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Article

Transforming credit risk assessment: A systematic review of AI and machine learning applications

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Abstract: Credit risk assessment is one of the most important aspects of financial decision-making processes. This study presents a systematic review of the literature on the application of Artificial Intelligence (AI) and Machine Learning (ML) techniques in credit risk assessment, offering insights into methodologies, outcomes, and prevalent analysis techniques. Covering studies from diverse regions and countries, the review focuses on AI/ML-based credit risk assessment from consumer and corporate perspectives. Employing the PRISMA framework, Antecedents, Decisions, and Outcomes (ADO) framework and stringent inclusion criteria, the review analyses geographic focus, methodologies, results, and analytical techniques. It examines a wide array of datasets and approaches, from traditional statistical methods to advanced AI/ML and deep learning techniques, emphasizing their impact on improving lending practices and ensuring fairness for borrowers. The discussion section critically evaluates the contributions and limitations of existing research papers, providing novel insights and comprehensive coverage. This review highlights the international scope of research in this field, with contributions from various countries providing diverse perspectives. This systematic review enhances understanding of the evolving landscape of credit risk assessment and offers valuable insights into the application, challenges, and opportunities of AI and ML in this critical financial domain. By comparing findings with existing survey papers, this review identifies novel insights and contributions, making it a valuable resource for researchers, practitioners, and policymakers in the financial industry.

Keywords: artificial intelligence; machine learning; credit risk assessment; credit default prediction; peer-to-peer lending
JEL Classification: C45; C55; C61; G17; G21; G32

1. Introduction

Credit risk assessment, a crucial part of financial institutions' operations, has received significant attention in recent years, owing to advancements in AI and ML technologies. This literature review provides an overview of AI and ML approaches to credit risk assessment, highlighting key studies and developments in the field. Advancements in AI and ML techniques have transformed the finance industry, credit risk assessment in particular, by offering more accurate predictions, improved efficiency, and enhanced decision-making capabilities (Boguslauskas et al., 2011; Çallı and Coşkun, 2021; Chen et al., 2016).

This literature review is organized into sections that discuss the specific themes and methodologies emerging from the reviewed references. It examines the key findings, methodologies, and contributions of these studies, shedding light on the evolving landscape of credit risk assessment and its integration into AI and ML technologies. Bastos and Matos (2022) used XGBoost and decision trees to provide insights into risk assessment. Bastos (2022) found that boosted decision trees outperformed other models. Bitetto et al. (2023) used various PCA methods to measure financial soundness effectively. de Castro Vieira et al. (2019) found that advanced algorithms like Bagging, Boosting, and Random Forest effectively reduce default rate and credit losses in credit risk management. Feki et al. (2012) demonstrated that Gaussian Bayes models, as well as multiclass SVM, significantly improve prediction performance with a limited number of variables, simplifying risk assessment for financial institutions.

Guo et al. (2020) applied ML methods to investigate the correlation between abnormal returns as well as default risk. The results show that abnormal returns significantly trigger default risk, shedding light on the dynamics of financial markets and credit risk assessment. The CART model performed best in assessing credit risk. This model focuses on evaluating the effectiveness of a BP neural network-based algorithm and logistic regression in reducing investor risk. The BP neural network-based algorithm outperformed logistic regression, highlighting the potential of advanced neural network algorithms for risk assessment.

Among the many approaches applied in the field of credit risk assessment, gaps remain in the synthesis of these methods into a unified framework. Many of the research has focused on single methodologies such as statistical, machine learning (ML), or deep learning techniques independently, often overlooking the advantages of integrated models. Bhattacharya et al. (2023) demonstrate the predictive strength of ML over traditional statistical models, suggesting that combining the interpretability of statistical methods with the advanced predictive capabilities of ML could yield a more robust assessment framework. Similarly, studies highlight the need for optimized feature selection and algorithmic combinations, as effective credit risk prediction depends on the identification of key features and the fine-tuning of algorithms, with recent works by Bellotti et al. (2021) emphasizing this need. These findings suggest that an integrated approach could enhance both the accuracy and reliability of credit risk models by capitalizing on the strengths of diverse methodologies, thereby creating a holistic assessment framework that addresses the complex nature of credit risk.

Furthermore, credit risk models must address the interpretability and adaptability challenges posed by deep learning, which, while effective, often function as “black boxes” (Fitzpatrick and Mues, 2021; Li, 2022). Financial institutions, which rely on transparent models for compliance and user trust, require interpretability in these high-stakes models. Moreover, credit risk frameworks often lack the adaptability to dynamic market conditions, underscoring the need for models that incorporate real-time data and adjust to economic fluctuations. Ethical considerations also remain underexplored, as AI and ML applications could inadvertently perpetuate bias if not carefully designed (Nazareth and Ramana, 2023). This research addresses these concerns by focusing on interpretable deep learning approaches that include real-time adaptability, while also prioritizing fairness and algorithmic accountability to ensure the ethical application of credit risk models, supporting informed and equitable financial decision-making.

This systematic review explores the literature on AI and ML applications for credit risk assessment. It provides an overview of the methodologies, datasets, and approaches used in recent research. By categorizing and evaluating these techniques, this review examines the current landscape of credit risk assessment from both consumer and corporate perspectives. Credit risk assessment is crucial for lending decisions, financial stability, and the overall health of the financial industry. Traditional methods often rely on historical data and statistical models; however, AI and ML have revolutionized how financial institutions evaluate and manage credit risk. These advanced techniques offer improved accuracy, efficiency, and adaptability in creditworthiness assessments. The references in this review cover various subtopics in credit risk assessment, such as P2P lending, default prediction, the explainability of ML models, feature selection, and different algorithms. By exploring these references, we aim to provide insights into the methodologies, techniques, and opportunities for credit risk assessment using AI and ML. The Antecedents, Decisions, and Outcomes (ADO) framework offers a structured lens through which this literature may be analysed, elucidating the inputs, processes, and outputs involved in credit risk assessment.

Moving forward, the research questions framed within the ADO framework serve as guiding inquiries to explore the key aspects of the reviewed literature and deepen the understanding of AI and ML approaches in credit risk assessment.

RQ1. Which countries or regions were the primary subjects of the reviewed studies on AI and ML for credit risk assessment?

RQ2. What methods were used in the reviewed studies on AI and ML approaches to credit risk assessment?

RQ3. What were the findings of the reviewed studies on AI and ML approaches to credit risk assessment?

RQ4. What were the dominant analysis techniques employed in the reviewed papers on AI and ML approaches to credit risk assessment?

RQ1 focuses on the Antecedents by investigating the geographic scope of the reviewed studies, identifying the primary regions where AI and ML-based credit risk assessment research has been concentrated. RQ2 delves into the Decisions aspect by examining the methods utilized in the reviewed studies, elucidating the analytical techniques and modeling approaches employed for credit risk assessment. RQ3 addresses the Outcomes by seeking to understand the results and findings of the reviewed studies, including performance metrics, predictive accuracies, and comparative analyses of different AI and ML approaches. Finally, RQ4 explores the dominant analysis techniques within the Decisions component, identifying the primary algorithms, methodologies, and modeling techniques commonly used in credit risk assessment research. Through this systematic exploration, the ADO framework facilitates a comprehensive examination of the evolving landscape of AI and ML approaches in credit risk assessment, providing valuable insights for both researchers and practitioners in the field.

The importance of credit risk assessment is extremely significant. It has a direct impact on lending decisions, financial stability, and the overall health of the financial industry. Traditional methods rely on historical data and statistical modelling.

However, the emergence of AI and ML has caused a shift in the evaluation and management of credit risks. These advanced techniques offer better accuracy, efficiency, and adaptability in creditworthiness assessments.

This review includes references covering various subtopics in credit risk assessment, such as P2P lending, default prediction, explainability of ML models, feature selection, and application of different algorithms. By examining these references, we aim to provide insights into the latest methodologies, techniques, and connections in the field of credit risk assessment, using AI and ML.

2. Literature review

The field of credit risk assessment has experienced a notable surge in research activity, especially with the advancements in data processing methods. These methods encompass a wide range of techniques, including systematic literature review methods, applied statistical and econometrics methods, AI/ML techniques, and deep learning approaches. Each category offers distinct insights and methodologies to address the complexities of credit risk assessment. Systematic literature review methods, as demonstrated by studies like (Ahmed et al., 2022) and Ariza-Garzón et al. (2021) play a crucial role in identifying research trends and gaps in AI/ML applications within finance and credit risk assessment, providing valuable insights for further exploration.

Statistical and econometrics methods have long been the cornerstone of credit risk assessment, encompassing regression analysis, ARCH/GARCH models, and meta-analysis. While studies such as those conducted by Bhattacharya et al. (2023) have highlighted the efficacy of machine learning techniques over traditional statistical methods, there remains an unexplored territory in integrating these methods with emerging technologies to enhance predictive power and accuracy.

AI/ML techniques offer promising approaches for credit risk assessment, with algorithms like logistic regression, random forest, and neural networks being widely employed. Despite the demonstrated effectiveness of these techniques in predicting credit defaults and assessing borrower risk profiles, there exists a research gap in understanding the optimal combination of features and algorithms to achieve the highest predictive performance. Bellotti et al. (2021) have contributed to this understanding; yet more research is needed to fully leverage the potential of AI/ML techniques in credit risk assessment.

Deep learning techniques, including CNNs and RNNs, have emerged as powerful tools for credit risk modelling, capable of capturing complex patterns and improving prediction accuracy. However, there is a need for further research into the interpretability and explainability of deep learning models in credit risk assessment. While studies by Fitzpatrick and Mues (2021) and Li (2022) have explored the potential of deep learning, the robustness of these models to changing market dynamics remains an open question.

The research gap lies in synthesizing these diverse methodologies to develop holistic and robust credit risk models. Future research should focus on integrating systematic literature review methods, applied statistical/econometrics methods, AI/ML techniques, and deep learning approaches to develop comprehensive credit risk assessment frameworks. Additionally, addressing the interpretability challenges associated with advanced machine learning and deep learning models is crucial to enhance trust and transparency in credit risk assessment decisions.

Moreover, there is a need for developing dynamic credit risk models that can adapt to evolving market conditions and regulatory requirements, incorporating real-time data streams and feedback mechanisms. Finally, examining the ethical implications of AI/ML applications in credit risk assessment, including fairness, bias mitigation, and algorithmic accountability, is essential to ensure responsible and ethical use of these technologies in the financial industry. By addressing these research gaps, researchers can contribute to the development of more accurate, transparent, and ethical credit risk assessment frameworks, supporting informed decision-making in the financial sector.

3. Survey approaches

3.1. Methodology

This study used the PRISMA Reporting Items for Systematic Reviews and Meta-Analyses methods. The survey method involved reviewing academic papers and articles within a specific timeframe to extract relevant information on AI and ML in credit risk assessment. This methodology ensured a comprehensive analysis, including diverse studies. The survey method for this literature review involved a systematic search of academic papers on credit risk assessment using the AI and ML approaches.

3.2. Keywords search

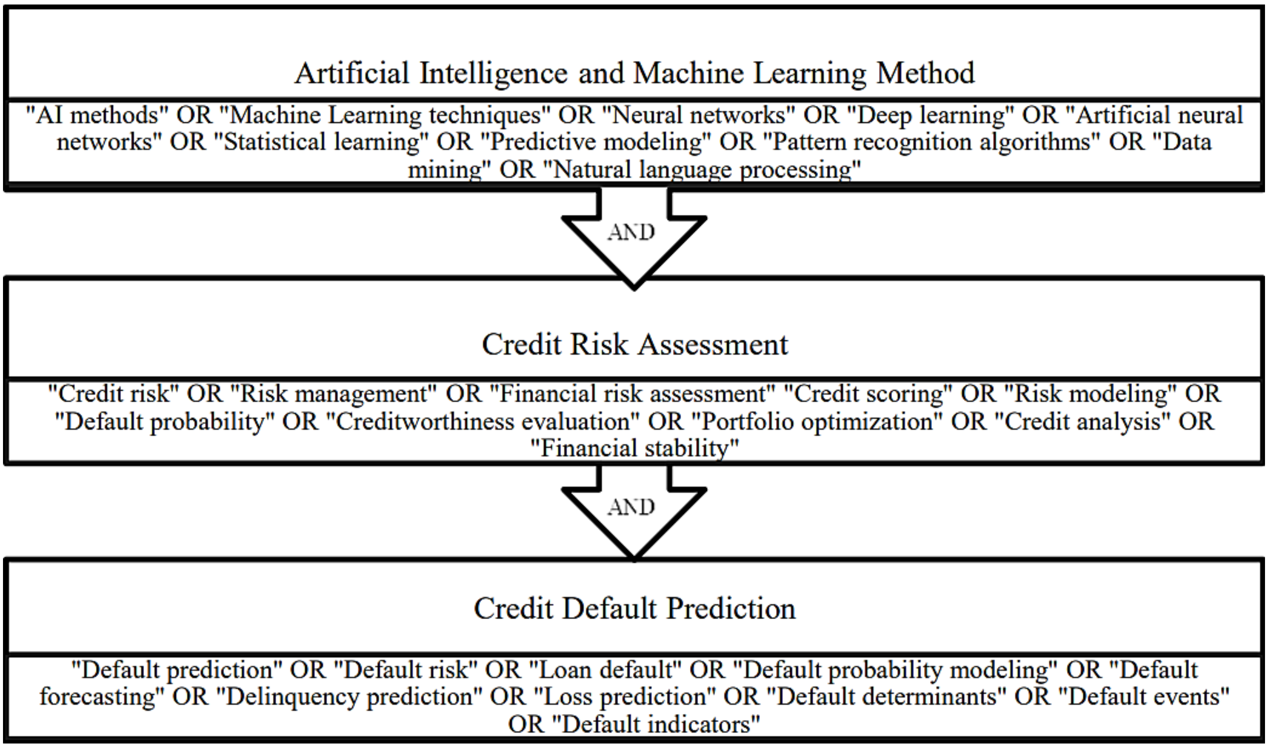

Figure 1. Database search terms using Scopus and Web of Science advanced search criteria.

3.3. Inclusion and exclusion criteria

Specific inclusion and exclusion criteria were used to ensure the quality and relevance of articles included in the review. The inclusion criteria focused on articles on credit risk assessment, machine learning, artificial intelligence, or related topics. Peer-reviewed journal articles, conference papers, and scholarly publications were also considered. The exclusion criteria were used to eliminate articles that did not meet the research focus, such as those not addressing credit risk assessment, papers that were not peer-reviewed or published in reputable sources and articles that did not use machine learning or AI methods.

3.4. Classification framework

A framework is presented to categorize articles based on their focus on consumer or corporate credit risk. Table 1 presents the PICOS framework, which supports the analysis of the literature. The literature review identified common approaches and methodologies for applying AI and ML to credit risk assessment. The taxonomy and categorization of computing approaches provides a synopsis of the techniques used for credit risk assessment with artificial intelligence and machine learning.

Table 1. PICOS framework of the literature survey.

Criteria	Inclusion	Exclusion
Population	• Borrowers involved in P2P lending platforms. • Lenders involved in P2P lending platforms. • Credit risk assessors involved in P2P lending platforms.	Individuals or institutions not directly involved in P2P lending platforms.
Intervention/ Exposure	• Machine learning methods are used to assess credit risk on P2P lending platforms. • Utilizing big data.	Methods that do not involve machine learning or big data.
Comparator/ Context	• Evaluating machine learning methods versus traditional credit risk assessment approaches. • Comparing different machine learning algorithms.	Studies not involving direct comparisons or focused solely on traditional methods.
Outcome	• Improved accuracy in credit risk assessment. • Reduced default rates. • Enhanced decision-making capabilities for lenders.	Outcomes unrelated to credit risk or not influenced by machine learning techniques.
Study Characteristics	• A comparative analysis of machine learning methods. • Traditional approaches on real-world P2P lending data to assess their effectiveness.	Studies lacking real-world data or that do not involve comparative analysis.

Source: authors' compilation.

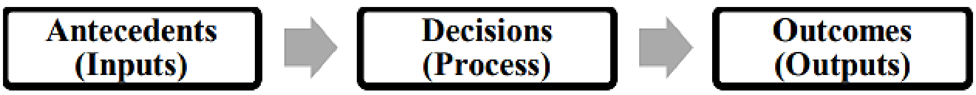

Figure 2. ADO Framework.

3.5. The datasets and methodologies of the examined publications

The datasets and approaches used in the reviewed articles were discussed in this survey. The characteristics of the datasets and techniques employed in the credit risk assessment were also examined in detail. Various datasets and approaches have been employed for credit risk assessment in the reviewed articles. These studies use a wide range of datasets, including financial data, credit histories, and borrower information. Some articles have focused on publicly available datasets, whereas others may have used proprietary or specialized data sources. The reviewed articles used different approaches for credit risk assessment. These include systematic literature review methods, applied statistical and econometric methods, AL/ML techniques, and deep learning methods. The choice of approach depended on the specific research question and characteristics of the dataset being analysed.

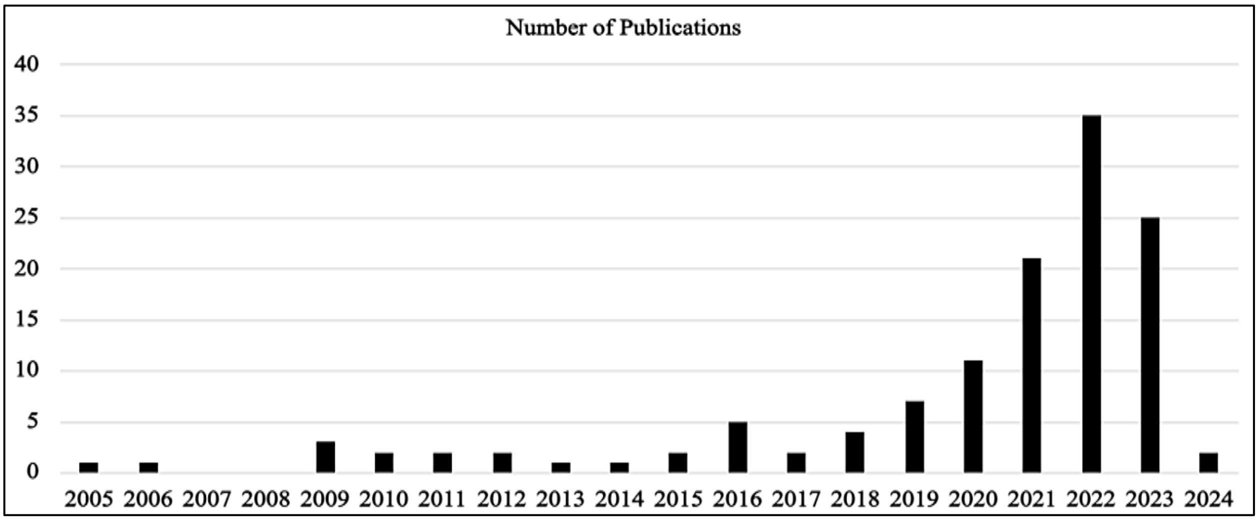

Figure 3. Time frame of publications for literature review.

Source: authors' compilation.

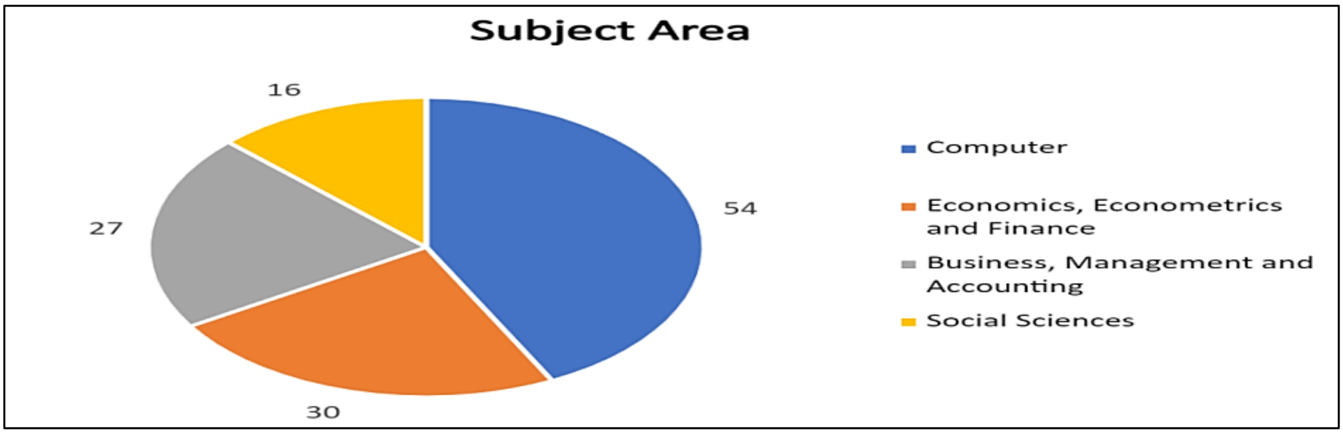

Figure 4. Subject area of the literature survey.

Source: authors' compilation.

Figure 4 highlights that the subject area, which includes Computer Science, Economics, Econometrics and Finance, Business, Management and Accounting, and Social Sciences, excludes a wide range of disciplines. These excluded disciplines include Decision Sciences, various branches of Engineering, Mathematics, Energy, Multidisciplinary Studies, Arts and Humanities, Psychology, Neuroscience, Genetics and Molecular Biology, as well as Agricultural and Biological Sciences.

Figure 5. Word Cloud of the selected literature review. Source: The authors used R programming with the bibliometrix package.

Figure 5 presents a word cloud emphasizing the improvement of lending practices through advanced technologies, including machine learning, artificial intelligence, and big data. These technologies can improve credit scoring models and evaluate borrower risks. The word cloud indicates a shift in lending practices and mentions the potential for borrowers to earn an interest on their loans. The fairness of advanced technologies in lending is an important consideration. The word cloud encompasses credit scoring, deep learning, machine learning, risk assessment, decision-making, decision trees, information classification, and healthcare. Key terms in the word cloud include artificial intelligence, machine learning, risk assessment, decision-making, and credit scoring. These terms suggest that AI/ML can be utilized to evaluate risk and make decisions in various fields. Other notable terms include deep learning, decision trees, information classification, and health care. These terms suggest that AI/ML can be employed to develop advanced algorithms for solving complex problems.

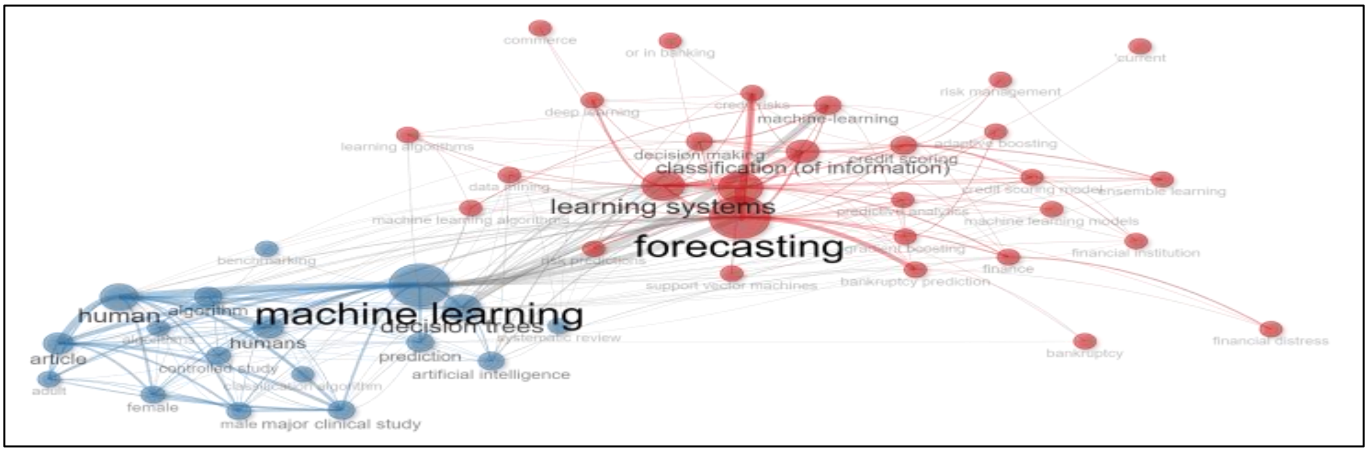

Figure 6. Co-occurrence Network of selected literature review.
Source: The authors used R programming with the bibliometrix package.

Figure 6 illustrates the co-occurrence network, highlighting the connections between concepts in learning systems and machine learning. The nodes represent concepts, and the edges represent relationships. The thickness of the edges indicated the relationship strength. The central nodes are "machine learning" and "forecasting," highlighting their significance. Other important concepts include "artificial intelligence," "models," "data," and "algorithms." The network also reveals strong relationships between machine learning and concepts such as "natural language processing," "computer vision," and "robotics." Machine learning is versatile and effective in solving problems. Significant relationships in the network include "forecasting" and "decision-making," "artificial intelligence" and "human-machine interaction," "models" and "data," and "algorithms" and "optimization." These relationships demonstrate how machine learning can be applied to problem-solving in various fields.

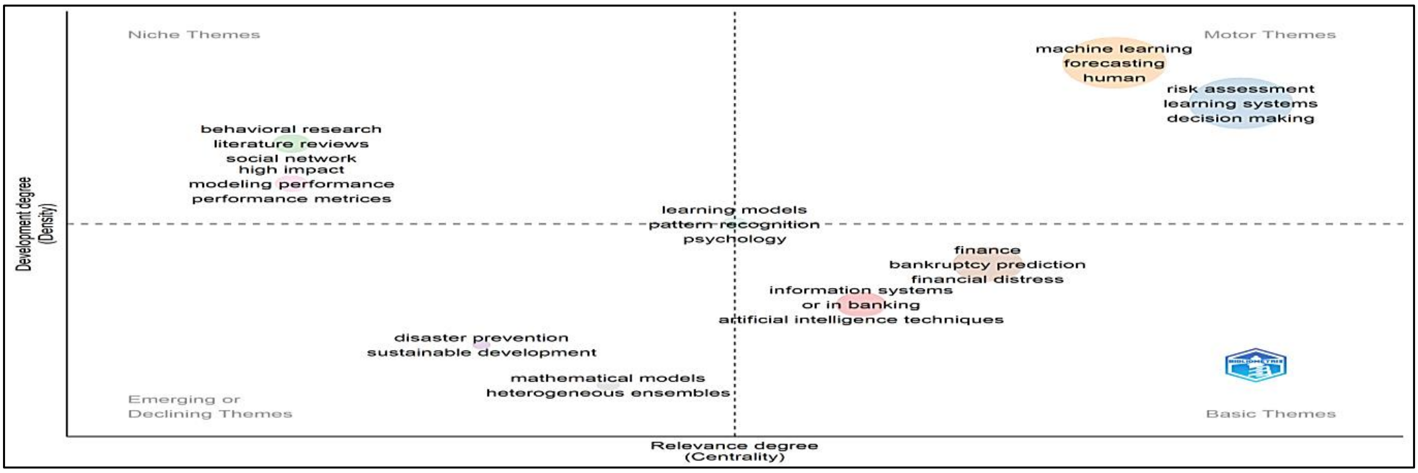

Figure 7. Thematic Map of selected literature reviews. Source: The authors used R programming with the bibliometrix package.

Figure 7 presents the thematic map, showcasing various interconnected topics in machine learning and artificial intelligence. These topics were divided into three categories: niche themes, core themes, and emerging or declining themes. The map also illustrates the relationships between different topics, serving as a valuable resource for gaining insight into the field. This can support the identification of new research areas or facilitate delving deeper into specific topics.

4. Data processing methods

The literature review reveals a diverse set of data-processing methods applied to credit risk assessment. These approaches can be broadly categorized into four groups.

4.1. Systematic literature review methods

The PRISMA model illustrates the process of selecting studies for a systematic review of the effects of exercise interventions on brain function during cognitive decline. This review included studies from various databases and registries. **Figure A1** shows in the appendix that, after removing duplicates and Q-ranked classification, the study considered only Q-1 ranked journals only, where 73 studies were considered eligible for review. Of these, 238 were excluded for various reasons such as wrong setting, indication, outcomes, intervention, study design, route of administration, and patient population. A total of 73 studies were included in this review. The flow diagram indicates common reasons for exclusion, such as incorrect study designs and outcomes. This suggests that only studies addressing the research questions and measuring relevant outcomes were included. The inclusion of 73 studies indicated a substantial body of research on the effects of exercise interventions on brain function in cognitive decline. This indicates that there is sufficient evidence to draw meaningful conclusions.

- Ahmed et al. (2022) used bibliometric and software analysis to study AI and ML applications in finance, noting an increasing trend in publications since 2015 with a focus on bankruptcy prediction, stock price prediction, and portfolio management. Ariza-Garzón et al. (2021) identified research trends and gaps in finance using bibliometric analysis and literature review. Boguslauskas et al. (2011) developed a credit risk assessment model using statistical analysis and logistic regression, evaluating reliability with Mahalanobis Distances. Çallı and Coşkun (2021) reviewed 12 studies with the PRISMA methodology to identify predictors for outcome variables, finding mixed results for several factors.
- Chen et al. (2016) emphasized the importance of incorporating intelligent methods in credit risk assessment. Ciampi et al. (2020) found that Kohonen map-based trajectories perform better in prediction models with payment behaviour-related variables. Corazza et al. (2021) found Elman networks had lower classification errors in credit risk assessment compared to classical neural networks and logistic regression. Djeundje and Crook (2022) developed models considering credit application characteristics and estimated additional losses in stress testing.
- Guo et al. (2021) created a credit assessment framework validated with P2P loan datasets, proposing a lender composition score for loan evaluations and comparing it with other variables using Prosper data. Khemakhem and Boujelbene (2018) used SMOTE, ANN, and decision trees to highlight the importance of relationship duration and ownership structures in corporate banking credit risk assessment. Nazareth and Ramana (2023) reviewed 126 articles following the PRISMA standard, concluding that machine learning models are successful in forex prediction. Ribeiro-Navarrete et al. (2022) used bibliometric techniques to identify significant articles on credit risk assessment, utilizing co-citation, bibliographic coupling, and keyword co-occurrence analyses. Shi et al. (2022) found deep learning models outperform traditional ML and statistical algorithms in credit risk estimation, with ensemble methods proving more accurate.

4.2. Applied statistical and econometrics methods

Some studies have leveraged statistical learning techniques to model credit risk. These methods include the mean, median, mode, correlation coefficient, ADF Test, regression, ARCH, GARCH, EGARCH, FIGARCH, and FIEGARCH models. The strengths and limitations of these traditional approaches have also been explored.

Bhattacharya et al. (2023) found that machine learning techniques outperformed traditional statistical methods in credit risk analysis, with ensemble classifiers showing high accuracy and reliability. Kočenda and Iwasaki (2022) used meta-analysis and Bayesian model averaging to study CAMELS variables' impact on bank survival, finding minimal influence from these and other factors on bank stability. Kolte et al. (2023) analysed market volatility in industrialized and developing economies using AI, ML, and econometrics, utilizing a GARCH framework to reveal volatility dynamics in the EU.

Statistical learning approaches encompass traditional statistical methods and techniques used for credit risk assessment. These methods often involve regression analysis, logistic regression, and other statistical modelling techniques to examine the connections between various predictor variables and credit default outcomes.

4.3. AI/ML techniques

A significant portion of the reviewed articles employed various AI/ML algorithms, such as logistic regression, random forest, decision trees, gradient boosting, support vector machines, and k-nearest neighbours. The effectiveness of these methods in credit risk prediction is discussed and their relative advantages are assessed.

Ariza-Garzon et al. (2020) found XGBoost to be the most efficient among DT, RF, XGBoost, and LR for financial analysis. Assous (2022) used CHAID models and found capital ratios influential in cost efficiency for Saudi banks. Härdle et al. (2009) compared SSVM and logistic analysis in credit risk assessment, while Hughes et al. (2022) used stochastic frontier estimation to identify credit risk as the main driver of higher non-performing loan ratios at large banks. Jiang et al. (2021) introduced the U-MIDAS-Logit-GL model, which outperformed others in credit risk assessment. Kaposty et al. (2020) found RF most effective for LGD forecasting. Kellner et al. (2022) used Quantile Regression Neural Network for improved quantile forecasts. Kim and Sohn (2010) found SVM superior in accuracy for SMEs.

Korangi et al. (2023) used a multimodal approach for credit risk assessment, highlighting the importance of different data channels. Kou et al. (2014) found RF to outperform traditional classifiers like LR in credit scoring. Li et al. (2006) demonstrated SVM and fusion models' effectiveness for loan evaluation and accuracy improvement. Lin (2009) identified significant variables for bank distress and borrower default prediction using logistic regression and random forest. Yang et al. (2022) developed the MLP-ESM model for high prediction accuracy. Ma et al. (2021) created a successful CR assessment system for P2P lending borrowers using neural networks. Munkhdalai et al. (2019) showed high prediction accuracy in credit risk assessment using Light GBM and feature selection techniques.

Ribeiro et al. (2012) highlighted the potential of neural networks and innovative approaches in credit risk assessment. Sigrist and Leuenberger (2023) demonstrated the efficacy of machine learning methods in credit risk assessment using linear hazard models and DNN. Song et al. (2023) and Sousa et al. (2016) presented novel credit rating strategies and highlighted the superiority of dynamic modelling. Sun et al. (2023) improved prediction performance using feature selection and Shapley values. Valluri et al. (2022) emphasized non-traditional variables and class imbalance in classification tasks using Random Forest. Wang et al. (2021) explored sentiment analysis and PCA correlation, showing their potential in predicting platform collapse and ensuring reliable data analysis.

Woo and Sohn (2022) proposed a credit scoring model using job categories and MBTI types. Xia et al. (2021) showed the effectiveness of AHP-LSTM and HSE models for credit risk prediction. Yang et al. (2023) improved credit risk prediction with the HDNN algorithm. Yıldırım et al. (2021) used various ML methods, including LR and CNN, for default risk prediction. Zhang and Yu (2024) and Zhang et al. (2023) introduced frameworks for comprehensive credit risk assessment using adaptive feature cross-compression. Zhu et al. (2023) evaluated different classifiers and integrated ML with logistic regression, contributing valuable insights to credit risk assessment.

4.4. Deep learning techniques

Deep learning has made neural networks important for credit risk assessment. This section explores how neural networks, such as CNNs and RNNs, are used in credit risk modelling.

Fitzpatrick and Mues (2021) explore various linear and non-linear methods, as well as ensemble methods, for credit risk prediction. They present the findings using tables and graphs and analyse the differences among the methods. Li et al. (2022) introduce a fusion algorithm combining DAE and LSTM networks for credit risk prediction. The algorithm outperforms GRNN along with LSTM models, indicating its potential.

Kristóf and Virág (2022) investigate machine learning methods, particularly a C5.0 decision tree model along with deep learning NN, for predicting bank failure risk. They find that ML methods are suitable and identify key predictors. Lin et al. (2022) propose a penalized DL model for default risk prediction. The SAFE-DNN, as well as Cox-DAC models, outperform the Nnet-survival-L1 model, indicating the importance of feature selection in improving deep learning model performance.

Liu et al. (2021) introduce the DeepSeIMF model, a DL model based on incremental matrix factorization technology, for personalized investment recommendation services. The authors evaluate the model's performance using metrics such as HR and NDCG. These metrics indicate the model's ability to provide accurate investment recommendations tailored to individual investors. The authors demonstrate the effectiveness of the DeepSeIMF model in delivering personalized investment recommendations through a comprehensive evaluation.

Deep learning techniques were the most advanced and complex methods reviewed. They included neural networks such as feed forward, recurrent, and convolutional. These approaches were used for feature extraction, pattern recognition, and complex credit risk modelling.

5. Discussions

This section provides in-depth discussions of the existing studies related to credit risk assessment using machine learning techniques. It also includes summary tables that highlight the key findings and methodologies of the reviewed papers.

The literature review provides a comprehensive overview of the diverse set of data processing methods applied to credit risk assessment, categorized into four main groups: systematic literature review methods, applied statistical and econometrics methods, AI/ML techniques, and deep learning techniques. These methods have been instrumental in advancing the field of credit risk assessment, offering various approaches to model credit default probability, enhance predictive accuracy, and improve decision-making processes in financial institutions.

RQ1 focuses on the Antecedents aspect, aiming to identify the primary regions where AI and ML-based credit risk assessment research have been concentrated. The literature review reveals that research in this area is conducted globally, with studies from various countries and regions contributing to the advancement of credit risk assessment methodologies.

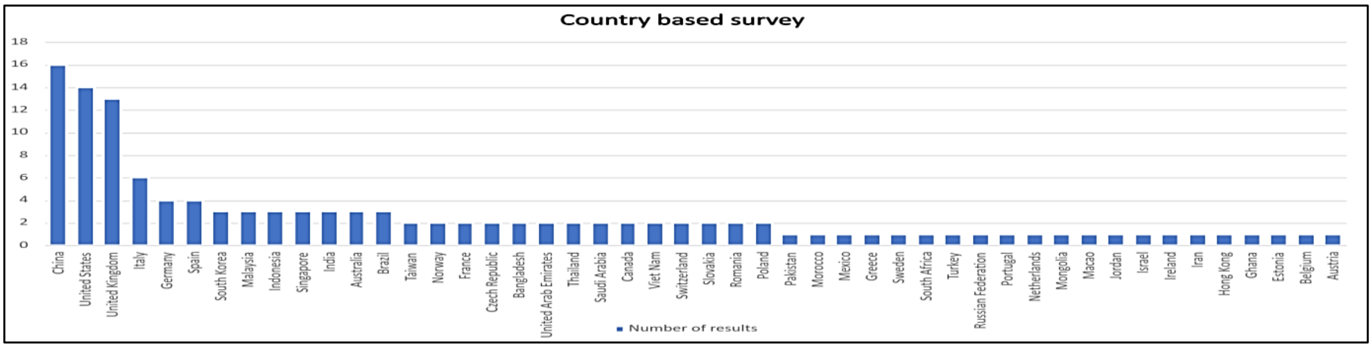

Figure 8. Countries included of the literature survey.

Source: authors' compilation.

RQ1 focuses on the geographic scope of the studies included in the review and seeks to identify the areas where AI and ML based credit risk assessment research has been concentrated. Previous research has been conducted in various countries. Countries such as the United States, China, the United Kingdom, and European Union member states feature prominently in the reviewed literature.

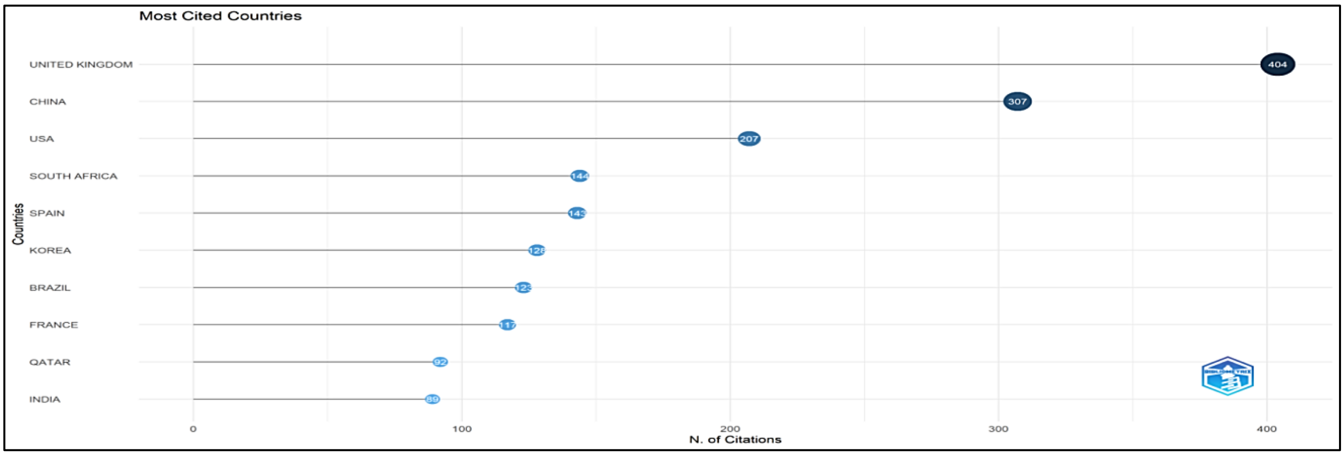

Figure 9. Most Cited Countries included of the literature survey.

Source: The authors used R programming with the bibliometrix package.

This indicates a widespread interest and engagement in utilizing AI and ML techniques for credit risk assessment across different geographical locations.

In RQ2, the Decisions aspect is explored by examining the methods used in the reviewed studies. The literature reveals a wide range of analytical techniques and modelling approaches employed for credit risk assessment. These include traditional statistical methods such as regression analysis, logistic regression, and econometric models, as well as advanced AI and ML techniques such as decision trees, random forests, support vector machines, and neural networks. The diversity of methods reflects the complexity of credit risk assessment and the need for tailored approaches to capture the nuances of credit default prediction.

RQ3 addresses the Outcomes aspect by seeking to understand the results and findings of the reviewed studies. The literature review demonstrates that AI and ML-based approaches to credit risk assessment have yielded promising outcomes, including improved predictive accuracy, enhanced decision-making capabilities, and better risk management practices.

Table 2. Methodologies and results of the machine learning based on the reviewed papers.

Authors	Methods used	Outcomes
Bellotti et al. (2021)	• Cubist, boosted trees, and random forests • MARS algorithm	• Cubist and boosted trees perform better than other regression methods. • Variables related to the bank recovery process enhance forecasting performances.
Chang et al. (2018)	• Collection and consolidation of data • XGBoost for model construction	• Credit risk assessment model constructed with XGBoost method • Improvement of loan business efficiency
Chen et al. (2011)	• Support Vector Machine (SVM) • Logistic and Discriminant Analysis (DA)	• SVM model outperforms logit model in predicting bankruptcy • Eight most important predictors related to bankruptcy identified
Yang F. et al. (2022)	• Blockchain for credit data storage • Automated machine learning pipeline for credit scoring model construction	• BACS method reduces time consumption compared to other methods. • BACS achieves significant advantage in credit scoring performance.
Feldman and Gross (2005)	• Classification and Regression Trees (CART) algorithm • Logistic regression classification	• Borrowers' features are stronger predictors of default. • Mortgage features are used if costs are equal.
Jiang et al. (2022)	• sinhTSA-MLP default identification model • Other existing methods for credit default identification	• Classification rate reaches 77.35% • Classification rate reaches 96.48%

Source: authors' compilation.

Studies have reported significant advancements in credit risk prediction models, with machine learning algorithms outperforming traditional statistical methods in many cases. These outcomes underscore the potential of AI and ML techniques to revolutionize credit risk assessment in the financial industry.

Finally, RQ4 explores the dominant analysis techniques within the Decisions component, identifying the primary algorithms, methodologies, and modelling techniques commonly used in credit risk assessment research. The literature review highlights the prevalence of machine learning algorithms such as random forests, gradient boosting, and neural networks in credit risk modelling. These techniques offer advantages in handling complex data structures, capturing nonlinear relationships, and improving predictive accuracy. Additionally, deep learning techniques, including convolutional and recurrent neural networks, have emerged as powerful tools for feature extraction and pattern recognition in credit risk assessment.

Table 3. ADO Framework of SLR.

Antecedents (Inputs)	Decisions (process)	Outcomes (Outputs)
Traditional Data: borrower demographics, credit history (Bhattacharya et al., 2023; Valluri et al., 2022)	Data Preprocessing: cleaning, feature engineering, scaling (Ahmed et al., 2022; Ariza-Garzón et al., 2021; Shi et al., 2022)	Credit Risk Score: borrower's likelihood of default (Giudici et al., 2024; Li et al., 2018; Shi et al., 2022)
Alternative Data: social media activity, digital footprint (Kristóf and Virág 2022; Woo and Sohn 2022)	Model Selection: choosing an appropriate machine learning algorithm (Babaei and Bamdad 2023; Li 2022; Robisco and Martínez 2022)	Risk Classification: categorizing borrowers into risk groups (Kruppa et al., 2013; Sousa et al., 2016)
Platform Data: loan characteristics, borrower behaviour (Chang et al., 2018; Sun et al., 2023;)	Model Training: training the model on historical data (Florez-Lopez and Ramon-Jeronimo 2015; Lin et al., 2022)	Improved Risk Management: informed decisions on loans (Bhattacharya et al., 2023; Fitzpatrick and Mues 2021)
	Model Tuning: optimizing the model's hyperparameters (Guo et al., 2021; Yang et al., 2023)	Increased Transparency: explaining credit risk assessments (Song et al., 2023; Sun et al., 2023; Twala 2010)
	Model Evaluation: assessing model performance using metrics (Lyócsa et al., 2022; Liu et al., 2023)	

Source: authors' compilation.

The literature review provides valuable insights into the methodologies, techniques, and outcomes of AI and ML approaches to credit risk assessment. By examining the Antecedents, Decisions, and Outcomes framework, this discussion sheds light on the geographic scope of research, the diversity of methods used, the effectiveness of AI and ML techniques, and the dominant analysis techniques employed in credit risk assessment studies. These findings contribute to a deeper understanding of the evolving landscape of credit risk assessment and the integration of AI and ML technologies in financial decision-making processes.

This review's limitations include a focus on peer-reviewed academic sources, potentially overlooking relevant industry practices and proprietary data. The evolving nature of AI/ML technologies means that newer techniques and datasets may offer improved performance, which this review may not fully capture. Future research could explore the integration of explainable AI models and ethical considerations in credit risk assessment to enhance transparency and fairness in financial decision-making. Future research could delve deeper into the ethical implications of AI-driven credit scoring, explore the potential biases inherent in these models, and investigate how these technologies can be leveraged to promote financial inclusion.

6. Conclusions

This systematic and longitudinal review examines AI and ML approaches in credit risk assessment and credit default prediction, offering a detailed understanding of the evolving financial industry landscape. The advancements in AI and ML technologies, coupled with the increased availability of data, have revolutionized credit risk assessment by enhancing accuracy, efficiency, and adaptability in evaluating creditworthiness. This review highlights the international scope of research in this field, with contributions from various countries providing diverse perspectives.

Adhering to the PRISMA guidelines, the review employs a systematic literature review approach to rigorously examine academic papers, focusing on AI and ML techniques. The diverse range of datasets and analytical methods used in different studies underscores the flexibility and versatility of AI and ML in credit risk assessment. Key aspects such as model evaluation, feature engineering, data quality, and interpretability are emphasized for improving the accuracy and reliability of credit risk assessment models. By comparing findings with existing survey papers, this review identifies novel insights and contributions, making it a valuable resource for researchers, practitioners, and policymakers in the financial industry.

Studies on credit risk and machine learning in the context of Peer-to-Peer (P2P) lending often revolve around developing advanced models for assessing creditworthiness, particularly in the absence of traditional financial institution frameworks. Researchers typically explore statistical and machine learning models to predict borrower default risks, improving the accuracy and efficiency of credit scoring systems. With the growing volume of borrower data, there is a strong emphasis on machine learning techniques such as deep learning, neural networks, and ensemble methods, which enhance the adaptability and predictive power of these models.

The future of credit risk modeling in P2P lending will likely be shaped by a few key trends. First, there is a growing demand for machine learning models that are not only accurate but also transparent and interpretable. With increasing regulatory pressure and a push for explainability in AI-driven credit scoring, researchers will focus on making models more accessible to regulators and consumers alike. Another area of interest is the integration of credit risk models with principles of Regenerative Finance (ReFi), which may involve assessing borrowers based on their environmental and social behaviors, aligning financial decisions with sustainability goals. Additionally, enhancing the resilience and robustness of credit models will become a priority, ensuring that these systems can adapt to changing borrower behaviors or external market shocks. Finally, as AI-driven lending continues to impact financial inclusion, addressing the ethical and social consequences of these technologies, including fairness and bias reduction, will be central to future research in the field.

Future research should focus on developing more interpretable models, exploring advanced deep learning techniques, and integrating alternative data sources for credit risk assessment. Cross-disciplinary collaboration, involving experts in finance, data science, computer science, ethics, psychology, and behavioural economics, can lead to comprehensive solutions. Addressing equity and ethical considerations is crucial, with research needed to create equitable, transparent AI models and develop tools for detecting and mitigating bias.

Efforts should also enhance data quality and security measures, with privacy-preserving AI and federated learning research being valuable. Advancements in AI and ML models for real-time risk appraisal can revolutionize lending, with personalized credit scoring models improving risk assessments and financial inclusion. The integration of blockchain technology can enhance data security and streamline the lending process. Research should explore AI and ML's compliance with financial regulations and conduct longitudinal studies on their impact on credit risk appraisal.

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Appendix

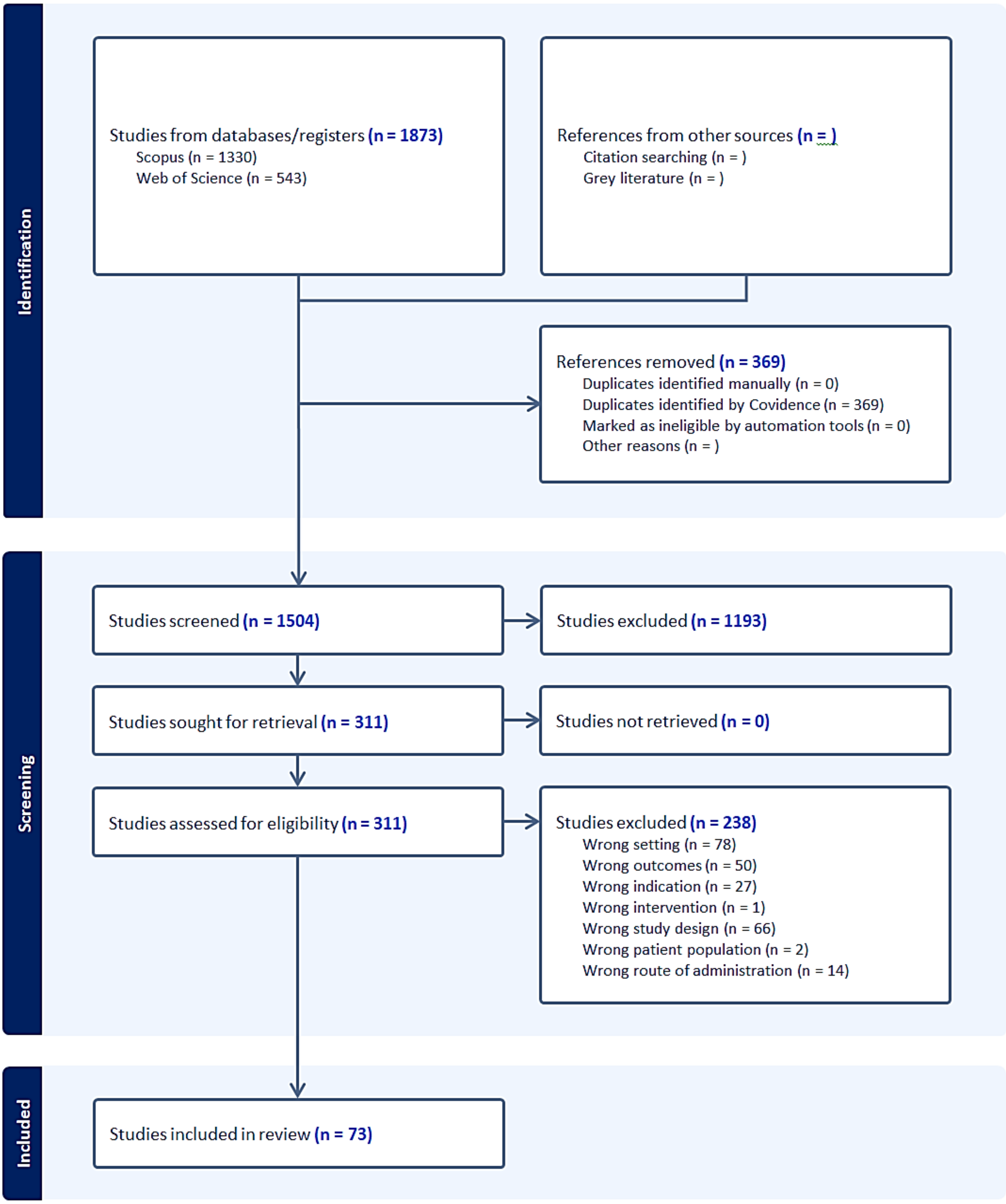

Figure A1. PRISMA model of the literature survey.

Source: authors' compilation (Website used: https://app.covidence.org/reviews/363707).

Table A1. Journal rank.

Journal	Q-rank 2023	ABDC rank	ABS rank
Annals of Operations Research	Q1	A	3
Applied Soft Computing Journal	Q1		
Artificial Intelligence Review	Q1		
Complexity	Q1		
Computational Intelligence and Neuroscience	Q1		
Data Science and Management	Q1		
Electronic Commerce Research and Applications	Q1	C	2
European Journal of Operational Research	Q1	A*	4
Expert Systems with Applications	Q1	C	
Finance Research Letters	Q1	A	2
Financial Innovation	Q1		
Forecasting	Q1		
IEEE Access	Q1		
Information Sciences	Q1		
Intelligent Systems with Applications	Q1		
International Journal of Forecasting	Q1	A	3
International Journal of Forecasting	Q1	A	3
International Review of Financial Analysis	Q1	A	3
International Transactions in Operational Research	Q1	B	
Journal of Banking and Finance	Q1		3
Journal of Economic Surveys	Q1	A	2
Journal of Forecasting	Q1	A	2
Journal of Global Information Management	Q1	A	2
Journal of Marketing Analytics	Q1	C	
Journal of Real Estate Finance and Economics	Q1	A	3
Journal of the Operational Research Society	Q1	A	3
Journal of Visual Communication and Image Representation	Q1		
Multimedia Tools and Applications	Q1		
Neural computing and applications	Q1		
PLoS ONE	Q1		
Quantitative finance	Q1	A	3
Research in international business and finance	Q1	B	2
Resources policy	Q1	B	2
Review of accounting and finance	Q1	B	2
Review of managerial science	Q1		2
SAGE open	Q1		
Small business economics	Q1	A	3
Statistics and computing	Q1	A	
Sustainability (Switzerland)	Q1		
Technological and economic development of economy	Q1		
Technological forecasting and social change	Q1	A	3

Source: author' compilation.