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# AI in Finance: A Systematic Literature Review

**Rustandi Rustandi [1*], Andi Harmoko Arifin [2]**
[1,2] Universitas Terbuka, Indonesia
*Email : rustandi1277@gmail.com **

***Abstract**. Research on Artificial Intelligence (AI) in finance has been growing significantly alongside its increasing implementation in the financial sector. This development raises questions about the specific financial areas and AI technology applications that are most frequently explored as research topics within AI in finance. This study aims to address these questions by employing a systematic literature review (SLR) method, analyzing journal articles indexed in Scopus (Q1–Q4) and published between 2020 and 2024. A search conducted using Publish or Perish on the Scopus database identified 496 records, which were subsequently filtered to 94 articles using the PRISMA protocol. The selected articles were examined through bibliometric analysis using VOSviewer, followed by content analysis. The findings reveal that fintech and risk management are the most frequently discussed financial areas in AI in finance research. Moreover, machine learning emerges as the most commonly addressed AI technology application in this domain. Notably, the combination of machine learning and risk management stands out as the most prominent research topic.*

***Keywords** Artificial Intelligent, AI, Finance, Systematic Literature Review*

## 1. INTRODUCTION

Artificial Intelligence (AI) has been applied across various sectors within the financial industry. According to a survey conducted by (Y. Cao & Zhai, 2022), the implementation of AI in finance spans areas such as quantitative analysis, credit valuation, digital banking, and economic development. More specifically, AI is also utilized in applications such as personalized banking, risk management, fraud detection and prevention. The AI technologies that generally support Finance include Natural Language Processing (NLP) and machine learning (L. Cao, 2022).

AI is not a novel concept, it originated as an idea envisioned by scientists, mathematicians, and philosophers since ancient civilizations, who imagined artificial beings possessing human-like intelligence. However, AI was formally established as a field of research in 1956 during a conference at Dartmouth College, where John McCarthy and other thought leaders proposed studying how machines could simulate various aspects of human learning and intelligence. Early developments of AI focused on creating algorithms capable of solving problems such as algebra and basic language processing (Hassani et al., 2020).

With the start of the third industrial revolution, AI grew rapidly due to advancements in computing technology, further boosted by the rise of Big Data. Today, AI is a key part of the fourth industrial revolution, affecting various industries through tools like digital assistants, self-driving cars, and predictive analytics. (Hassani et al., 2020). Initially, AI was utilized in the financial sector to detect and assess risks, as well as to address issues related to information

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asymmetry (Mhlanga, 2020). he use of AI in finance has expanded to areas like decision-making, personalized customer service, and generative AI for sentiment analysis (Chen et al., 2023). One of the key areas impacted by AI is fintech, where it has driven rapid progress, including advanced data analytics and improved payment security with fraud detection systems (Hendershott et al., 2021). This questions:

- RQ1: Which areas within the financial sector are most frequently discussed in research on the topic of AI in finance?
- RQ2: What types of artificial intelligence technology applications are being used in the finance field?

The results of this research are expected to provide insights into the development of studies related to the implementation of AI in the financial sector over the past five years.

## 2. LITERATURE REVIEW

For the past century, banks and the financial industry have relied on data-driven decisions. They are also early adopters of AI, recognizing that major errors in data analysis can lead to significant financial losses (Sri, 2021). According to the McKinsey Global Survey in 2020, the financial and banking sector ranks third in adopting AI, following the telecommunications and automotive sectors (Herrmann & Masawi, 2022).

AI technology in the financial industry has rapidly advanced, from automation in transactions to the use of machine learning and deep learning for predictive analysis and risk management. According to (Sezer et al., 2020), AI has transformed the financial industry by helping institutions process large data and make faster, more accurate decisions. AI with deep graph learning allows financial institutions to analyze data in real time, reducing potential risks in financial systems (Balmaseda et al., 2023).

The use of AI in finance has become a popular research topic, explored through quantitative, qualitative methods, and literature reviews. In his study, (Bhatore et al., 2020) employed a Systematic Literature Review methodology related to the use of AI in credit risk assessment, with a publication range between 1993 and 2019. He found that Ensemble and Hybrid models with neural networks and SVM are being increasingly used for credit assessment, NPA prediction, and fraud detection. In a systematic review of 35 years of AI use in banking, financial services, and insurance, (Herrmann & Masawi, 2022) found that banks are increasingly using AI for credit risk analysis and fraud detection. They also found that AI is widely used to improve customer experience through automation.

## 3. METHODS

This research uses a Systematic Literature Review methodology to study AI implementation in the financial sector. A systematic review gathers and evaluates evidence to better understand a specific topic (Randles & Finnegan, 2023). A Systematic Literature Review is an approach used to assess existing evidence by selecting relevant studies, synthesizing findings, and evaluating the quality of the evidence (Kitchenham & Charters, 2007).

Systematic literature reviews generally have two main stages: preparing and analyzing the literature. The PRISMA protocol is a common framework for conducting such reviews. PRISMA, which stands for "Preferred Reporting Items for Systematic Reviews and Meta-Analyses," provides guidelines for clear and thorough reporting to improve the quality and consistency of these reviews. This protocol was first introduced by (Moher et al., 2009) and was later further developed by (Page et al., 2021).

The stages of literature preparation according to the PRISMA protocol consist of identification, screening, eligibility, and inclusion (Moher et al., 2009). The identification stage involves searching various academic sources and databases for articles related to the research topic using specific keywords, including databases like PubMed and Scopus. The PRISMA protocol requires recording the number of articles found during this search. In the screening stage, studies are filtered by title and abstract, and the number of articles that don't meet the inclusion criteria is recorded. The inclusion and exclusion criteria are set before screening. In the eligibility stage, articles that passed the initial screening are reviewed in detail to ensure they meet the criteria. All articles that pass and meet the criteria are included in the review for synthesis and analysis.

The literature search began using the Publish or Perish (PoP) tool and was conducted in the Scopus database, covering the years 2020 to 2024. Scopus was chosen to ensure articles from reputable journals. The search results, based on keywords, are shown in Table 1. The 496 articles found will now be screened using the PRISMA protocol.

**Table 1. Publish or Perish Input Keywords**

| Searching Input | Search Type | Total |
|---|---|---|
| AI AND Finance | Title | 89 |
| Artificial Intelligent AND Finance | Title | 7 |
| AI AND Finance | Keywords | 200 |
| Artificial Intelligent AND Finance | Keywords | 200 |
| Total Articles | | 496 |

***Source**: Author's own work*

The PRISMA protocol was applied in accordance with the predefined inclusion and exclusion criteria. Figure 1 presents the flow diagram of the literature screening process according to the PRISMA protocol for the systematic review of AI applications in the financial sector.

Inclusion Criteria:

- Records classified as articles.
- Articles published between 2020 and 2024.
- Articles addressing Artificial Intelligence in Finance.
- Articles written in English.
- Articles published in Scopus-indexed journals in quartiles Q1, Q2, Q3, or Q4.
- Full-text access to articles is available and downloadable.

Exclusion Criteria:

- Records classified as non-articles (e.g., books or chapters, reviews, or editorials).
- Articles not written in English.
- Articles that do not discuss AI in the financial sector.
- Articles from journals not ranked in Scopus quartiles Q1, Q2, Q3, or Q4.
- Articles where the full-text is inaccessible or cannot be downloaded.

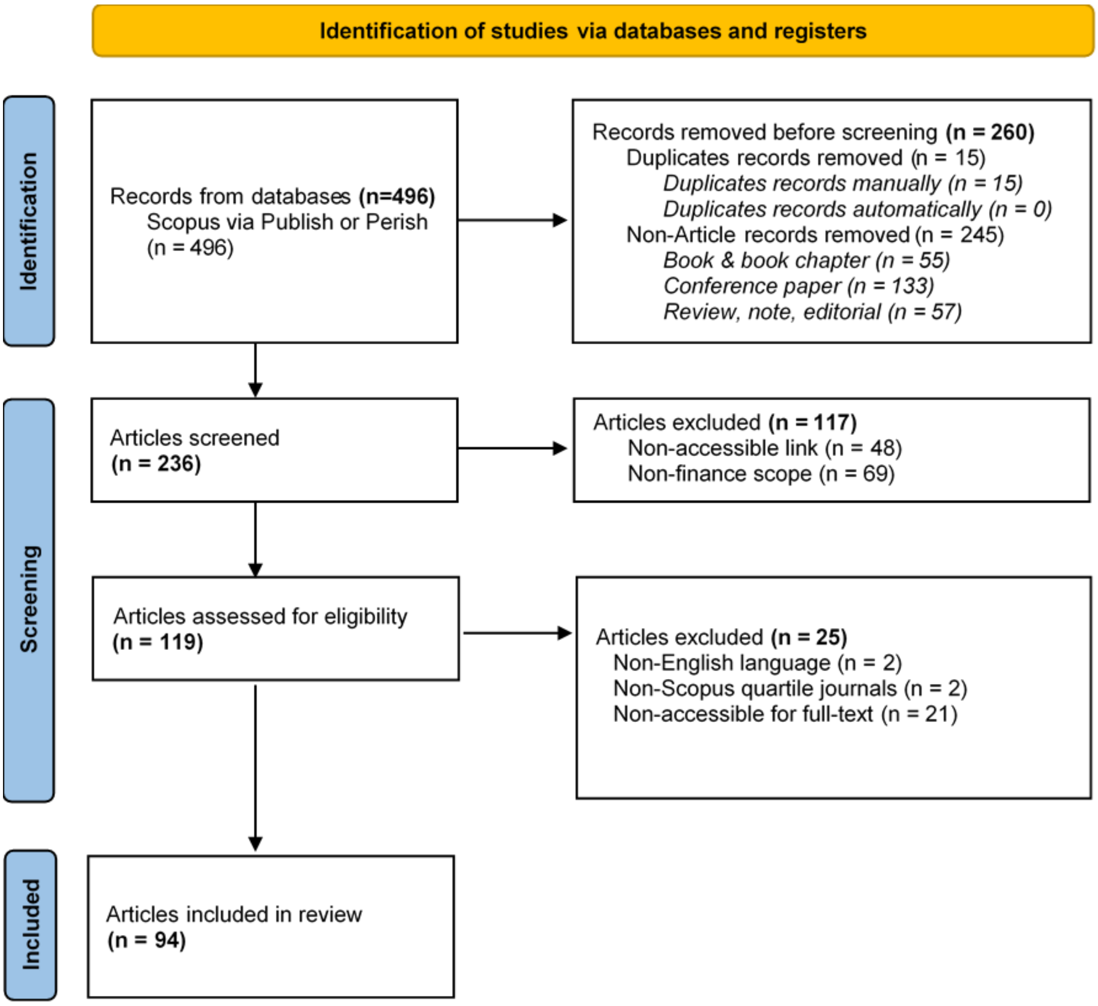


**Figure 1 PRISMA Protocol**

**Source:** Author's Own Work using template retrieved from (Prisma, 2024)

Using the PRISMA protocol, 94 articles with full-text PDFs were identified, focusing on AI in the financial sector. These articles were published in Scopus-indexed journals from Q1 to Q4 between 2020 and 2024. Further analysis, including bibliometric analysis with VOSviewer and content analysis with the SciSpace tool, will be conducted to address the research questions.

## 4. RESULTS

The citation files (.ris) for the 94 articles from the screening process were downloaded from Scopus and merged using the Mendeley Desktop tool. The combined citation file, including abstracts, was analyzed with VOSviewer. Co-occurrence analysis was performed, filtering similar terms using a custom thesaurus and focusing on the most frequent terms. The bibliometric analysis revealed four interconnected clusters, shown in Figure 2, with the terms in each cluster listed in Table 2.

**Table 2. The Four Clusters**

| Cluster 1 | Cluster 2 | Cluster 3 | Cluster 4 |
|---|---|---|---|
| deep learning | crime | algorithm | blockchain |
| financial data | fraud detection | artificial intelligence | fintech |
| financial managements | investments | data mining | internet of things |
| forecasting | learning systems | decision making | |
| information management | machine learning | sustainability | |
| neural networks | risk assessment | | |

***Source:*** *Auhtor's own using VOSviewer bibliometric analysis*

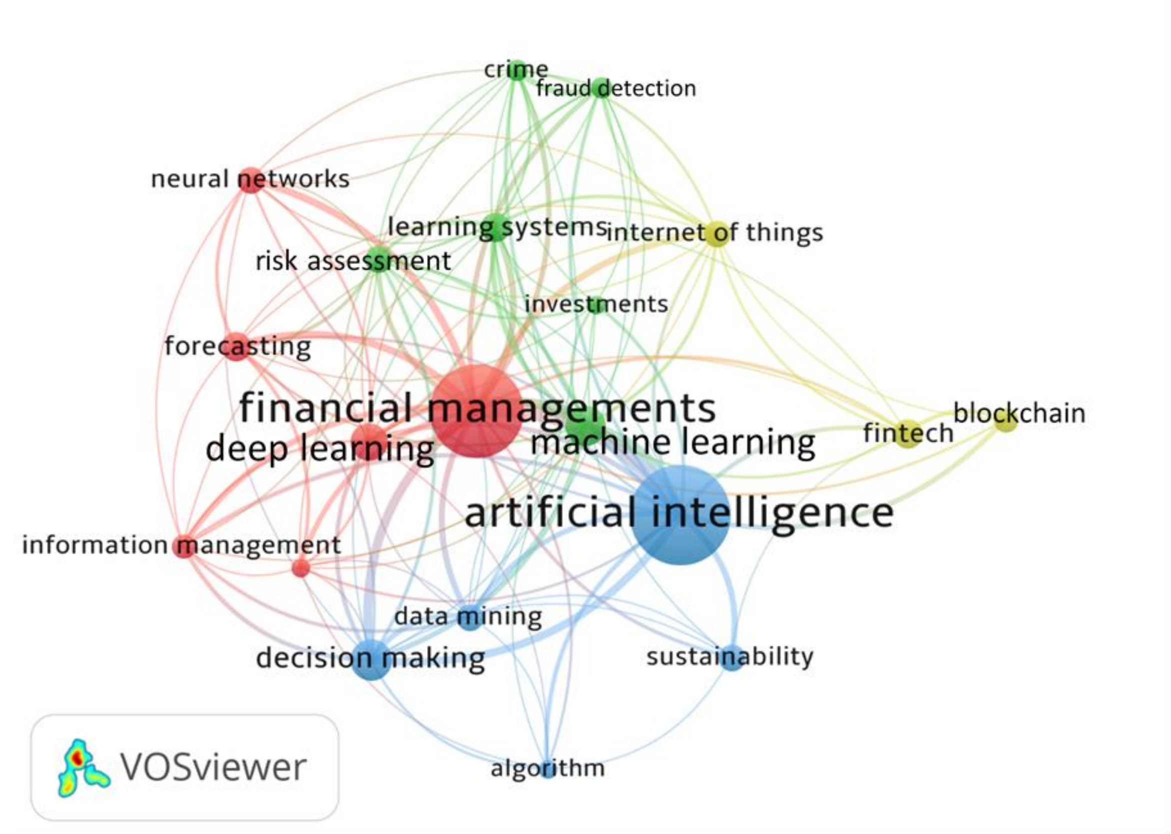


**Figure 2. Network Visualization of Bibliometric Analysis**

**Source:** Author's own using VOSviewer Bibliometric Tool

The majority of the 94 articles analyzed in this study use quantitative research methods. Literature reviews and conceptual studies are the next most common methods. A detailed breakdown of all research methods used is provided in Table 3 and shown in Figure 3.

**Table 3. Research Methods Used in Literatures**

| Research Methods | Publish Year | | | | | | % |
|---|---|---|---|---|---|---|---|
| | 2020 | 2021 | 2022 | 2023 | 2024 | Total | |
| Quantitative | *8* | *5* | *20* | *7* | *4* | 44 | 46,8 |
| Literature Review | *2* | *2* | *6* | *5* | *3* | 18 | 19,1 |
| Conceptual | *4* | *4* | *4* | *1* | *1* | 14 | 14,9 |
| Other | *1* | *2* | *3* | | *1* | 7 | 7,4 |
| Mixed Methods | *1* | *3* | *1* | *2* | | 7 | 7,4 |
| Qualitative | *2* | | *1* | *1* | | 4 | 4,3 |
| Total | 18 | 16 | 35 | 16 | 9 | 94 | 100 |

**Source:** Author's own work

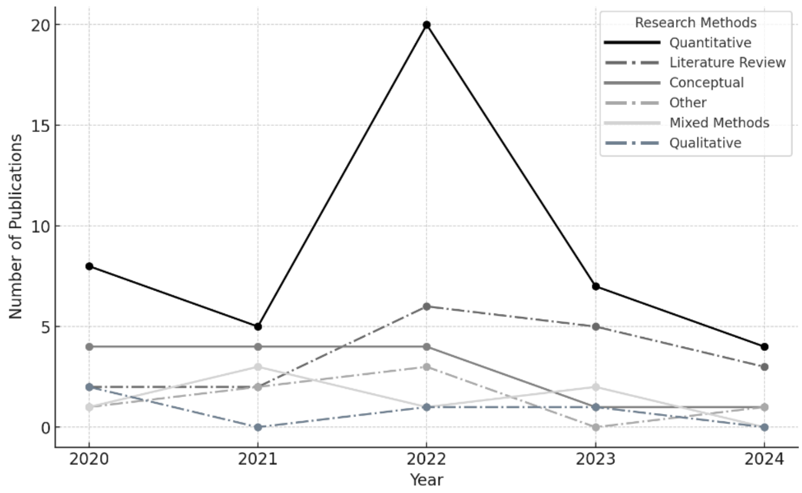


**Figure 3. Research Methods Used in Literatures**

***Source:*** *Author's own work*

This study uses data from the Scopus database to ensure the quality of the articles analyzed. The PRISMA protocol was applied to include only Scopus-indexed articles from quartiles Q1 to Q4. Articles from Q1 and Q2 journals made up 70% of the referenced literature. A detailed breakdown of the articles by Scopus quartile during the study period is shown in Table 4 and Figure 4.

**Table 4. Scopus Quartile of Literatures**

| Scopus Quartile | Publish Year | | | | | | % |
|---|---|---|---|---|---|---|---|
| | 2020 | 2021 | 2022 | 2023 | 2024 | Total | |
| Q1 | *3* | *4* | *14* | *8* | *4* | 33 | 35,1 |
| Q2 | *10* | *3* | *12* | *6* | *2* | 33 | 35,1 |
| Q3 | *3* | *4* | *8* | *1* | *1* | 17 | 18,1 |
| Q4 | *2* | *5* | *1* | *1* | *2* | 11 | 11,7 |
| Total | 18 | 16 | 35 | 16 | 9 | 94 | 100 |

***Source:*** *Author's own work*

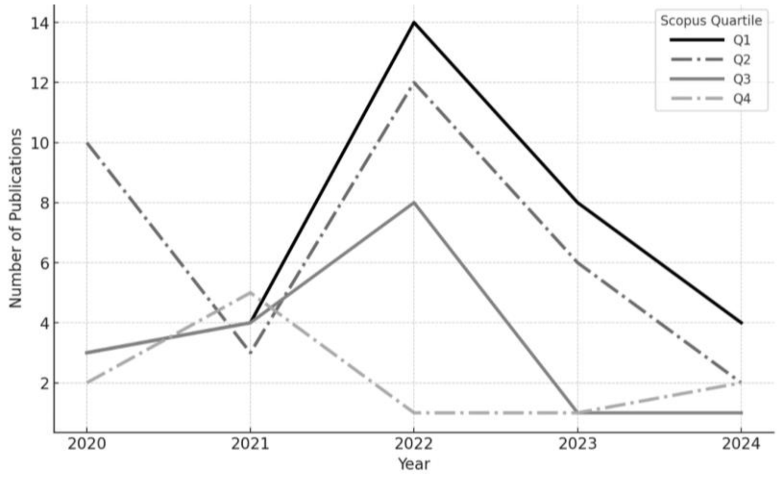


**Figure 4. Scopus Quartile of Literatures**

***Source:*** *Author's own work*

Nearly half of the research articles analyzed in this study did not specify a particular country as the research setting, categorized as "neutral" in terms of country setting. Among the remaining articles, China was the most frequently used research setting, followed by the United States and the United Kingdom. A detailed summary of the country settings used in the analyzed literature is provided in Table 5.

The 94 articles analyzed in this study were published across 68 journals. The journal Computational Intelligence and Neuroscience published the highest number of articles (6 articles), followed by Sustainability (Switzerland) with 5 articles. The four journals contributing the most articles to this study are shown in the table Table 6.

**Table 5. Country Setting Used in Articles**

| Country Setting | Total | Country Setting | Total |
|---|---|---|---|
| Neutral | 45 | South Korea | 1 |
| China | 20 | Sweden | 1 |
| United States | 4 | Turkey | 1 |
| United Kingdom | 4 | Vietnam | 1 |
| South Afrika | 2 | Australia-India | 1 |
| Poland | 2 | Australia- Germany-Japan | 1 |
| Indonesia | 2 | China-India-Pakistan-Indonesia | 1 |
| European Countries | 2 | Netherland-USA-Spain | 1 |
| Bahrain | 1 | USA-China-UK-Taiwan-South Korea-Canada | 1 |
| Iran | 1 | | |
| Saudi Arabia | 1 | Developing Countries | 1 |
| | Total = 94 | | |

**Source:** Author's own work

**Table 6. List of Journals**

| No | Journal | Total |
|---|---|---|
| **1** | **Computational Intelligence and Neuroscience** | **6** |
| **2** | **Sustainability (Switzerland)** | **5** |
| **3** | **Wireless Communications and Mobile Computing** | **4** |
| **4** | **Mobile Information Systems** | **4** |
| **5** | **Other 64 Journals** | **75** |
| | **Grand Total** | **94** |

**Source:** Author's own work

"Machine learning" is the most common phrase related to AI applications in the reviewed literature, followed by "artificial intelligence" and "intelligent systems." A full list of AI-related phrases found in the analyzed literature is presented in Table 7.

**Table 7. AI Application**

| AI Application | Article | AI Application | Article |
|---|---|---|---|
| Machine Learning | 51 | Simulation of Human Intelligent | 5 |
| Artificial Intelligent (General) | 27 | | |
| Intelligent System | 12 | Artificial Neural Network | 5 |
| Deep Learning | 9 | Generative AI | 3 |
| Data Mining | 8 | Prediction System | 3 |
| Language Model/NLP | 6 | Big Data Analysis | 3 |

***Source:*** *Author's own work*

"Machine learning" is most often linked to "risk management" in the financial sector, appearing in 7 articles, followed by "fintech" in 6 articles. In comparison, "artificial intelligence" is more commonly associated with "decision-making," "fintech," and "financial data management," each mentioned in 3 articles. A summary of these associations is provided in Table 8.

**Table 8. Financial Area of AI Application**

| Financial Area of AI Application | Article | Financial Area of AI Application | Article |
|---|---|---|---|
| **Machine Learning** | **51** | **Artificial Intelligent (General Term)** | **27** |
| Risk Management | 7 | Decision making | 3 |
| Fintech | 6 | Fintech | 3 |
| Financial Service | 4 | Financial Data Management | 3 |
| Fraud Detection | 4 | Other Financial Area | 18 |
| Investment | 4 | | |
| Banking | 4 | | |
| Asset Pricing | 3 | | |
| Other Financial Area | 19 | | |

**Source:** Author's own work

The most common phrase related to the financial sector is "fintech," mentioned in 15 articles, followed by "risk management" in 13 articles. "Financial services" and "banking" are next, each appearing in 9 articles. A detailed list of the most mentioned phrases is in Table 9.

**Table 9. Financial Area**

| Financial Area | Article | Financial Area | Article |
|---|---|---|---|
| Fintech | 15 | Accounting | 4 |
| Risk Management | 13 | Financial Management | 4 |
| Financial Service | 9 | Internet Finance | 3 |
| Banking | 9 | Green Finance | 3 |
| Decision making | 8 | Supply Chain Finance | 3 |
| Fraud Detection | 6 | Financial Crisis Prediction | 3 |
| Investment | 5 | Asset Pricing | 3 |
| Financial Data Management | 4 | | |

**Source:** Author's own work

As the most common phrase in the financial sector, "fintech" is most often linked to "machine learning," appearing in 6 articles. Similarly, "risk management," the second most common phrase, is also frequently associated with "machine learning," appearing in 7 articles. A summary of these associations is in Table 10.

**Table 10. AI Application of Financial Area**

| AI Application of Financial Area | Article | AI Application of Financial Area | Article |
|---|---|---|---|
| **Fintech** | **15** | **Risk Management** | **13** |
| Machine Learning | 6 | Machine Learning | 7 |
| Generic AI | 3 | Artificial neural Network | 1 |
| Intelligent System | 2 | Data Mining | 1 |
| Big Data Analysis | 1 | Deep Learning | 1 |
| Cybersecurity | 1 | Generic AI | 1 |
| Graph Learning | 1 | Language Model/NLP | 1 |
| Prediction System | 1 | Prediction System | 1 |

**Source:** Author's own work

The top combination of financial sector areas and AI applications is "risk management – machine learning," appearing in 7 articles, followed by "fintech – machine learning" in 6 articles. The top six combinations are listed in Table 11.

**Table 11. Combination of Financial Area & AI Application**

| Combination of Financial Area & AI Application | Article |
|---|---|
| **Risk Management - Machine Learning** | **7** |
| **Fintech - Machine Learning** | **6** |
| **Investment - Machine Learning** | **4** |
| **Fraud Detection - Machine Learning** | **4** |
| **Banking - Machine Learning** | **4** |
| **Financial Service - Machine Learning** | **4** |

**Source:** Author's own work

## 5. DISCUSSION

Artificial Intelligent Application

The literature analysis in this study showed that machine learning is the most widely used AI application. It is a technique that uses data mining and statistical methods to analyze relationships, uncover patterns, and transform data into knowledge to support decision-making (Zhang, 2021). Several areas of the financial sector, including risk management, have adopted machine learning. In risk management, machine learning is mainly used to detect fraud and assess financial risks (Beytollahi & Zeinali, 2020; R. Cao et al., 2021; Junswang et al., 2022; Kumar, 2022; Li, 2023; Mhlanga, 2022; Vaiyapuri et al., 2022).

Machine learning in fintech is widely used to improve financial services and decision-making. It helps with credit risk evaluation, enhances credit scoring and risk management through big data, and provides personalized financial products based on users' needs (Y. Cao & Zhai, 2022; Shao et al., 2022). Additionally, machine learning empowers fraud detection systems in digital payments and transactions, thereby enhancing the security of financial operations (Bayram et al., 2022). Peer-to-peer lending platforms and crowdfunding use machine learning to match loans, assess borrower credibility, and lower transaction costs, making financial services more accessible (Bayram et al., 2022; Shao et al., 2022). These applications show how machine learning is transforming financial inclusion and efficiency in the fintech sector.

Machine learning is also used in credit assessment, fraud detection, algorithmic trading, and risk evaluation. These applications help institutions analyze large datasets, identify patterns, and create predictive models to improve customer experiences and secure transactions (Biju et al., 2024; Buckley et al., 2021; Lee, 2020). Additionally, ML is applied in sustainable finance, such as Environmental, Social, and Governance (ESG) investing, by leveraging data collection and analysis to evaluate sustainability performance (Hughes et al., 2021). These applications show how ML drives financial innovation, reduces costs, and improves decision-making in the industry (Biju et al., 2024; Herrmann & Masawi, 2022).

<u>Financial Sector Areas</u>

In the financial sector, this study found that fintech is the most discussed area in the literature. While machine learning is the main focus, other technologies like big data analysis and prediction systems are also important. AI, powered by big data and prediction systems, is widely used in fintech for tasks like fraud detection, credit assessment, and personalized financial services.

AI systems use machine learning and predictive models to analyze large-scale financial data, uncover hidden patterns, detect anomalies, and provide real-time fraud prevention (Hendershott et al., 2021; Zhou et al., 2021). Advanced techniques like "graph embedding" and "distributed computing" improve the analysis of large datasets, helping fintech companies identify risks and make more accurate predictions (Zhou et al., 2021). AI-driven prediction systems offer personalized financial recommendations, enhancing customer experiences by customizing services to individual needs, thus supporting financial inclusion and efficiency in the digital economy (Hendershott et al., 2021; Zhou et al., 2021).

Implementation of AI Applications on Financial Sector Areas

Machine learning in risk management, especially for fraud detection, is a key topic in the literature reviewed. It uses techniques like attention mechanisms to find hidden patterns and anomalies in transaction data (R. Cao et al., 2021; Mhlanga, 2020). Machine learning is also used in credit risk assessment to analyze large datasets, predict credit defaults, and evaluate financial health using advanced algorithms for feature selection and optimization (Junswang et al., 2022; Vaiyapuri et al., 2022). AI, powered by machine learning, improves the detection and management of financial crises by offering real-time solutions for changing risk environments (Beytollahi & Zeinali, 2020; Vaiyapuri et al., 2022). Overall, machine learning in modern financial risk management focuses on improving accuracy, reducing fraud, and enhancing decision-making processes (Beytollahi & Zeinali, 2020; Junswang et al., 2022).

The next most discussed topic in AI's implementation in finance is machine learning in fintech. It is widely used in areas like fraud detection, risk assessment, and service personalization. In fraud detection, advanced models like deep learning and graph embedding help identify hidden patterns in large datasets, enabling real-time fraud prevention (Bayram et al., 2022; Zhou et al., 2021). Machine learning models analyze various datasets to assess borrowers' creditworthiness, optimize loan pricing, and improve financial inclusion (Buckley et al., 2021; R. Cao et al., 2021). Fintech platforms use machine learning to offer personalized financial services, like customized investment advice and predictive analytics for customer needs, improving user experience and efficiency (R. Cao et al., 2021; Lăzăroiu et al., 2023).

Machine learning in investment and banking is a widely discussed topic. In investment, machine learning is used in algorithmic trading to improve efficiency, accuracy, and accessibility, including in peer-to-peer lending and blockchain-based tokenized bonds (Biju et al., 2024; Lee, 2020). Second, machine learning also plays a key role in alternative ESG assessment by analyzing data without human input, enabling faster and more informed investment decisions (Biju et al., 2024; Hughes et al., 2021). Third, machine learning is used in regulation and risk management to reduce market risks, lower compliance costs, and detect anomalies or fraud (Biju et al., 2024; Hughes et al., 2021; Rawindaran et al., 2021). Lastly, this technology is used in credit scoring, insurance underwriting, and advanced trading, improving financial accessibility and inclusion, but also raising issues with algorithmic bias and data privacy (Biju et al., 2024; Rawindaran et al., 2021).

Machine learning in banking uses advanced algorithms for key functions like credit analysis, customer service, portfolio optimization, and automated trading. It helps process large data sets, identify patterns, and make predictions, such as credit scores and loan risks. It also supports services like chatbots to improve customer experience and automate regulatory tasks. However, challenges like algorithmic bias and the need for proper oversight emphasize the importance of responsible AI governance (Biju et al., 2024; Choithani et al., 2024; Herrmann & Masawi, 2022; Srinadi et al., 2023).

## 6. CONCLUSION

Artificial intelligence (AI) has been widely applied in the financial sector. A systematic review of 94 relevant articles addressed two research questions posed at the outset of the study. The findings revealed that several areas within the financial domain, such as fintech and risk management, have implemented AI technologies. Among these, machine learning emerged as the most frequently discussed AI application in financial research. Notably, the combination of machine learning and risk management was identified as the most extensively examined topic in studies exploring AI implementation in finance.

These findings provide valuable insights and serve as a reference for future research on AI in the financial sector. Specifically, the bibliometric analysis in this study offers potential ideas for subsequent investigations. However, this research is not without limitations, particularly the reliance on data from a single database. Future studies are encouraged to utilize a broader range of literature databases while maintaining quality by selecting reputable journals.

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