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Research Article

Mapping Research on Financial Inclusion and Credit Scoring: A Systematic Review with NLP-Assisted Thematic Analysis

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ABSTRACT

This study develops a systematic literature review examining the relationship between financial inclusion, credit risk/credit scoring models, and algorithmic fairness in emerging economies. It is grounded in a theoretical framework that links access to credit with poverty and inequality reduction, as well as the role of artificial intelligence and machine learning in financial decision-making and their alignment with the Sustainable Development Goals. The search was conducted in Scopus following PRISMA guidelines and was complemented by Natural Language Processing techniques, bibliometric analysis, and science mapping applied to a final corpus of 63 articles. The results identify five thematic clusters that articulate approaches related to risk, financial inclusion, ethics and algorithmic fairness, microfinance and digitalization, evidencing a transition from traditional models toward data-intensive approaches. The study concludes that models based on artificial intelligence and alternative data offer opportunities to expand financial inclusion; however, they also introduce risks of bias and opacity. Therefore, governance frameworks and algorithmic fairness principles are required to balance predictive efficiency, equity, and sustainable development.

Keywords: Financial inclusion, Credit scoring, Credit risk assessment, Artificial intelligence, Machine learning, Natural Language Processing, Algorithmic fairness, Emerging economies.

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INTRODUCTION

Financial inclusion has become established as a necessary condition for economic and social development, as it facilitates households' and firms' access to savings, payment, insurance, and credit services under secure and affordable conditions. International organizations recognize financial inclusion as a cross-cutting enabler of the 2030 Agenda and as directly contributing to the achievement of several Sustainable Development Goals (SDGs), particularly SDG 1 (No Poverty), SDG 8 (Decent Work and Economic Growth), and SDG 10 (Reduced Inequalities), among others. In emerging economies, where large segments of the population remain excluded from the formal financial system, access to productive credit and basic consumption financing becomes a key mechanism for income generation, resilience to shocks, and the reduction of structural gaps.

In this context, credit risk and credit scoring models have become a central component of financial infrastructure. The way these models are designed and operated determines who gains access to credit, under what conditions, and at what cost; thus, their impact extends beyond a strictly technical dimension and is closely linked to equity and social justice. Recent studies document that financial digitalization, the use of alternative data, and the deployment of artificial intelligence and machine learning solutions make it possible to expand credit outreach, improve predictive accuracy, and serve traditionally underserved segments, particularly in microfinance and small-business banking. At the same time, the literature warns of risks of bias and discrimination that may arise when decisions are automated without adequate frameworks for algorithmic fairness, transparency, and accountability.

The intersection between financial inclusion, credit risk, and algorithmic fairness has given rise to an increasingly interdisciplinary field that integrates finance, data science, regulation, and social impact. Studies range from the design of predictive models based on big data and machine learning to analyses of data governance, algorithmic bias, and the

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distributive effects of digital credit on vulnerable populations. However, despite the dynamism of this field, the available knowledge remains fragmented across thematic subfields-social, technological, ethical, and institutional-that are often addressed in isolation. While multiple empirical applications exist in emerging-economy contexts, a significant gap persists regarding a systematic and integrated perspective that maps how these approaches interconnect, identifies the conceptual and methodological patterns shaping the recent agenda, and highlights areas that remain relatively underexplored.

This gap is particularly relevant given that the expansion of digital credit and automated evaluation models in emerging economies is frequently presented, at least in policy discourse, as a strategy to accelerate progress toward SDGs related to poverty reduction, inequality, productive inclusion, and innovation. Nevertheless, evidence on whether artificial intelligence-based solutions effectively enhance financial inclusion or, conversely, reproduce and amplify pre-existing exclusions remains scattered. The absence of a structured synthesis limits the capacity of regulators, financial institutions, and policymakers to align financial innovation with sustainable development goals and principles of algorithmic fairness.

Against this backdrop, a systematic review is warranted to organize and synthesize the available evidence on the relationship between financial inclusion, credit risk, and algorithmic fairness in emerging economies, using tools capable of capturing the field's multidimensional complexity. This study develops a systematic literature review based on the Scopus database and guided by PRISMA guidelines, complemented by Natural Language Processing (NLP) techniques, bibliometric analysis, and science mapping. Drawing on a final corpus of 63 studies, the analysis identifies thematic clusters that articulate socio-financial approaches and enables visualization of the field's conceptual structure and its recent evolution.

Accordingly, the overall objective of this research is to systematically analyze recent literature on financial inclusion, credit scoring, and algorithmic fairness in emerging economies through bibliometric techniques, science mapping, and NLP, in order to characterize the thematic structure of the field, identify its principal research streams, and recognize gaps that may inform future academic and public policy agendas. Specifically, the study aims to: (i) describe how data-driven and artificial intelligence-based credit risk models have been linked to financial inclusion objectives; (ii) examine how the literature addresses bias risks and algorithmic fairness concerns in credit decision-making; and (iii) discuss the implications of these findings for advancing SDGs related to poverty reduction, inequality, inclusive growth, and financial innovation in emerging economies.

METHODOLOGY

The present study was conducted as a systematic literature review supported by Natural Language Processing (NLP) techniques, with the aim of identifying, refining, and analyzing scientific evidence on financial inclusion and its relationship with credit risk assessment and credit scoring models, incorporating artificial intelligence and machine learning approaches applied to credit decision-making. To ensure rigor, transparency, and process traceability, PRISMA guidelines were followed so that each stage-identification, screening, eligibility, and inclusion-was documented and could be replicated. Within this framework, the PRISMA flow diagram is presented as Figure 1 and quantitatively summarizes the filtering decisions made from the initial retrieval to the final set of included studies.

During the identification phase, the search was conducted exclusively in the Scopus database on February 21, 2026. Scopus was selected because it provides broad multidisciplinary coverage of peer-reviewed literature in economics, finance, business, computer science, social sciences, decision sciences, and mathematics, while ensuring metadata standardization and indexing consistency required for bibliometric and Natural Language Processing (NLP) analyses. Furthermore, the use of a single database facilitated methodological consistency, transparency, and reproducibility throughout the review process.

The search strategy was designed using a structured Boolean equation integrating terms related to financial inclusion, access to credit, credit scoring, credit risk assessment, machine learning, and artificial intelligence. The search was performed in the title, abstract, and keywords fields using the following query:

TITLE-ABS-KEY (("financial inclusion" OR "access to credit" OR unbanked OR underbanked OR microfinance OR microcredit OR "digital financial inclusion") AND (("credit scoring" OR "credit risk assessment" OR "default prediction" OR "loan approval") OR ("machine learning" W/3 (credit OR lending)) OR ("artificial intelligence" W/3 (credit OR lending))))

The initial search retrieved 295 records. Subsequently, a language filter was applied to restrict the results to English-language publications, reducing the dataset to 289 records. The document type was then limited to articles and review papers, resulting in 168 records. To ensure unrestricted access to the full text required for text mining, semantic analysis, verification, and reproducibility purposes, an Open Access filter was applied, yielding 65 records. Finally, the search was restricted to the subject areas of Economics, Econometrics and Finance; Business, Management and Accounting; Computer Science; Social Sciences; Decision Sciences; and Mathematics. This final filtering stage resulted in a corpus of 63 studies included in the systematic review.

During the eligibility stage, the 65 accessible texts were examined to confirm that the central focus addressed credit risk and credit scoring within financial inclusion contexts, rather than merely mentioning them tangentially. This review identified two documents whose contributions did not address credit risk analysis as a primary focus or did not fully comply with the thematic scope; these were excluded. Consequently, the process concluded with 63 studies included in the systematic review, consistent with the decision flow reported in the PRISMA diagram (Figure 1). Additionally, since no sources external to the selected database were incorporated, searches through other methods (websites, organizations, or citation tracking) remained at zero, preserving methodological consistency by working with a single high-quality repository.

QUALITY ASSESSMENT

To ensure the thematic and methodological relevance of the selected studies, a quality assessment procedure was conducted during the eligibility stage. Each document was evaluated according to five criteria: (i) direct relevance to financial inclusion, (ii) explicit focus on credit scoring or credit risk assessment, (iii) methodological transparency, (iv) availability of complete bibliographic metadata, and (v) consistency with the scope of the review. Studies that did not meet the core thematic requirements were excluded from the final corpus. This procedure contributed to the robustness, consistency, and reliability of the evidence included in the review.

Once the final corpus was consolidated, data extraction and preparation for NLP-based analysis were conducted using a reproducible Python workflow. Records were exported from Scopus in structured CSV format and subsequently normalized to reduce errors caused by spelling variations and to improve comparability across documents. During this preparation stage, cleaning routines were performed, including duplicate removal, standardization of bibliographic fields (titles, keywords, affiliations, and sources), correction of special characters, handling of missing values, and verification of the consistency of abstracts and keywords.

A textual corpus was then constructed primarily from titles, abstracts, and keywords, as these components concentrate the conceptual content of each publication and enable efficient semantic analysis without processing full texts when the objective is to map themes, approaches, and research patterns.

NLP and Topic Modeling Procedure

The NLP analysis was conducted using a reproducible Python-based workflow. The dataset exported from Scopus in CSV format was processed using Python libraries for data cleaning, text preprocessing, vectorization, topic modeling, and visualization. The workflow was implemented in Python using Pandas, NumPy, Scikit-learn, NLTK, Matplotlib, and Plotly, which facilitated data preparation, semantic processing, topic extraction, and graphical representation of the results.

The preprocessing stage included lowercasing, tokenization, removal of punctuation marks, removal of English stopwords, lemmatization, and elimination of non-informative terms. After preprocessing, the corpus was transformed into a numerical representation using Term Frequency-Inverse Document Frequency (TF-IDF), which allowed the identification of terms with higher discriminatory capacity across the analyzed documents.

Topic modeling was then applied to identify latent thematic structures within the corpus. Several topic solutions were explored, and the five-topic structure was retained because it provided the best balance between semantic coherence, interpretability, and consistency with the research objective. The resulting topics were interpreted through their most representative terms and through manual validation of the articles associated with each cluster.

In addition, co-occurrence analysis was used to examine conceptual relationships among terms, while dimensionality-reduction techniques were applied to visualize the distribution of topics in two-dimensional and three-dimensional spaces. Sentiment polarity analysis was also performed as an exploratory tool to identify linguistic tendencies in the corpus. However, polarity results were interpreted with caution, since scientific texts generally use neutral and formal language; therefore, polarity scores were considered indicators of discursive emphasis rather than direct measures of authors' opinions.

From an ethical standpoint, this study relied exclusively on publicly accessible academic sources with open access in Scopus and did not involve human subject intervention or the processing of sensitive personal data. Therefore, ethics committee approval was not required. Nevertheless, principles of scientific integrity were observed by ensuring proper citation practices, respect for intellectual property, transparency in inclusion and exclusion criteria, and faithful reporting of the selection and analysis process. In addition, any form of result manipulation was avoided, prioritizing methodological traceability and coherence among the data, the PRISMA flow (Figure 1), and the final interpretation of the evidence.

RESULTS

Figure 2 illustrates the formation of five thematic clusters that represent the main research streams in recent literature on financial inclusion, credit scoring, and algorithmic fairness. The spatial distribution reveals a clear differentiation among social, ethical, technological, and financial approaches, confirming the multidimensional nature of the field. The proximity between certain clusters suggests conceptual interrelationships, whereas the separation of others reflects distinct levels of thematic specialization.

Within the social domain (Topic 1), studies focus on the determinants of financial inclusion, access to credit, and structural

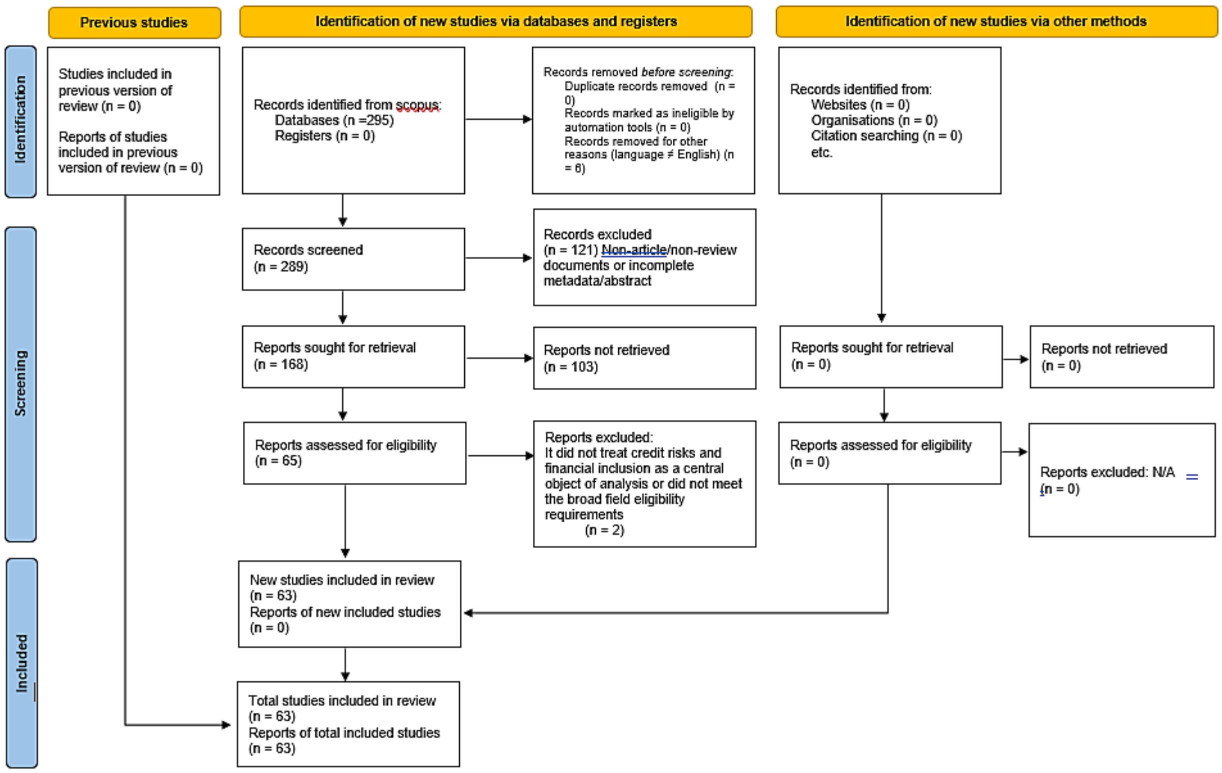

Figure 1: Search strategy for the review.

inequalities affecting vulnerable populations. This cluster appears close to the ethics and credit theme (Topic 2), indicating that the literature recognizes that credit decisions are not driven solely by financial variables but also by dimensions of equity, transparency, and fairness in access to financial services. The relationship between these two topics reflects growing scholarly interest in examining the social impacts of credit and the potential biases that may reproduce financial exclusion.

The computational and digital topic (Topic 3) appears clearly differentiated and positioned in the upper area of the map, suggesting its innovative role and function as a technological driver within the field. This cluster groups research related to artificial intelligence, machine learning, big data, and digital systems applied to credit risk assessment. Its proximity to the credit risk and machine learning topic (Topic 0) confirms that algorithmic tools constitute the technical core of contemporary predictive models aimed at improving risk assessment accuracy and optimizing financial decision-making.

Finally, the microfinance and banking topic (Topic 4) is located in a more independent zone, reflecting its applied orientation toward financial sustainability, productive inclusion, and institutional strengthening. Its relative proximity to credit risk studies suggests that risk management is a central element for sector stability, particularly in emerging economies where microfinance plays a critical role in economic development.

Overall, the configuration presented in Figure 2 reveals that the literature is evolving toward an integrative approach in which technology, ethics, and financial inclusion converge to redefine traditional credit evaluation models. This convergence highlights a transition from exclusively financial approaches toward intelligent and socially responsible systems capable of balancing predictive efficiency with equity and inclusive access to credit.

Figure 3 presents the most productive authors within the corpus of Scopus-indexed publications related to the study topic. This visualization enables the identification of the relative contributions of researchers leading scientific output, revealing a concentration of knowledge production within a small group of scholars who have consistently contributed to the development of the field.

The figure shows that Blanco-Oliver, A. stands out as the author with the highest number of publications, suggesting academic leadership and significant influence in the theoretical and methodological consolidation of the area. This author's body of work indicates active participation in contemporary debates related to financial inclusion, risk assessment, and credit-related technologies. At a second level of productivity is Lara-Rubio, J., whose contributions demonstrate research continuity and a relevant presence in the field's evolution.

A third group of authors-Pino-Mejías, R., Bravo, C., and Wang, H.-exhibits similar levels of productivity, indicating sustained participation, although more focused on specific research lines.

The presence of these authors reflects the geographical and disciplinary diversity of the field, integrating perspectives from both emerging economies and technologically advanced contexts, thereby enriching the development of scientific knowledge.

From a literature review perspective, the distribution shown in Figure 3 suggests that the advancement of the field is supported by consolidated research nuclei that serve as theoretical and methodological reference points. At the same time, it reveals the presence of emerging academic networks that contribute to thematic expansion, particularly in areas such as machine learning applied to credit risk, digital financial inclusion, and algorithmic equity. This configuration confirms that knowledge is constructed collaboratively, with key authors shaping the research agenda and facilitating the field's evolution toward interdisciplinary and innovative approaches.

Figure 4 presents the conceptual structure of the field through the spatial distribution of topics and the frequency of associated terms. The two-dimensional representation based on principal components (PC1 and PC2) allows the observation of semantic proximity among themes, while the size of the circles reflects their relative relevance within the analyzed corpus. This visualization facilitates understanding of how research streams are organized and which concepts articulate knowledge surrounding credit scoring, financial inclusion, and algorithmic fairness.

Topic 1 stands out due to its larger size, indicating its centrality within the literature. Its position suggests that it functions as an organizing axis of the field, integrating discussions on credit, evaluation models, and financial risk management. This predominance is reinforced by the high frequency of terms such as *credit, risk, model*, and *financial*, evidencing that credit risk assessment remains the dominant conceptual core of academic research. The recurring presence of these terms confirms that predictive models continue to focus on improving risk measurement and financial decision-making.

In contrast, topics located in peripheral positions reflect thematic specializations that broaden the scope of the field. Topic 3 is situated in an intermediate zone, suggesting its role as a bridge between traditional approaches and technological innovations. The frequency of terms such as *machine learning, prediction, accuracy*, and *method* highlights the growth of computational approaches aimed at improving scoring model accuracy. This trend confirms the transition toward advanced analytical systems that incorporate artificial intelligence and machine learning to optimize credit evaluation.

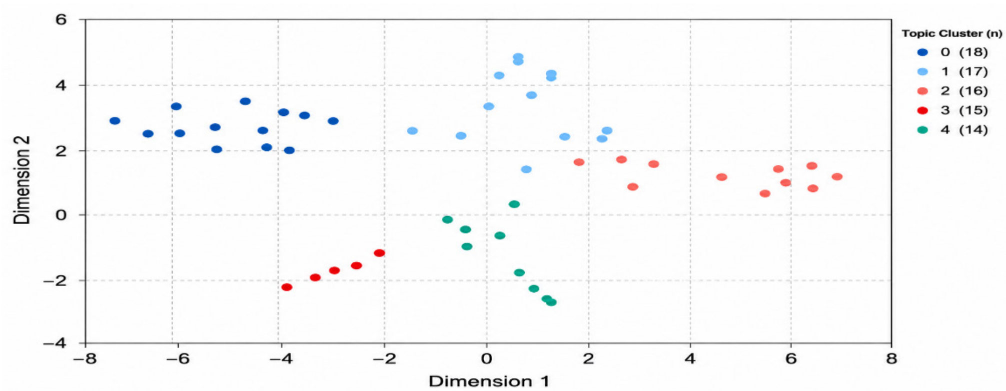

Figure 2: Two-Dimensional Topic Map.

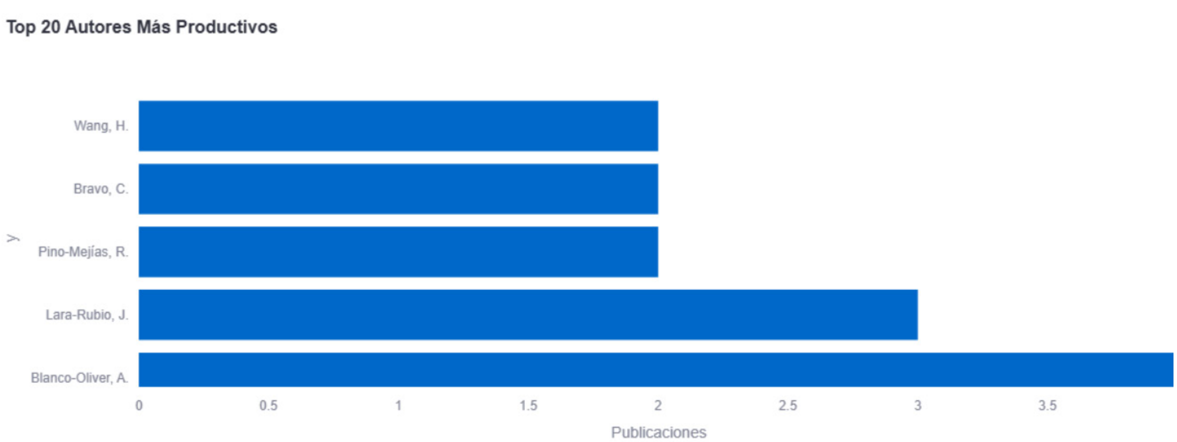

Figure 3: Most Productive authors in the reviewed corpus.

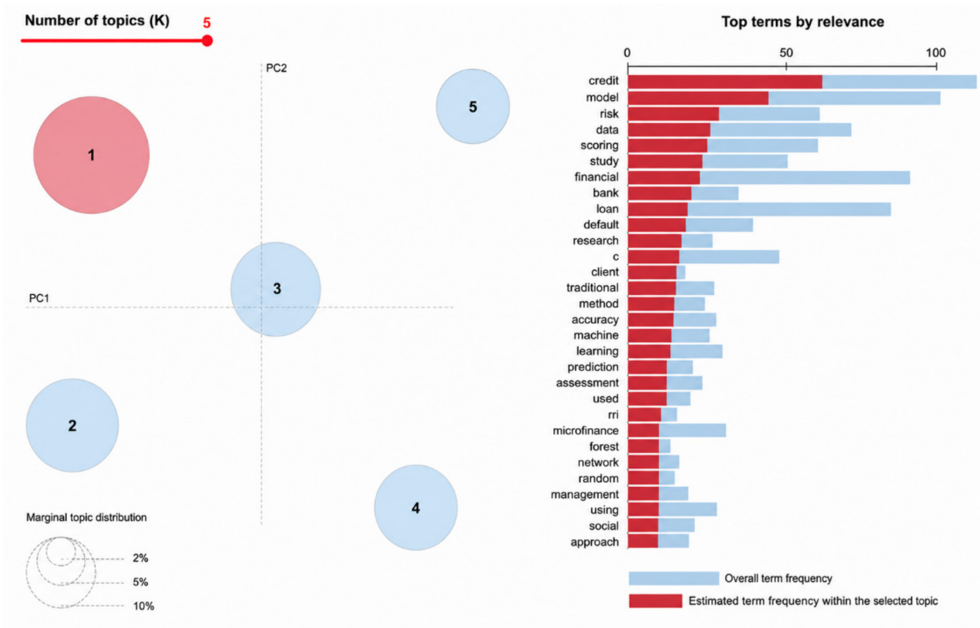

Figure 4: Conceptual Structure through Topic Distribution.

Topics 2 and 4 appear in more distant positions, indicating specialized areas linked to social inclusion, traditional methods, and microfinance. The presence of terms such as *microfinance, social*, and *approach* suggests growing interest in integrating social dimensions into financial analysis, particularly in emerging-economy contexts where access to credit plays a crucial role in economic development. These approaches reflect an evolution toward more inclusive and socially responsible models.

Finally, Topic 0 appears differentiated in the upper area of the conceptual plane, suggesting an emerging line of research. Its location indicates relative thematic independence, possibly associated with new digital and analytical approaches seeking to redefine traditional credit evaluation methods.

Overall, Figure 4 reveals a conceptual structure in which credit risk constitutes the core of the field, while artificial intelligence, microfinance, and social approaches expand its scope toward more inclusive, accurate, and technologically advanced models. This configuration evidences the evolution of the literature toward an interdisciplinary paradigm in which predictive efficiency is complemented by equity, financial inclusion, and technological innovation.

Figure 5 displays the distribution of sentiment polarity values within the analyzed corpus, ranging from –1 to 1. The visualization combines a histogram with a density curve, allowing observation of both the frequency of values and their relative concentration.

Overall, the figure reveals a clear skew toward positive values, indicating a predominantly positive linguistic tendency in the terminology used within abstracts, titles, and keywords across the analyzed corpus.

The highest concentration of values is located near the positive end of the axis, particularly between 0.8 and 1, indicating that the literature tends to emphasize benefits, advances, and opportunities associated with the use of digital technologies, machine learning models, and financial inclusion strategies.

Nevertheless, the figure also reveals the presence of neutral and some negative values, although in significantly smaller proportions. These values reflect critical perspectives within the literature, particularly concerning ethical risks, algorithmic bias, data privacy, and potential financial exclusion effects derived from the use of automated models. The existence of these less positive evaluations indicates that the field is not homogeneous and that an academic debate exists aimed at assessing the social and regulatory implications of financial technologies.

From an interpretative perspective, the observed distribution suggests that the literature evolves within a framework of cautious optimism: on the one hand, it recognizes the transformative potential of artificial intelligence and financial digitalization; on the other, it maintains ongoing concern for ensuring transparency, equity, and user protection. In this sense, Figure 5 demonstrates that scientific discourse not only focuses on technological innovation but also incorporates critical reflections aimed at promoting more just, inclusive, and socially responsible financial systems.

It is important to note that sentiment polarity in scientific texts should not be interpreted as a direct measure of authors' opinions or attitudes. Rather, polarity scores reflect linguistic patterns and the prevalence of positively or negatively associated terms within the corpus. Therefore, the results are interpreted as indicators of thematic emphasis rather than explicit judgments regarding the effectiveness or desirability of the analyzed technologies.

Figure 6 presents a three-dimensional map of articles that simultaneously integrates the temporal dimension (year of publication), a thematic or subjectivity dimension (located on the corresponding axis), and sentiment polarity (sentiment axis), while also distinguishing articles with positive and negative orientations through color coding. This representation enables a comprehensive visualization of how the discursive tone of the literature evolves over time and how articles are distributed according to their predominant thematic emphasis.

Overall, the figure shows a high concentration of points in the most recent time range, suggesting sustained growth in scientific production in recent years. The greatest density of articles is clustered in a zone where positive polarity predominates, consistent with the previously observed trend: much of the literature addresses advances in credit evaluation models, data analytics, and machine learning from an opportunity-oriented perspective, highlighting improvements in predictive accuracy and expansion of credit access, particularly in contexts where financial inclusion is considered a priority.

However, Figure 6 also reveals the presence of some negatively polarized points, which are more dispersed and less numerous. These studies tend to occupy positions suggesting a more critical discourse, which may be associated with research lines emphasizing risks and limitations, such as algorithmic bias, discrimination in automated models, transparency challenges, and regulatory tensions. The dispersion of these points indicates that, although fewer in number, critical contributions appear across different periods rather than being confined to a single timeframe, reflecting that the debate on ethics and algorithmic fairness remains active and cross-cutting.

Taken together, Figure 6 suggests that the literature is structured around a dominant core of publications with a positive tone that has grown over time, while a smaller subset introduces cautionary and critical perspectives. This coexistence reinforces the notion of a maturing field in which technological innovation in credit scoring and digital finance advances alongside necessary discussions on social impacts, equity, and ethical implications. Thus, the 3D map not only synthesizes the temporal evolution of the corpus but also illustrates how the tone of academic discourse accompanies the expansion of the field toward more comprehensive and socially responsible approaches.

Figure 7 presents a heat map relating publication year to average sentiment polarity (classified as negative, neutral, and positive). The color scale facilitates interpretation of tonal intensity: values closer to green indicate higher average positive polarity, whereas reddish tones represent negative polarity. This type of visualization synthesizes how the discursive "climate" of the literature evolves over time, offering a rapid reading of prevailing trends.

The figure reveals a consistent pattern of predominance of positive polarity across virtually all years represented, with a marked concentration in the "Positive" category. This suggests that, as the field consolidates, the literature tends to construct a discourse largely oriented toward contributions, improvements, and opportunities, particularly regarding the development of credit scoring models, the use of machine learning, and the digitalization of financial services. The continuity of green tones within the positive block indicates that this favorable orientation is not episodic but sustained over time, consistent with a research agenda focused on innovation and the expansion of analytical capabilities for credit decision-making.

At the same time, negative polarity appears sporadically and with lower intensity, reflecting specific years in which the average shifts toward less favorable values. This pattern is typically associated with studies emphasizing field limitations, risks, or tensions, such as algorithmic bias, transparency challenges, regulatory implications, and potential financial exclusion effects. From a literature review perspective, the limited yet present occurrence of negative values is significant because it demonstrates that the debate is not unilateral: alongside the narrative of technological progress, a critical line of inquiry examines the social and ethical costs of automation in credit decisions.

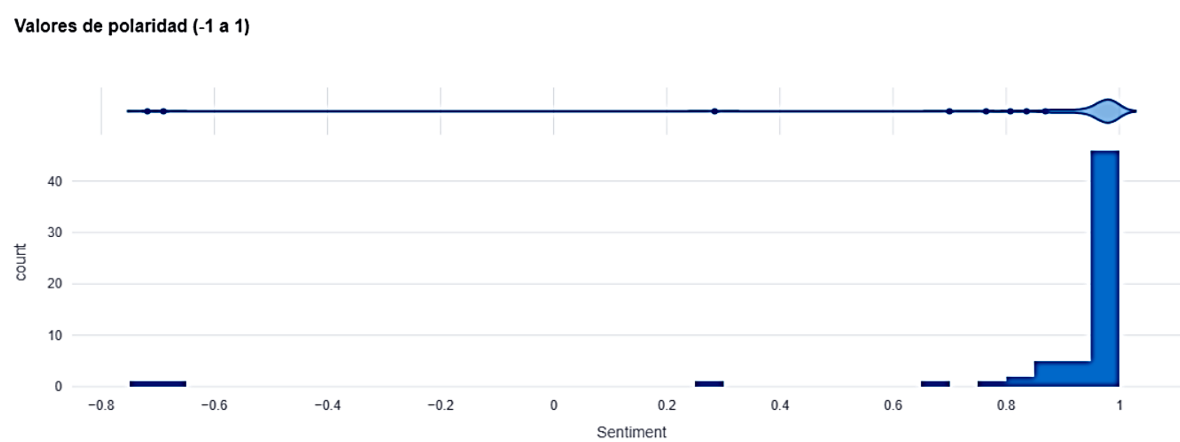

Figure 5: Sentiment polarity distribution.

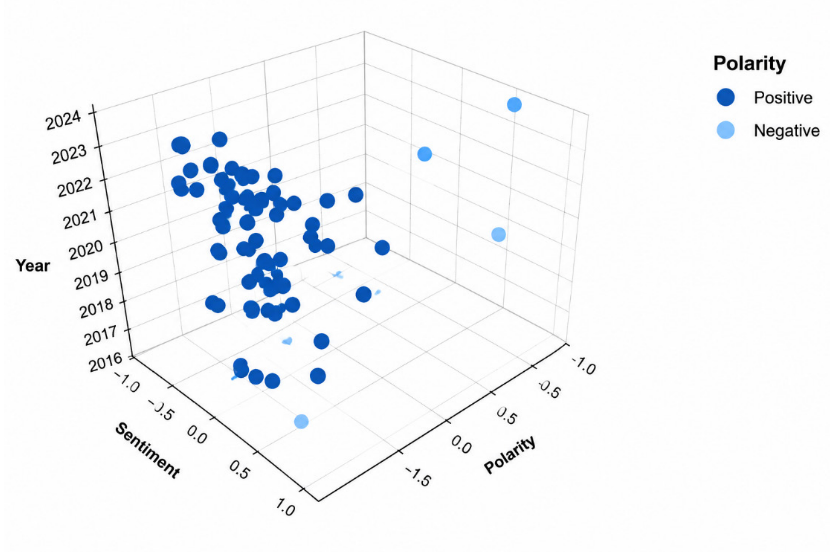

Figure 6: Three-Dimensional Map of Articles.

Overall, Figure 7 suggests an evolution of the corpus characterized by dominant optimism accompanied by critical episodes that function as a conceptual counterbalance. This combination is indicative of a maturing field: research promotes data-driven solutions and predictive models while progressively incorporating concerns related to equity, accountability, and credit sustainability. Thus, the heat map not only confirms the general orientation of academic discourse but also helps identify moments when the literature emphasizes the need for ethical and governance frameworks for the use of technologies in credit evaluation.

Figure 8 presents the TF-IDF growth curves of emerging terms within the analyzed corpus, enabling the identification of the temporal evolution of key concepts and their relative relevance in the literature. TF-IDF weights reflect the importance of each term within a given period; therefore, the observed variations indicate not only frequency of use but also the capacity of these terms to differentiate emerging thematic trends within the field.

Throughout the analyzed period, a dynamic pattern is observed in the terms *financial, loan, risk*, and *data*, revealing shifts in research emphases. The term *loan* exhibits one of the most pronounced peaks around 2020, suggesting increased academic interest in credit allocation mechanisms and financing processes, possibly associated with global economic uncertainty and the need to strengthen access to credit. Subsequently, its relevance stabilizes, indicating that it remains a central component of financial discourse.

The term *data* shows significant growth beginning in 2021, reflecting the increasing centrality of data in credit evaluation and in the digital transformation of the financial system. This rise coincides with the expansion of big data, advanced analytics, and artificial intelligence, elements that have redefined traditional risk assessment models. In parallel, the term *risk* presents fluctuations that highlight its cross-cutting character: although consistently relevant, its intensity increases during periods when the literature emphasizes risk management in response to changing economic conditions and emerging sources of uncertainty.

Meanwhile, the term *financial* maintains a relatively stable presence over time, confirming its structural role within the field. However, the increases observed in recent years suggest an expansion of the financial perspective toward digital, inclusive, and sustainable dimensions.

Overall, Figure 8 reveals a thematic evolution in which the traditional focus on credit and risk is progressively complemented by a growing emphasis on data use and analytical technologies. This transition reflects a shift toward an information-driven financial paradigm characterized by automation and predictive models, in which risk management and credit access are redefined through digital tools. The observed dynamics confirm that the literature is adapting to technological and economic transformations, consolidating an interdisciplinary approach that integrates finance, data science, and digital innovation.

THEMATIC SYNTHESIS OF THE REVIEWED LITERATURE

The reviewed literature shows that financial inclusion, credit scoring, and algorithmic fairness have progressively converged into an interdisciplinary research field. Rather than evolving as separate domains, recent studies indicate that credit risk assessment is increasingly shaped by the interaction between data-intensive technologies, institutional governance, and concerns about equitable access to finance. In this sense, research on fair lending and algorithmic transparency has emphasized the need to evaluate credit scoring models not only according to predictive performance but also in relation to bias, explainability, accountability, and their potential effects on financially excluded

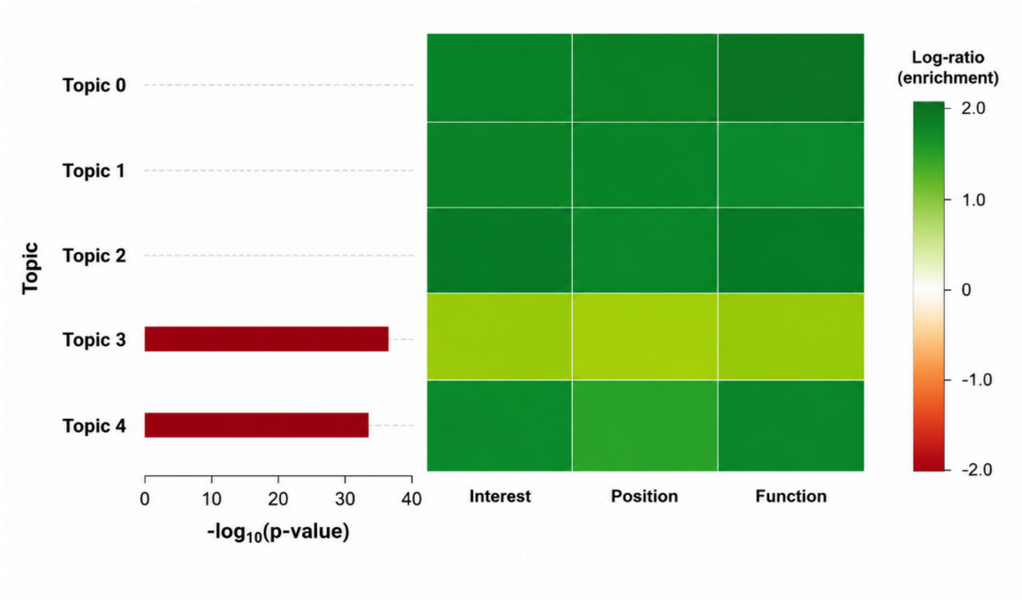

Figure 7: Heat map of publications by year and sentiment polarity.

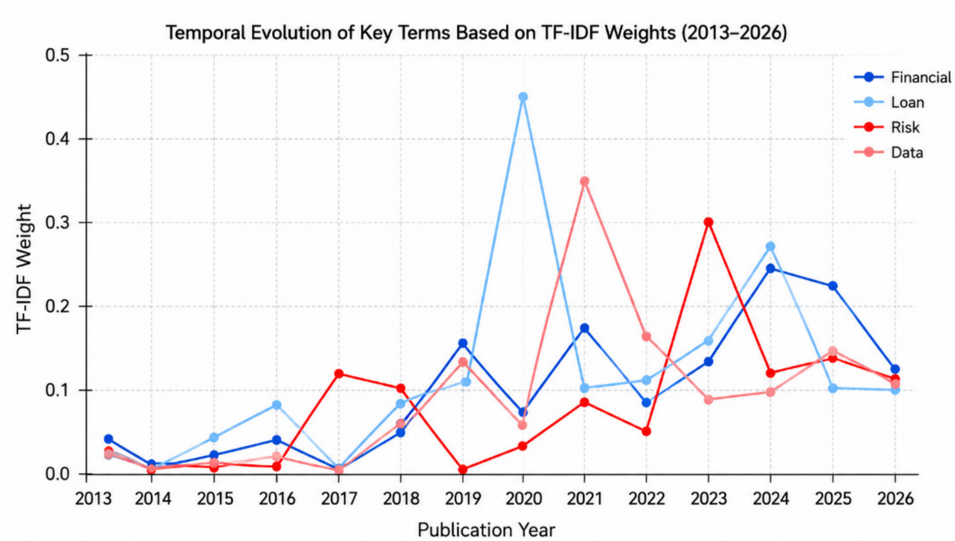

Figure 8: TF-IDF growth curves of emerging terms.

populations (Abbas, 2025; Caro *et al.*, 2026; Liu & Liang, 2025; Sekhar & Saheb, 2026).

From a technological perspective, machine learning and artificial intelligence have become central tools for improving credit risk prediction. Studies in this stream examine how alternative data, hybrid models, neural networks, and automated decision systems can increase predictive accuracy and expand access to credit for borrowers with limited or no formal credit history (Achalapong & Satitsamitpong, 2025; Alamsyah *et al.*, 2025; Björkegren & Grissen, 2020; Dushimimana *et al.*, 2020; Kazimoto & Baadel, 2025; Li *et al.*, 2024; Óskarsdóttir *et al.*, 2019). However, this literature also cautions that data-driven scoring systems may reproduce structural inequalities when data sources, model design, or institutional practices are not subject to adequate governance.

Institutional and regulatory approaches complement these technological discussions by highlighting the role of financial ecosystems, fintech-bank collaboration, and policy frameworks in supporting inclusive credit markets. In this line, studies have examined how digital financial services, innovative scoring mechanisms, and regulatory adaptation can contribute to broader financial inclusion, particularly in emerging economies where traditional credit information is often scarce or unevenly distributed (Adam *et al.*, 2025; Allen *et al.*, 2021; Hiller & Jones, 2022; Mhlanga, 2021; Phan *et al.*, 2024; Roa *et al.*, 2021; van Braak *et al.*, 2025; Vuković *et al.*, 2025).

A further research stream focuses on microfinance, small-scale lending, and vulnerable borrowers. These studies show that credit scoring models can support institutional sustainability and improve loan allocation, but they also reveal persistent concerns regarding gender, informality, rurality, ethnicity, and unequal access to productive credit (Blanco-Oliver *et al*., 2013, 2024; Collins *et al*., 2023; Cubiles-de-la-Vega *et al*., 2013; Gonzales Martínez *et al*., 2020; Medina-Olivares *et al*., 2022; Wellalage & Thrikawala, 2021). This evidence reinforces the need to evaluate financial inclusion outcomes beyond loan approval rates, incorporating social impact, borrower protection, and fairness criteria.

Finally, earlier and foundational studies provide the historical and methodological basis for understanding the transition from traditional credit scoring to automated, data-driven systems. Contributions on statistical scoring, decision trees, psychometric models, mobile phone data, weather data, and behavioral information demonstrate how the field has progressively expanded the sources and techniques used for credit risk assessment (Chen *et al*., 2018; Fine, 2024; Langley, 2014; Römer & Musshoff, 2018; Sadok *et al*., 2022; Serrano-Cinca *et al*., 2016; Zhang *et al*., 2018). Overall, the reviewed evidence suggests that the future of credit scoring in emerging economies depends on balancing predictive efficiency with transparency, fairness, and development-oriented financial inclusion.

CONCLUSION

This systematic review, based on 63 Scopus-indexed studies and analyzed using Natural Language Processing (NLP), bibliometric techniques, and science mapping, provides an integrated characterization of the field linking financial inclusion, credit risk models, and algorithmic fairness in emerging economies. The combined use of PRISMA for document selection and computational tools for semantic analysis ensured a traceable and reproducible process, from the initial 295 records to the final corpus examined.

The findings show that recent literature is organized around five thematic clusters that connect social, ethical, technological, risk-oriented, and microfinance/banking perspectives. Credit risk assessment remains the conceptual core of the field, while artificial intelligence, machine learning, alternative data, and digital financial services are increasingly reshaping traditional scoring models. At the same time, the reviewed studies highlight that technological innovation alone is insufficient to guarantee inclusive outcomes.

The evidence suggests that AI-based and data-driven credit scoring models can expand credit access for underserved populations, particularly in emerging economies where formal credit histories are limited. However, these models may also reproduce bias, opacity, discrimination, and pre-existing exclusion if they are not accompanied by adequate governance, transparency, explainability, and fairness mechanisms. Therefore, the future of credit scoring should not be evaluated only by predictive accuracy but also by its contribution to equitable and responsible financial inclusion.

This review contributes by systematizing a fragmented body of literature and by showing that financial inclusion, credit scoring, and algorithmic fairness must be addressed as interconnected dimensions of responsible financial innovation. The findings are relevant for researchers, regulators, policymakers, and financial institutions seeking to align digital credit systems with sustainable development goals, poverty reduction, inequality reduction, and inclusive economic growth.

The study also has limitations. The analysis was restricted to Scopus-indexed, English-language, open-access publications within selected subject areas. Future studies could expand the review to other databases, languages, grey literature, institutional reports, and regional case studies. Further research should also examine how algorithmic fairness principles are operationalized in real credit decision-making processes and how they affect vulnerable borrowers in practice.

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ABBREVIATIONS

AI: Artificial Intelligence; **ML:** Machine Learning; **NLP:** Natural Language Processing; **PRISMA:** Preferred Reporting Items for Systematic Reviews and Meta-Analyses; **SDGs:** Sustainable Development Goals; **TF-IDF:** Term Frequency-Inverse Document Frequency.

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