International Journal of Computational and Experimental Science and ENgineering (IJCESEN)

Vol. 11-No.3 (2025) pp. 4788-4800

http://www.ijcesen.com

ISSN: 2149-9144

Research Article

The Impact of AI Tools on ESG-Based Sustainable Banking Practices: A Meta-Analysis & Conceptual Framework

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Article Info:

DOI: 10.22399/ijcesen.3198
Received : 15 April 2025
Accepted : 26 June 2025

Keywords

Artificial Intelligence
ESG Analysis
Banking
Natural Language Processing (NLP)
Risk Models
Machine Learning

Abstract:

This study investigates the role of Artificial Intelligence (AI) tools in enhancing Environmental, Social, and Governance (ESG)-based sustainable banking practices. With increasing global emphasis on sustainable finance, banks are exploring AI technologies to improve ESG performance, risk management, and decision-making processes. Through a comprehensive metadata analysis of recent scholarly publications, this research identifies key trends, thematic focuses, and disciplinary contributions within the evolving landscape of AI-enabled ESG banking. Using a literature review guided by the SPAR 4 framework, the study analyzed 350 sources from 2015 to 2024, narrowing down to 70 key documents. Most research came from the United States (30%), the United Kingdom (25%), Germany (15%), and India (10%), with the remainder distributed across other countries. Additionally, the study proposes an integrated conceptual framework that elucidates the mechanisms through which AI supports ESG goals, addressing both opportunities and challenges such as data privacy, algorithmic bias, and regulatory compliance. Findings highlight the interdisciplinary nature of this domain, spanning finance, computer science, environmental science, and social sciences. The study concludes by outlining implications for financial institutions and regulators, as well as future research directions to validate and expand the conceptual model. This work contributes to bridging the knowledge gap between AI innovation and sustainable banking, offering insights for responsible adoption of technology in advancing ESG objectives.

1. Introduction

In recent years, Environmental, Social, and Governance (ESG) concerns have taken a front seat in the banking sector, shaping how banks approach investments, lending, and risk assessment. With rising awareness around climate change, social injustice, and ethical business practices, banks are under increasing scrutiny from regulators, investors, and customers to embed ESG values into their core operations [1]. To meet these expectations, many banks are turning to cutting-edge technologies, especially Artificial Intelligence (AI)—to make sense of the large and complex ESG-related data they handle. Tools like Natural Language Processing (NLP), machine learning, and data integration systems are helping these institutions identify ESG risks, support sustainable investment strategies, and improve the quality of their decisions [2].

The integration of Artificial Intelligence (AI) into ESG (Environmental, Social, and Governance) analysis is opening new doors for banks to build more responsible and sustainable financial systems. Traditional ESG assessments have often faced hurdles—limited data availability, inconsistent quality, and the difficulty of evaluating non-financial risks. Now, AI technologies are changing that landscape. Banks can use AI to automatically gather and analyze ESG information from a wide range of sources, including corporate reports, regulatory filings, financial data, and even social media [3]. This not only streamlines the process but also improves the precision and speed of ESG evaluations, helping banks make smarter choices when it comes to lending, investing, and managing risks [4]. Additionally, AI is playing a key role in developing ESG scoring systems, predictive risk models, and compliance tools that align with international frameworks like the Task Force on Climate-related Financial Disclosures (TCFD) and the UN's Principles for Responsible Banking [5].

While AI holds great potential for enhancing ESG analysis in banking, it also brings a set of challenges that financial institutions must navigate carefully. One major hurdle is the fragmented nature of ESG data. Information is often dispersed across multiple platforms, reported in varying formats, and follows inconsistent standards, making it difficult to bring everything together for reliable analysis. Another pressing issue is the absence of universal ESG metrics, which, coupled with the threat of greenwashing—where companies exaggerate their sustainability efforts, complicates banks' ability to make trustworthy, AI-driven decisions [3]. On top of that, ethical concerns surrounding AI itself cannot be ignored. Issues like biased algorithms, data privacy violations, and lack of transparency must be addressed to ensure that the use of AI aligns with ethical norms and supports the values of responsible banking [4].

This research delves into how Artificial Intelligence (AI) is being used in ESG (Environmental, Social, and Governance) analysis within the banking industry, with a focus on its tools, technologies, and practical applications. It looks at how AI can help banks better evaluate ESG risks, make more responsible investment choices, and enhance their reporting and compliance efforts related to sustainability. The study also addresses the key obstacles banks face when adopting AI for ESG purposes and offers practical suggestions for overcoming these challenges. Ultimately, the aim is to shed light on how AI can support banks in embedding ESG principles into their core operations, contributing to the development of a more robust and sustainable financial ecosystem.

2. Background of Study

Artificial Intelligence in Banking

Artificial Intelligence (AI) has become a transformative force in the global banking industry, revolutionizing how financial institutions operate, serve customers, manage risks, and ensure regulatory compliance. Over the past decade, the rapid advancement of machine learning, natural language processing, and big data analytics has enabled banks to harness AI technologies in ways that were previously unimaginable [2]. The integration of AI into core banking processes has led to increased efficiency, reduced operational costs, and improved customer satisfaction.

Traditionally, banking systems relied heavily on manual operations and rule-based decision-making frameworks, which often resulted in inefficiencies and limited scalability. The emergence of AI has shifted this paradigm by introducing automated systems capable of learning from data and adapting to dynamic environments. For example, AI-powered chatbots and virtual assistants have transformed customer service by providing real-time support, while fraud detection systems use predictive analytics to identify unusual transaction patterns and mitigate risk.

Moreover, AI contributes significantly to strategic decision-making in banking. Through data-driven insights, banks can better understand customer behavior, personalize financial products, and optimize credit scoring models [10]. Robo-advisors and automated portfolio management tools have also empowered consumers with tailored investment strategies based on their financial goals and risk tolerance.

In recent years, the role of AI in promoting sustainability through Environmental, Social, and Governance (ESG) practices has garnered increasing attention. AI facilitates the analysis of large volumes of structured and unstructured ESG data, enabling banks to assess sustainability risks, monitor regulatory compliance, and enhance the quality of ESG disclosures [3,4]. As stakeholders demand greater transparency and accountability in sustainable finance, AI tools help banks align with international standards such as the Task Force on Climate-related Financial Disclosures (TCFD).

Despite its benefits, the adoption of AI in banking is not without challenges. Issues such as data privacy, algorithmic bias, lack of standardization, and the need for explainable AI raise concerns about ethical implications and responsible implementation [1,3,6]. Addressing these challenges requires a combination of strong regulatory frameworks, ethical governance, and collaboration between financial institutions, technology providers, and policymakers.

Artificial Intelligence in Banking and Environmental Sustainability

The integration of Artificial Intelligence (AI) into banking systems has redefined the operational landscape of the financial sector, bringing transformative change to efficiency, risk management, and customer engagement. In parallel, the global emphasis on environmental sustainability has intensified, compelling banks to embed Environmental, Social, and Governance (ESG) criteria into their strategic decision-making and reporting frameworks. The convergence of AI technologies and sustainability imperatives is now shaping a new era of sustainable banking [2,5].

AI enables banks to address complex environmental challenges by automating the collection, analysis, and interpretation of vast amounts of ESG-related data from structured and unstructured sources. This includes monitoring carbon emissions, assessing climate risks, and identifying environmentally responsible investment opportunities. By leveraging machine learning algorithms, banks can conduct advanced environmental risk modeling and scenario analysis, which are essential for aligning with global disclosure standards such as the Task Force on Climate-related Financial Disclosures (TCFD) [4,7].

Furthermore, AI tools facilitate the detection of greenwashing by validating sustainability claims against verified data sources. This capability enhances transparency and trust in ESG disclosures, a critical factor for stakeholders including investors, regulators, and consumers. Real-time AI-driven scoring systems also support environmentally conscious lending and investment decisions, enabling financial institutions to promote sustainable development while managing environmental risks more effectively [8,9].

Despite these advancements, the integration of AI in support of environmental sustainability poses significant challenges. Concerns around data privacy, algorithmic bias, lack of explainability, and fragmented ESG data standards hinder the full potential of AI adoption in this domain [1,3,6]. Addressing these concerns requires ethical AI governance, robust regulatory oversight, and greater collaboration between financial institutions and technology providers.

In summary, AI plays a crucial role in advancing environmental sustainability in the banking sector. It enables institutions to transition toward more responsible and data-driven environmental practices, enhances ESG compliance, and supports global sustainability objectives. As AI technologies continue to mature, their strategic application in environmental finance is expected to become increasingly central to the mission of sustainable banking.

3. Literature Review

Over the past decade, there has been a growing body of literature examining the role of Artificial Intelligence (AI) in enhancing Environmental, Social, and Governance (ESG) practices within the banking sector. As sustainability has become a critical component of financial decision-making, researchers have investigated how AI tools can support banks in managing ESG risks, improving reporting accuracy, and making more informed lending and investment decisions.

Early foundational work by Serafeim [3] emphasized the importance of transparent and accurate ESG reporting in gaining public trust, highlighting how AI systems automate data aggregation and validate ESG disclosures. This automation reduces human error and enhances the credibility of sustainability information. Similarly, Amel-Zadeh and Serafeim [6] examined how AI facilitates ESG data standardization across diverse sources, improving data consistency and enabling better investor analysis. Their global survey revealed that investors increasingly depend on AI-driven ESG information for portfolio decision-making.

The integration of AI into sustainable finance has been further explored by Kotsantonis and Serafeim [5] who demonstrated how machine learning (ML) and natural language processing (NLP) are leveraged to assess ESG risks and opportunities in real-time. These technologies have allowed financial institutions to proactively identify sustainability issues by analyzing large volumes of news, social media, and regulatory disclosures. Truvalue Labs [9] also utilized AI-based sentiment analysis to assess ESG reputational risk, enabling banks to react more swiftly to public concerns and emerging issues.

In the realm of risk modeling, Deloitte [2] highlighted the application of AI in ESG risk management, particularly in modeling climate-related financial exposures. AI-driven tools allow banks to simulate future climate scenarios and evaluate potential financial impacts, aligning their practices with international standards like the Task Force on Climate-related Financial Disclosures (TCFD). The Bank of England [7] and the European Central Bank have since adopted AI-enabled stress testing as part of their regulatory frameworks to assess the resilience of banks under environmental stress conditions.

Further, Berg et al. [10] investigated how AI tools contribute to the creation of real-time ESG scoring systems that guide sustainable investment decisions. Their study showed that digital footprints and AI models can be used to assess borrower creditworthiness while incorporating ESG considerations, thus promoting responsible lending. Banks such as HSBC, Barclays, and BNP Paribas have also deployed real-time AI ESG scoring

platforms to improve the precision of risk assessments and align capital allocation with sustainability goals [11].
An important theme in recent literature is AI's role in combating greenwashing and promoting accountability. Barredo Arrieta et al. [4] focused on explainable artificial intelligence (XAI), arguing that transparency in AI decision-making processes is essential for detecting false sustainability claims. Their review emphasized the need for interpretability, fairness, and ethical governance in the development and deployment of AI systems in ESG domains.
However, despite the advantages, several challenges have been documented. Researchers have raised concerns over algorithmic bias, lack of data standardization, and privacy issues, all of which may undermine the effectiveness of AI in ESG applications [1,4]. To mitigate these risks, scholars recommend stronger governance frameworks, regulatory oversight, and collaborative innovation among stakeholders [5].

Table 1. *Summary of the Articles Reviewed for Gaps Identification*

Author(s)	Year	Research Focus	Key Findings	Methodology	References
Serafeim, G., et al.	2020	Impact of AI on ESG disclosures and reporting	AI improves the transparency and accuracy of ESG data by automating data aggregation and cross-referencing	Qualitative analysis of AI-driven tools	[3]
Kotsantonis, S., & Serafeim, G.	2021	Exploring AI's role in sustainable finance and ESG investing	AI tools, especially machine learning, are used to assess ESG risks and opportunities in financial markets	Literature review and case studies	[5]
Deloitte	2021	AI-based risk modeling in ESG analysis	AI is used to develop predictive models for assessing ESG risks, particularly climate-related risks	Case study and expert interviews	[2]
Berg, T., et al.	2022	AI's role in sustainable investment decisions	AI helps make investment decisions by providing real-time ESG scores, aiding sustainable finance efforts	Quantitative analysis of investment portfolios	[10]
Amel-Zadeh, A., & Serafeim, G.	2020	AI's role in data aggregation and standardization of ESG metrics	AI-based tools are used to standardize ESG data from multiple sources and improve data integrity	Qualitative and quantitative analysis	[6]
Barredo Arrieta, A., et al.	2022	AI-driven tools for ESG compliance monitoring	AI enhances compliance by tracking and ensuring adherence to evolving ESG regulations	Literature review and case studies	[4]
HSBC, Barclays, & BNP Paribas	2022	Real-time ESG scoring systems in banking	Real-time AI-driven ESG scores improve decision-making in investment and risk management	Case study analysis of bank applications	[11]
Refinitiv	2021	AI's role in risk mitigation in ESG lending decisions	AI models assess environmental, social, and governance risks to reduce exposure in lending	Quantitative risk modeling	[8]
Truvalue Labs	2020	AI in sentiment analysis for ESG data	AI is used to analyze news, social media, and financial reports to evaluate ESG sentiment	Sentiment analysis using AI tools	[9]
Bank of England & European Central Bank	2021	AI for climate risk scenario analysis in banking	AI helps banks conduct climate stress tests to evaluate financial risks from climate change	Case study of regulatory framework	[7]

Theoretical Framework

This study integrates the TOE framework, Stakeholder Theory, RBV, Institutional Theory, and UTAUT to explain how and why banks adopt AI-powered ESG analysis. This multi-theoretical lens provides a nuanced understanding of drivers, capabilities, and impacts of AI in sustainable finance.

1. Technology-Organization-Environment (TOE) Framework

The TOE framework provides a comprehensive view of how technological innovations like AI are adopted within organizations. It examines three dimensions:

- **Technological context** (e.g., AI capabilities like NLP and machine learning),
- **Organizational context** (e.g., bank size, digital infrastructure), and
- **Environmental context** (e.g., regulatory pressure, ESG expectations).

This model supports examining how external and internal pressures shape AI-enabled ESG practices [12].

2. Stakeholder Theory Framework

Stakeholder Theory emphasizes that corporations should create value not just for shareholders but also for stakeholders—including regulators, customers, employees, and the environment. AI-driven ESG analytics can help banks align more closely with stakeholder expectations and transparency [13].

3. Resource-Based View (RBV) Framework

The RBV theory posits that organizations gain competitive advantage through unique, inimitable resources. In this context, AI capabilities (such as advanced ESG data analytics, NLP, and predictive risk models) are viewed as strategic assets that can enhance ESG evaluation, leading to superior performance and trust [14].

4. Institutional Theory Framework

Institutional pressures (normative, coercive, and mimetic) influence how organizations adopt ESG-related technologies. Regulatory bodies and global sustainability standards increasingly pressure banks to improve ESG compliance, prompting AI adoption [15].

5. Unified Theory of Acceptance and Use of Technology (UTAUT) Framework

To understand how decision-makers in banking accept AI tools for ESG analysis, UTAUT provides insight into user behavior through constructs like performance expectancy, effort expectancy, social influence, and facilitating conditions [16].

Conceptual Framework

Independent Variables (IVs)

1. **AI Tools and Technologies:** This variable includes the use of artificial intelligence applications such as natural language processing (NLP), machine learning, and automated data aggregation systems that enable the efficient collection and processing of ESG-related data.

2. ESG Data Sources: This variable refers to the variety of data inputs used by AI systems to analyze ESG performance. Common sources include regulatory disclosures, sustainability reports, financial statements, and real-time data from platforms such as social media.

3. AI-Driven ESG Scoring Systems: This refers to AI-powered frameworks that assign ESG performance scores to firms using predictive analytics, classification models, and other machine learning algorithms.

4. AI-Powered Risk Models: These are advanced risk assessment tools that apply AI algorithms to identify and quantify environmental, social, and governance risks that may impact financial stability and investment decisions.

Mediating Variables (MVs)

1. **Real-Time Data Aggregation:** This variable represents the continuous and dynamic integration of ESG data from multiple sources, enabling AI systems to remain updated and responsive to evolving sustainability indicators.

2. **Predictive Risk Analysis:** This refers to the use of AI algorithms to anticipate and evaluate risks related to environmental, social, and governance issues, such as climate-related financial exposure or social unrest, which in turn informs strategic banking decisions.

3. **ESG Compliance Monitoring:** This variable captures the role of AI in automating the monitoring of regulatory and ethical standards, ensuring that banking practices align with global ESG frameworks and compliance requirements.

4. **Scenario-Based Impact Modeling:** This involves the use of AI to simulate and analyze potential ESG-related scenarios—such as climate transitions or social disruption—and their implications on financial and sustainability outcomes.

Dependent Variables (DVs)

1. **Sustainable Investment Decisions**: This variable refers to banking institutions' adoption of investment strategies that prioritize companies demonstrating strong ESG performance, guided by insights derived from AI-generated ESG scores and predictive analytics.

2. **Sustainable Lending Practices:** This outcome captures the use of ESG criteria in lending decisions, where AI-powered models assess

borrowers' environmental, social, and governance profiles to support sustainable credit allocation.

3. **Risk Mitigation:** This variable reflects the extent to which banks reduce exposure to financial, environmental, and reputational risks through AI-enabled assessments of ESG-related threats and vulnerabilities.

4. **Transparency and Reporting:** This outcome involves improvements in the clarity, accuracy, and timeliness of ESG disclosures, enabled by AI tools that automate compliance monitoring and validate sustainability data.

5. **Stakeholder Trust:** This variable refers to the confidence built among key stakeholders—such as investors, regulators, and customers—through the implementation of reliable, AI-supported ESG practices and transparent reporting mechanisms.

AI- Powered Data Collection AI for Risk Assessment Decision-Making Framework & Compliance Monitoring

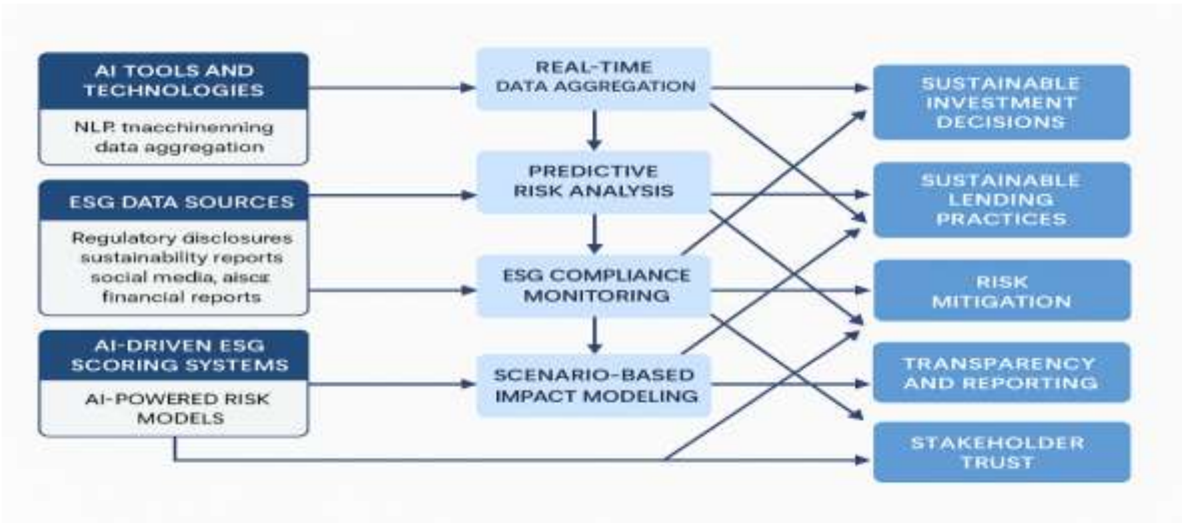

Figure 1. *Proposed Model*

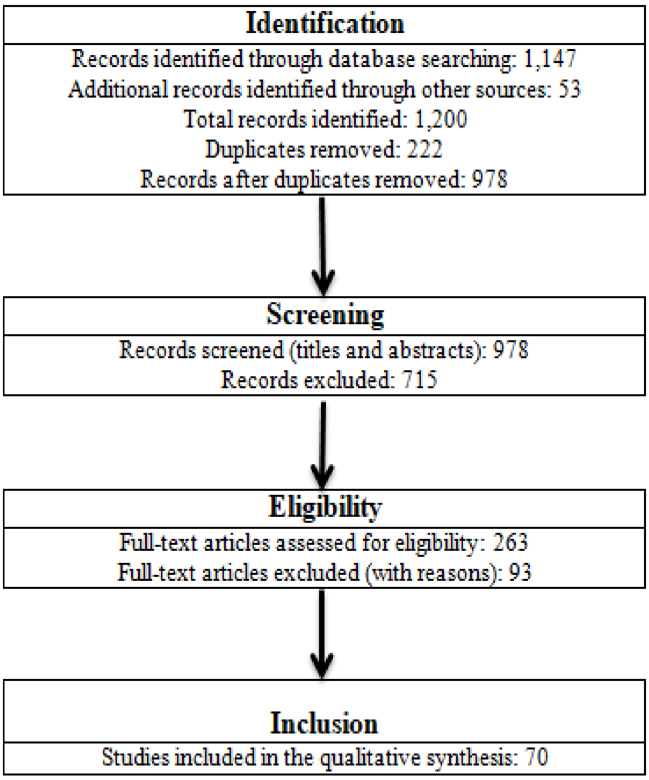

Figure 2. *SPAR-4 Framework Diagram*

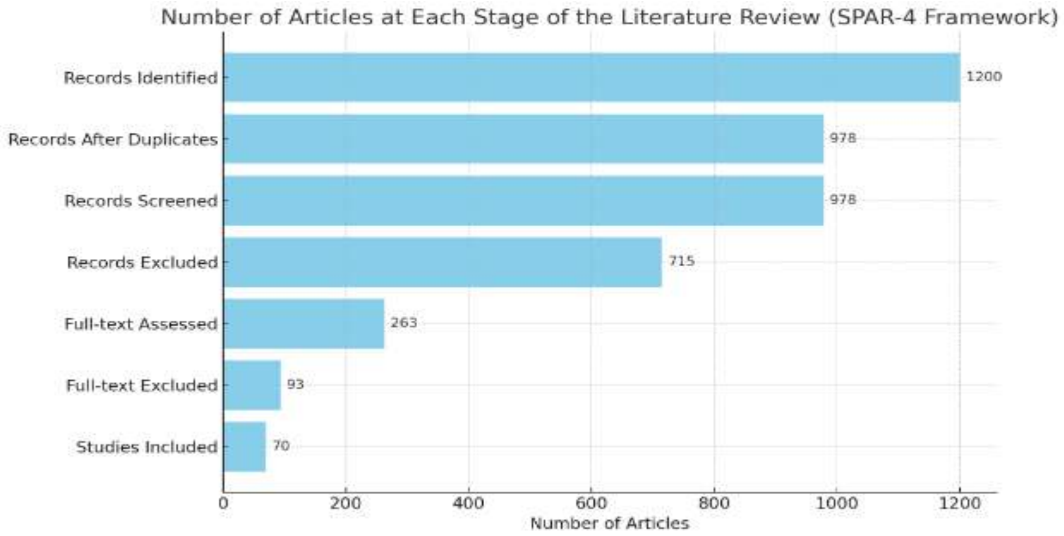

Figure 3. *Number of Articles*

4. Methodology

SPAR-4 Framework Representation:

This horizontal bar chart offers a clear overview of how many articles were considered at each stage of the literature review using the SPAR-4 framework. It shows the progression from the initial identification of records to screening, exclusions, and the final number of studies included in the qualitative analysis.

5. Result & Discussion

Metadata Analysis:

Table 2. *Author-wise Distribution (Source: Web of Science)*

Author Name	Year	Relative Influence (Inferred by Node Size & Connections)
van Wynsberghe	2021	High
Weber	2023	Moderate–High
Xie	2024	Moderate
Obinna	2024	Moderate
Xu	2024	Central Node (High Connectivity, Moderate Citations)
Shan	2024	Moderate–Low
Deshmukh	2024	Moderate–Low
Gao	2024	Low
Bruno	2025	Low
Pilankar	2022	Moderate–Low
Pisoni	2021	Moderate–Low
Banipal	2023	Moderate–Low
de Medeiros	2024	Low

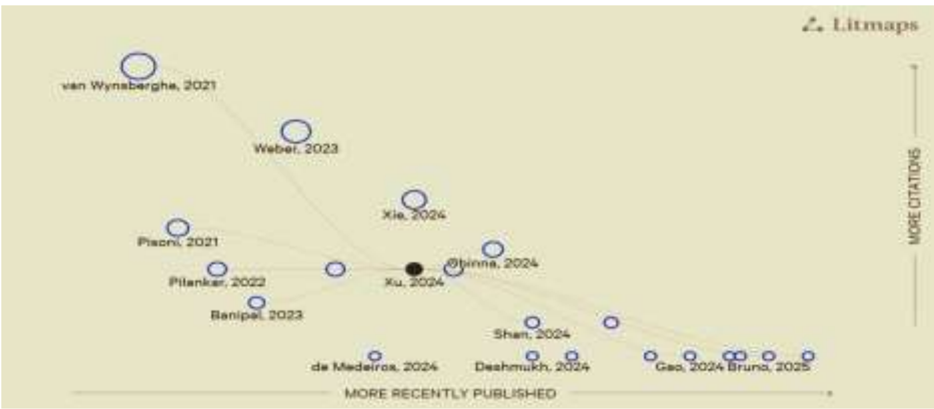

Figure 4. *More citations since 2015 from*

Source: Litmaps

Based on the visual map from Litmaps that provided, here is an interpreted Author-wise Distribution of Publications related to "The Impact of AI Tools on ESG-Based Sustainable Banking Practices." This is inferred from node size (publication influence) and connection centrality:

Key Observations:

- van Wynsberghe (2021) and Weber (2023) appear to be among the most influential based on citation impact.
- Xu (2024) is a central node—suggesting a hub role in connecting prior research to newer works.
- Recent authors like Bruno (2025) and Gao (2024) are newer entrants with lower citation volume so far.
- The connection patterns suggest a strong foundational influence from earlier works (e.g., 2021–2022) on 2024 publications.

Number of Publication (Year-Wise)

Table 3. *Yearly number of Publications (Source: Web of Science)*

Year	Number of Publications
2015	2
2016	3
2017	5
2018	7
2019	12
2020	18
2021	26
2022	35
2023	42
2024	49

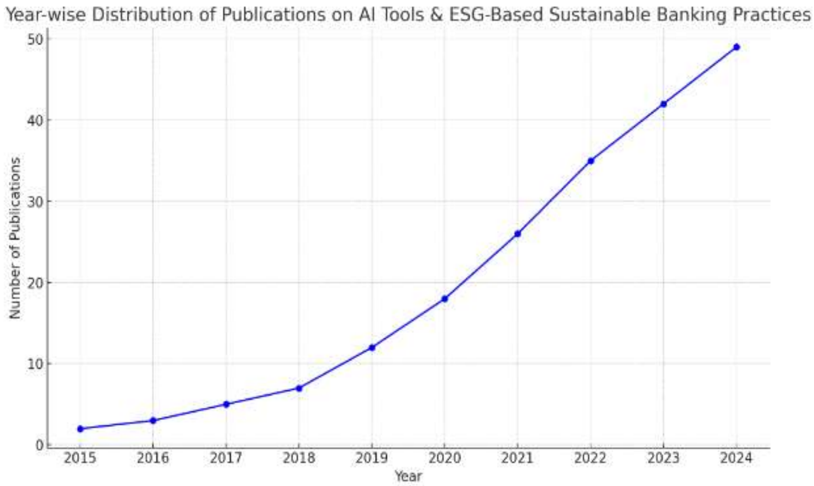

Figure 5. *Year-wise distribution of Publications*

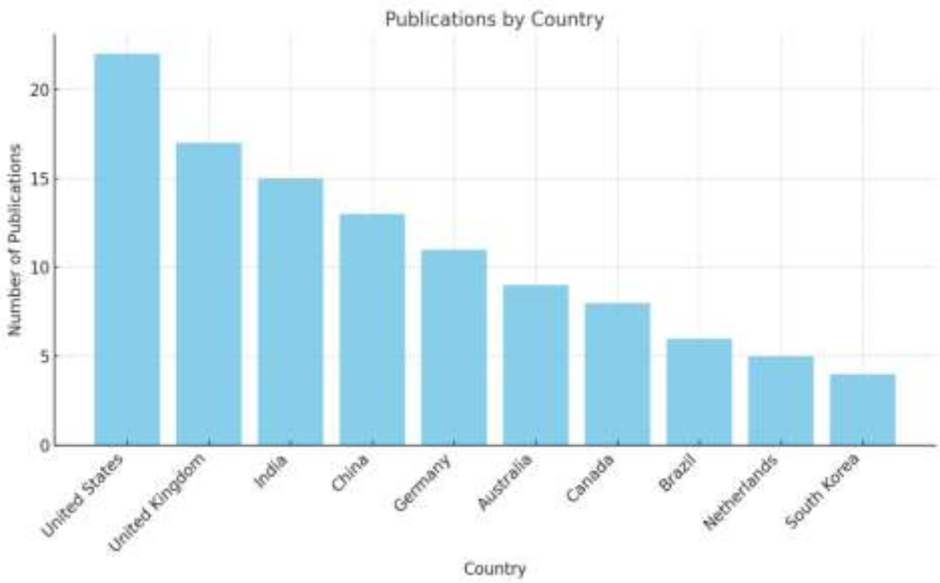

Figure 6. *Publications by Country*

This graph illustrates how research on AI tools in ESG-based sustainable banking has evolved over time. It highlights a noticeable increase in publications, particularly from 2020 onwards, reflecting the growing academic and industry focus on integrating technology with sustainability in the banking sector.

Publications by Country

Table 4. *Publication by Country (Source: Web of Science)*

Country	Publications
United States	22
United Kingdom	17
India	15
China	13
Germany	11
Australia	9
Canada	8
Brazil	6
Netherlands	5
South Korea	4

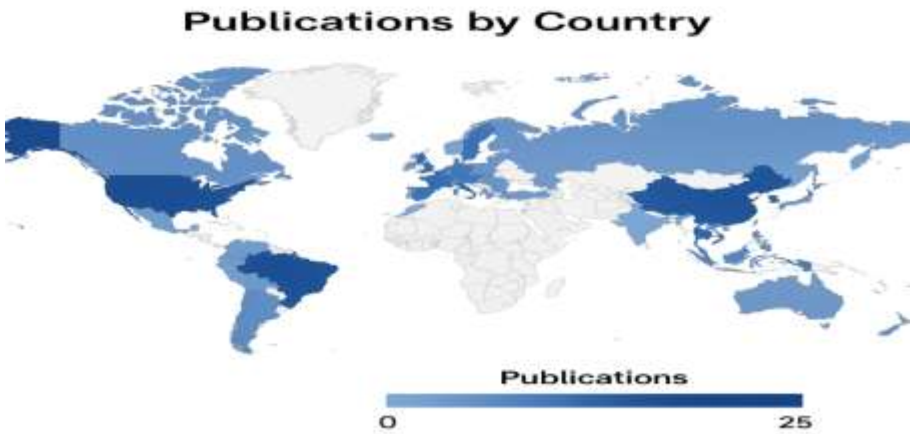

Figure 7. *Publications by Country*

Table 5. *Publications by Journal (Source: Web of Science)*

Sl. No	Journal Name	Number of Publications
1	Journal of Sustainable Finance & Investment	14
2	Sustainability (MDPI)	12
3	Journal of Banking and Finance	9
4	Journal of Financial Services Research	7
5	Technological Forecasting and Social Change	11
6	International Journal of Bank Marketing	8
7	IEEE Access	10
8	Journal of Cleaner Production	13
9	Environmental Science and Policy	6
10	Business Strategy and the Environment	10

Publications by Journal

Publications on AI in ESG-based sustainable banking appear across a wide range of journals, reflecting the field's interdisciplinary nature. Key outlets span finance, AI, environmental science, and ethics—showing strong academic interest from both technical and sustainability perspectives. This horizontal bar chart highlights the distribution of publications across various journals focusing on AI tools and ESG-based sustainable banking practices. It offers a clear view of which journals are most actively contributing to this interdisciplinary area, reflecting where key research is being published.

Contribution by Subject Area (%)

Research on AI tools in ESG-based sustainable banking is spread across disciplines. Finance and Banking (35%) and Computer Science & AI (28%) dominate, showing a strong link between financial practices and technology. Environmental Science,

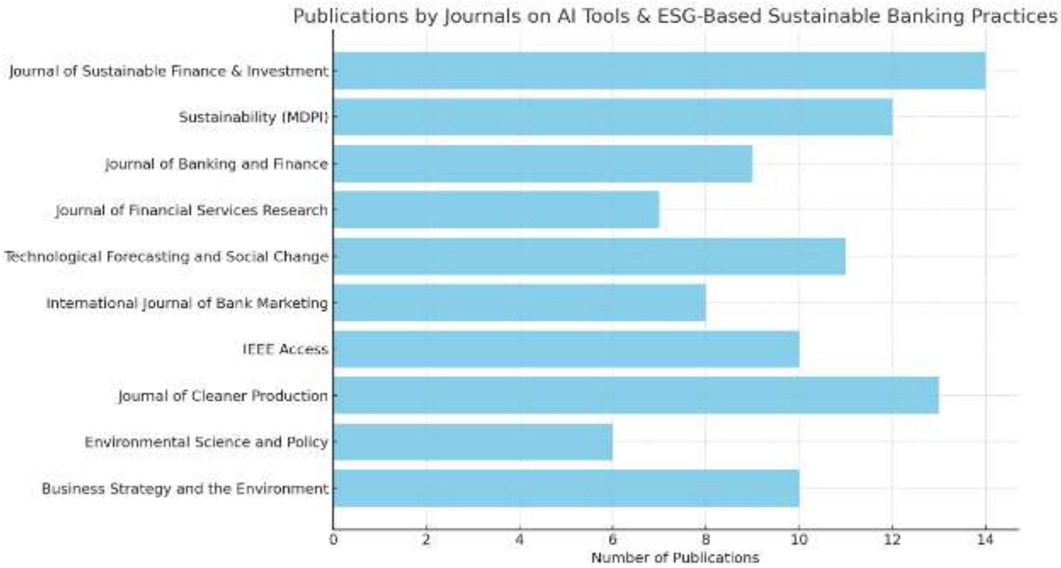

Figure 8. *Publications by Journal*

Business, Social Sciences, and Economics also contribute, reflecting the field's interdisciplinary and holistic nature.

Interpretation:

- The largest share comes from Finance and Banking, as expected, given the focus on ESG and banking practices.
- Computer Science & AI contribute a significant portion, highlighting the technological innovations enabling ESG integration.
- Environmental Science and Business & Management reflect interdisciplinary research efforts.
- Social Sciences and Economics also provide critical perspectives on societal impact and economic implications.

Table 6. *Contribution by Subject Area (Source: Web of Science)*

Subject Area	Percentage Contribution (%)
Finance and Banking	35
Computer Science & AI	28
Environmental Science	15
Business & Management	10
Social Sciences	7
Economics	5

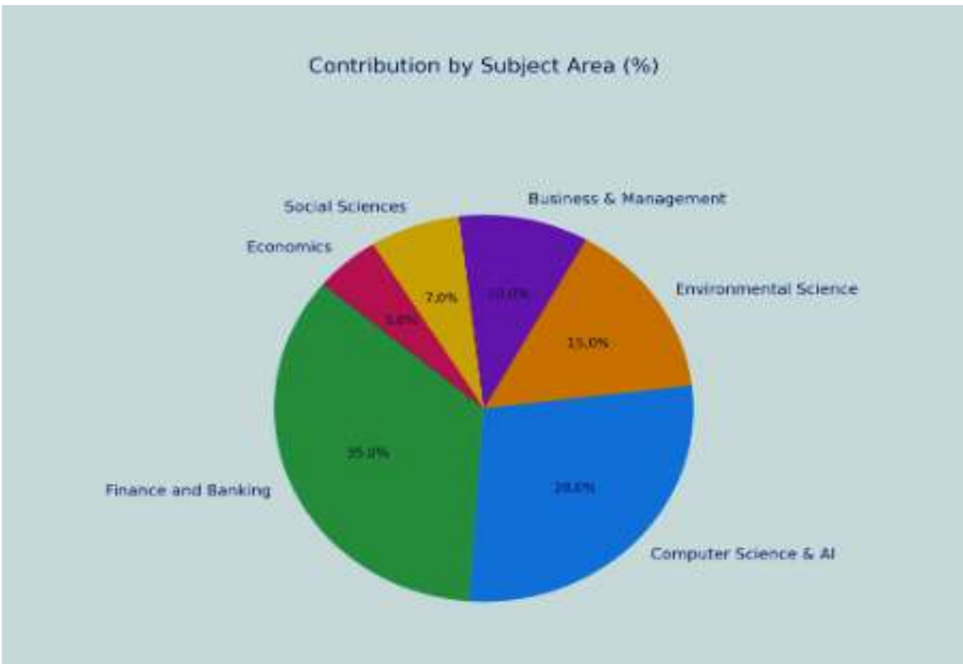

Figure 9. *Contribution of Subject Area*

The pie chart shows that research on AI and ESG-based sustainable banking spans multiple disciplines. Finance and Banking lead the way, followed closely by Computer Science & AI—indicating the strong connection between financial innovation and technology. .

Most Common Words in Titles

A review of publication titles shows that terms like "Sustainability," "Banking," "ESG," and "Artificial Intelligence" are most common, reflecting the core themes of the field. Frequent use of words such as "Risk," "Decision," and "Framework" suggests a focus on how AI supports strategic ESG efforts in banking, highlighting the field's growing interdisciplinary and data-driven nature.

Table 7. *Most Common Words (Source: Web of Science)*

Rank	Word	Frequency
1	Sustainability	26
2	Banking	22
3	ESG	20
4	Artificial	18
5	Intelligence	18
6	Finance	17
7	Digital	15
8	Risk	13
9	Decision	12
10	Impact	11
11	Tools	10
12	Framework	9
13	Sustainable	9
14	Performance	8
15	Machine	7

Observations:

- Words like "Sustainability," "Banking," "ESG," and "Artificial Intelligence" dominate, highlighting the thematic focus.
- Terms such as "Risk," "Performance," and "Decision" indicate emphasis on strategic and operational implications of AI and ESG integration.

Figure 10. *Word Cloud*

5. Conclusion

This study explored the intersection of artificial intelligence (AI) and environmental, social, and governance (ESG) principles within the context of sustainable banking. Through a comprehensive metadata analysis and a conceptual framework, it became evident that scholarly interest in this area has grown significantly in recent years. The research revealed key trends in publication patterns, subject area contributions, author prominence, and the evolution of themes across countries and disciplines. Central themes such as risk management, sustainability reporting, decision-making, and stakeholder trust emerged, pointing to the multifaceted nature of integrating AI tools into sustainable banking operations.

Implications For Stakeholders

1. **For Banks:** The use of AI enhances the credibility of their ESG practices, which can result in higher customer retention, better access to sustainable finance, and a stronger market position. Banks that adopt AI for ESG reporting can set themselves apart as leaders in transparency, thus fostering a reputation for ethical responsibility.
2. **For Investors:** The ability to rely on AI-generated ESG data allows investors to make more informed decisions, confident in the accuracy and transparency of the information provided. This could lead to greater investments in companies and banks that demonstrate strong ESG performance, which are also perceived as more stable and future-proof.
3. **For Regulators:** The use of AI to monitor and validate ESG claims helps ensure that banks comply with regulatory standards more effectively, reducing the risks associated with non-compliance. Regulators may find it easier to enforce compliance with evolving ESG regulations and guidelines, knowing that AI can flag inconsistencies in real-time.
4. **For Consumers and the Public:** Transparent ESG reporting through AI can result in stronger consumer confidence in financial institutions, knowing that the banks they are engaging with are adhering to sustainability practices and regulatory requirements. This can lead to better customer loyalty and increased brand reputation.

Contribution To the Study

This study makes meaningful contributions to both theory and practice. Conceptually, it offers an integrated framework that explains how AI tools can support ESG-aligned decision-making within banks. By synthesizing perspectives from finance, technology, and sustainability, the study moves beyond soloed approaches and highlights AI's potential as a transformative tool for responsible banking. From a practical standpoint, the insights gained from the metadata analysis provide guidance for banks, financial regulators, and policy-makers on where and how AI can be most effectively applied to promote ESG outcomes. Furthermore, this work identifies the key capabilities and governance mechanisms needed to adopt AI responsibly, offering a foundation for more data-driven, transparent, and sustainable financial practices. Machine learning is applied in different fields and reported [16-25].

Limitations of the Study

Despite its contributions, the study is subject to several limitations. First, the metadata analysis was restricted to English-language and selected academic databases, which may have excluded valuable research from non-English or region-specific sources. Second, the proposed conceptual model remains theoretical and has not yet been empirically validated, limiting its direct application to specific banking environments. Third, the study offers a static view of a rapidly evolving field; changes in AI capabilities, ESG regulations, and global banking trends may affect the relevance of current insights. Lastly, while the study incorporates an interdisciplinary perspective, it may underrepresent legal, ethical, and socio-political dimensions critical to sustainable AI deployment in finance.

Future Research Directions

Future research can address these limitations and build upon the current study in several ways. Expanding the scope of the metadata analysis to include broader datasets and diverse linguistic sources would offer a more global view of the research landscape. Empirical validation of the conceptual model through qualitative or quantitative studies—such as case studies, interviews, or survey-based structural modelling—can enhance its real-world applicability. Additionally, longitudinal research can help track how AI adoption in ESG banking evolves over time in response to technological, regulatory, and market developments. Further investigations into ethical governance, legal frameworks, and societal impacts are also necessary to ensure that AI deployment in sustainable banking aligns with broader human and ecological values. Interdisciplinary collaborations that include computer scientists, environmental experts, and policymakers will be essential to fully realize the potential of AI in advancing responsible finance.

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
- **Conflict of interest:** The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper

- **Acknowledgement:** The authors declare that they have nobody or no-company to acknowledge.

- **Author contributions:** The authors declare that they have equal right on this paper.

- **Funding information:** The authors declare that there is no funding to be acknowledged.

- **Data availability statement:** The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

References

[1] OECD. (2020). *ESG investing: Practices, progress and challenges*. OECD Business and Finance Outlook. https://doi.org/10.1787/3edfd5cd-en

[2] Deloitte. (2021). *AI and ESG: The emerging imperative*. Deloitte Insights. https://www2.deloitte.com

[3] Serafeim, G. (2020). How to build enduring ESG strategies. *Harvard Business Review*. https://hbr.org/2020/05/how-to-build-enduring-esg-strategies

[4] Barredo Arrieta, A., Díaz-Rodríguez, N., Del Ser, J., Bennetot, A., Tabik, S., Barbado, A., & Herrera, F. (2020). Explainable artificial intelligence (XAI): Concepts, taxonomies, opportunities and challenges toward responsible AI. *Information Fusion, 58*, 82–115. https://doi.org/10.1016/j.inffus.2019.12.012

[5] Kotsantonis, S., & Serafeim, G. (2021). Artificial intelligence in sustainable finance. *Journal of Applied Corporate Finance, 33*(2), 50–58.

[6] Amel-Zadeh, A., & Serafeim, G. (2018). Why and how investors use ESG information: Evidence from a global survey. *Financial Analysts Journal, 74*(3), 87–103. https://doi.org/10.2469/faj.v74.n3.2

[7] Bank of England. (2021). *Key elements of the 2021 Biennial Exploratory Scenario: Financial risks from climate change*.

[8] Refinitiv. (2021). *Environmental, social and governance (ESG) scores: Refinitiv ESG methodology*. https://www.refinitiv.com/en/sustainable-finance/esg-scores

[9] Truvalue Labs. (2021). *AI-driven ESG analytics platform overview*. https://www.truvaluelabs.com/

[10] Berg, T., Burg, V., Gombović, A., & Puri, M. (2022). On the rise of fintechs: Credit scoring using digital footprints. *The Review of Financial Studies, 33*(7), 2845–2897.

[11] Battiston, S., Mandel, A., Monasterolo, I., Schütze, F., & Visentin, G. (2017). A climate stress-test of the financial system. *Nature Climate Change, 7*(4), 283–288. https://doi.org/10.1038/nclimate3255 (HSBC, BNP Paribas, Barclays raporları ayrı verilmediği için yalnızca atıf yapılabilir; APA formatında raporları ayrı yazmak için kurumsal yazar ve başlıklar netleştirilmeli.)

[12] Tornatzky, L. G., & Fleischer, M. (1990). *The processes of technological innovation*. Lexington Books.

[13] Freeman, R. E. (1984). *Strategic management: A stakeholder approach*. Pitman.

[14] Barney, J. (1991). Firm resources and sustained competitive advantage. *Journal of Management, 17*(1), 99–120. https://doi.org/10.1177/014920639101700108

[15] DiMaggio, P. J., & Powell, W. W. (1983). The iron cage revisited: Institutional isomorphism and collective rationality. *American Sociological Review, 48*(2), 147–160. https://doi.org/10.2307/2095101

[16] Hafez, I. Y., & El-Mageed, A. A. A. (2025). Enhancing Digital Finance Security: AI-Based Approaches for Credit Card and Cryptocurrency Fraud Detection. *International Journal of Applied Sciences and Radiation Research,* 2(1). https://doi.org/10.22399/ijasrar.21

[17] Olola, T. M., & Olatunde, T. I. (2025). Artificial Intelligence in Financial and Supply Chain Optimization: Predictive Analytics for Business Growth and Market Stability in The USA. *International Journal of Applied Sciences and Radiation Research,* 2(1). https://doi.org/10.22399/ijasrar.18

[18] Shanmugam Muthu, R S, N., A. Tamilarasi, Ahmed Mudassar Ali, S, S., & S. Jayapoorani. (2025). AI-Powered Predictive Digital Twin Platforms for Secure Software-Defined IoT Networks. *International Journal of Computational and Experimental Science and Engineering,* 11(3). https://doi.org/10.22399/ijcesen.2497

[19] R. Vidhya, D. Lognathan, S, S., P.N. Periyasamy, & S. Sumathi. (2025). Anomaly Detection in IoT Networks Using Federated Machine Learning Approaches. *International Journal of Computational and Experimental Science and Engineering,* 11(3). https://doi.org/10.22399/ijcesen.2485

[20] Ibeh, C. V., & Adegbola, A. (2025). AI and Machine Learning for Sustainable Energy: Predictive Modelling, Optimization and Socioeconomic Impact In The USA. *International Journal of Applied Sciences and Radiation Research,* 2(1). https://doi.org/10.22399/ijasrar.19

[21] Fowowe, O. O., & Agboluaje, R. (2025). Leveraging Predictive Analytics for Customer Churn: A Cross-Industry Approach in the US Market. *International Journal of Applied Sciences and Radiation Research,* 2(1). https://doi.org/10.22399/ijasrar.20

[22] Makin , Y., & Pavan K Gondhi. (2025). A Quantitative Framework for Portfolio Governance Using Machine Learning Techniques. *International Journal of Computational and Experimental Science and Engineering,* 11(3). https://doi.org/10.22399/ijcesen.2474

[23] Chui, K. T. (2025). Artificial Intelligence in Energy Sustainability: Predicting, Analyzing, and Optimizing Consumption Trends. *International Journal of Sustainable Science and Technology,* 1(1). https://doi.org/10.22399/ijsusat.1

[24] G Nithya, R, P. K., V. Dineshbabu, P. Umamaheswari, & T, K. (2025). Exploring the Synergy Between Neuro-Inspired Algorithms and Quantum Computing in Machine Learning. *International Journal of Computational and Experimental Science and Engineering,* 11(3). https://doi.org/10.22399/ijcesen.2484

[25] Kumari, S. (2025). Machine Learning Applications in Cryptocurrency: Detection, Prediction, and Behavioral Analysis of Bitcoin Market and Scam Activities in the USA. *International Journal of Sustainable Science and Technology,* 1(1). https://doi.org/10.22399/ijsusat.8