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Data and Techniques Used in Consumer Credit Rating Model: A Systematic Review

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Abstract

Consumer credit rating models are fundamental to financial risk management, yet the industry is undergoing a paradigm shift from traditional statistical methods to complex Artificial Intelligence (AI) techniques. This systematic review aims to consolidate existing knowledge regarding the evolution of data and techniques in credit rating, identifying key trends and geographical disparities. A Systematic Literature Review (SLR) was conducted using Scopus, ScienceDirect, and Web of Science. From 741 initial results, 110 peer-reviewed articles were selected and analyzed based on methodological approaches and data categories. The results indicate a transition in techniques; while Neural Networks (39 papers) and Ensemble Methods have emerged as dominant tools for handling non-linear data, traditional Logistic Regression (31 papers) remains relevant for its interpretability. Regarding data, Credit History and Financial Information remain the primary inputs, though alternative sources like digital footprints are increasingly utilized. Geographically, China leads global research output (56 papers), reflecting rapid fintech adoption. The study concludes that the future of credit rating lies in Hybrid Models and Explainable AI (XAI) to balance predictive accuracy with regulatory transparency. Future research should prioritize ethical frameworks for alternative data integration.

Keywords: *consumer credit rating, credit scoring models, credit scoring criteria, systematic review*

1. Introduction

Credit rating is to classify and differentiate between "good" and "bad" customers during the course of assessing a borrower's qualification for credit. The financial institutions should grant credit to "good" customers in order to increase revenue and reject "bad" customers in order to avoid losses (Lee et al., 2002; Lim & Sohn, 2007). Consumer credit rating plays a pivotal role in the financial industry by differentiating between "good" and "bad" borrowers, serving as the cornerstone of risk management and economic stability. Historically, credit assessment relied on subjective judgment—the "5 C's of Credit"—until Durand (1941) introduced quantitative scoring, marking a shift toward objective, statistical decision-making. Traditional statistical methods such as discriminant analysis and logistic regression dominated the field for decades (Hand & Henley, 1997; Thomas, 2000), until the emergence of machine learning algorithms in the 2000s began to reshape credit risk assessment practices (Khandani et al., 2010).

In recent decades, the explosion of "Big Data" and computational power has precipitated a second paradigm shift: moving from traditional statistical methods, such as Logistic Regression, to sophisticated Machine Learning (ML) and Artificial Intelligence (AI) techniques. Concurrently, the definition of creditworthiness has expanded beyond traditional financial history to include alternative data sources, such as digital footprints and utility payments, aiming to foster financial inclusion for "thin-file" consumers.

To understand this rapid evolution, several systematic reviews have been conducted. Louzada et al. (2016) provided foundational insights into binary classification techniques but predates the widespread adoption of Deep Learning. Çallı and Coşkun (2021) offered a longitudinal analysis of credit predictors, yet their scope amalgamates corporate and individual risk, potentially obscuring consumer-specific nuances. More recent syntheses by Ayari et al. (2025) and Roy and Vasa (2025) have extensively covered AI and ML applications. However, these reviews often generalize across diverse financial domains—blending Consumer, Peer-to-Peer (P2P), and Corporate lending—or focus predominantly on algorithmic performance while underemphasizing the granular implications of alternative data integration (Hlongwane et al., 2024).

Despite this extensive body of work, a critical research gap remains. Existing literature tends to analyze data traits and modeling techniques in isolation or within broad financial contexts. There is a notable absence of a consolidated review that specifically examines the *interplay* between diverse data sources and methodological techniques exclusively within *consumer* credit rating models. Furthermore, the emergence of advanced technologies, such as Large Language Models (Golec & AlabdulJalil, 2025), necessitates an updated synthesis that addresses how specific data-technique combinations impact model interpretability, fairness, and regulatory compliance. The pain point for researchers and practitioners lies in navigating this fragmented landscape without a unified framework that links data characteristics directly to algorithmic suitability.

2. Objectives

The primary purpose of this systematic review is to consolidate existing knowledge regarding the evolution and application of consumer credit rating models. To achieve this, the study focuses on classifying the methodological techniques currently applied in consumer credit rating models, recommendations for future research directions by synthesizing current gaps related to model interpretability, data ethics, and the inclusion of underrepresented consumer segments.

3. Materials and methods

The paper reviews the results of various research on consumer credit scoring models using a structured methodology for reviews, known as "Systematic Literature Review" (SLR). The review process follows the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 guidelines (Page et al., 2021) to ensure transparency, reproducibility, and systematic rigor in study selection and data extraction. SLR provides a clear and organized approach for identifying key issues and optimization areas in consumer credit rating.

The first step involves setting review objectives related to consumer credit rating models, followed by a systematic search for relevant literature with strict limitation to peer-reviewed scientific articles. Unlike general resources such as web pages or books, this review confines itself to academic research published in peer-reviewed journals and conference proceedings. From an initial pool of articles filtered through specific search criteria, the study narrows down the selection to approximately 110 key papers. These selected articles are then analyzed to answer focused research questions, with information obtained forming the backbone of the review.

This systematic review addresses four key research questions:

RQ1: What are the most used techniques in the consumer credit rating models?

RQ2: What is the most common data used in the consumer credit rating models?

RQ3: What are the trending research topics in consumer credit rating research?

RQ4: What are the countries originated in the research papers?

3.1 Search sources and equations

Initially, review objectives related to consumer credit rating models were established. Following this, a systematic search for relevant literature was conducted, with a strict limitation on scientific articles. Unlike general resources such as web pages or books, this review confines itself to peer-reviewed academic research to ensure validity and reliability. The search was conducted using three primary databases: Scopus, ScienceDirect, and Web of Science. The search terms utilized were "consumer credit rating," "personal credit rating," "individual credit rating," "consumer credit scoring," "personal credit scoring," "individual credit scoring," "consumer credit evaluation," "personal credit evaluation," "individual credit evaluation," "consumer credit assessment," "individual credit assessment," and "personal credit assessment."

After using each search term mentioned above, all resulted articles are extracted and consolidated under Rayyan – Intelligent Systematic Review platform and processed further. The total of articles that are extracted and consolidated are as follows:

Table 1 Consolidated matrix of the resulting number by source

Source	Number of articles
Scopus	204
ScienceDirect	396
Web of Science	146
Total	**741**

3.2 Exclusion process

To avoid selection bias and fit the criteria, the study employed a list of objective exclusion criteria. Using these, many of the articles were excluded. These will then be used to answer the research questions objectively and will not introduce bias. The criteria were designed in such a way that they reflected the objectives of the study, and this led to defining a sum of 4 exclusion criteria, which are listed in Table 2 below.

Table 2 Exclusion criteria

No.	Description
EC1	The article is a duplicate of another article
EC2	The abstract of the articles is not very relevant
EC3	The article is in non-English language
EC4	The full text is not available

The study selection process followed a four-stage screening approach. In the first stage (EC1), duplicate articles across the three databases were identified and removed, reducing the pool from 741 to 525 unique articles. In the second stage (EC2), abstracts were independently screened by two reviewers to assess relevance to consumer credit rating models, with disagreements resolved through discussion. This reduced the sample to 312 articles. In the third stage (EC3), non-English language articles were excluded, resulting in 309 articles. Finally, in the fourth stage (EC4), full-text availability was verified, yielding a final sample of 110 articles for detailed analysis as shown in Figure 1.

3.3. Data extraction and analysis

After applying the above criteria, 110 articles remained for detailed analysis. In relation to the first two research questions, regarding the analysis phase, credit rating models' techniques and data are gathered and classified. More specifically, these techniques are classified in broad terms, such as neural networks or statistical methods, while the data type is more focused and may include personal, financial, and credit history information.

Categories for each dimension were developed based on similar ideas found in literature. In addition, to validate the levels of categorization, articles published in peer-reviewed journals were used, and views of the co-authors were used in discussions on the categorization schema. All techniques and data used were further validated by comparing them to the existing literature on the topic in question and industry practices in general. To address potential conceptual overlaps, we distinguished between core modeling techniques (methods directly used for credit risk prediction, such as logistic regression, neural networks, and decision trees) and supporting procedures (techniques used for data preparation, model validation, and performance evaluation, such as feature selection, cross-validation, and ROC curve analysis). This distinction ensures clarity in interpreting the frequency counts and prevents conflating preprocessing steps with primary modeling approaches.

Frequencies of these techniques and data types are then counted and tabulated to identify the most used methods and categories in existing research. Finally, the results are synthesized to provide insights into the evolution of techniques and data usage in consumer credit rating models, highlighting both traditional and advanced methodologies as well as both traditional and alternative data.

Regarding the third question, the process involves performing qualitative analysis on the abstracts, introduction sections, and keywords of each paper to identify the main topics addressed as well as reading through the text to discern key themes, methodologies, and areas of focus for recent studies published from 2020 to 2025. The identified themes from the content analysis are then categorized into broader topics. Like the previous research questions, cross-referencing peer-reviewed articles and discussing among co-authors to reach consensus on the categorization schema are also conducted to ensure the validity of the categorization. A trend analysis is then conducted to identify emerging topics in consumer credit rating research to help further discuss the implications of the identified trends, potential gaps in the literature, and suggestions for future research directions.

In relation to the last research question, the country information is systematically extracted from the metadata of each research paper. This includes noting the affiliations of the authors and any institutional information provided in the papers. Once the information is collected, a frequency analysis is used to count the number of papers affiliated to each country. The frequency results are then visualized into a chart to illustrate the distribution of these research articles across different countries. The final step includes interpreting and discussing the results about the geographical allocation of consumer credit rating research articles on global dimensions.

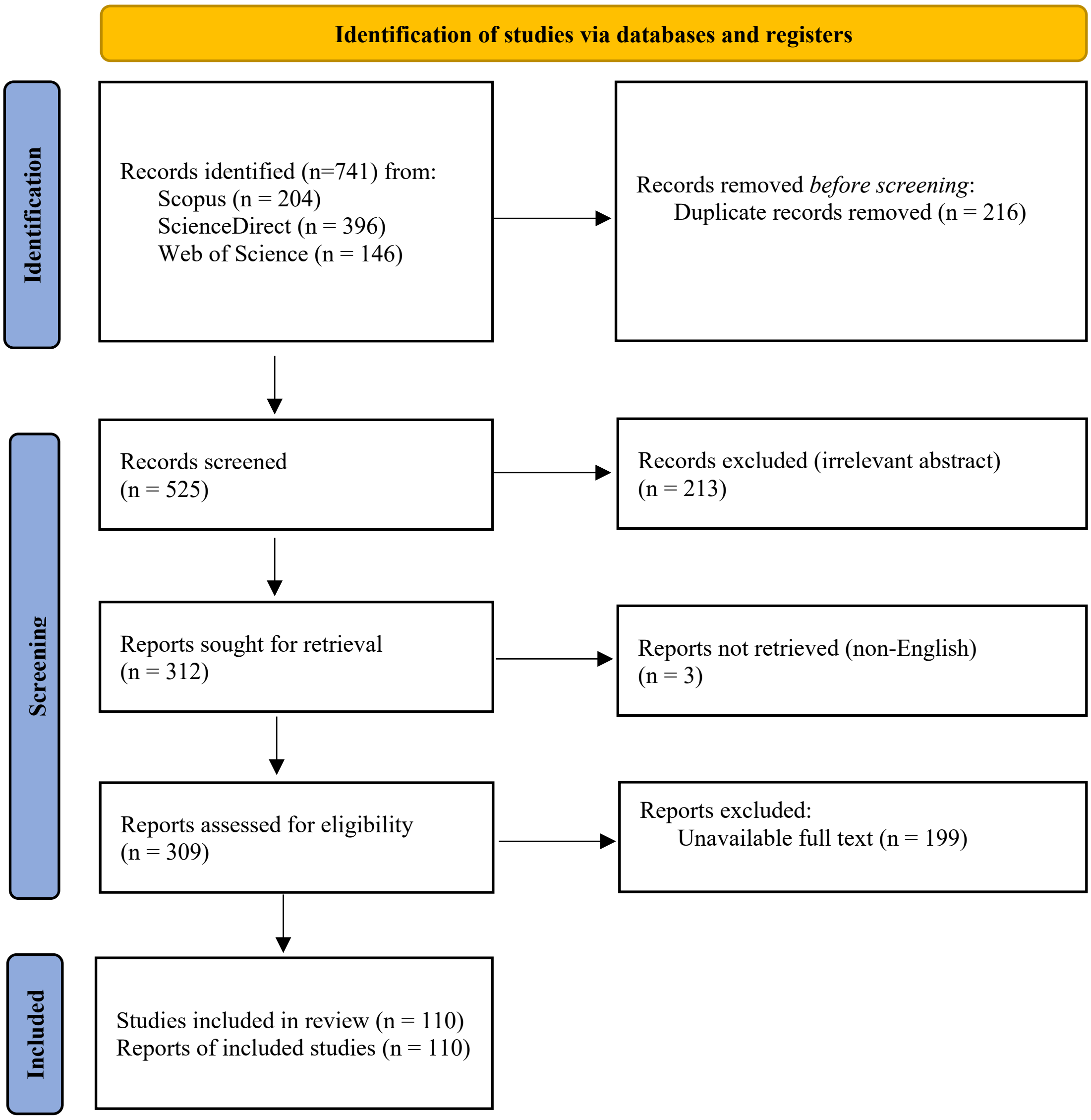

Figure 1 PRISMA flow diagram of the systematic review process

4. Results and discussion

4.1 RQ1. What are the most used techniques in consumer credit rating models?

From 110 filtered articles, it was observed that there were around 330 specific techniques used in these research. Therefore, to answer the research question more effectively, these 330 techniques were classified into these 21 general technique categories. As noted in Section 3.3, we distinguish between **core** modeling techniques that directly perform credit risk prediction and supporting procedures that facilitate data preparation, model validation, and performance assessment. This classification is presented in Table 3 below.

Table 3 Categories of commonly used techniques in consumer credit rating model

No.	Category	Techniques
Core Modelling Techniques		
1	Neural Networks	Neural Networks (NN), Convolutional Neural Network (CNN), Deep Learning, Multi-Layer Perceptron (MLP), Recurrent Neural Networks (LSTM, Bidirectional LSTM), Fuzzy Adaptive Network, Artificial Neural Networks (ANN), Radial Basis Function (RBF), Neural Network, Residual Neural Networks, Neural Estimation, Neuro-Rule Algorithm, Natural Language Processing (NLP), Bidirectional Encoder Representations from Transformers (BERT), Bootstrapping Language-Image Pre-training (BLIP-NLP), Lipschitz Recurrent Neural Network (LRNN), Generative Adversarial Network (GAN)
2	Support Vector Machine (SVM)	Support Vector Machine (SVM), Improved Support Vector Machine (IFOA-SVM), Linear SVM, Core Vector Machines (CVM), Ball Vector Machines (BVM), Sequential Minimal Optimization (SMO), Pegasos, Kernel Methods
3	Linear Regression	Linear Regression, Lasso Regression, Multivariate Adaptive Regression Splines (MARS), Linear Probability Model, Autoregressive Integrated Moving Average Model (ARMA), Regularization Technique
4	Decision Trees	Decision Tree, C5.0 Algorithm, Classification Trees, Random Forest, Gradient Boosting Decision Tree (GBDT), XGBoost, LightGBM, Decision Tree Method
5	Logistic Regression	Logistic Regression, Optimized Logistic Regression, Ridge Logistic Regression, Logit Model, Probit Model
6	Fuzzy Logic	Fuzzy Logic, Fuzzy Comprehensive Evaluation, Fuzzy Inference System, Fuzzy Correlation, Fuzzy Comprehensive Evaluation
7	Evolutionary Algorithms	Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Adaptive Particle Swarm Optimization (APSO), Simulated Annealing, Improved Fruit Fly Optimization Algorithm (IFOA), Cuckoo Search Algorithm, Hidden Layer Learning Vector Quantization
8	Bayesian Networks	Naive Bayes, Bayesian Network, Bayesian Style Frequency Matrix (BFM), Probabilistic Models, Bayesian Optimal Filter
9	Hybrid Methods	Hybrid Data Mining Technique, Hybrid Metaheuristics (NSBGOA and SelCrossMut NSBGOA), Stacking Generalization, Multi-Objective Optimization, Metaheuristic Hybridization, Hybrid Imbalanced Learning Framework
10	Ensemble Methods	Ensemble Learning, Bagging, AdaBoost, LogitBoost, MultiBoost, Stacking Ensemble, Random Jungle, Catboost, Gradient Boosting, Ensemble Learning, Bootstrap Sampling, Random Forest
11	Evaluation Metrics & Measures	Accuracy Measurement, Precision Measurement, Recall Measurement, ROC Curve Analysis, AUC Value Calculation, Confusion Matrix Analysis, Classification Techniques
12	Clustering Methods	K-Means, Agglomerative Hierarchical Clustering (AHC), Cluster-Based Method
13	Other ML Techniques	k-Nearest Neighbor (k-NN), Supervised Learning, Graph-Based Methods
14	Statistical Methods	Statistical Analysis, Regression Analysis, T-Test, Multivariate Adaptive Regression Splines (MARS), Econometric Methodology, Covariance Risk Measurement, Statistical Fairness Criteria, Time Series Analysis, Discriminant Analysis, Nonparametric Estimation
Supporting Procedures		
15	Feature Selection Methods	Recursive Feature Elimination (RFE), Principal Component Analysis (PCA), ReliefF, Information Gain, Gain Ratio, Gini Index, Correlation-Based Feature Subset Evaluation (CFS), Feature Engineering, Clustering-Based Undersampling, Feature Importance Analysis, Forward Selection, Recursive Partitioning Algorithms, Relief Algorithm
16	Validation Approach	Cross-Validation, 10-Fold Cross-Validation, K-Fold Cross-Validation
17	Decision-Making Methods	Analytic Hierarchy Process (AHP), Delphi Method, Expert Systems

No.	Category	Techniques
18	Evaluation Methods	Benchmarking Accuracy, Profit-Based Classification Performance Measure, ROC Curve Analysis, Gini Coefficient, Kolmogorov-Smirnov (KS) Statistic
19	Data Preprocessing Techniques	Data Cleaning, Standardization, One-Hot Encoding, Min-Max Normalization, Z-Score Standardization, SMOTE Algorithm, Dimension Reduction using pdC-RF Algorithm, Data Transformation, Outlier Detection
20	Dimensionality Reduction Techniques	Principal Component Analysis (PCA), Kernel Approximation, t-SNE Technique, Distance Covariance-based Sufficient Dimension Reduction (DCOV-SDR), Majorization-Minimization (MM) algorithm, MMRN algorithm.
21	Other Techniques	Blockchain Technology, Markov Chain Modeling, Portfolio Analysis, Social Interaction Feature Analysis, Risk Assessment, Smart Contracts, Sentiment Analysis, Explainable AI (XAI), SHAP values

Using the above classification table, each technique category was counted if they were used in those research as follows:

Table 4 The most used technique categories in consumer credit rating model

Rank	Techniques	Type	Frequency
1	Neural Networks	Core	39
2	Statistical Methods	Core	33
3	Logistic Regression	Core	31
4	Support Vector Machine (SVM)	Core	29
5	Other Techniques	Supporting	29
6	Decision Trees	Core	26
7	Ensemble Methods	Core	26
8	Feature Selection Methods	Supporting	21
9	Evolutionary Algorithms	Core	17
10	Clustering Methods	Core	14
11	Data Preprocessing Techniques	Supporting	12
12	Validation Approach	Supporting	10
13	Other Machine Learning Techniques	Core	9
14	Evaluation Metrics & Measures	Supporting	8
15	Bayesian Networks	Core	8
16	Fuzzy Logic	Core	7
17	Decision-Making Methods	Supporting	6
18	Dimensionality Reduction Techniques	Supporting	3
19	Hybrid Methods	Core	3
20	Linear Regression	Core	3
21	Evaluation Methods	Supporting	1

From the above table, it seems that contemporary consumer credit rating models have indicated a clear trend of adopting advanced data analysis techniques. Among the techniques used, Neural Networks emerged as the most popularly used technique, appearing in 39 research articles. This may be because, through neural networks, hidden and complex nonlinear relationships across the data are able to be elicited, particularly when dealing with temporal credit behavior patterns (Wang et al., 2019) and multi-dimensional consumer data (Zhu et al., 2018). Advanced architectures such as LSTM with attention mechanisms have demonstrated superior performance in capturing sequential dependencies in credit data (Wang et al., 2019), while hybrid deep learning approaches have proven effective in real-world credit card risk assessment (Fonseca et al., 2020).

Despite the rise of such sophisticated methods, traditional Statistical Methods still stand out. Our review identified 33 usages; thus, ascertaining the fact that they are still very relevant; they form the foundation upon which more complex models may be built. Techniques like regression analysis, discriminant analysis, and probabilistic models provide a robust foundation upon which more complex models can be built. This is further supported by the fact that popular Machine Learning techniques are in wide use: for instance, Support Vector

Machines with 29 occurrences and Logistic Regression with 31 occurrences, while Decision Trees appear in 26 occurrences. The algorithms extract the pattern from the data very well to predict binary outcomes for credit risk that classifies them as either good or bad.

More interestingly, our review reflects a recent increase in the interest in developing more robust and stable credit models; this is presented by Ensemble Methods, which had as many as 26 usages. These methods integrate several models for improved accuracy and stability in the prediction. Some of the techniques, such as bagging and boosting, consider a set of individual models to provide a strong and reliable predictive system. In addition, the considerable occurrence of Feature Selection Methods underlines the importance of data quality in constructing an accurate credit scoring model. Fundamentally, these supporting procedures play a huge role in the reliability and efficiency of the credit scoring models on the road to identifying the most relevant features and checking the integrity of data.

The choice of modeling technique often depends on the type and volume of data available. Neural Networks and Ensemble Methods are frequently employed when large datasets with diverse features (including alternative data sources such as digital behavior and social media) are available, as they can effectively handle high-dimensional, non-linear relationships. Conversely, logistic regression and traditional statistical methods are preferred when interpretability is paramount, particularly in regulatory environments where model transparency is required (Kozodoi et al., 2022). The rising emphasis on explainable AI (XAI) and SHAP values (appearing in the "Other Techniques" category with 29 occurrences) reflects growing regulatory pressure for model interpretability, especially under frameworks such as GDPR and Basel III, which demand transparency in automated decision-making processes affecting consumers.

4.2 RQ2. What are the most used data in consumer credit rating models?

Like the above questions, consolidation of all the data used in 110 filtered articles showed that there were too many unique data used in that research. Therefore, to answer the research question more effectively, these data were then classified into these 12 categories and 29 subcategories as follows:

Table 5 Categories of commonly used data in consumer credit rating model

No.	Category	Subcategory	Data
1	Personal Information	Demographics	Age, gender, marital status, number of children, years of education, birthplace
		Residential Information	Residential type, zip code, residential region, home ownership, years of residence in local area, type of dwelling, duration of residence, time at present address
		Contact Information	Phone number, duration of phone number, shutdown time of phone number
		Employment Information	Occupation, job type, employment status, position, company type, business sector, years of services, time with employer, main activity of the firm, duration of present employment, number of companies where the user has worked, number of years since user started career, previous professional activity, previous positions, previous employers
2	Financial Information	Income	Monthly income, annual income, other income, total income, social security, net income, free income, debt-to-income ratio
		Assets	Personal assets, fixed assets, current assets, bank credit balances, time deposits balance, saving account, house ownership, car ownership, other property
		Expenses	Total annual expenditure, average monthly free cash flow
3	Loan Specifics	Loan Terms	Interest rate, principal payment, grace period, repayment period, loan amount, loan application type, loan grade, loan verification status, loan purpose, loan performance, debt-to-income ratio, revolving credit utilization rate
		Loan Characteristics	Loan purpose, return mode, surety, portfolio segments, collateral type, FTV facility count, land certificate status, financing purpose
4	Credit Information	Credit History	Credit history, credit score, length of credit history, default or not, previous default information, credit amount, credit failure times, default cost,

No.	Category	Subcategory	Data
			recovery percentage at default, credit card history, credit card overdue days, credit card overdue amount, number of inquiries about credit history, number of bad loans in the past, overdue times, maximum overdue days, amount of successful loans, amount of failed loans, previous loans granted, previously denied loans, total number of past and current loans, number of existing credits at this bank
		Credit Behavior	Number of open credit lines and loans, number of times 30-59 days past due, number of times 60-89 days past due, number of times 90 days late, number of real estate loans or lines, total number of fees paid in credit history, number of arrears, number of loans, number of institutions, number of credit cards held, number of credit accounts, number of institutions providing loans
		Credit Request History	Credit request history, number of credit applications, time of inquiry by organization, reasons for inquiry, number of accounts held
		Credit Scores	Credit score, FICO score
5	Transaction Information	Transaction History	Transaction history, payment performance, days in arrears, number of payments, overdue repayment time, repayment duration, accumulative amount of transactions, cumulative number of transactions, number of returns, number of bad reviews
		Payment Details	Payment instrument for installments, credit card used for down payment, down payment amount, installment amount, number of installments, daily payments, micro-credit repayment, credit card payment, cash, shopping, fund purchase, security purchase, transfer to others, transfer to self, transportation, deposit, transaction date, transaction time, transaction location
6	Social Interactions	Communication Frequency	Contact frequency with lending agency, contact frequency with bank, total number of contacts, contact frequency with lawyer, contact frequency with court
7	Digital Behavior	App Usage Patterns	App usage patterns
		Mobility Patterns	Mobility patterns, telecommunication patterns
		Online Behavior	Online operation behavior data, user behavior, event types, event vectors, hidden states of LSTM, attention weights
8	Social media	Social Network Analysis	Social network relationship data, engagement metrics, sentiment analysis of posts
		User Behavior	Number of followers, number of friends
9	Legal Records	Criminal Records	Criminal penalty, criminal record
		Legal Proceedings	Legal proceedings initiated by borrower, legal proceedings initiated against borrower, number of disputes, law and discipline cases
		Penalty	Public security penalty, transportation penalty
10	Macroeconomic Factors	Economic Indicators	Local unemployment rate, economic shocks, market conditions, recovery value
11	Credit Risk Factors	Default Risk	Probability of default, loss given default, exposure at default, transition probabilities, credit risk indicators, default probability, creditworthiness, portfolio segments
		Risk Assessment	Default correlations, maturity, risk weights, credit risk, risk index
12	Other	Voice Characteristics	Characteristics of voices before and after person defaulted (pitch, formant, and the speaker's dependency and independence)

Using the above classification table, each data categories and sub-categories were counted if they were used in the related research as follows:

Table 6 The most used data categories in consumer credit models

No.	Data Categories Most Commonly Used	Number of Research
1	Credit Information	57
2	Financial Information	53
3	Personal Information	49
4	Loan Specifics	16
5	Credit Risk Factors	12
6	Digital Behavior	8
7	Social media	7
8	Transaction Information	6
9	Macroeconomic Factors	6
10	Legal Records	5
11	Other (Sentiment/News)	2
12	Social Interactions	1

Table 7 The most used data sub-categories in consumer credit models

No	Data Sub-Categories Most Commonly Used	Number of Research
1	Credit History	48
2	Demographics	47
3	Income	29
4	Loan Terms	21
5	Contact Information	16
6	Loan Characteristics	14
7	Credit Behavior	12
8	User Behavior / Digital Footprints	9
9	Economic Indicators	6
10	Default Risk	6
11	Transaction History	5
12	Social Network Analysis	5
13	Payment Details	4
14	Assets	4
15	Employment Information	3

Analyzing categories and their subcategories of data relevant to the personal credit rating models as table above helps outlining the most important features related to creditworthiness of a person. It can be observed that the most utilized category is “Credit Information”, with a frequency count of 57. The representation of these datasets involves fundamental measures on various types of payment history, level of debt, and credit utilization that are essential in determining the credit score of a borrower, which also acts as most important pillars in most popular credit rating models used in the world such as FICO, SCHUFAR, etc. Indeed, this very element makes the first category important: to construct reliable credit models that can predict repayment behavior and risk, one needs to have reliable data on credit.

Then it is followed closely by “Financial Information”, which, besides other things, contains information concerning the subject's financial situation, such as income and outstanding loans. The category is important in assessing the general financial health of borrowers and appears in 53 filtered research. To this end, the lenders consider the applicant's level of income and their financial commitments, which make understanding the debt repayment capability of the debtor critical. Because of this, personal credit rating models should capture financial data to present an all-rounded view about an applicant's credit risk. This confirms the fact that the industry will continue to move away from simplistic scoring systems toward more subtle and complex ones.

“Personal Information”, with 49 references, further emphasizes demographic data as an influential role in shaping credit rating models. These demographic data, such as whether age and/or employment status or residential stability, provide a deeper insight into the borrowing behavior and capability of repayment. For example, the younger the borrower, the fewer the credit histories they may have, but they could well be at another stage of life regarding income growth potential, which can differently affect their credit risk profile. Thus, demographic variables should be incorporated into credit rating models to help lenders make a clean distinction of how different segments of consumers should be treated for better predictability.

It also goes to reiterate how “Loan Specifics” and “Credit Risk Factors” are relevant given that they are two components that complete a personal credit model. With 16 references, loan specifics could refer to the amount, the terms, and interest rates that control the loan to ascertain the nature of repayments. While factors indicative of “Credit Risk Factors” include those factors that may indicate a potential default, such as missed payments or high credit utilization rates, with 12 references. These are some of the main factors which provide the basis for developing personal credit rating models and to which elements must be given if scoring algorithms are to become representative and robust enough to capture complex realities of individual borrowers.

The relationship between data types and modeling techniques is significant for both predictive performance and regulatory compliance. Traditional data sources (credit history, financial information, personal information) are typically analyzed using interpretable methods such as logistic regression and decision trees, facilitating transparency and regulatory approval (Kozodoi et al., 2022). In contrast, alternative data sources (digital behavior, social media, transaction patterns) are often processed using advanced machine learning techniques such as neural networks and ensemble methods, which can extract complex patterns but pose interpretability challenges (Ahmed & Iqbal, 2025; Kong, 2025). This trade-off between predictive power and explainability has become a central concern in recent credit scoring literature, particularly with the implementation of regulations such as GDPR in Europe and fair lending laws in the United States, which require transparency and accountability in automated credit decisions (Kozodoi et al., 2022).

Besides, though only used in some research, it seems that any model of consumer credit is also, however, based on factors of macroeconomic and legal records since factors like the rate of unemployment and economic shocks affect the repayment ability, while legal history in relation to bankruptcy, for instance, is a warning to the lenders who want to handle the risk. Besides, digital behavior, transaction history, and even social media interactions have all become major indicators of creditworthiness. Pioneering work by Guo et al. (2016) demonstrated that social media footprints could be systematically mined to extract creditworthiness signals, while Ma et al. (2018) successfully utilized meta-level phone usage data for default prediction in P2P lending. More recently, researchers have explored the dynamics of social interaction features and their temporal impact on credit assessment performance (Muñoz-Cancino et al., 2023b), and even voice characteristics have been investigated as novel predictive features (Lee, 2021). These alternative data sources have proven particularly valuable for assessing thin-file borrowers who lack traditional credit histories (Muñoz-Cancino et al., 2023a).

4.3 RQ3. What are the trending research topics in consumer credit rating research?

Before answering the question, the 105 filtered research papers are narrowed down to 38 articles published from 2020 to 2025 (the most recent 6 years). From that, the articles are further analyzed into common trending topics as follows:

Table 8 Trending topics in recent consumer credit rating research

Trending Topic	Number of Research
Machine Learning Approaches for Credit Scoring	20
Hybrid and Ensemble Methods for Credit Risk Assessment	11
Big Data, Multi-Source Data & Alternative Data	9
Explainable AI (XAI) and Interpretability	7
Data Mining and Feature Selection	6
Fairness, Ethics, and Regulation (GDPR/Basel)	5
Sentiment Analysis & NLP	2

Data analysis on trending topics in personal credit rating indicates various decisive insights into current research trends, as well as points of focus within the research area.

First, there is an outstanding topic related to “Machine Learning Approaches for Credit Scoring”, with 20 research references. This indicates great interest in the application of machine learning techniques in credit scoring systems. The diversity of the methodologies represented in the references puts into view that the researchers are working with a wide variety of approaches, including supervised and unsupervised learning algorithms, feature engineering, and model evaluation techniques. This trend underlines the potential that machine learning interventions might make the realm of credit assessment far more accurate and efficient.

"Hybrid and Ensemble Methods for Credit Risk Assessment" topic, with 11 research references, indicate a growing interest in the combination of multiple models to enhance predictive performance. This paper intends to combine several data sources or methodologies in pursuit of improving credit risk assessment by enhancing the accuracy and robustness of the results. There is an indication of gradual development in the direction of more sophisticated analytical frameworks that will leverage strengths from various modeling techniques.

Further, Data Mining and Feature Selection in Credit Evaluation received 6 research references, showing that data-driven techniques play a vital role in refining the processes involved in credit evaluation. Efficient feature selection is of the highest importance in improving model performance and interpretability; hence, there is continuous effort in finding the most relevant variables of creditworthiness. The focus here on data mining techniques indicates an interest in raising the quality of insights one can get from credit data.

Another central area is "Big Data and Multi-Source Data Integration", also with 9 research references. Including approaches for big data are a result of the increasing diverse data sources available for credit evaluation. Integrating data from multiple sources will give richer knowledge of the behavior of borrowers, which is essentially required for better risk assessments. This trend indicates the possibility of making use of big information to enhance the decision-making process in credit scoring.

This is followed by "Explainable AI and Interpretability in Credit Scoring", another major area of focus represented by 7 research references. Regarding the sensitive area of AI for credit scoring, the element of explainability is crucial. The emphasis on interpretability underlines concerns regarding transparency by automated decisions and, particularly, regulatory compliance with fairness and accountability. The emphasis on interpretability reflects growing regulatory pressure, particularly under frameworks such as GDPR (which includes a "right to explanation" for automated decisions) and Basel III (which requires transparency in credit risk models used by financial institutions). Research in this area focuses on developing techniques such as SHAP (SHapley Additive exPlanations) values, LIME (Local Interpretable Model-agnostic Explanations), and attention mechanisms to make complex models more transparent without significantly sacrificing predictive accuracy (Bastani et al., 2019; Chen et al., 2023). This balancing act between model

Finally, the topic of "Fairness and Ethics in Credit Scoring" has the least number of references, only 5. However, this area is of critical importance because it deals with the ethical implications of automated credit-scoring models. The emphasis on fairness would thus be indicative of an increasing awareness of possible biases in such systems, particularly regarding their disproportionate adverse effects on marginalized groups. Recent research has demonstrated that even seemingly neutral algorithms can perpetuate historical biases present in training data, leading to discriminatory outcomes based on protected characteristics such as race, gender, or socioeconomic status (Kozodoi et al., 2022). Researchers are exploring methods to ensure credit scoring procedures promote equity and do not disproportionately disadvantage vulnerable populations, including fairness-aware machine learning techniques, bias detection algorithms, and regulatory compliance frameworks.

Overall, the data suggests a shifting landscape of personal credit rating research, wherein technological advancement is increasingly matched by ethical considerations. The rise of machine learning with AI speaks to a real pivot in credit-scoring methodologies, while interpretability and fairness evoke transparency and equity. Future research will do better if these ethical dimensions receive a greater emphasis so that new methodologies promote accuracy in credit scoring systems while upholding their integrity and fairness.

4.4 RQ4. What are the countries originated the research papers?

Below is the graph showing interest in personal credit rating model research within the global context; China is leading by a big margin with 56 papers. Such leadership reflects the country's rapid fintech innovation, exemplified by companies like Ant Financial, which has revolutionized personal credit scoring through disruptive technological integration (Zhang, 2016). This research dominance has evolved over more than a decade, with Chinese commercial banks pioneering retail exposure credit scoring models as early as 2009 (Yang et al., 2009). The enormous growth in China's consumer credit market, combined with advanced alternative data availability and regulatory support for fintech innovation, has created a fertile environment for credit scoring research.

The United States follows, representing this research area with 11 papers. The U.S., being the leading financial innovator, is unrelenting in its efforts to develop new and advanced models for credit rating, which itself is indicative of mature financial markets in the U.S. and the great consumer and corporate finance role played by these systems. The output of research will thus give an indication of the interest taken in refining the techniques for better accuracy and reliability of credit evaluation.

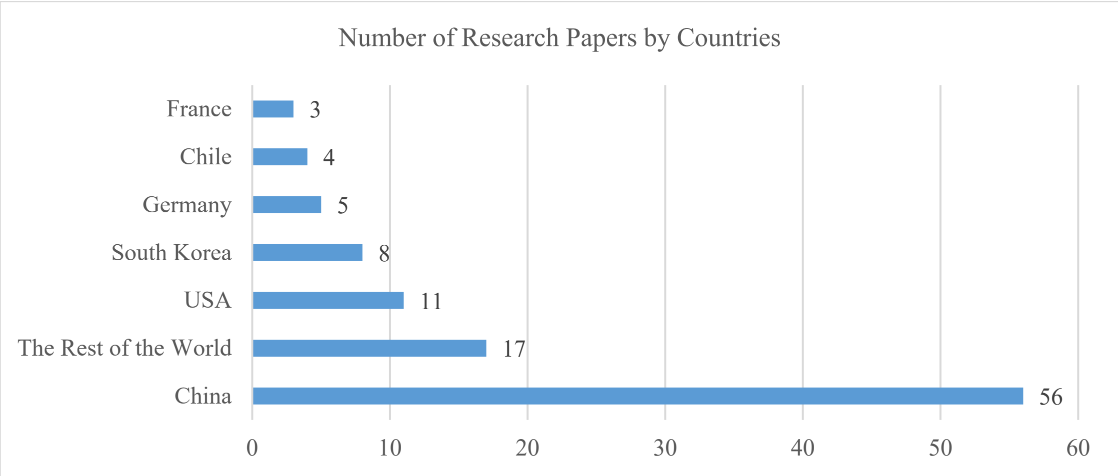

Figure 2 Numbers of Research Papers by Countries

Other countries, like South Korea, Germany, Chile, and France, show states of research activity with 8, 5, 4, and 3 papers, respectively. This is influenced by the fact that not only are their financial markets of variable size but also those within different regulatory environments and specific academic interests. Contributions coming from these countries, though small, sign for a broad approach to the understanding and improvement of personal credit rating systems.

Finally, the category "The Rest of the World," with 17 papers, indicates that indeed there is a wide but scattered interest in personal credit rating research across various countries (such as Indonesia, Portugal, Poland, Azerbaijan, Thailand, etc.). It also means that though some have concentrated research efforts in this area, there is broad recognition globally of the importance of credit systems. Therefore, this graph may be considered an indicative factor of the immense role that personal credit rating models have begun to play in fostering economic development and financial stability around the world.

5. Conclusion

This systematic review has synthesized the current state of research on data and techniques applied in consumer credit rating models. It follows from this that traditional statistical methods and sophisticated machine learning methods are both part of the most important camp for the accurate assessment of creditworthiness. There is evidence of an emphatic shift toward more sophisticated methodologies, including neural networks and ensemble methods, which help with predictive accuracy and model stability. Besides, analytics of widely used categories of data demonstrate that credit history and financial information retain the top position in assessing consumer credit risk. In contrast, new data sources-social media activity and digital pattern behavior-started to take the lead in defining credit score models. This diversification of sources testifies to the further evolution of credit rating systems as a response to the growing complexity of consumer profiles. The relationship between modeling techniques and data types carries significant implications for both model performance and regulatory compliance. While advanced machine learning methods can extract complex patterns from alternative data sources, they pose interpretability challenges that conflict with regulatory requirements for transparency and fairness. Future research must address this fundamental tension by developing methods that maintain high predictive accuracy while ensuring explainability and compliance with regulations such as GDPR and Basel III.

Furthermore, the future research direction should be related to investigating the underrepresented areas, among which are integrated alternative data sources and the ethical use of data in credit scoring. Hence, this could help the researchers supplement the existing gap by making the practice of credit assessment more inclusive and nondiscriminatory for both clients and financial institutions.

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