Mapping the Landscape: A Bibliometric Analysis of Rating Agencies in the Era of Artificial Intelligence and Machine Learning

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Abstract. *In the ever-evolving financial landscape, the integration of artificial intelligence (AI) and machine learning (ML) is revolutionising creditworthiness assessment. The vast body of literature on credit rating indicates a growing prevalence of these techniques in the rating processes. Although these methods boast high predictive accuracy, concerns about their robustness, equity, and explainability affect the confidence of various parties in rating agencies. This comprehensive study explores the dynamic intersection of these cutting-edge technologies with rating agencies, presenting an in-depth literature review employing a bibliometric analysis that uses the Bibliometrix and Biblioshiny packages from R. The paper makes a significant contribution by analysing the literature across three prominent databases: Web of Science, Scopus, and arXiv. The empirical findings indicate that despite a recent growing interest, the relatively limited number of documents implies that, while there is a wide literature about credit rating in general, when it comes to rating agencies, the literature is much more limited. This limitation may stem from a certain lack of transparency in the methods and processes used by rating agencies and the complex nature of these entities. The literature witnessed growth after the 2008 global financial crisis, where rating agencies faced significant criticism, and post-pandemic, indicating a need for more adaptable and precise ratings. The examination of the topic reveals a recent shift in focus within AI-driven rating agencies towards accountable governance. While traditional attention persists on artificial intelligence techniques and finance, the emerging emphasis on ethical considerations, societal impacts, and performance evaluation underscores a changing landscape. This transition underscores the growing importance of integrating ethical considerations and societal impacts into the operational frameworks of AI-powered rating agencies, emphasising the necessity for responsible and transparent decision-making practices.*

Keywords: Rating agencies, Artificial intelligence**,** Machine learning**,** Risk assessment**,** Accountable governance

Introduction

In the context of the actual globalised economy and changing financial markets, rating agencies stand as indispensable pillars, providing objective creditworthiness assessments to guide investors

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and stakeholders in navigating the intricate world of debt instruments and financial obligations. Over the years, the evolution and impact of rating agencies have been significant, especially considering their responses to critical financial events, technological advancements, and economic downturns.

In terms of definition, rating agencies are considered information providers that evaluate the quality of an issue or issuer to diminish information asymmetry (Ebenroth & Dillon, 1993), contributing to the enhancement of transparency in financial markets (Cowan, 1991). More specifically, rating agencies, also known as credit rating agencies (CRAs), are organisations responsible for evaluating and rating the creditworthiness of debt instruments or entities issuing financial obligations.

Rating agencies originated in the late 1800s due to significant shifts in the capital market, primarily driven by the rise of the corporate sector and a decreased reliance on public financial aid. The 1800s witnessed substantial corporate growth, notably in the US railroad industry, creating a demand for alternative funding beyond traditional banking sources. Corporations increasingly turned to the bond market for capital, where government-issued instruments historically considered secure were joined by riskier corporate offerings. This introduction of higher-risk instruments spurred the need for credit risk evaluation services, leading to the emergence of rating agencies to assess and manage the risks associated with these evolving financial products (Sylla, 2002).

The historical trajectory of rating agencies has been marked by several milestones and challenges. Notably, the financial crisis of 2008 revealed inherent weaknesses in the functioning of these agencies. During the 2008 crisis, rating agencies were not able to define the ratings assigned correctly, especially for complex issues. This has led to a heated debate on the solution to reforming the sector to increase the objectivity and quality of the information provided by raters and overcome the risk of more decades of stagnation for the rating business (Mattarocci, 2014). Moreover, the worldwide economic downturn caused by the pandemic has led to the resurgence of the potential for sovereign defaults, particularly in emerging and developing economies. This has brought focus on the role of establishments responsible for foreseeing these defaults, namely, the global credit rating agencies. According to Griffith-Jones and Kraemer (2021), the four main challenges posed by rating agencies, especially from a developing and emerging economies perspective, include potential bias in ratings, pro-cyclicality of ratings, governance issues and conflicts of interest, and incorporation of climate risk.

The study of rating agencies and the methods employed for risk assessment has achieved extensive research and study over the past few decades. This paper aims to conduct a bibliometric analysis focused on the intersection of rating agencies and artificial intelligence/machine learning (AI/ML) within the context of risk assessment. The objective is to comprehensively summarise the existing research landscape, assess the current state of AI/ML integration in rating agencies' methodologies, and outline potential future directions from a statistical viewpoint. Therefore, the analysis seeks to expose: (1) the conceptual framework while accentuating the main themes and patterns, (2) the intellectual configuration while highlighting the manner in which the authors' work impacts the entire scientific community, and (3) the social structure elucidating the dynamics of interactions among authors, institutions or countries.

Literature review

Credit rating has a long history, and multiple methodologies have been proposed for assigning ratings over time. Achieving an accurate measure of credit risk is a challenging task for various reasons. Firstly, the financial landscape is complex and dynamic, with various factors influencing creditworthiness. Additionally, the inherent uncertainty and unpredictability in financial markets make it difficult to develop foolproof models. Any type of inaccuracy has spillover and contagion consequences since rating changes affect the pricing of many other assets. Thus, the necessity for an improvement in the methodology of credit rating becomes imperative to relieve the tension (Ozturk et al., 2016).

The increased volume of data and computational power, coupled with advancements in technology and the need for quick decisions and forecasts, have determined rating agencies and researchers to adjust their methodologies accordingly. Consequently, there has been a growing interest in utilising artificial intelligence for credit scoring assessments. Despite their high predictive accuracy, machine learning techniques may not be robust, equitable or explainable enough. Therefore, the concerned parties, including business users, auditors, regulators and end consumers, might not trust the results (Giudici et al., 2024). To address these concerns, alongside traditional and modern AI-based methods, hybrid approaches have been proposed. These hybrid methods aim to compensate for the shortcomings of pure AI models and limit criticisms. By combining elements of multiple techniques, these hybrid approaches seek to strike a balance between predictive accuracy and the interpretability, robustness, and fairness required in the rating process.

Standard statistical techniques such as discriminant analysis, principal component analysis, logit, probit and other regression methods have been utilised by researchers for an extended period of time, forming the foundation of traditional credit scoring methodologies (Horrigan, 1996; Kapland & Urwitz, 1979; Kim et al., 1993; Altman & Saunders, 1997). Adapted versions of these methods have been created to enhance the efficacy of credit scoring models, and recent papers are still using traditional statistics methods and new developments. For instance, Irmatova (2016) presented a novel rating model to forecast the rating of 30 countries based on principal component analysis and the k-means clustering method. Logistic regression was used by Doğan et al. (2022) to forecast corporate credit scores, and the results were compared with those derived from machine learning methods. However, complex patterns and non-linear interactions in the data are frequently missed by traditional models because of limitations like feature selection and model complexity.

With the rapid advancement of technology and data, new models based on machine learning and artificial intelligence have appeared. Some of the most well-known AI techniques used for assigning ratings are: artificial neural networks (ANN), Support Vector Machines (SVM), k-Nearest Neighbors (k-NN) and Classification and Regression Trees (CART). Among the earliest research to create an ANN model to predict corporate bond ratings were those by Dutta and Shekhar (1988) and Surkan and Singleton (1990). The impact of their contributions extends to practical applications in the financial industry, influencing the evolution of credit risk assessment tools. Many researchers are interested in artificial neural network models because of their greater accuracy, adaptability and robustness (Maher & Sen, 1997; Daniels & Kamp, 1999; Brennan & Brabazon, 2004; Chen et al., 2011). Support Vector Machine techniques, on the other hand, are recognised for their classification ability (Kim & Sohn, 2010; Vapnik, 2013; Maldonado et al., 2017). Furthermore, several researchers highlight the decision tree-based approach's superior degree of interpretability and flexibility in feature extraction (Lee et al., 2006; Paleolog et al., 2010; Trivedi, 2020).

In addition, some authors have worked on hybrid models that incorporate multiple techniques. This strategy involves integrating the capabilities of diverse methodologies, such as statistical models, machine learning algorithms, and expert-based systems, to develop a comprehensive and more robust credit scoring framework. By capitalising on the reciprocal benefits of varied methodologies, researchers aspire to mitigate the constraints of singular models and enhance overall predictive accuracy. For example, Wu and Hsu (2012) presented an upgraded decision support model that combines the relevance of decision trees and support vector machines. Also, Lessman et al. (2015) investigated 41 classification algorithms used to forecast the likelihood of default on retail loans. The authors evaluated numerous datasets and criteria before concluding that their hybrid strategy outperformed previous methods.

Thus, the extensive literature in the credit rating domain suggests that artificial intelligence and machine learning techniques are becoming increasingly prevalent in rating processes. While machine learning models have demonstrated high predictive performance, they inherently possess a non-transparent, "black-box" nature. Consequently, rating agencies may opt for hybrid approaches to balance accuracy, interpretability, and transparency.

Data and methodology

Broadus (1987) defined bibliometrics as the statistical and mathematical analysis of research's quantitative features. In a similar manner, the Online Dictionary of Library and Information Science (ODLIS) describes bibliometrics as the application of statistical and mathematical techniques to examine and detect trends in the usage of materials and services within a library or to examine the evolution over time of a particular body of literature, particularly with regard to its authorship, publication, and use (ODLIS, 2022).

For a comprehensive bibliometric analysis, this article utilises three of the most well-known databases: Web of Science, Scopus and arXiv.org. Given the study's objective to obtain an overview of literature concerning rating agencies and the utilisation of artificial intelligence and machine learning techniques, the query "rating agenc*" AND ("artificial intelligence" OR "machine learning") was utilised for document extraction. The asterisk in "rating agenc*" captures all potential derivatives of the words, while quotes ensure precise formulations. As depicted in Figure 1, results from the three databases were merged, yielding 54 documents spanning 1996 to 2023. Analysis of these documents regarding trends, key authors, prominent sources, keywords, and more was conducted using the Bibliometrix and Biblioshiny packages in R. The Bibliometrix package offers a set of tools for quantitative bibliometrics research in the R programming language, identifying research streams and themes using keywords found in papers (Aria & Cuccurullo, 2017). Meanwhile, Biblioshiny provides an interactive interface for visualising the results.

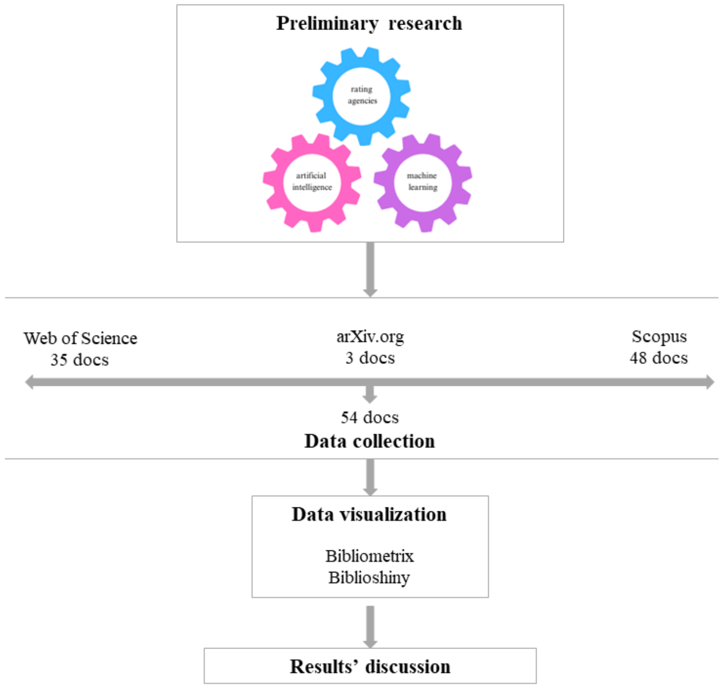

Figure 1. Research methodology

Source: Authors' own research.

Results and discussions

Table 1. Main information on documents

Category	Description	Results
Summary	Timespan	1996-2003
	Sources (Journals, Books, etc)	50
	Documents	54
	Annual Growth Rate %	8.9
	Document Average Age	4.69
	Average citations per doc	6.907
Document	Keywords Plus (ID)	226
	Author's Keywords (DE)	173
	Article	33
	Article; early access	3
	Article; proceedings paper	2
	Book chapter	2
	Conference paper	7
	Proceedings paper	5
	Review	1
	Review; early access	1
Author	Authors	158
	Authors of single-authored docs	3
	Single-authored docs	3
	Co-Authors per Doc	3.07
	International co-authorships %	9.259

Source: Authors' own research.

Investigation of the bibliometric landscape of research on rating agencies between 1996 and 2023 reveals an average growth rate of 8.9%, indicating a steady expansion of interest in research on rating agencies in the context of artificial intelligence and machine learning. Despite this growing interest, based on the relatively small number of documents, it can be concluded that even though there is a vast amount of literature regarding credit rating in general, the literature is much more limited when it comes to rating agencies. This limitation may stem from a certain lack of transparency in the methods and processes used by rating agencies and the complex nature of these entities.

A closer examination of the document types reveals that articles comprise the majority (33), followed by conference papers (7), book chapters (2), and proceedings papers (5). This distribution suggests a focus on extended and in-depth research on rating agencies, as evidenced by the majority of articles.

The analysis of single-authored documents (3) and co-authored documents with an average of 3.07 authors per document indicates a collaborative approach to rating agency research. International co-authorships, representing 9.25% of the total, suggest that rating agency research is a global endeavour with contributions from researchers worldwide.

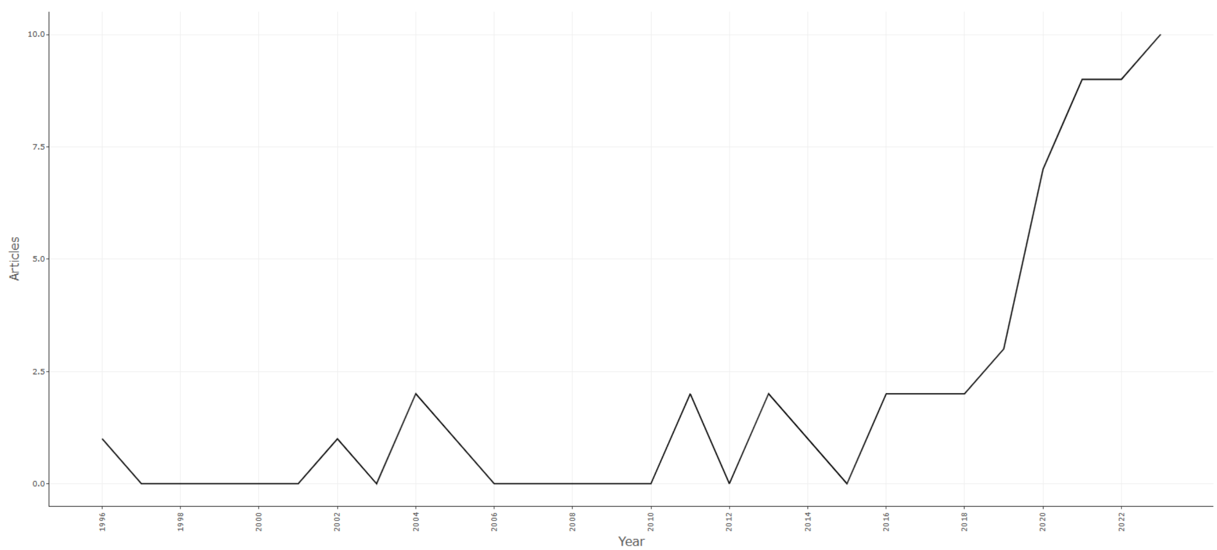

Figure 2. Annual scientific production

Source: Authors' own research

An essential measure of an academic field's development is the quantity of papers that have been published in it. Changes in the number of publications immediately reflect changes in the amount of scientific information on the subject, as the growth of knowledge is highly proportional to the number of journal articles (Zeng et al., 2021; Hao et al., 2021; Fahimnia et al., 2015). Rating agencies have been operating for more than 150 years. Their position has expanded from information collectors and providers to quasi-official credit risk arbitrators across the global financial system. They gathered information that, at the time, would have been too difficult and expensive for their clients to collect themselves. Following the 1929 stock market disaster, they took on a more formal role. Since then, there has been an increase in investor confidence in the ratings of these agencies. Figure 2 shows a considerable increase in the number of articles published on rating agencies and AI/ML in the last 25 years. The first article, *Performance of AI tools vis-a-*

vis multiple discriminant analysis in anticipating default among high-yield bonds (Ashby et al., 1996), was published in 1996 and compared the predictive power of an AI model using neural networks and genetic algorithms to the multiple discriminant analysis (MDA) models for predicting default using high-yield bonds.

As depicted in Figure 2, the period from 2006 to 2010 witnessed an absence of published articles on the subject. However, in 2011, there were two articles as a result of the need to analyse the repercussions of the global crisis. Following the 2008 global financial crisis, economists, politicians, the media, market players, and formal regulatory authorities all criticised rating agencies. The explanation was straightforward: rating agencies failed to accomplish their duty in financial markets, which was to quantify and signal financial (default) risk in an efficient, effective, and timely manner. Since 2015, there has been a steady increase in the number of papers on this subject in the context of the abnormal stock market shock that showed the huge destructive effect of asset bubbles (Yang, 2017). Moreover, the biggest increase in the number of documents was in 2020 due to the COVID-19 pandemic. For instance, in the context of the challenges brought about by the COVID-19 pandemic, lenders have constrained the provision of credit facilities. This underscored the necessity for a credit-rating model to possess adaptability, enabling it to generate credit scores or rates that align with the prevailing financial conditions (Ubarhande & Chandani, 2021). Most notably, 2023 saw the highest number of documents (10), with artificial intelligence playing a significant role in this increase.

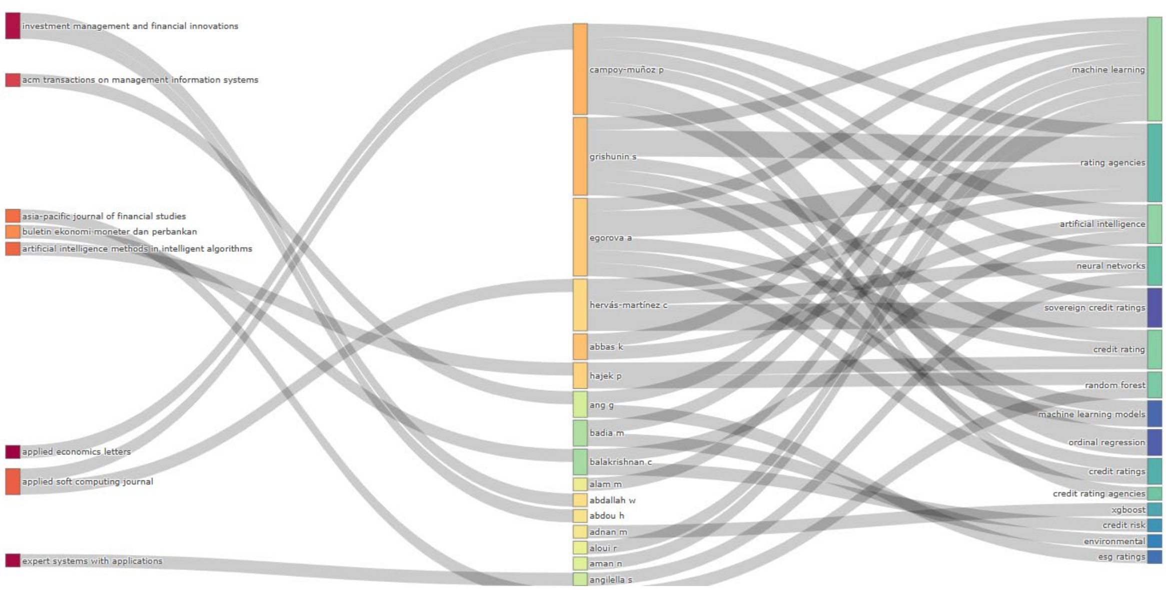

Figure 3. Three field plot (sources – authors – keywords)

Source: Authors' own research.

The three-field plot is commonly used to visually examine the link between sources, nations, affiliations, keywords, prominent authors, cited sources, author-keywords, etc. Relevant components are shown with different colours in rectangle diagrams. The association between various elements, including nations, sources, well-known authors, author-keywords, etc., is shown by the height of the rectangle. More connections between different components are indicated by wider rectangles (Kuman et al., 2021).

Figure 3 shows the diagram for research about rating agencies in the context of AI or ML on the relation between source (left), author (middle) and author keyword (right). The analysis determined which terms were most often used by various authors and publications in the literature on rating agencies. The study of the top sources, authors and keywords revealed that certain keywords, such as “machine learning”, “rating agencies”, “artificial intelligence”, and "neural networks", were frequently used by authors Campoy-Munoz P, Grishunin S and Egorova A. These authors published in journals like Applied Soft Computing Journal and Investment Management and Financial Institutions.

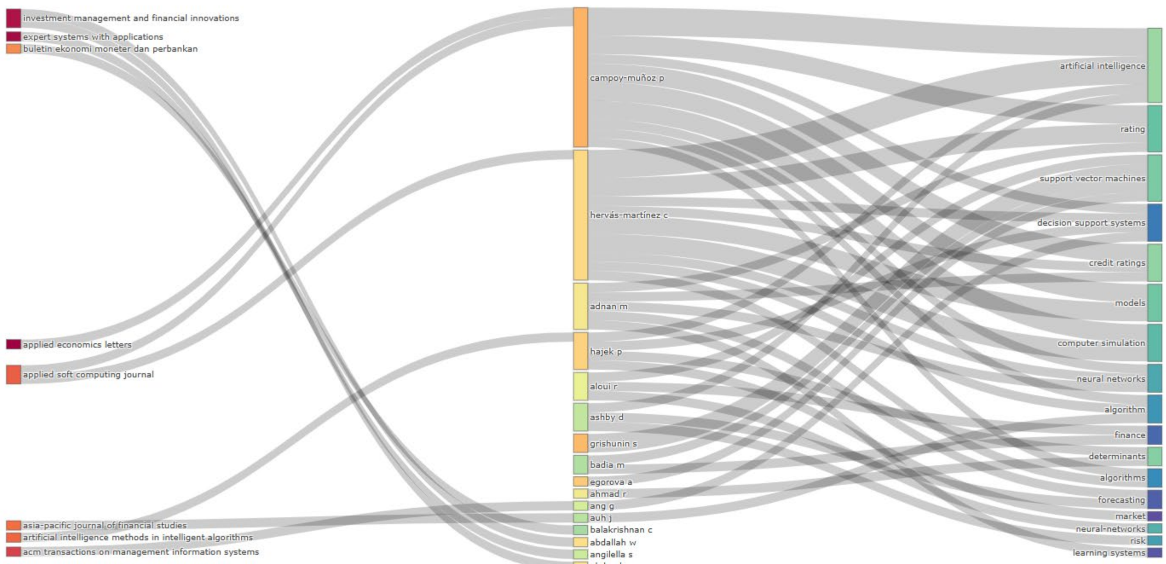

Figure 4. Three field plot (sources – authors – keywords plus)

Source: Authors’ own research.

Similarly, Figure 4 shows the diagram for research about rating agencies and the use of AI or ML on the relation between source (left), author (middle) and author keyword-plus (right). The analysis identified the most frequently utilised keyword-plus combinations among various authors and published journals. Investigation into the top keyword-plus instances, authors and sources revealed a primary focus on seven keywords: "artificial intelligence", "support vector machines", "rating", "models", "computer simulation", "credit ratings" and "decision support systems". Moreover, four authors, Campoy-Munoz P, Hervas-Martinez C, Adnan M, and Hajek P, played a significant role, contributing to publications in sources such as Investment Management and Financial Innovation, along with the Applied Soft Computing Journal.

Table 2. **Most important sources**

Source	H-index	G-index	M-index	TC	NP	PY_start
Expert Systems with Applications	2	2	0.1	41	2	2005
Investment Management and Financial Innovations	2	2	0.25	18	2	2017
Applied Economics Letters	1	2	0.25	9	2	2021
Sustainability	1	2	0.25	17	2	2021

Source: Authors’ own research.

Table 2 lists the most significant sources in decreasing order based on the H-index and G-index, with a G-index value greater than 2. Expert Systems with Applications and Investment Management and Financial Innovations are recognised as the journals with the highest H-index (2) in the subject of rating agencies in the context of AI and ML. Sustainability and Applied Economics Letters are two other publications that are pertinent to this topic, based on the G-index. According to Costas and Bordons (2007), the G-index provides superior ranking placement compared to the H-index.

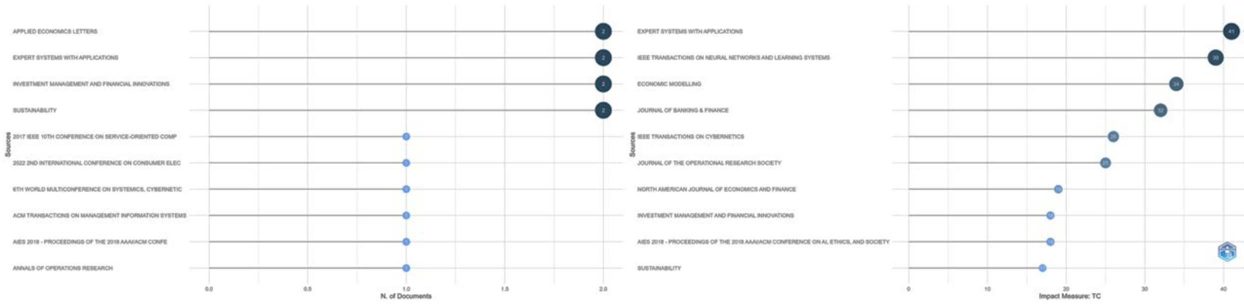

Figure 5. Most relevant sources in terms of documents and citations

Source: Authors' own research.

Applied Economics and Letters, Expert Systems with Applications, Investment Management and Financial Innovations, and Sustainability stand out as the sources with the most documents about rating agencies that use AI or ML, with two documents each. Among these journals, Expert Systems with Applications also stands out as the source with the most citations. Other cited sources include IEEE Transactions on Neural Networks and Learning Systems, Economic Modelling, and Journal of Banking & Finance.

Table 3. Most important authors

Author	H-index	G-index	M-index	TC	NP	PY_start
Campoy-Muñoz P	2	3	0.167	37	3	2013
Hervás-Martínez C	2	2	0.167	36	2	2013
Abbas K	1	1	0.25	2	2	2021
Abdallah W	1	1	0.125	10	1	2017
Abdou H	1	1	0.125	10	1	2017
Alam M	1	1	0.333	1	1	2022
Aloui R	1	1	0.2	25	1	2020
Altman E	1	1	0.5	4	1	2023
Aman N	1	1	0.333	1	1	2022
Ang G	1	1	0.5	1	1	2023

Source: Authors' own research

Table 3 shows the top 10 most relevant authors in the literature regarding rating agencies utilising AI or ML, ordered in descending order by their H-index and G-index. One of the most popular author-level metrics for quantifying research production is the H-index, created by J.E. Hirsch (2005), which measures the productivity and influence of authors. A researcher has to have a minimum of h citations across a certain number of publications (h) in order to have a H-index. In contrast, the G-index, developed by Leo Egghe in reaction to the H-index, is an author-level indicator prioritising highly cited works.

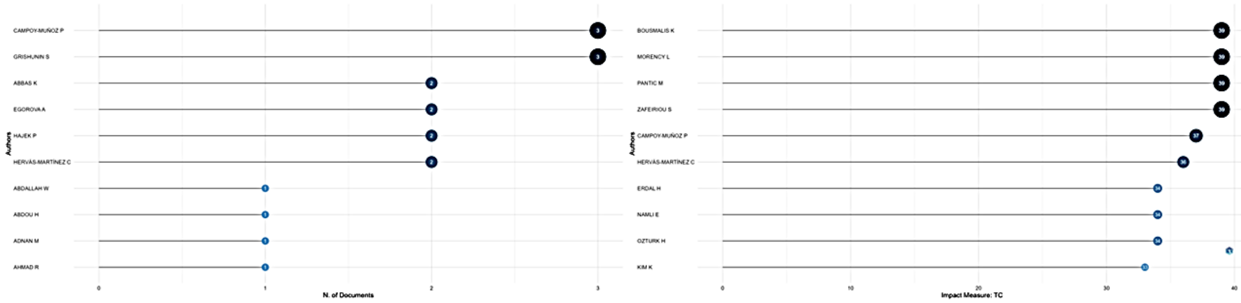

Figure 6. Most relevant authors in terms of documents and citations

Source: Authors' own research

Campoy-Muñoz P and Grishunin S stand out as authors with a prolific output, having. authored three documents each concerning rating agencies and AI/ML. Meanwhile, authors like Bousmalik S, Morency L, Pantic M, and Zafeiriou S have garnered substantial attention, evidenced by each receiving 39 citations. This distinction suggests that while Campoy-Muñoz P and Grishunin S have contributed significantly in terms of quantity, the work of Bousmalik S, Morency L, Pantic M, and Zafeiriou S has gained notable recognition within the academic sphere, indicated by the higher number of citations their publications have received.

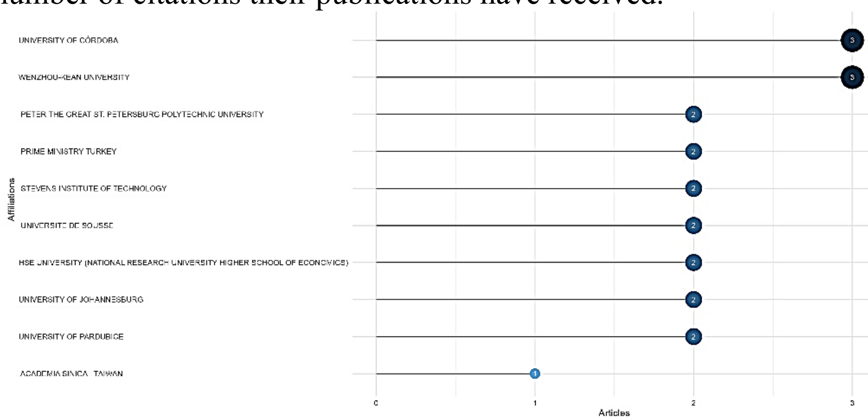

Figure 7. Most relevant affiliations

Source: Authors' own research.

From the perspective of authors' affiliations, the University of Córdoba in Spain and Wenzhou-Kean University in China emerge as the leading institutions with the highest number of publications on the analysed topic. Their active contributions to scholarly literature indicate a strong academic presence and commitment to research in the analysed field. This prolific output underscores the dedication of these universities to advancing knowledge and understanding within the domain of rating agencies in the context of artificial intelligence and machine learning, showcasing their significant role in contributing valuable insights and studies to the academic community.

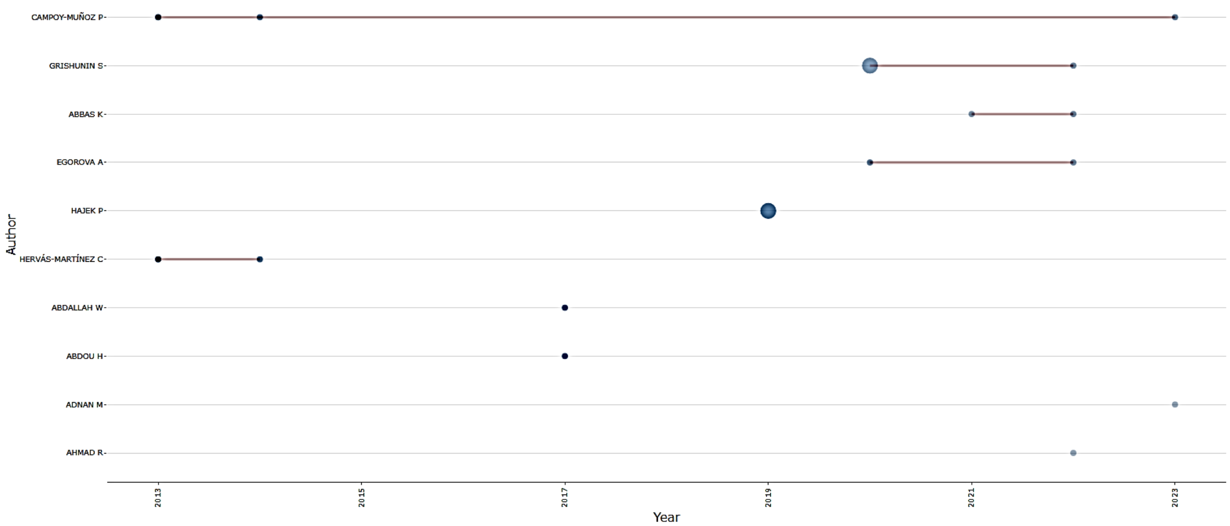

Figure 8. Authors' production over time

Source: Authors' own research.

Regarding the production over time, it is notable that Campoy-Muñoz P has demonstrated the most consistent interest in this topic, boasting a decade-long experience since publishing the first article in 2013. Conversely, other noteworthy authors in the field, such as Grishunin S, Abbas K, and Egorova A, have become actively engaged more recently.

Table 4. Most productive countries

Country	Frequency of production
USA	16
China	9
Spain	9
Italy	6
Belgium	5
Russia	5
South Korea	5
India	4
Colombia	3
Tunisia	3

Source: Authors' own research.

Table 4 displays the countries that have made the most substantial contributions to the literature in the analysed field. According to the findings, the USA stands out as the primary contributor, accounting for the highest number of documents with a total of 16, showcasing a significant research output in this area. Meanwhile, countries like China and Spain follow closely, each contributing nine documents to the literature. This distribution of contributions among these countries may also indicate varying levels of research emphasis, resources, or academic interest in the field, showcasing a diverse landscape of international involvement and collaboration in the analysed study area.

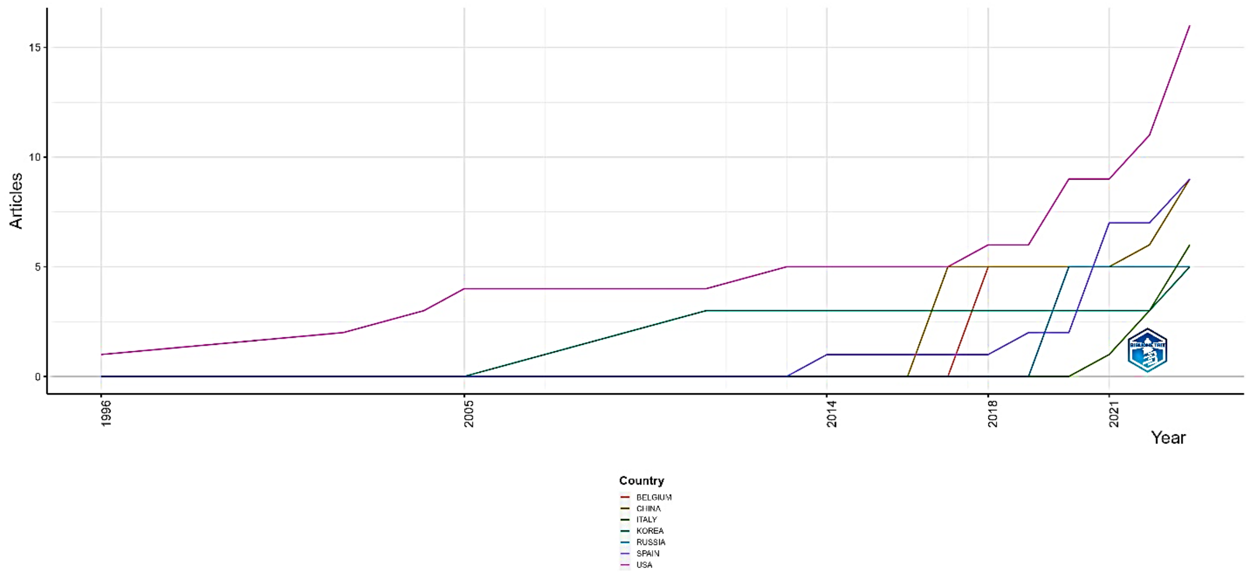

Figure 9. Countries' production over time

Source: Authors' own research.

When considering the production over time, it becomes evident that the USA holds the most extensive experience in this field. It stands as the country that published the first article in this domain and has also produced the highest number of articles. On the other hand, countries like Italy and Russia have displayed a notably increased interest and have started publishing works in this area in recent years. This indicates a promising trend of expanding research interest and involvement from these countries in this particular area of study.

Table 5. Most Cited Global Documents

Rank	Year	Title	Journal	Authors	Citations
1	2013	Infinite Hidden Conditional Random Fields for Human Behavior Analysis	IEEE Transactions on Neural Networks	Konstantinos Bousmalis, Stefanos Zafeiriou, Louis-Philippe Morency, Maja Pantic	39
2	2016	Modelling sovereign credit ratings: The accuracy of models in a heterogeneous sample	Economic Modelling	Huseyin Ozturk, Ersin Namli, Halil Ibrahim Erdal	34
3	2005	Predicting bond ratings using publicly available information	Expert Systems with Applications	Kee S. Kim	33
4	2018	Subjectivity in sovereign credit ratings	Journal of Banking & Finance	Lieven De Moor, Prabesh Luitel, Piet Sercu, Rosanne Vanpée	32
5	2013	Addressing the EU Sovereign Ratings Using an Ordinal Regression Approach	IEEE Transactions on Cybernetics	Francisco Fernández-Navarro, Pilar Campoy-Muñoz, Mónica-de la Paz-Marín, César Hervás-Martínez, Xin Yao	26

Rank	Year	Title	Journal	Authors	Citations
6	2020	Machine learning models and cost-sensitive decision trees for bond rating prediction	Journal of the Operational Research Society	Sami Ben Jabeur, Amir Sadaaoui, Asma Sghaier, Riadh Aloui	25
7	2020	A comparative study of forecasting corporate credit ratings using neural networks, support vector machines, and decision trees	The North American Journal of Economics and Finance	Parisa Golbayani, Ionuţ Florescu, Rupak Chatterjee	19
8	2018	Towards Composable Bias Rating of AI Services	Proceedings of the 2018 AAAI/ACM Conference on AI, Ethics, and Society	Biplav Srivastava, Francesca Rossi	18
9	2021	Alternative ESG Ratings: How Technological Innovation Is Reshaping Sustainable Investment	Sustainability	Arthur Hughes, Michael A. Urban, Dariusz Wójcik	17
10	2022	ESG score prediction through random forest algorithm	Computational Management Science	Valeria D'Amato, Rita D'Ecclesia, Susanna Levantesi	15

Source: Authors' own research.

By analysing the highly cited literature in the field of rating agencies in the context of AI and ML, it is possible to see the academic papers and major research scholars that have made a significant impact in this field and then to deeply analyse the seminal literature and theoretical foundations of the field. According to Table 5, the most cited article is *Infinite Hidden Conditional Random Fields for Human Behavior Analysis* (Bousmalis et al., 2013), published in IEEE Transactions on Neural Networks. The authors present how they learn the model hyperparameters for infinite hidden conditional random fields (iHCRF) with an effective Markov-chain Monte Carlo sampling technique, and they explain the process that underlines the model with the Restaurant Franchise Rating Agencies analogy. The second is *Modelling sovereign credit ratings: The accuracy of models in a heterogeneous sample* (Ozturk et al., 2016), published in Economic Modelling, where authors explore the prediction performance of several artificial intelligence techniques in predicting sovereign credit ratings in heterogeneous samples. The third most cited paper is *Predicting bond ratings using publicly available information* (Kim, 2005), published in Expert Systems with Applications, which developed a model that uses an artificial intelligence technique to predict bond ratings using financial and non-financial variables. Last but not least, among these articles, *A comparative study of forecasting corporate credit ratings using neural networks, support vector machines, and decision trees* (Golbayani et al., 2020) appears in all three databases used for the bibliometric analysis.

Figure 10. Word cloud

Source: Authors' own research.

A word cloud, as defined by Atenstaedt (2012), is a visual representation of word frequency. The larger the term appears in the graphic, the more frequently the keyword occurs in the text under analysis. The word cloud presented in Figure 10 reflects a strong focus on artificial intelligence techniques through keywords such as "support vector machines", "neural-networks", "determinants", "models", "algorithm", "performance" etc. Terms like "corporate social responsibility", "information asymmetry", "bias", "risk", "impact" highlight the significance of ethical considerations in AI-driven rating agencies actions. Accountable governance involves addressing biases, ensuring fairness, and considering the societal impacts of automated decision-making in the financial domain.

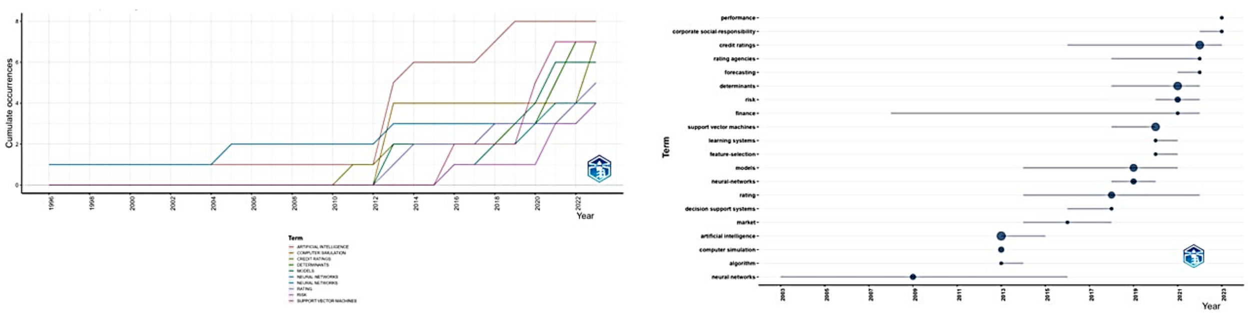

Figure 11. Topic trends and word growth

Source: Authors' own research.

In Figure 11, a topic trends diagram provides an image related to the dynamics of the main topics and some insights into recent topics. Thus, terms like "artificial intelligence", "neural networks", and "finance" have long been prevalent in literature, indicating sustained attention and exploration in these areas over time. However, the focus on concepts such as "corporate social responsibility", "performance", and "forecasting" has emerged more recently. This shift in emphasis reflects an evolving landscape in which newer concerns related to ethical considerations, societal impacts, and the evaluation of performance and creditworthiness have gained prominence.

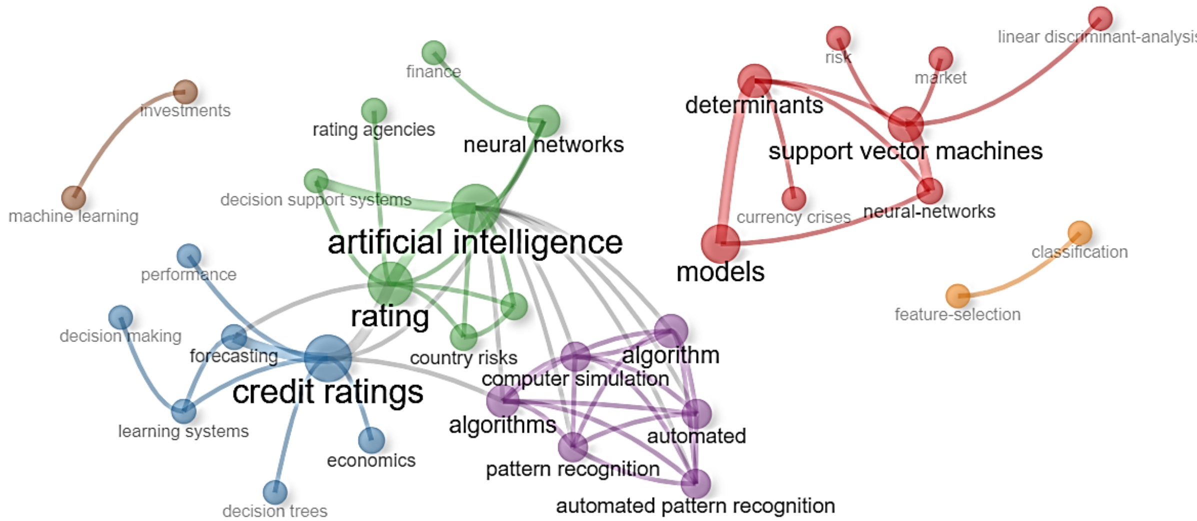

Figure 12. Co-occurrence network

Source: Authors' own research.

Keyword co-occurrence analysis allows us to describe the core content and structure of the field of rating agencies and, at the same time, indicates the research frontiers of the field. The size of the displayed nodes in Figure 12 indicates the frequency of the keyword's occurrence in the article, with more frequency indicating greater importance of the research topic characterised by the keyword. Topic similarity is represented by the distance between the elements of individual pairs. There can be distinguished three main subfields:

- The green subfield is focused on AI-related methodologies applied to the decision-making process and encompasses terms like “artificial intelligence”, “rating”, “neural networks”, "decision support systems", etc.
- The blue subfield employs predictive analysis and performance evaluation within the context of rating agencies and encompasses terms such as "credit ratings", "forecasting", "learning systems", "performance", etc.
- The red subfield emphasises various modelling approaches and determinants related to predictive modelling or analysis within the studied domain and includes terms such as "determinants", "support vector machines", "models", "neural networks", etc.
- The purple subfield is focused on algorithmic approaches and includes terms like "algorithms", "computer simulation", "pattern recognition", etc.

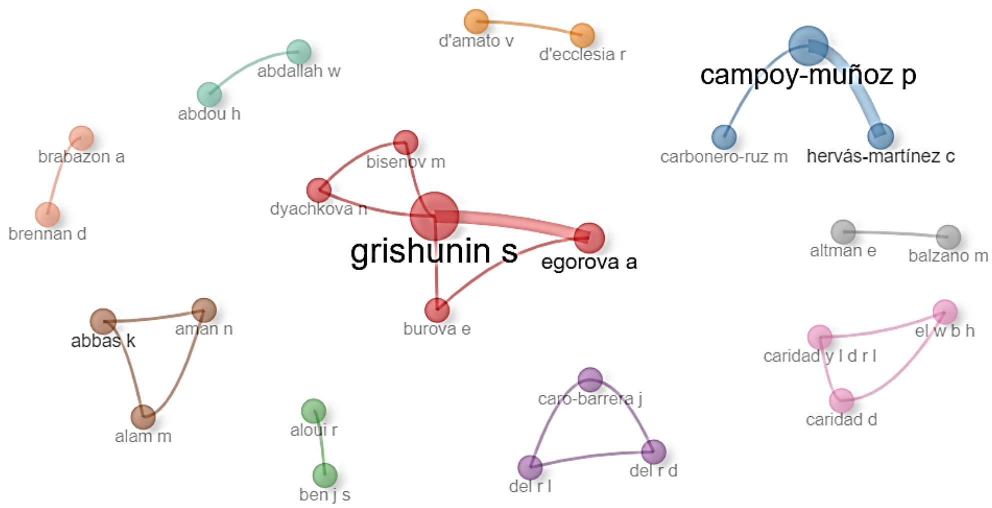

Figure 13. Collaboration network

Source: Authors' own research.

The collaboration network from Figure 13 depicts the interactions and connections between authors within the field of rating agencies using artificial intelligence or machine learning techniques. Grishunin S have the highest Betweenness and PageRank and collaborates with authors such as Egorova A, Bisenov M, Burova E and Dyachkova N. Apart from this cluster, nine other clusters can be distinguished: four clusters consisting of three authors each and five clusters consisting of two authors each.

Conclusion

Analysing the literature on rating agencies within the context of artificial intelligence and machine learning through bibliometric analysis holds substantial significance. This examination offers a comprehensive understanding of the evolving landscape where traditional finance intersects with cutting-edge technology. It provides insights into trends, key authors, influential sources, emerging topics, and the evolution of methodologies. Such an analysis aids in identifying critical research gaps, directing future investigations, and informing policy decisions within the realm of finance, technology, and regulatory frameworks. Moreover, it facilitates the recognition of pivotal areas for innovation, ensuring ethical compliance, and fostering the development of more effective, informed, and responsible practices within the sphere of rating agencies and financial systems.

The study makes a significant contribution by analysing the literature on rating agencies in the context of artificial intelligence and machine learning, utilising three databases: Web of Science, arXiv, and Scopus. The descriptive bibliometric analysis highlights yearly publication trends, with a continuous increase starting with 2015 due to the abnormal stock market. Furthermore, this topic has experienced a notable surge starting from 2020, attributed in part to the COVID-19 pandemic and the advancements in artificial intelligence. The unprecedented global health crisis prompted an accelerated shift toward digitalisation and automation across various sectors, including the financial landscape.

Papers addressing rating agencies are mainly published in Applied Economics and Letters, Expert Systems with Applications, Investment Management and Financial Innovations, and Sustainability, while the most productive countries are the USA, China and Spain. Campoy-Muñoz P and Grishunin S are the top contributors in terms of document count on this topic, whereas

Bousmalik S, Morency L, Pantic M, and Zafeiriou S have garnered significant academic acknowledgement, evident from the substantial citations their works have received. The most cited documents include Bousmalis et al. (2013), Ozturk et al. (2016), and Kim (2005), each making significant contributions to the analysed field and serving as prominent benchmarks.

The topic analysis reflects a shift in recent focus within AI-driven rating agencies towards accountable governance. While longstanding attention persists on artificial intelligence techniques and finance, newer emphasis on ethical considerations, societal impacts, and performance evaluation signifies an evolving landscape. This shift highlights the increasing importance of integrating ethical considerations and societal impacts into the operational frameworks of AI-powered rating agencies, emphasising the need for responsible and transparent decision-making practices.

In conclusion, with the evolution of big data and artificial intelligence techniques, there is a growing emphasis among researchers on leveraging extensive datasets and intelligent algorithms to enhance the evaluation and forecasting capabilities of rating agencies. However, machine learning and deep learning models are often perceived as opaque or black-box models, lacking transparency and interpretability. Consequently, rating agencies may opt for hybrid approaches to balance accuracy with interpretability and transparency. As the credit rating landscape evolves, striking the right balance between the power of artificial intelligence and the need for transparency is crucial for ensuring the credibility and acceptance of credit ratings in the financial industry.

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