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Artificial Intelligence Credit Scoring in Bank Financing: A Systematic Literature Review

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Abstract. Advances in Artificial Intelligence (AI) have transformed the banking sector, particularly credit scoring systems, by improving the accuracy of credit risk assessment and the efficiency of financing decisions. However, AI implementation also presents challenges related to transparency, algorithmic bias, data protection, and governance. This study aims to analyze the development of Artificial Intelligence Credit Scoring in banking financing using a Systematic Literature Review (SLR) approach. The study follows the PRISMA 2020 guidelines and analyzes 30 scientific articles published between 2020 and 2025. The findings indicate that Random Forest is the most widely used algorithm, followed by XGBoost, Support Vector Machine (SVM), and Artificial Neural Network (ANN)/Deep Learning. The dominance of ensemble-based algorithms reflects the growing use of models capable of processing complex data patterns and improving credit risk prediction. Despite their potential to enhance operational efficiency and financing decisions, AI-based credit scoring systems face challenges involving the limited transparency of black-box models, algorithmic bias, personal data protection, and the need for comprehensive AI governance. As a conceptual contribution, this study proposes the Integrated Artificial Intelligence Credit Scoring Framework (IAICSF), which integrates the Data Foundation, AI Analytical Layer, Decision Layer, and Governance and Ethical Layer. In Islamic finance, the framework incorporates maqashid al-sharia, justice (‘adl), and customer rights protection as normative principles. The findings emphasize that successful AI credit scoring implementation depends not only on algorithmic accuracy but also on transparency, accountability, fairness, and effective governance.

Keywords: Artificial Intelligence; Banking; Credit Scoring; Machine Learning; Systematic Literature Review.

1. INTRODUCTION

Digital transformation has driven the use of Artificial Intelligence (AI) in various banking functions, including risk analysis, fraud detection, process automation, and data-driven decision-making. One rapidly growing application of AI is Artificial Intelligence Credit Scoring (AI Credit Scoring), which involves the use of Artificial Intelligence and Machine Learning algorithms to support faster, more adaptive, and data-driven credit risk assessments and financing decisions.

AI Credit Scoring is an evolution of credit scoring systems that utilizes Machine Learning algorithms to identify risk patterns based on the characteristics and data of prospective borrowers. Unlike conventional approaches, which tend to use a more limited set of variables and rules, AI enables the processing of large amounts of data and the identification of more complex relationships. Dastile et al. (2020) demonstrate that the Machine Learning approach has the potential to improve the quality of credit risk predictions compared to a number of conventional statistical approaches.

Lending is one of the primary functions of banking that carries an inherent risk in the form of potential default. Therefore, the quality of feasibility analysis and risk assessment of

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prospective borrowers is a critical factor in maintaining the quality of the lending portfolio. In this context, the development of AI credit scoring becomes relevant because it offers the ability to process data and identify risk patterns in a more adaptive manner. Raihan et al. (2024) demonstrate that the application of Artificial Intelligence in Islamic banking can improve operational efficiency and service quality, as well as help minimize management risk. In Islamic financing, financing decisions are also based on the characteristics and considerations of prospective customers (Sitorus et al., 2024).

In the banking financing process, AI Credit Scoring functions as a decision-support mechanism that translates the characteristics and data of prospective borrowers into risk level estimates. The results of this modeling can be used as input in credit risk assessment and the financing decision-making process. Thus, AI Credit Scoring is not only related to the generation of credit scores but also to decision quality, process efficiency, and risk management. Findings by Nasution et al. (2024) also indicate that the use of AI can improve service quality by enhancing responsiveness and user satisfaction.

Developments in AI credit scoring indicate a shift from the use of simple statistical models toward the application of various machine learning algorithms, such as Random Forest, XGBoost, Support Vector Machines, and Artificial Neural Networks. However, these developments not only present opportunities to improve predictive performance but also raise issues regarding interpretability, potential algorithmic bias, personal data protection, and objective and consistent AI governance compared to manual assessments. Advances in digital financial technology also indicate that the use of technology is playing an increasingly important role in supporting digital-based economic activities and financial services (Najib et al., 2025). These advancements are also driving the growth of Sharia-compliant fintech, which integrates Sharia principles with digital technology and presents new opportunities and challenges for the financial industry and regulators (Syahputra et al., 2023).

In Indonesia, the digital transformation of the banking sector continues to evolve as financial institutions increasingly adopt digital technologies. The Financial Services Authority (OJK) is promoting the development of Innovative Credit Scoring that leverages Artificial Intelligence, Machine Learning, and Big Data Analytics to improve the quality of credit risk analysis while expanding access to financing for the public. This innovation is considered crucial given that credit inclusion rates in Indonesia remain relatively low compared to financial account ownership rates. Therefore, AI Credit Scoring is viewed as a strategic solution to support the expansion of more inclusive and sustainable access to financing.

Although research on Artificial Intelligence in the financial sector is growing rapidly, there are still several research gaps. First, methodologically, most studies focus on comparing algorithm performance and improving the accuracy of credit risk predictions, while syntheses that link technical dimensions to decision-making processes and governance remain limited. Second, theoretically, research on Machine Learning, Explainable AI, fairness, and AI Governance is still largely fragmented. Third, contextually, the integration of AI Credit Scoring with the characteristics of Islamic banking financing and the principles of maqashid syariah has not yet been extensively developed. Fourth, from a practical perspective, improvements in algorithm accuracy have not always been translated into an implementation framework that links data quality, credit scoring, credit risk assessment, loan decisions, consumer protection, and AI governance. Based on these gaps, this study aims to conduct a systematic synthesis of developments in AI credit scoring while formulating the Integrated Artificial Intelligence Credit Scoring Framework (IAICSF) as an integrative conceptual framework.

Research on AI credit scoring has advanced rapidly in recent years. Most studies have focused on developing machine learning algorithms, improving the accuracy of credit risk predictions, utilizing alternative data, and developing Explainable Artificial Intelligence models to enhance system transparency. However, there are still several research gaps that require further attention.

Based on these gaps, this study aims to conduct a Systematic Literature Review (SLR) on the implementation of Artificial Intelligence Credit Scoring in banking finance. Unlike previous studies, which tended to focus on technical aspects and algorithm performance, this study integrates various findings related to the implementation of AI Credit Scoring, the algorithms used, benefits, challenges, and governance implications through a systematic literature synthesis. In addition, this study produces the Integrated Artificial Intelligence Credit Scoring Framework (IAICSF) as a conceptual contribution that integrates aspects of data, AI algorithms, credit risk assessment, explainable AI, responsible AI, fair lending, and AI governance in the implementation of AI credit scoring in the banking sector.

2. RESEARCH METHOD

Research Design

This study employs a Systematic Literature Review (SLR) approach to identify, evaluate, and synthesize research findings regarding the implementation of Artificial Intelligence Credit Scoring in banking finance. The SLR method was chosen because it enables a systematic, transparent, and replicable synthesis of the literature through structured stages of searching, selecting, evaluating, and analyzing scientific articles. Unlike traditional literature reviews, which tend to be narrative in nature, the SLR applies stricter procedures in the literature identification and selection process, thereby minimizing researcher bias and enhancing the validity of the synthesis results.

The research was conducted in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA 2020) guidelines developed by Page et al. (2021). These guidelines served as a reference throughout the process of identifying, screening, assessing eligibility, and selecting the articles to be analyzed. By using PRISMA, the research process becomes more systematic and transparent, making it easier for other researchers to replicate the study's steps.

Research Question (RQ)

This study is structured around a Research Question (RQ) designed to guide the systematic process of literature search, selection, and synthesis. The RQ was formulated to ensure that the selected articles are truly relevant to the study's objectives, namely to identify the implementation of Artificial Intelligence Credit Scoring in banking finance, the challenges faced, and the direction of its future development. Based on these research objectives, the Research Question used is as follows.

Table 1. Research Question.

Code	Research Question
RQ1	How is Artificial Intelligence Credit Scoring implemented in banking financing based on research findings from 2020–2025?
RQ2	Which Artificial Intelligence algorithms are most widely used in credit scoring systems in the banking sector?
RQ3	What are the benefits and challenges of implementing Artificial Intelligence Credit Scoring in the banking sector?
RQ4	What development agenda and implementation framework for Artificial Intelligence Credit Scoring can be formulated based on the results of the literature review?

Literature Review Strategy

The literature review was conducted using several reputable international scientific databases specializing in publications in the fields of technology, finance, and banking. The literature search was conducted using a combination of databases and scientific platforms relevant to the fields of technology, finance, and banking, including Scopus, ScienceDirect, SpringerLink, IEEE Xplore, Wiley Online Library, Taylor & Francis Online, and Google Scholar as a supplementary source. Multiple sources were used to broaden the scope of literature identification and minimize potential search bias.

The search strategy employed a combination of keywords structured using Boolean operators (AND, OR, and the wildcard symbol *) to ensure a broad yet precise coverage of articles. Keywords were grouped into three main pillars: (1) AI Technologies (Artificial Intelligence, Machine Learning, Deep Learning, Explainable AI, XAI), (2) Financial Domain (Credit Scoring, Credit Risk Assessment, Loan Approval, Automated Lending, Alternative Data, Fair Lending), and (3) Industry Context (Banking, Bank, Financial Institution, Islamic Banking). Details of the literature search strategy are presented in Table 2.

Table 2. Literature Search Strategy.

Aspect	Description
Database	Scopus, ScienceDirect, SpringerLink, IEEE Xplore, Wiley Online Library, Taylor & Francis Online, Google Scholar
Year Range	2020–2025
Language	English and Indonesian
Document Type	Peer-reviewed scientific journal articles (research articles and systematic/review articles) directly relevant to AI Credit Scoring, Credit Risk Assessment, or Loan Approval in the banking and finance sectors
Keywords	Artificial Intelligence, Machine Learning, Deep Learning, Explainable AI, Credit Scoring, Credit Risk Assessment, Loan Approval, Alternative Data, Banking, Islamic Banking
Boolean Search	(“Artificial Intelligence” OR “AI” OR “Machine Learning” OR “Deep Learning” OR “Explainable AI” OR “XAI”) AND (“Credit Scoring” OR “Credit Risk Assessment” OR “Loan Approval” OR “Automated Lending” OR “Alternative Data”) AND (“Bank*” OR ‘Banking’ OR “Financial Institution*” OR “Islamic Banking”)

Inclusion and Exclusion Criteria

To obtain relevant and scientifically sound literature, the article selection process is conducted based on predetermined inclusion and exclusion criteria. These criteria are established to ensure that the analyzed articles are relevant to the research topic, meet adequate publication quality standards, and provide information that supports the literature synthesis process.

The document type criteria are limited to scientific journal articles that have undergone a peer-review process. This restriction is implemented to maintain consistency in the quality of evidence and enhance the reliability of the literature synthesis. The details of the inclusion and exclusion criteria in this study are presented in Table 3.

Table 3. Inclusion and Exclusion Criteria.

Criteria	Inclusion	Exclusions
Year of Publication	Articles published between 2020 and 2025	Articles published before 2020 or after 2025
Language	English and Indonesian	Languages other than English and Indonesian
Document Type	Peer-reviewed scientific journal articles in the form of research articles or review articles	Books, undergraduate theses, master’s theses, doctoral dissertations, non-peer-reviewed research reports, and popular/opinion articles
Research Topic	Directly addressing the application of Artificial Intelligence or Machine Learning in credit scoring, credit risk assessment,	Articles that only discuss Artificial Intelligence in general, AI Governance in general, Explainable AI in general, Islamic Finance in general, or digital banking

	loan approval, automated lending, or the use of alternative data for risk assessment in the banking sector and financial institutions.	without a direct connection to credit scoring, credit risk assessment, or financing decisions.
Article Availability	Articles are available in full text and can be accessed via	Articles for which only the abstract is available or that are inaccessible/behind a paywall
Database	Scopus, ScienceDirect, SpringerLink, IEEE Xplore, Wiley Online Library, Taylor & Francis Online, and Google Scholar	Duplicate articles or those from sources whose authenticity cannot be verified

Literature Selection Process Based on PRISMA 2020

The literature selection process in this study followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA 2020) guidelines developed by Page et al. (2021). The PRISMA guidelines were used to ensure that the processes of identification, screening, eligibility assessment, and inclusion of articles were conducted systematically, transparently, and in a replicable manner.

The literature selection process consisted of four main stages (identification, screening, eligibility, and inclusion), with the following details regarding the number of articles and the reasons for exclusion:

Identification: An initial search of scientific databases using a Boolean search strategy yielded a total of 412 records (Scopus = 95, ScienceDirect = 88, SpringerLink = 74, IEEE Xplore = 43, Wiley = 39, Taylor & Francis = 28, Google Scholar = 45). After checking for duplicates (duplicate removal), 52 duplicate articles were excluded, leaving 360 articles.

Screening: A total of 360 articles were screened based on their titles, abstracts, and keywords. At this stage, 275 articles were excluded because they were not relevant to the topic of credit scoring, did not focus on the banking/financial sector, or were not empirical research or review articles.

Eligibility: Of the 85 articles for which full text was sought, 10 were not fully accessible (reports not retrieved). Subsequently, 75 full-text articles were evaluated in depth based on inclusion and exclusion criteria. A total of 45 articles were excluded for specific reasons: they did not focus on AI/ML techniques (n = 18), did not discuss credit risk analysis (n = 15), had insufficient data or outcomes (n = 8), and were not in English or Indonesian (n = 4).

Included: The final stage yielded a number of core studies that met all eligibility criteria and were used as the basis for the empirical synthesis. Supporting literature on XAI, AI governance, fairness, and Islamic economics perspectives was used separately to enrich the interpretation and development of the framework.

The flow of article allocation and selection from the initial stage to the final included articles is presented in detail in Figure 1 using the PRISMA 2020 flowchart.

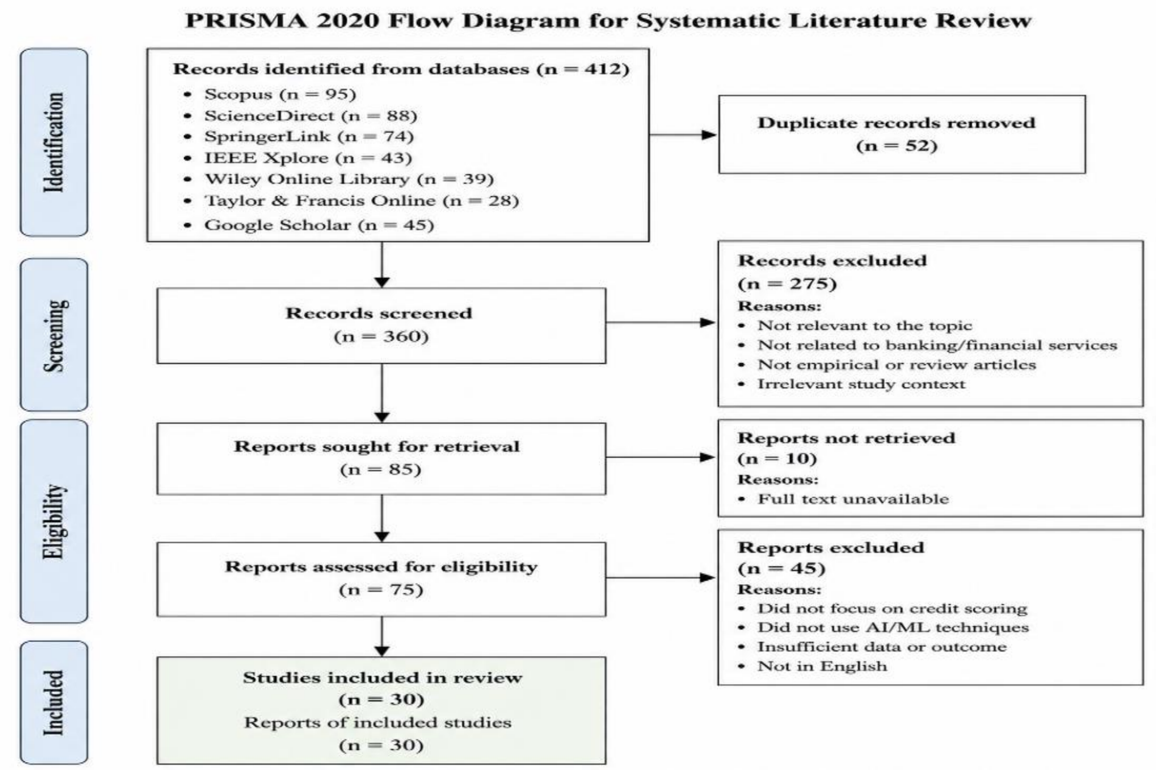

Figure 1. Flowchart of Literature Selection Based on PRISMA 2020.

Based on the selection process using the PRISMA 2020 guidelines, 412 articles were identified from various scientific databases. After removing duplicate articles and conducting a screening process based on titles, abstracts, and full-text reviews, the articles that passed the selection were used as core studies in the main synthesis. Supporting literature discussing XAI, AI governance, fairness, and Islamic economic perspectives was categorized as supporting literature and was not used to calculate algorithm frequency.

Quality Assessment

To ensure that the articles used in this study possess adequate methodological quality and are scientifically sound, a Quality Assessment (QA) was conducted on all 30 articles that met the inclusion criteria. This stage aimed to evaluate the methodological quality, research relevance, and completeness of the information presented in each article so that the literature synthesis process would be based on high-quality sources.

The quality assessment process followed the Systematic Literature Review guidelines developed by Kitchenham and Charters (2007), with adjustments made to account for the characteristics of research on Artificial Intelligence Credit Scoring in the banking sector. Each article is evaluated using five main indicators (QA1–QA5) based on a measurable qualitative scoring scale: Yes (2), Partially (1), and No (0). The assessment criteria rubric is presented in Table 4.

Tabel 4. Quality Assessment Criteria.

Code	Indikator Penilaian	Yes (Score 2)	Partial (Score 1)	No (Score 0)
QA1	Clarity of Research Objectives	Explicit and specific research objectives	Objectives are described in general terms	Objective not explained
QA2	Appropriateness of Methodology	Methods described in a logical and transparent manner	Methods are described briefly/with limited detail	Method not explained
QA3	Relevance of the Topic	The research focuses directly on AI credit scoring, credit risk assessment, or loan decision-making in the financial/banking sector.	Discusses AI/credit implicitly	Irrelevant to the context
QA4	Clarity of the Topic	Research findings are presented clearly and supported by data	Results are presented in a less in-depth manner	Results unclear/no data provided
QA5	Reputation of the Publication	Peer-reviewed journal articles published in verifiable scientific sources.	Verified national journal/preprint server	Source not verified

Source: Adapted from Kitchenham and Charters (2007).

The assessment was conducted independently for all criteria across the 30 articles analyzed to ensure the transparency and reproducibility of the study. The total score from these five indicators was then used to determine the quality level of the articles, which were categorized into three levels: High (score 8–10), Moderate (score 5–7), and Low (score 0–4). The breakdown of individual scores per article from QA1 to QA5 is presented in Table 5.

Table 5. Breakdown of Article Quality Assessment Scores.

No.	Author & Year	QA1	QA2	QA3	QA4	QA5	Total Score	Category
1.	Dastille, Celik, & Potsane (2020)	2	2	2	2	2	10	High
2.	Bussmann, Giudici, Marinelli, & Papenbrock (2021)	2	2	2	2	2	10	High
3.	Dastile & Celik (2021)	2	2	2	2	2	10	High
4.	Bücker, Szepannek, Gosiewska, & Biecek (2022)	2	2	2	2	1	9	High
5.	Diaconescu & Neagoe (2020)	2	2	2	2	2	10	High
6.	Ayari, Guetari, & Kraïem (2025)	2	2	2	2	2	10	High
7.	Bussmann, Giudici, Marinelli, & Papenbrock (2020)	2	2	2	2	2	10	High
8.	Kozodoi, Jacob, & Lessmann (2022)	2	2	2	2	2	10	High
9.	Assef & Steiner (2020)	2	1	2	1	1	7	Medium
10.	Demajo, Vella, & Dingli (2020)	2	2	2	2	1	9	High

11.	Torrent, Visani, & Bagli (2020)	2	1	2	1	1	7	Medium
12.	Vilone & Longo (2020)	2	2	2	2	1	9	High
13.	Bi & Bao (2024)	2	2	2	2	1	9	High
14.	Rida (2024)	2	1	2	1	1	7	Medium
15.	Roy & Vasa (2025)	2	2	2	2	2	10	High
16.	Azwar, Usman, & Abdullah (2025)	2	2	2	2	2	10	High
17.	Iqbal et al. (2025)	2	2	2	2	2	10	High
18.	Hamadou, Yumna, Hamadou, & Jallow (2024)	2	2	2	2	2	10	High
19.	Chen, Giudici, Liu, & Raffinetti (2024)	2	2	2	2	2	10	High
20.	Sain & Adinugraha (2025)	2	2	2	2	1	9	High
21.	Marzuki (2025)	2	1	2	1	1	7	Medium
22.	Gerling & Lessmann (2024)	2	2	2	2	2	10	High
23.	Batool, Zowghi, & Bano (2025)	2	2	2	2	2	10	High
24.	Chethan, Munilakshmi, & Ramesh (2024)	2	1	2	2	1	8	High
25.	Gomes, Neves, & Correia (2024)	2	2	2	2	2	10	High
26.	Ahmed & Iqbal (2025)	2	1	2	1	1	7	Medium
27.	Khemakhem & Boujelbene (2023)	2	2	2	2	2	10	High
28.	Bhattarai et al. (2024)	2	2	2	2	2	10	High
29.	Bhatore, Mohan, & Reddy (2020)	2	2	2	2	2	10	High
30.	De Cnudde et al. (2020)	2	1	2	1	1	7	Medium

Source: Data analysis and researcher assessment (2026).

Based on the evaluation results in Table 5, most articles demonstrated very good methodological quality. According to the evaluation, 24 articles fell into the high-quality category, while 6 articles fell into the moderate-quality category. Articles in the high-quality category were used as the primary sources in the synthesis, while those in the moderate-quality category were used selectively based on topic relevance and the completeness of the required information. A summary of the distribution of article quality is presented in Table 6.

Table 6. Summary of Quality Assessment Categories.

Category Score	**Score Range**	**Number of Articles**	**Percentage**	**Decision**
High	8-10	24	80%	Approved for Synthesis
Medium	5-7	6	20%	Approved with Conditions
Low	0-4	0	0%	Issued
Total		30	100%	

Source: Researcher's data analysis (2026)

Articles Meeting the Inclusion Criteria

Based on the literature selection process using the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA 2020) guidelines, a total of 30 articles were identified that met all inclusion criteria and were used as the primary sources in this study. These articles were published between 2020 and 2025 and were sourced from various reputable scientific databases, namely Scopus, ScienceDirect, SpringerLink, IEEE Xplore, Wiley Online Library, Taylor & Francis Online, and Google Scholar as a supplementary source. All articles were selected because they were relevant to the implementation of Artificial Intelligence Credit Scoring in the banking sector, whether discussing the development of machine learning algorithms, credit risk assessment, loan approval, Explainable Artificial Intelligence (XAI), or the application of AI in financing decision-making.

General characteristics of the analyzed articles include information on the authors, year of publication, article title, database, and research focus. This information served as the basis for the literature synthesis process to identify research developments, the methods used, the benefits of implementing AI Credit Scoring, the challenges faced, and opportunities for future research. Summaries of the articles meeting the inclusion criteria are presented in Table 7.

Table 7. Core Studies Used in the Synthesis of Artificial Intelligence Credit Scoring.

No	Author & Year	Article Titles	Database / Journal	Key Focus Areas of the Methodology
1	Dastile, Celik, & Potsane (2020)	Statistical and Machine Learning Models in Credit Scoring: A Systematic Literature Survey	Applied Soft Computing / Scopus	Performance Evaluation of Machine Learning & Ensemble Methods vs. Conventional Statistical Methods
2	Bussmann, Giudici, Marinelli, & Papenbrock (2021)	Explainable Machine Learning in Credit Risk Management	Computational Economics / SpringerLink	Application of Explainable AI (XAI) in Credit Risk Modeling
3	Dastile & Celik (2021)	Making Deep Learning-Based Predictions for Credit Scoring Explainable	IEEE Access / IEEE	Development of Interpretability in Deep Learning Models for Credit Scoring
4	Bücker, Szepannek, Gosiewska, & Biecek (2022)	Transparency, Auditability, and Explainability of Machine Learning Models in Credit Scoring	Journal of the Operational Research Society / Taylor & Francis	Transparency and Auditability of Machine Learning Models in Credit Scoring
5	Diaconescu & Neagoe (2020)	Credit Scoring Using Deep Learning Driven by Optimization Algorithms	IEEE Xplore / IEEE	Optimization of Deep Learning Algorithms for Credit Scoring Prediction Accuracy

6	Ayari, Guetari, & Kraïem (2025)	Machine Learning-Powered Financial Credit Scoring: A Systematic Literature Review	Artificial Intelligence Review / SpringerLink	Performance Analysis of Random Forest, XGBoost, and Machine Learning Algorithms
7	Kozodoi, Jacob, & Lessmann (2022)	Fairness in Credit Scoring: Assessment, Implementation, and Profit Implications	European Journal of Operational Research / ScienceDirect	Fairness Testing and Bias Mitigation in Credit Scoring Algorithms
8	Roy & Vasa (2025)	Transforming Credit Risk Assessment: A Systematic Review of AI and Machine Learning Applications	Journal of Infrastructure, Policy and Development	The Transformation of AI/ML Applications in Banking Credit Risk Analysis
9	Chen, Giudici, Liu, & Raffinetti (2024)	Measuring Fairness in Credit Ratings	Journal of Financial Stability / ScienceDirect	Measuring Fairness and Bias in Credit Rating Modeling Algorithms
10	Marzuki (2025)	Algorithmic Bias Risks in AI-Based Credit Scoring at Islamic Banks	Maliki Interdisciplinary Journal / SINTA	Analysis of AI credit scoring algorithm bias in the context of Islamic banking
11	Ahmed & Iqbal (2025)	The Role of Artificial Intelligence in Enhancing Credit Risk Management: A Systematic Literature Review	Pakistan Journal of Humanities and Social Sciences	The role of AI in improving the effectiveness of banking credit risk management
12	Bhattarai et al. (2024)	Artificial Intelligence in Banking: Credit Scoring Applications	IEEE Xplore / IEEE	Applications of AI/ML algorithms for creditworthiness assessment decisions
13	Bhatore, Mohan, & Reddy (2020)	Machine Learning Techniques for Credit Risk Evaluation: A Systematic Literature Review	IEEE Access / IEEE	Mapping of machine learning techniques for credit risk evaluation
14	De Cnudde et al. (2020)	Credit Scoring Using Alternative Data: Opportunities and Challenges	Journal of the Operational Research Society	Use of alternative data for inclusive credit scoring modeling

The core studies used in this synthesis focus directly on the application of artificial intelligence and machine learning in credit scoring, credit risk assessment, alternative data, fairness, and financing decision-making. Meanwhile, literature on Explainable Artificial Intelligence, Responsible AI, AI Governance, and Islamic economics was used as supporting literature to deepen the interpretation of results and strengthen the development of the

Integrated Artificial Intelligence Credit Scoring Framework (IAICSF). The distinction between core studies and supporting literature was made to maintain the homogeneity of the units of analysis while allowing for a more comprehensive discussion of technical and governance aspects.

Table 8. Supporting Literature for Strengthening Interpretation and the Framework.

No	Author & Year	Article Titles	Database / Journal	Role in the Research
1	Bussmann et al. (2020)	Explainable AI in Fintech Risk Management	Frontiers in AI / Frontiers	Supporting Literature (XAI Framework in Risk Management)
2	Assef & Steiner (2020)	Ten-Year Evolution on Credit Risk Research: A Systematic Literature Review	Ingeniería e Investigación	Supporting Literature (Contextualization of Credit Risk Research Trends)
3	Demajo, Vella, & Dingli (2020)	Explainable AI for Interpretable Credit Scoring	CS & IT Conference Proceedings	Supporting Literature (Principles of XAI Model Interpretability)
4	Vilone & Longo (2020)	Explainable Artificial Intelligence: A Systematic Review	Information Fusion / ScienceDirect	Supporting Literature (Taxonomy & Concepts of Explainable AI)
5	Azwar, Usman, & Abdullah (2025)	Artificial intelligence and Islamic finance: A Scopus-based literature mapping	Journal of Islamic Law on Digital Economy	Supporting Literature (Mapping AI in the Islamic Finance Domain)
6	Iqbal et al. (2025)	AI in Islamic finance: Global trends, ethical implications, and bibliometric insights	Review of Islamic Social Finance	Supporting Literature (Ethical Implications of AI in Islamic Finance)
7	Hamadou et al. (2024)	Unleashing the Power of Artificial Intelligence in Islamic Banking	Modern Finance	Supporting Literature (Case Studies on AI Implementation in Islamic Banks)
8	Sain & Adinugraha (2025)	Artificial Intelligence and Islamic Finance: Enhancing Sharia Compliance	Journal of Business Management & Islamic Banking	Supporting Literature (Integration of AI with Sharia Compliance Principles)
9	Gerling & Lessmann (2024)	Artificial Intelligence in Banking: A Systematic Review	Management Review Quarterly / SpringerLink	Supporting Literature (General Landscape of AI Adoption in the Banking Sector)
10	Batool, Zowghi, & Bano (2025)	AI Governance: A Systematic Literature Review	AI and Ethics / SpringerLink	Supporting Literature (AI Governance Framework)
11	Chethan, Munilakshmi, & Ramesh (2024)	Role of Artificial Intelligence in Banking Sector	Educational Administration: Theory and Practice	Supporting Literature (Review of AI's Role in Bank Operations)
12	Gomes, Neves, & Correia (2024)	Explainable Artificial Intelligence (XAI) in Finance: A Systematic Review	SpringerLink	Supporting Literature (Application of XAI in the Financial Industry)
13	Khemakhem & Boujelbene (2023)	Artificial Intelligence Applications in Banking: A Review	Wiley Online Library	Supporting Literature (General Perspectives on AI Applications in Banking)

Data Analysis Techniques

The data obtained from 30 articles that met the inclusion criteria were analyzed using a structured thematic analysis technique based on the procedures outlined by Braun and Clarke (2006), with adjustments for a Systematic Literature Review (SLR). The analysis was conducted systematically through five methodological stages: (1) Open Coding, (2) Categorization, (3) Theme Development, (4) Cross-Study Synthesis, and (5) Framework Construction.

Open Coding: Researchers performed initial data extraction from each article by assigning codes (initial coding) to data variables, machine learning algorithms, credit risk assessment processes, loan approval, and ethical elements such as Explainable AI (XAI), algorithmic bias, governance, and Sharia principles.

Categorization: Initial codes sharing common concepts were grouped into specific categories, such as data quality, the efficiency of ensemble/deep learning algorithms, the limitations of black-box models, and regulatory compliance.

Theme Development: The data categories are organized into main themes that address the Research Questions (RQ1–RQ4), namely: (a) Implementation of AI Credit Scoring, (b) Frequency and Performance of AI Algorithms, (c) Strategic Benefits and Challenges, and (d) Research Agenda and Governance Implications.

Cross-Study Synthesis: Researchers conducted a cross-study analysis to identify consistency in findings, differences in algorithm performance, and research gaps in the literature.

Framework Construction: The results of the thematic synthesis were integrated into four main layers: the Data Foundation, the AI Analytical Layer, the Decision Layer, and the Governance and Ethical Layer. These four layers form the basis for the development of the Integrated Artificial Intelligence Credit Scoring Framework (IAICSF), with the principles of maqashid syariah serving as the normative orientation within the context of Islamic finance.

The coding process was conducted independently by the researchers involved in the study. Differences in interpretation or theme grouping were resolved through discussion until a consensus was reached on the final categories and themes. This procedure was used to enhance the consistency of the synthesis process and the accountability of the development of the IAICSF as a conceptual framework resulting from the integration of literature findings.

3. RESULTS AND DISCUSSION

Implementation of Artificial Intelligence Credit Scoring in Banking Financing

The implementation of Artificial Intelligence (AI) in credit scoring systems has become one of the key innovations in the digital transformation of the banking sector. Based on a synthesis of core studies, the implementation of Artificial Intelligence in credit scoring reflects a shift from the use of predictive models to estimate credit risk toward decision support systems that integrate data, algorithms, risk assessment, and financing decision-making processes. In general, the analyzed studies indicate that AI has the potential to enhance the ability to process complex data and support the efficiency of the risk assessment process, although model performance remains influenced by data characteristics, evaluation methods, and algorithm configurations.

The synthesis results show that Random Forest, XGBoost, Support Vector Machine (SVM), and Artificial Neural Network/Deep Learning are the most frequently appearing groups of algorithms in AI credit scoring research. However, frequency of use does not automatically indicate that an algorithm always produces the best performance, as modeling results are influenced by data characteristics, class imbalance, feature engineering, and model configuration.

However, improved accuracy is not enough if the AI system is not supported by transparency and accountability. Black-box AI models can make it difficult to explain the basis for decision-making to regulators and customers. Therefore, the implementation of Explainable Artificial Intelligence (XAI) is essential to improve model interpretability and strengthen trust in credit scoring systems. Bussmann et al. (2021), Dastile and Celik (2021), and Golec and AlabdulJalil (2025) emphasize that a good AI model must not only be accurate but also easy to understand and accountable.

In addition to transparency, various studies also highlight the importance of implementing Responsible AI, Fair Lending, and AI Governance to ensure that credit scoring systems do not produce discriminatory decisions and remain compliant with ethical principles and data protection regulations. Bahlool et al. (2025) emphasize the importance of balancing model performance, fairness, and the ability to explain prediction results, while Mathen and Paul (2025) stress the need for transparent and accountable AI governance. In the context of Islamic banking, Akbar et al. (2024) and Harisandi et al. (2023) explain that the use of technology must remain oriented toward the maqashid al-sharia, the principle of justice (‘adl), transparency, and the protection of customer rights.

Overall, the implementation of Artificial Intelligence Credit Scoring has significantly contributed to improving the accuracy, efficiency, and quality of credit assessments in the banking sector. However, its development must be integrated with the principles of Explainable AI, Responsible AI, and AI Governance, as well as Islamic economic values, so that the resulting system is not only technically superior but also transparent, fair, and sustainable.

Comparison of Artificial Intelligence Algorithms in Credit Scoring

A synthesis of 30 articles shows that various Artificial Intelligence (AI) algorithms have been applied in credit scoring systems to improve the accuracy of credit risk predictions. Each algorithm has different characteristics, strengths, and limitations; therefore, its selection must be tailored to the characteristics of the data and the needs of the financial institution. Dastile et al. (2020) explain that machine learning-based algorithms are better equipped to process complex data than conventional statistical methods. These findings are supported by Bhatore et al. (2020) and Roy and Vasa (2025), who demonstrate that advancements in AI have driven the adoption of more adaptive algorithms in the credit scoring process.

To answer Research Question 2 (RQ2) regarding the most widely used algorithms, a quantitative analysis was conducted on the 30 articles examined. As shown in Table 8, ensemble learning-based algorithms, particularly Random Forest (RF) and XGBoost, were the most widely used techniques. Random Forest was used in 14 articles (46.7%), while XGBoost was used in 12 articles (40.0%). Meanwhile, black-box algorithms based on Deep Learning and Artificial Neural Networks (ANN) were applied in 9 articles (30.0%).

Table 9. Frequency of AI/ML Algorithm Use in 30 SLR Articles.

No.	Algoritma AI / Machine Learning	Number of Articles (n = 30)	Percentage (%)	References in the Main Article
1.	Random Forest (RF)	14	46,7%	Dastile et al. (2020); Ayari et al. (2025); Bhattarai et al. (2024)
2.	XGBoost / Gradient Boosting	12	40,0%	Ayari et al. (2025); Roy & Vasa (2025); Bhatore et al. (2020)
3.	Support Vector Machine (SVM)	10	33,3%	Bhattarai et al. (2024); Dastile et al. (2020); Diaconescu & Neagoe (2020)
4.	Artificial Neural Network (ANN) / Deep Learning	9	30,0%	Diaconescu & Neagoe (2020); Dastile & Celik (2021); Roy & Vasa (2025)
5.	Logistic Regression (LR)	7	23,3%	Dastile et al. (2020); Bücker et al. (2022); Rida (2024)
6.	Decision Tree (DT)	5	16,7%	Bhatore et al. (2020); Ayari et al. (2025)

Source: Researcher's data analysis (2026)

Note: A single article may use more than one algorithm; therefore, the total frequency of algorithm use does not necessarily equal the number of core studies

Logistic Regression is still widely used as a baseline model because of its simple structure and ease of interpretation, although its ability to handle nonlinear data relationships is limited. Therefore, recent research has focused more on developing algorithms such as Random Forest, XGBoost, Support Vector Machine (SVM), and Artificial Neural Network (ANN). Dastile et al. (2020) explain that ensemble learning-based algorithms can improve prediction accuracy, while Diaconescu and Neagoe (2020) demonstrate that combining deep learning with optimization algorithms yields better model performance.

Based on their frequency of appearance in the analyzed studies, Random Forest and XGBoost are the most widely used algorithms in AI credit scoring research. Random Forest has the advantage of reducing overfitting and producing more stable predictions, while XGBoost offers a high level of accuracy through the boosting process (Ayari et al., 2025). Furthermore, Bhattarai et al. (2024) state that Support Vector Machines (SVMs) remain effective for classification tasks, while Roy and Vasa (2025) emphasize that Artificial Neural Networks (ANNs) and Deep Learning are capable of recognizing more complex data patterns, even though interpreting these models is relatively more difficult due to their "black box" nature.

Table 10. Comparison of Characteristics, Advantages, and Limitations of AI Algorithms in Credit Scoring.

Algorithm	Advantages	Limitations	Synthesis Findings
Logistic Regression	Easy to interpret, simple	Less effective for nonlinear relationships	Suitable as a baseline model
Decision Tree	Easy to understand	Prone to overfitting	Effective for simple classification
Random Forest	High accuracy, stable, reduces overfitting	Requires greater computational power	Among the most frequently used algorithms in the analyzed studies
XGBoost	Very high accuracy, efficient, capable of handling complex data	Requires parameter tuning	Demonstrates competitive performance across a number of studies, depending on data characteristics and model configuration
Support Vector Machine (SVM)	Good for classification and high-dimensional data	Less efficient with very large datasets	Suitable for medium-sized datasets
Artificial Neural Network (ANN)	Capable of recognizing complex patterns	Difficult to interpret	Used to handle complex data patterns, but presents interpretability challenges
Deep Learning	Very accurate on large datasets	Black-box in nature and computationally intensive	Holds great potential when combined with Explainable AI

As research evolves, the focus of algorithm development is no longer solely on improving accuracy, but also on aspects of Explainable Artificial Intelligence (XAI), fairness, and AI governance. Bussmann et al. (2021) and Golec and AlabdulJalil (2025) emphasize the importance of model transparency and interpretability so that prediction results can be understood and accounted for. Furthermore, Bahlool et al. (2025) and Mathen and Paul (2025) explain that striking a balance between accuracy, fairness, transparency, AI governance, and responsible AI is a key factor in supporting the implementation of accountable, ethical, and regulatory-compliant AI in the banking sector.

Framework for Implementing Artificial Intelligence Credit Scoring in Banking Financing

Based on a synthesis of the 30 articles analyzed, this study proposes a conceptual framework named the Integrated Artificial Intelligence Credit Scoring Framework (IAICSF). This framework is the result of integrating various research findings regarding the implementation of Artificial Intelligence (AI) in credit scoring systems within the banking sector. Dastile et al. (2020) explain that the implementation of AI in credit scoring requires structured stages ranging from data processing to the prediction process. In line with this, Roy and Vasa (2025) as well as Ayari et al. (2025) demonstrate that the integration of various Machine Learning algorithms is a key factor in enhancing the effectiveness of credit scoring systems.

The Integrated Artificial Intelligence Credit Scoring Framework (IAICSF) was developed based on a literature review, positioning the implementation of AI credit scoring as an integrated system consisting of four main layers. First, the Data Foundation, which encompasses data collection, data quality, alternative data, data preprocessing, feature engineering, and data protection. Second, the AI Analytical Layer, which encompasses algorithm selection, machine learning modeling, model validation, and performance evaluation. Third, the Decision Layer, which links modeling results to credit score generation, credit risk assessment, and financing decisions or loan approvals. Fourth, the Governance and Ethical Layer, which encompasses Explainable Artificial Intelligence, fairness, Responsible AI, accountability, and AI Governance as control mechanisms applied across all stages. In the context of Sharia-compliant financing, the implementation of the framework is guided by the principles of maqashid al-Sharia: justice (‘adl), public interest, protection of assets, and protection of customer rights.

The next step is the application of machine learning algorithms such as Random Forest, XGBoost, Support Vector Machine (SVM), Artificial Neural Network (ANN), and Deep

Learning to generate a credit score as the basis for credit risk assessment. Bhattarai et al. (2024) state that the use of AI algorithms can improve the accuracy of creditworthiness assessments, while Bussmann et al. (2021) emphasize that credit scoring results can support the loan approval process in a faster, more objective, and more consistent manner.

In addition to outlining the implementation workflow, the IAICSF also identifies Explainable Artificial Intelligence (XAI), Responsible AI, Fair Lending, and AI Governance as supporting components that must be implemented at every stage of the process. Bahlool et al. (2025) emphasize the importance of balancing accuracy, fairness, and transparency, while Mathen and Paul (2025) explain that the implementation of Responsible AI and AI Governance is necessary to ensure that AI systems operate transparently, accountably, and in compliance with regulations. Thus, the implementation of IAICSF is not only focused on improving prediction accuracy but also supports responsible and sustainable AI governance.

Unlike previous studies, which generally focused on a single aspect such as algorithm performance, explainability, fairness, or governance IAICSF integrates the relationships between data foundations, AI-based analytical processes, financing decision-making, and ethical and governance mechanisms into a single conceptual framework. Thus, the novelty of IAICSF lies not in the creation of new algorithms, but in the integration of dimensions that were previously studied in isolation into a more systematic framework for implementing AI credit scoring. A comparison of IAICSF's novelty with previous research frameworks is presented in Table 10.

Table 11. Conceptual Position of IAICSF in the Literature on Artificial Intelligence Credit Scoring.

Research/Studies	Data	ML	Credit Risk Assesment	Loan Decision	XAI	Fairness	AI Govennnace	Islamic Perspective
Dastile et al. (2020)	✓	✓	✓	-	-	-	-	-
Bussmann et al. (2021)	✓	✓	✓	✓	✓	-	-	-
Kozodoi et al. (2022)	✓	✓	✓	-	-	✓	-	-
Bucker et al. (2022)	✓	✓	✓	-	✓	-	✓	-
IAICSF	✓	✓	✓	✓	✓	✓	✓	✓

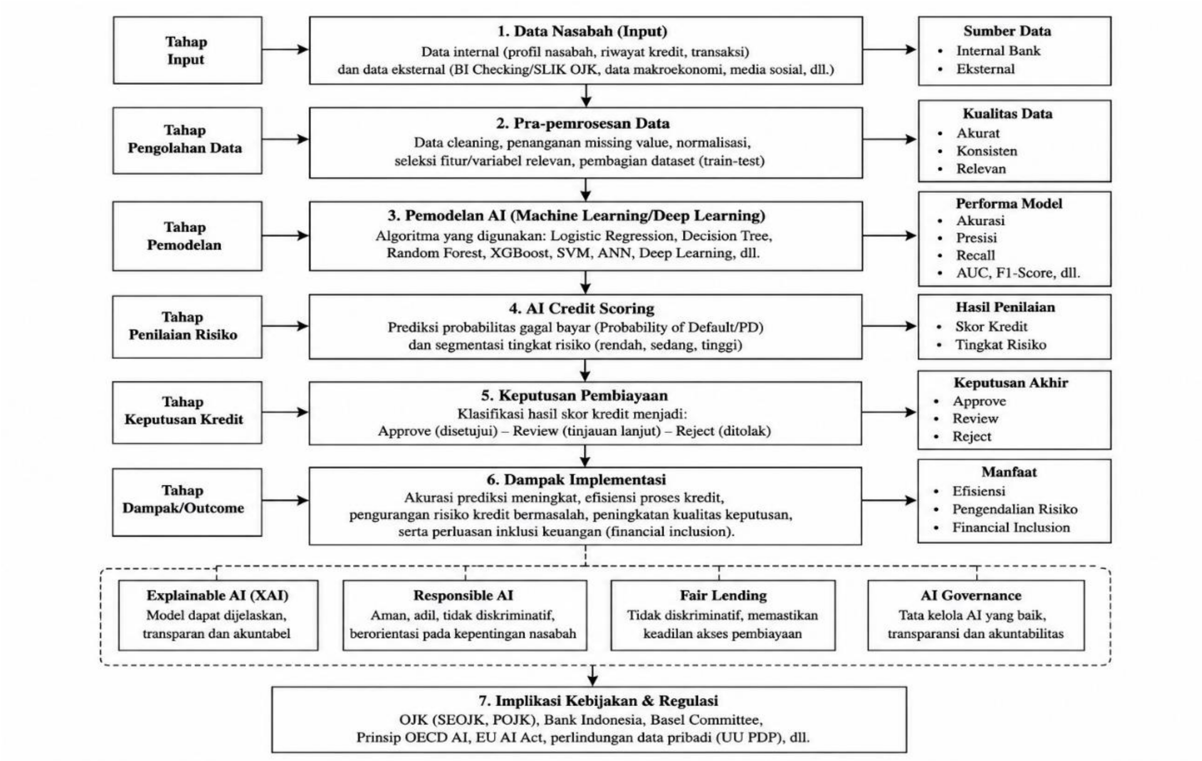

Figure 2. Integrated Artificial Intelligence Credit Scoring Framework (IAICSF).

Based on Figure 2, the Integrated Artificial Intelligence Credit Scoring Framework (IAICSF) illustrates the implementation workflow of AI Credit Scoring, beginning with the collection of prospective borrower data, followed by the data preprocessing stage, modeling using AI algorithms, credit score generation, and culminating in the credit risk assessment and loan approval processes. This framework demonstrates that the success of AI credit scoring is determined not only by model performance but also by the interconnection between data quality, model validity, the decision-making process, transparency, fairness, accountability, and governance. Therefore, IAICSF views AI credit scoring as a socio-technical system, not merely a matter of algorithm selection.

Challenges in Implementing Artificial Intelligence Credit Scoring in Banking Financing

To provide a comprehensive overview of the literature synthesis results related to Research Question 3 (RQ3), the findings regarding the main benefits and strategic challenges in implementing Artificial Intelligence Credit Scoring in the banking sector are summarized in a synthesis matrix. As presented in Table 11, the main benefits of AI focus on improving prediction accuracy, operational efficiency, and expanding financial inclusion, while the main challenges are dominated by issues of transparency (black box), algorithmic bias, personal data protection, and AI governance.

Table 12. Synthesis Matrix of Benefits and Challenges in the Implementation of AI Credit Scoring.

Categories	Key Dimensions	Number of Studies	Summary of Literature Findings
Benefits	Risk Prediction Accuracy	22 Studies	Improved Area Under the Curve (AUC) accuracy and default risk classification.
	Operational Efficiency	18 Studies	Automation of data analysis speeds up the loan approval process and reduces the costs of manual analysis.
	Financial Inclusion	12 Studies	The use of alternative data (e-commerce, e-wallets) opens up access to financing for unbanked customers.
Challenges	Interpretability (Black Box)	19 Studies	Difficulty in explaining the decision logic of complex algorithms to customers and regulators.
	Algorithmic Bias Risk	15 Studies	Potential discrimination against certain groups due to biased training data.
	Personal Data Protection	14 Studies	Challenges related to privacy, cybersecurity, and regulatory compliance (such as the Personal Data Protection Act).
	AI Governance	11 Studies	The lack of comprehensive algorithmic audit standards and a banking accountability framework.

Source: Synthesis and analysis by the researcher (2026)

Note: A single article may be categorized under more than one benefit or challenge, so the sum of frequencies across categories does not necessarily equal the total number of articles

Policy Implications

Table 13. Implications of Implementing AI Credit Scoring.

Stakeholders	Key Implications
Financial Regulators	Development of AI governance principles, algorithm audits, model transparency, and model risk management
Banks	Model validation, performance monitoring, Explainable AI, and control of algorithmic bias
Fintech Companies	Responsible AI, cybersecurity, alternative data quality, and consumer protection
Islamic Banks	Integration of fairness, maqashid syariah, protection of customer rights, and governance compliance
Data Managers	Personal data protection, consent, data security, and accountability for data use

Overall, the implementation of Artificial Intelligence Credit Scoring requires synergy among regulators, the banking industry, fintech companies, academics, and technology developers to create an AI ecosystem that not only improves the accuracy and efficiency of financing but also ensures transparency, fairness, data security, and the sustainability of the financial sector’s digital transformation.

The Islamic Economics Perspective on the Implementation of Artificial Intelligence Credit Scoring

The implementation of Artificial Intelligence (AI) Credit Scoring in the Islamic banking sector aims not only to improve the efficiency and accuracy of financing assessments but must also align with the principles of Islamic economics. According to Chapra (1992), the Islamic financial system is oriented toward achieving public interest (maqashid syariah) through fair, transparent, and responsible economic practices. Therefore, the development of AI in Islamic banking must take these values into account so that the resulting benefits are not merely technical but also consistent with Sharia objectives.

One of the core principles of Islamic economics is justice (‘adl). In the implementation of AI credit scoring, the algorithms used must be capable of generating objective financing decisions without causing discrimination. Additionally, the application of Explainable Artificial Intelligence (XAI) is crucial so that the decision-making process can be understood by both customers and regulators. Bussmann et al. (2021) emphasize that the transparency of AI models is a key factor in building trust in credit scoring systems.

The protection of customer rights is also a crucial aspect in the application of AI in Islamic banking. The use of personal data must be conducted securely, with customer consent, and in compliance with applicable data protection regulations. According to Neagoe (2020), the implementation of AI Governance is necessary to ensure that AI systems operate responsibly, transparently, and are capable of minimizing the risk of data misuse.

Furthermore, Akbar and Harun (2025) explain that the development of Islamic finance must remain oriented toward the public good and the protection of the public’s interests. In line with this, Fudaili et al. (2025) emphasize the importance of sound financial governance to enhance efficiency while maintaining compliance with Sharia principles. Thus, the Islamic economics perspective within the IAICSF is not positioned as a normative add-on after the modeling process is complete, but rather as a guiding principle that influences the governance of data usage, model development, decision-making, and the protection of customer rights. This approach enables the development of AI Credit Scoring in Islamic banking that is not only technically efficient but also oriented toward justice, the public good, and accountability.

Table 14. Integration of Sharia Economic Principles into the IAICSF.

Principles	Principles of AI Credit Scoring	Implementation
'Adl	Non-discriminatory decisions	Fairness and bias monitoring
Amanah	Accountability in decision-making	AI governance and auditing
Maslahah	Providing social benefits	Financial inclusion
Hifz al-Mal	Asset protection	Responsible credit decisions
Transparency	Clarity of decisions	Explainable AI
Customer Protection	Protection of user rights	Data privacy and consent

Research Agenda

A synthesis of 30 articles shows that research on Artificial Intelligence Credit Scoring is still dominated by the development of algorithms to improve the accuracy of credit risk predictions. Meanwhile, research on transparency, governance, ethics, data protection, and implementation in the Islamic banking sector remains relatively limited. Therefore, future research should focus not only on improving model performance but also on developing AI systems that are transparent, fair, accountable, and compliant with evolving regulations.

Based on the results of the literature synthesis, this study proposes several research agendas that can serve as a reference for the future development of Artificial Intelligence Credit Scoring, as presented in Table 14.

Table 15. Research Agenda Based on Research Gaps in Artificial Intelligence Credit Scoring.

Research Gap	Research Opportunities
Black-box model	Development of Explainable AI
Algorithmic bias	Fair Lending and Fairness Metrics
Model accountability	Responsible AI and AI Governance
Data privacy	Privacy-Preserving AI and Federated Learning
Islamic banking context	Maqashid-Oriented AI Credit Scoring
Alternative data	Financial Inclusion and Responsible Data Use
Model performance	Hybrid Machine Learning and Model Validation

Source: Researchers' synthesis (2026).

These findings indicate that the direction of development for Artificial Intelligence Credit Scoring is no longer focused solely on improving prediction accuracy, but also on strengthening transparency, governance, data security, and the responsible use of AI. Thus, the proposed research agenda is expected to serve as a reference for researchers and practitioners in developing more innovative, inclusive, and sustainable Artificial Intelligence Credit Scoring systems.

Research Limitations

This study has several limitations that should be considered when interpreting the results of the synthesis. First, this study only includes scientific articles published between 2020 and 2025; therefore, it does not yet represent developments in research on Artificial Intelligence Credit Scoring after that period. Second, this study employs a Systematic Literature Review approach without conducting a meta-analysis or measuring effect sizes; consequently, the findings focus more on conceptual synthesis than on a quantitative evaluation of the algorithms' effectiveness. Third, the analyzed articles are limited to publications in Indonesian and English, so it is possible that relevant research in other languages has not been included. Fourth, although the search was conducted across several relevant databases and scientific platforms, there remains the potential for database selection bias and limitations in indexing coverage, meaning that other relevant studies may not have been identified. Nevertheless, the literature selection process was conducted systematically, thereby still providing a comprehensive overview of the development of Artificial Intelligence Credit Scoring implementation in the banking sector.

4. CONCLUSION AND RECOMMENDATIONS

This study conducted a systematic literature review to analyze the development of artificial intelligence (AI) credit scoring in the banking and financing sectors. The synthesis results indicate that the implementation of AI credit scoring has evolved from the use of algorithms as risk prediction tools toward decision support systems that integrate data quality, machine learning modeling, credit risk assessment, and financing decisions. In terms of algorithms, Random Forest and XGBoost were the most frequently used algorithms in the analyzed studies, followed by Support Vector Machines and Artificial Neural Networks/Deep Learning. However, the synthesis results also indicate that no single algorithm is universally superior under all conditions, as model performance is influenced by data characteristics, feature engineering, evaluation methods, and algorithm configuration.

The main benefits of implementing AI credit scoring include improved risk prediction capabilities, operational efficiency, accelerated analysis processes, and the potential to expand financial inclusion through the use of alternative data. On the other hand, the main challenges include the limited interpretability of black-box models, algorithmic bias, personal data protection, and the need for AI governance and accountability.

The main conceptual contribution of this research is the Integrated Artificial Intelligence Credit Scoring Framework (IAICSF), which integrates four layers: the Data Foundation, the AI Analytical Layer, the Decision Layer, and the Governance and Ethical Layer. This framework demonstrates that the success of AI Credit Scoring implementation is determined not only by algorithmic accuracy but also by data quality, transparency, fairness, accountability, and governance. In the context of Islamic finance, the principles of maqashid al-sharia justice (‘adl), public interest, and the protection of customer rights can serve as a normative orientation for the development of responsible and sustainable AI credit scoring.

Based on the research findings, banks and financial institutions need to implement AI credit scoring responsibly by improving data quality, ensuring model transparency through Explainable AI, controlling algorithmic bias, protecting customer data, and establishing AI governance. In Islamic banking, the implementation of AI credit scoring must also be aligned with the principles of maqashid al-sharia, justice (‘adl), public interest, and the protection of customer rights. Further research is recommended to conduct empirical testing of the IAICSF and to develop AI models that are more transparent, fair, secure, and aligned with the characteristics of Islamic financing.

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