journal of Intelligent & Fuzzy Systems*	https://doi.org/10.3233/JIFS-221652	13

Table 3 shows the most highly cited scholarly articles on the application of artificial intelligence and machine learning in credit rating studies. The table provides essential information such as the authors, year of publication, journal, DOI, and total number of citations, which together measure the quality and impact of each article. Careful examination reveals that highly cited papers, especially those by (Tsai & Chen, 2010) and (Li & Sun, 2021), are mainly centred on hybrid machine learning models and neural network methods, thereby forming early evidence that AI-based models are more effective than traditional credit rating models. Over the years, the body of literature has shifted from traditional modelling patterns to more sophisticated ensemble models, supply-chain analytics, and deep learning models, as evident in more contemporary highly cited papers. Moreover, the presence of interdisciplinary studies, such as those that investigate the political economy and institutional hegemony of credit rating agencies, suggests that AI-based credit rating studies have moved beyond accuracy and into the realm of governance and regulation.

In general, Table 3 illustrates a clear shift in research focus, thereby affirming that AI and ML have become integral components of contemporary credit rating systems and thus offer a compelling rationale for their use as the analytical underpinning of the current study.

4.6. Impact of AI on Credit Rating System

As evident from Table 4, Artificial Intelligence (AI) has been able to enhance the accuracy, efficiency, and effectiveness of credit rating systems significantly, as various studies have shown the clear superiority of AI-based models over traditional statistical models. Moreover, the application of supply-chain-driven data has also been able to enhance the effectiveness of credit rating systems, particularly for SMEs, by considering external relational aspects rather than only financial aspects (Ren *et al*., 2024; Wu *et al*., 2022). Moreover, AI-based models have also been able to enhance the prediction capability of credit rating systems in a cost-sensitive and Basel-compliant manner (Sun *et al*., 2022), process non-numeric and unstructured data efficiently using RBF neural networks (Li & Sun, 2021), and provide transparent and explainable decision-making using SHAP-based interpretation (Yang *et al*., 2025). Moreover, deep learning and GNN architectures have enhanced the resistance of the system to attacks and made the credit rating system less vulnerable. Overall, the results obtained in this study have validated that AI not only enhances predictive capabilities but also enhances security, inclusiveness, transparency, and real-time adaptability in the credit rating process. Table 5 illustrates the clusters of literature on AI/ML with credit ratings. The clustering shown in the table groups the existing literature on AI and ML in credit rating into six categories based on the nature of the models, data, and focus of the study.

Table 4: Literature Showing Impact of AI on Credit Ratings

Sr.no.	Article	Objectives	Research Methodology	Research Findings
1	Tsai & Chen (2010)	To compare hybrid ML models for credit rating.	Bank dataset; tested four hybrid ML combinations.	Logistic regression and neural networks gave the highest accuracy and profit.
2	Wu *et al*. (2014)	To build a multi-level credit rating model.	Two-stage model with data preprocessing and Bagging-DT classifier.	Two-stage Bagging-DT achieved 82.96% accuracy, better than traditional models.
3	Wang *et al*. (2024)	To assess the GF and GI impact on credit ratings.	Machine learning on Chinese firms (2018–2021).	GF lowers ratings (−0.26%), GI improves them (+0.15%); varies by firm type.
4	Wu *et al*. (2022)	To explore supply chain data in credit prediction.	Gradient Boosted Trees using supplier–customer linkages.	Supply chain features improved rating accuracy, especially for SMEs.
5	Yang *et al*. (2023)	To enhance prediction using optimized CatBoost.	SSA for parameter tuning, feature elimination, P2P data.	SSA-CatBoost outperformed CatBoost and other ML models.
6	Sun *et al*. (2022)	To design a cost-sensitive credit risk rating model maximizing risk-adjusted returns.	Meta-algorithm integrating machine learning (gradient boosting, SVM).	The proposed model effectively ranked corporate borrowers and reduced uncertainty, enhancing banks' decision accuracy.
7	Li & Sun (2021)	To improve credit rating accuracy for personal loans using an enhanced RBF neural network.	Used optimized segmentation and adaptive hidden-node selection in RBF neural network training.	The model showed improved precision and robustness, particularly for non-numeric data.
8	Ren *et al*. (2024)	To predict credit ratings using supply chain data through machine learning.	Applied LightGBM ensemble model using supplier–customer data from 2006–2020.	Incorporating previous-year supply chain information improved prediction; supplier data were more valuable than customer data.
9	Calabrese *et al*. (2025)	To assess whether credit rating scores predict financial constraints in innovative firms.	Empirical analysis using econometric models on Italian automotive firms (2017–2019).	Credit rating scores outperformed traditional indices in detecting financially constrained innovative firms.
10	Munoz-Izquierdo *et al*. (2022)	To examine whether Key Audit Matters enhance credit rating assessment.	Applied four ML methods using financial and audit data.	Combining audit KAMs with financial data increased credit rating accuracy to 84%, improving predictive capability.

11	Moon *et al.* (2011)	To develop a technology credit rating framework for SME funding.	Developed a cross-matrix scoring model integrating technology evaluation metrics.	The system effectively supported technology-based credit decisions and SME funding.
12	Liu *et al.* (2025)	To develop a robust graph neural network to defend against poisoning attacks in interbank credit rating models.	Proposed a Preferential Selective-Aware Graph Neural Network (PSAGNN) model.	PSAGNN effectively prevents structural and feature-based attacks; it outperforms existing models in robustness and accuracy for interbank credit rating prediction.
13	Liu (2025)	To improve enterprise credit rating accuracy through deep learning optimization.	Used convolutional neural networks with co-optimized structural parameters.	Achieved 91% prediction accuracy; co-optimization improved model fitting and robustness in corporate reputation rating.
14	Yang *et al.* (2025)	To enhance the prediction accuracy and explainability of machine learning in corporate credit rating.	Developed SSA-CatBoost, integrating Sparrow Search Algorithm for parameter optimization and SHAP for model explainability.	SSA-CatBoost achieved 99.1% accuracy; SSA improved parameter tuning; SHAP analysis explained feature importance and rating correlations.
15	Javadpour *et al.* (2021)	To enhance accuracy and efficiency in bank customer credit rating under big data and cloud environments.	Combined multiple predictive algorithms using Ordered Weighting Averaging (OWA).	Ensemble learning using OWA improved credit rating accuracy compared to individual algorithms.
16	Lee *et al.* (2025)	To examine human reliance and cognitive bias in using AI advice during credit rating decisions.	Conducted six longitudinal experiments with an AI-based corporate credit-rating system.	Users' trust in AI increased over time; decision reliance on AI varied with experience; additional data reduced but refined dependence on AI.
17	Assmuth (2018)	To analyze how bank credit rating behavior influences innovation and economic development.	Built an evolutionary two-sector model based on Nelson and Winter's framework.	Sector-insensitive rating benefits high-tech firms disproportionately; conservative credit assessments favor innovative sectors' long-term success.
18	Ding *et al.* (2019)	To design a dynamic and authentic credit rating model suited for complex e-commerce networks.	Applied clustering and classification on transactional data.	The dynamic model provided more reliable and adaptive credit ratings than traditional static systems.
19	Lu *et al.* (2025)	To design a deep learning model (iAMP-CRA) for accurate identification of antimicrobial peptides (AMPs) from protein sequences.	Used convolutional recurrent neural networks (CRNN).	The proposed iAMP-CRA model achieved high accuracy (0.919) on benchmark datasets, outperforming or matching state-of-the-art methods in AMP identification.
20	Helleiner & Wang (2018)	To examine BRICS' efforts to establish their own credit rating agency and its potential to challenge Western dominance.	Qualitative political economy analysis using institutional and structural power frameworks.	BRICS' CRA initiative lagged due to a lack of shared purpose; U.S.-based CRAs retain structural dominance.
21	Abdul-Rahman *et al.* (2023)	To assess community resilience using AI and social media data.	Text mining, NLP, and machine learning applied to Twitter data from six global university towns.	AI and big data enable low-cost, remote, and accurate assessment of urban community challenges.
22	Darwish (2025)	To improve corporate credit rating prediction accuracy through AI and feature selection.	Comparison of six ML algorithms.	Feature selection enhances accuracy; XGBoost performs best, improving interpretability and efficiency.

23	Zuo & Wu (2022)	To evaluate the impact of the ECR policy on green innovation in Chinese firms.	Empirical analysis using a DID model on 2010–2018 data.	ECR significantly promotes green innovation, especially in large, state-owned, and financially strong firms.
24	Wang *et al.* (2005)	To develop improved hydro-forming technology for CRA-lined pipes.	Theoretical stress–strain modeling and experimental validation.	The new hydraulic expansion method proved feasible, enhancing industrial pipe manufacturing.
25	Beltran (2025)	To analyze how EU regulations jointly enhance algorithmic security and privacy.	Regulatory and conceptual analysis of GDPR, DSA, AI Act, and CRA.	Combined EU laws create a robust framework for secure and trustworthy AI governance.
26	Wang *et al.* (2023)	To explore how CEOs' ecological experience influences green innovation and how tax credit rating and burden moderate this effect.	Quantitative analysis using Chinese listed firms' data (2014–2020).	CEOs' ecological experience increases green innovation; tax credit rating strengthens, and tax burden weakens the effect.

Source: Author's own compilation

Table 5 shows the clusters of literature on AI/ML with credit ratings. The clustering presented in the table classifies the existing literature on AI and ML in credit rating into six coherent groups based on the type of models used, data characteristics, and research focus.

Table 5: Clusters of AI/ML Models in Credit Rating

Cluster	AI/ML Models Used	Description	Sample References
Cluster 1	Hybrid ML, Bagging-DT, Gradient Boosting, SVM, LightGBM, OWA Ensemble, XGBoost	Ensemble techniques combine multiple algorithms to maximize accuracy and reduce error.	(Tsai & Chen, 2010), (Wu *et al.*, 2014), (Sun *et al.*, 2022b), (Ren *et al.*, 2024).
Cluster 2	CatBoost, SSA-CatBoost, Gradient Boosted Trees, XGBoost	Highly interpretable and powerful models are widely used for corporate and SME credit rating.	(Wu *et al.*, 2022), (Yang *et al.*, 2023), (Yang *et al.*, 2025).
Cluster 3	RBF-NN, CNN, CRNN, Deep Neural Networks, GNN-based clustering	Used for complex, nonlinear, textual, transactional, and sequence data.	(Li & Sun, 2021), (Liu *et al.*, 2025), (Liu, 2025).
Cluster 4	PSAGNN (Graph Neural Network), Network-linked ML, Supply-chain-based ML	Focus on relational data (supplier–customer, interbank networks).	(Wu *et al.*, 2022), (Ren *et al.*, 2024), (Liu *et al.*, 2025).
Cluster 5	ML + econometric models on GF/GI/ESG indicators	Evaluates ESG factors, green innovation, and ecological experience's impact on ratings.	(Wang *et al.*, 2024), (Zuo & Wu, 2022), (Wang *et al.*, 2023).
Cluster 6	Qualitative Models, Econometrics, Policy Analysis	Not directly using ML for credit rating; related to governance, policy, or innovation.	(Calabrese *et al.*, 2025), (Moon *et al.*, 2011), (Beltran, 2025).

Source: Author's own compilation

Cluster 1 represents an ensemble-based machine learning approach, including hybrid ML models, bagging decision trees, gradient boosting, SVM, LightGBM, OWA ensembles, and XGBoost, which aim to improve prediction accuracy and reduce classification error by combining multiple algorithms. Cluster 2 emphasizes optimized and interpretable boosting models that improve efficiency and reliability in corporate and SME credit rating applications. Cluster 3 centers on deep learning models designed to handle complex, nonlinear, and unstructured data such as text, transactional records, and sequential information. Cluster 4 highlights network- and relationship-based approaches that use relational data, including supply chain and interbank linkages, to capture interconnected credit risk dynamics. Cluster 5 integrates machine learning with an econometric framework to assess the influence of ESG, green finance, and sustainability-related indicators on credit ratings. Cluster 6 provides qualitative, econometric, and policy-oriented insights that contextualize AI-based credit rating systems within institutional, regulatory, and governance frameworks.

5. Conclusion

The current systematic review offers a holistic insight into the manner in which artificial intelligence is transforming the credit rating system paradigm, thereby signalling a major shift from the conventional analyst-based approach to a data-intensive, automated, and highly accurate model. Through a critical analysis of the literature available over the past two decades and the use of Biblioshiny to analyse bibliometric trends, the study confirms the steady rise in research related to AI-based credit rating systems, which is being fuelled by advances in machine learning, deep learning, and optimization algorithms. Notably, the study also indicates that current research is gradually shifting its focus from the accuracy of predictive models to the need for explainability, fairness, and transparency. This is primarily being fuelled by the need for regulatory compliance with SEBI, RBI, and international regulations such as the EU AI Act, which place significant emphasis on the interpretability of models and ethical decision-making in credit rating systems. The study indicates that tools such as SHAP and LIME are becoming increasingly important in bridging the gap between artificial intelligence and human trust, particularly in high-stakes financial decision-making. Moreover, the increasing trend of incorporating ESG factors, sustainability issues, supply chain factors, and audit-driven text information into credit rating models indicates a larger shift towards responsible and multi-faceted credit rating models that better capture real-world complexities and risks. In conclusion, the results of this literature review confirm that the future of credit rating lies in the responsible, innovative, and well-regulated application of artificial intelligence. By integrating highly effective predictive models with transparent approaches, sustainable data practices, and comprehensive governance structures, it is possible to achieve more accurate, timely, and fair credit ratings. The current research adds to the existing knowledge base by illustrating research trends, the development of methodologies, and the emergence of new themes that will define the future of credit rating models. As AI technology advances, there must be a continued effort to collaborate across research, financial, and regulatory communities to unlock the full potential of AI technology while maintaining the integrity and soundness of global financial markets.

6. Future Research Direction

Future studies should concentrate on improving the transparency and explainability of AI-powered credit rating models by incorporating explainable AI methods to satisfy regulatory requirements and mitigate concerns associated with “black-box” models. Further research is required to incorporate ESG and sustainability factors into AI-powered credit rating models, particularly with the growing importance of green innovation and environmental credit rating policies. Researchers can also further explore the application of alternative and non-traditional data sources, such as supply chain relationships, social media patterns, audit statements, and real-time transactional data, to improve the accuracy of predictions and dynamically capture changes in the behaviour of borrowers. Another area of interest involves improving the robustness and fairness of AI models by developing methods to defend against adversarial attacks, address algorithmic biases, and develop ethical AI frameworks specific to financial decision-making. The application of more advanced deep learning models, such as graph neural networks, transformers, and large language models, may provide opportunities to better analyse complex financial networks and unstructured text disclosures more effectively. Furthermore, future research should focus on developing real-time, constantly updated credit rating systems using cloud computing and time-series learning methods. Moreover, a comparative analysis of AI adoption in different countries may also offer important insights into the factors influencing the development of credit rating AI technologies. Finally, as human analysts continue to work with AI systems, it will be essential to investigate this relationship to improve the acceptance and accuracy of AI-assisted credit rating decisions.

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Authorship Contribution

Falak conceptualized the study, analysed, and wrote the manuscript.
Pooja Malhotra assisted in review and supervision. All authors approved the final manuscript.

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Declaration

The author hereby declares that this research paper is an original work conducted by the author. All sources and references have been properly acknowledged, and the work has not been submitted or published elsewhere.

Conflict of Interest

The author declares that they have no conflict of interest regarding the publication of this paper.

Data Availability Statement

Authors declare that data sharing is not relevant to this article as no new data were generated or analyzed in this study.

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