ARTIFICIAL INTELLIGENCE IN BANKING: A BIBLIOMETRIC REVIEW

BANKACILIKTA YAPAY ZEKA: BİBLİYOMETRİK BİR İNCELEME

Volkan DAYAN

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ABSTRACT

This study examines the existing scientific foundations on the connection between artificial intelligence (AI) and the banking sector. It reviews 218 peer-reviewed articles published between 2010 an d2024 and indexed in the Web of Science Core Collection. The literature is discussed in three dimensions, namely, intellectual structure, thematic structure and geographical distribution. With VOSviewer, the co-occurrence networks of key words, authors collaboration patterns, citation structures, and development of thematics are mapped to help to see the pre-existing research areas and the emergent trends. The results reveal that discipline has a solid foundation on technological base, especially machine learning, big data, and blockchain. Nonetheless, some more recent research has started to explore behavioral and more ethical concerns of AI, such as trust, explainability, and user acceptance. Although the thematic scope of the field has expanded, international and institutional collaboration remains limited. There are distinct research gaps that can be identified, especially in explainable AI in banking, green finance and cross-national comparative research. These results demonstrate the relevance of interdisciplinary cooperation in facilitating the responsible application of AI in the banking industry.

In order to add to the co-occurrence analysis, Latent Dirichlet Allocation (LDA) topic modeling was applied on 216 article abstracts (k = 5) to reduce potential bias in keyword-based analyses. The findings indicate that there are five recurring latent themes, namely credit risk and fraud detection; Know Your Customer (KYC) and Anti-Money Laundering (AML); trust and explainability in AI systems; AI applications in digital banking services; and Environmental, Social, and Governance (ESG) considerations. An important contribution of the research is the fact that the findings have been related to the theory of technology adoption, especially the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT). The results also have a policy implication in that they go in line with developments in AI governance systems today. Altogether, this paper summarizes the existing research on AI in the banking sector and outlines directions for future research.

ÖZ

Bu çalışmada, yapay zeka (AI) ile bankacılık sektörü arasındaki bağlantıya ilişkin mevcut bilimsel temelleri ele alınmıştır. 2010-2024 yılları arasında yayınlanan ve Web of Science Core Collection'da indekslenen 218 adet hakemli makaleyi incelenmiştir. Literatür, entelektüel yapı, tematik yapı ve coğrafi dağılım olmak üzere üç boyut dikkate alınmaktadır. VOSviewer ile anahtar kelimelerin eşzamanlılık ağları, yazarların iş birliği modelleri, atıf yapıları ve tematik gelişmeler haritalandırılarak, önceden var olan araştırma alanları ve ortaya çıkan yönelimler daha net bir şekilde ortaya çıkmıştır. Sonuçlar, disiplinin özellikle makine öğrenimi, büyük veri ve blok zinciri gibi teknolojik temellere dayandığını ortaya koymaktadır. Bununla birlikte, bazı daha yeni araştırmalar, güven, açıklanabilirlik ve kullanıcı kabulü gibi AI'nın davranışsal ve daha etik kaygılarını göstermektedir. Alanın tematik kapsamı genişlemiş olsa da, uluslararası ve kurumsal işbirliği sınırlı kalmaktadır. Özellikle bankacılık, yeşil finans ve ülkeler arası karşılaştırmalı araştırmalarda açıklanabilir AI konusunda belirgin araştırma boşlukları tespit edilmiştir. Bu sonuçlar, bankacılık sektöründe AI'nın sorumlu bir şekilde uygulanmasını kolaylaştırmada disiplinler arası işbirliğinin önemini göstermektedir.

Eşzamanlılık analizine ek olarak, anahtar kelimelerin önyargılı görüşlerini azaltmak için 216 makale özetine (k = 5) Latent Dirichlet Allocation (LDA) konu modellemesi uygulanmıştır. Bulgular, beş tekrar eden gizil tema olduğunu göstermektedir: kredi riski ve dolandırıcılık tespiti; Müşterini Tanı (KYC) ve Kara Para Aklamayla Mücadele (AML); AI sistemlerinde güven ve açıklanabilirlik; dijital bankacılık hizmetlerinde AI uygulamaları; ve Çevresel, Sosyal ve Yönetişim (ESG) hususları. Araştırmanın önemli bir katkısı, bulguların teknoloji benimseme teorisiyle, özellikle Teknoloji Kabul Modeli (TAM) ve Teknoloji Kabul ve Kullanımının Birleşik Teorisi (UTAUT) ile ilişkili olmasıdır. Sonuçlar, günümüzün AI yönetişim sistemlerindeki gelişmelerle uyumlu olması bakımından politika açısından da önemlidir. Bu makale, bankacılık sektöründe AI ile ilgili mevcut araştırmaları özetlemekte ve gelecekteki araştırmalar için yönlendirmeler sunmaktadır.

[1] Doç. Dr., Trakya Üniversitesi, Uzunköprü Uygulamalı Bilimler Yüksekokulu, volkandayan@trakya.edu.tr, Orcid No: 0000-0002-4297-4212

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INTRODUCTION

The introduction of artificial intelligence (AI) has triggered the paradigm shift in the sphere of contemporary banking, transforming it into a distant possibility to a key driving force of change. Not only have financial organizations over the last decade adopted new digital tools, but they have also begun to reconsider their relationships with customers, their approaches to risk, and the ways in which they deliver financial services. Under the contemporary banking conditions, a rather large portion of core banking operations such as fraud detection and credit scoring is based on the application of AI systems. This technological movement can be seen as both an indication of increased rate of innovation and, secondly, growing expectations by regulators and customers.

In order to maintain competitiveness and reliability, it is essential to adhere to the following principles. Financial institutions should not ignore the fact that AI is not only an instrument, but it has also become a constituent of data-driven strategy.

However, there is also a complicated chain of ethical, regulatory and societal issues that are brought up by the implementation of AI. Chatbots and robo-advisors can be used to make the process more efficient and more engaging to the customers. Nonetheless, concerns regarding prejudice, openness and confidential information have been expressed. In addition, it should be noted that AI-based risk models tend to be more scalable and faster than traditional risk models, but lack interpretability, an issue that is inconvenient in highly regulated financial services markets. These tensions only serve to strengthen the idea that research needs to be carried out to aid AI potential, as well as point to the repercussions.

Despite the growing interest, there still is no comprehensive literature on AI in banking. The existing literature is methodologically and theoretically fragmented: some studies concentrate on algorithmic modelling, while others explore behavioral dimensions of technology use. Although much has been reported about the technological aspect, there is also a gap in other issues like ethical governance, cross-country comparison, and impact on society. The fact that it is uneven makes it difficult to create a consistent image of how the field has developed and where it is moving .

To fill these gaps, the current research performs a bibliometric review of 218 peer-reviewed articles on the topic published since 2010 and indexed in the Web of Science Core Collection. The method of the current analysis is the combination of VOSviewer co-occurrence mapping and author collaboration networks and thematic clustering. The combination of such will allow us to map the intellectual terrain of the field of CS and follow new themes. The literature in the areas of machine learning, fintech, and user trust is mostly dominating, there is an increased interest in explainable artificial intelligence (AI) and technology in regard to environmental, social, and governance (ESG) as the analysis shows.

This paper presented three contributions that were being made on and the chart on the available literature and where the research gaps were found was taken. The initial contribution is based on the Latent Dirichlet Allocation (LDA) process based on VOSviewer to explain hidden structures in the abstracts of the articles. The second contribution depicts how trust, explainability, and adoption are considered based on the use of Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT). Finally, the study has policy implications based on concordance to AI governance discourses and ESG-regulation.

Research Questions

The following research questions guide this investigation:

- What are the dominant themes and research trends in AI-related banking literature between 2010 and 2024?
- How do the latent topics identified through Latent Dirichlet Allocation (LDA) correspond to the keyword clusters generated using VOSviewer?
- In what ways can these themes be interpreted through technology adoption frameworks, particularly the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT)?
- What methodological gaps and future research

opportunities are revealed by the current structure of AI research in the banking domain?

CONCEPTUAL FRAMEWORK AND LITERATURE BACKGROUND

The integration of AI into the banking sector has emerged as a dynamic area of both academic and practical interest, particularly in the context of financial services embracing digital transformation. AI, encompassing machine learning, natural language processing and expert systems, is being utilized more frequently in areas such as credit scoring, fraud detection, customer service and algorithmic trading (Russell & Norvig, 2016; Goyal et al., 2024).

Previous research has also highlighted the importance of AI operation in banking, starting with risk assessment and evaluation up to assessment of portfolios (Pattnaik et al., 2023; Nobanee et al., 2024). Research has shown that increase in the application of artificial intelligence in credit risk assessment helps in increasing precision in risk evaluation as opposed to statistical methods. This is done by using methodologies that include decision trees and neural networks. In addition, it is also found that there is increasing incorporation of AI in RegTech for the effective and real-time use of compliance and monitoring models.

Besides the technological points of view, there are more non-technical and more moral issues discussed in the extant literature. According to Goyal et al. (2024) the issues as trust and data security influence customer adoption significantly. Using the research conducted by Nica et al. 2024, the authors established the importance of adopting decision-making based on rotor fuzzy logic as well as explainability in situations with uncertain financial information. There is an increasing focus on insisting on the ethical nature of AI together with the need to make AI solutions more explainable and for the benefit of people.

The post-pandemic era has seen a further acceleration in scholarly interest, as financial institutions seek intelligent automation and remote decision-making capabilities (Manta et al., 2024). Bibliometric analyses indicate a notable increase in publication output since 2020, particularly concerning chatbots, mobile banking, and AI-powered customer engagement (Pattnaik et al., 2023; Goyal et al., 2024).

In addition, there has been emerging subfields pertaining to certain specific fields, for example, artificial intelligence Islamic finance. According to Tayachi et al. (2022), Malaysia and Indonesia appear to be at the forefront of Shariah-compliant AI in banking that advocates for new ethical models of banking in developing countries.

Hanif (2021) posits that the proliferation of intricate AI systems within the banking sector necessitates the implementation of Explainable AI (XAI) frameworks. These frameworks are particularly crucial for fostering user trust and ensuring regulatory compliance through transparent decision-making processes.

As Witzel and Bhargava (2023) emphasize, it is imperative for AI applications in banking to be aligned with ESG frameworks. This alignment is crucial to ensure sustainable innovation and to prevent long-term reputational or systemic risks.

Nobel et al. (2024) provides evidence that integrating XAI techniques such as SHAP and LIME significantly enhances the interpretability of fraud detection models applied to highly imbalanced banking datasets.

Mintah et al. (2023) caution that bibliometric visualizations, while useful for mapping intellectual landscapes, fall short in capturing the semantic nuances and theoretical implications embedded within literature.

Trivedi (2016) highlights the value of cross-country comparative methods, emphasizing that structural differences—be it institutional support or educational culture—significantly shape technological adoption outcomes, a factor often neglected in bibliometric maps.

As Schneijderberg and Götze (2021) contend, national academic systems ought to be evaluated not solely based on publication volume, but also on societal engagement and knowledge co-construction. These elements are presently underrepresented in bibliometric outputs.

Ikra et al. (2021) have expressed concerns regarding the overreliance on citation counts and co-authorship maps, proposing an alternative approach that incorporates content-based analysis to offer a more nuanced interpretation of financial innovation literature.

However, as this seems to suggest, the current research is still chaotic and disjointed. The majority of studies are characterized by an absence of interdisciplinary integration and contextual analysis, with a paucity of longitudinal or cross-country comparisons. A comprehensive bibliometric mapping of the kind performed in the present study can facilitate the identification of research gaps and promote conceptual consolidation within the AI–banking nexus.

The research is grounded in scientometric methods, and employs keyword co-occurrence, author collaboration, and citation network analyses via VOSviewer to map the cognitive structure of the field. The objective of the findings is to provide support to academics, practitioners and regulators in navigating the adoption of responsible and innovative AI in the banking sector.

Recent research findings highlight the implications of social contextual factors in deploying AI in banking focused on the intersections of technological innovation combined with the roles of human agency, digital literacy, and workforce transformation. Human capital is crucial in realizing the anticipated benefits of adopting AI since both customers and employees need specific adaptive skills and trust in organizations. Furthermore, financial inclusion has emerged as a significant area of research concern. Scholarly discourse has emerged on the subject, with scholars arguing that AI-driven models must be designed to extend access to underbanked populations rather than deepen existing inequalities. The thematic framework of this study encompasses three core concepts: social impact, human capital development, and inclusive financial access. These themes serve as a foundational theoretical triad, complementing the technological and ethical perspectives that inform the study.

Critical Review of Existing Literature

Although the literature on the discussion of the use of AI in the banking industry has been growing over the years, the literature available is marked with disunity and lack of an analytical framework. Many of the studies provide descriptive mappings or individual case studies without going through providing a comparison or critical analysis of the divergent methodologies. As an example, some of the papers follow bibliometric methods (e.g. co-occurrence or co-authorship analysis) and others apply experimental, qualitative, or hybrid methods but almost never is there any discussion on compatibility or limitation of these methods. Moreover, little questions the representativeness of datasets geographic or institutional biasness of the Web of Science index.

Moreover, most of the works in this area merely refer to the application of AI and do not analyze the premises on which algorithms are developed, the ethics of information or its practicality in various situations. Much though people recognize the ethical concerns of AI (e.g. explainability, mitigating bias and unfairness), they are often not properly formulated or sufficiently validated by research. Moreover, too little attention is paid to the fact that AI is affected by a great number of various regulations and cultures, which prevents the development of real general knowledge. Due to the lack of a single theoretical frame or systematic approaches, there are numerous gaps in which the discussion will require numerous improvements to be made to be more based not on showing tendencies but also taking a closer look at the factors behind these tendencies.

Findings indicate a literature preference in favor of bibliometric or survey-based methodology, at times to the cost of more analytical or longitudinal methodology. Unfortunately, the methods of quantitative mapping such as co-occurrence, citation analysis are highly employed and very little is said about interpretive viewpoints or current case studies.

It is worth noting, though, that a mere inspection of the available literature suggests that only a minute percentage of the studies (2 or so) adopt mixed methods with even less studies coming up with experimental and field-based results of the effect of AI on financial services and assessing an actual impact, which can be measured. Such methodological homogeny kills theory and constrains practicality of what might be deduced out of results. Further research to be applied in establishing the field should be distinguished in the mode of inductive case studies, comparative research with policy implications, simulation models, and participatory research strategies, which will be more in line with the socio-technical complex of AI in banking.

Despite the extensive amount of AI and banking research, most of it merely provides the major sides of the research and does not discuss the potential of contradictions and errors.

Some researchers rely on machine learning in testing credit risk but many of them end up with expert systems or fuzzy logic systems.

However, the number of studies comparing the practical and predictive value head-to-head is very low. The impact of AI on trust, customer satisfaction and financial inclusion remains an under-researched area. Furthermore, the epistemological assumptions that underpin algorithmic decision-making are addressed only in extant literature. Many studies also do not consider such aspects as the legislation concerning data and data quality itself. All these gaps in the study make it difficult to see the general trends and apply them to the other regions and time periods. More efficient assimilation and reflection of the existing ideas will help to develop cognition and practice in this field. It is imperative that the scope of the review extends beyond the mere presentation of findings; it must also elucidate the methodology employed in researching the issues, including any contentious aspects and the existing lacunae in knowledge.

METHODOLOGY AND DATA

The present study employs bibliometric techniques to map the intellectual, conceptual, and collaborative structures of AI research in banking. The present study collected data from the Web of Science Core Collection, which includes peer-reviewed articles published between 2010 and 2024. The search strategy was employed across all fields (title, abstract, author keywords) using search products for the term “artificial intelligence,” combined with the term “banking.” Selection was made for articles and reviews published in the English language because, for scientific rigor, it is acceptable to focus on English language articles. Conference proceedings and publications in languages other than English were excluded from consideration.

Following the screening process, a final set of 218 articles was obtained. The bibliographic information, incorporating such details as authorship, keywords, affiliations, and cited references, was exported in CSV format for the purpose of analysis.

Prior to analysis, a data cleaning process was conducted to enhance clarity and interpretability. Generic and ambiguous terms such as "system," "model," and "technology" were manually removed. The synonymous terms were unified, and minor typographical errors were corrected. A minimum threshold was applied for network generation: five occurrences for keywords, and one publication and citation for author and country analyses.

VOSviewer (version 1.6.20) was utilized to construct and visualize the bibliometric networks. The software facilitated the generation of keyword co-occurrence maps, co-authorship networks, country collaboration maps, citation networks, and thematic evolution diagrams.

Methodological Limitations of VOSviewer and Recommendations

Although VOSviewer also gives an opportunity to see graphs of co-occurrence, co-authorship and citation networks, the user should be aware of its potential disadvantages.

Their principal measures are frequency and proximity algorithms that are functional in detecting repeating patterns, but they ignore the meaning and context of the text. VOSviewer keyword co-occurrence maps do not distinguish between shallow and important relationships amongst keywords. There is also a lack of more complex topic modelling, temporal trend decomposition and sentiment analysis, which are increasingly being used in assessing the AI in banking.

The clusters generated by VOSviewer, in turn, often are closely related to each other, nevertheless, VOSviewer cannot visualize the high number of various ideas they contain. These reasons make it convenient to base on VOSviewer to do overview research and use additional tools when it is required.

One can learn more about the structure of discussions, the most important topics that can be discussed, and the stories that are being developed using Structural Topic Modeling

(STM) or full-text NLP with the assistance of Latent Dirichlet Allocation (LDA). The use of such methods in subsequent studies will make bibliometric studies clarify what is going on and give a more global view of what is going on in the field Blei et al., (2003); Griffiths and Steyvers, (2004).

Complementary Topic Modeling

LDA was used to analyze 216 abstracts to supplement co-occurrence mapping. Preprocessing of the texts involved processing them to lowercase and stop words were excluded and it was processed in both English and Turkish. An array of unigrams and bigrams was used to create a bag of words representation, which was made more robust. The parameter k was set to 5. As suggested in Table 1 the most common terms linked to each topic are reported. These words are also demonstrated in Figures 1-5. Table 2 shows the per-document distributions, and the full dataset can be found in the Appendix.

Limitations: The assignment of subject names is done according to the methods of heuristics and results can be prone to change based on the choice of k. Nonetheless, the use of stability tests has proven the existence of regular trends.

In addition to co-occurrence mapping, LDA was applied to the abstract corpus to extract latent thematic structures. This complementary topic modeling approach reduces keyword frequency bias and improves robustness by identifying coherent clusters that may not emerge through VOSviewer alone. The parameter was set to $k = 5$ after iterative evaluation of topic coherence. The most significant topic terms extracted from the LDA model are presented in Table 1.

Table 1. Top Terms Per Topic Identified by LDA Analysis

Topic	Top 8 terms
0	model, financial, robo, risk, learning, bank, credit, machine
1	ai, banks, financial, adoption, related, human, managers, design
2	financial, digital, banks, technologies, sector, information, fintech, technology
3	ai, perceived, technology, intention, customer, service, trust, adoption
4	financial, ai, fintech, services, technology, service, value, impact

Note. Each topic lists the eight most relevant terms identified by LDA.

According to table 1. topics can be categorized into different semantic clusters, from technology-focused topics (fraud detection, credit risk) to broader topics such as explainability, trust, and ESG. Some evidence as to the distribution of terms shown in the preceding table suggests that while the field has roots in technical and regulatory applications (for example, Know Your Customer/Anti-Money Laundering) there is a concurrent evolution into discussions that address ethical and sustainability topics. This dual focus demonstrates a research community that is grounded in practical issues and cognizant of broader social obligations.

The top terms associated with each topic are visualized in Figures 1 to 5, illustrating Topic 0 to Topic 4 respectively.

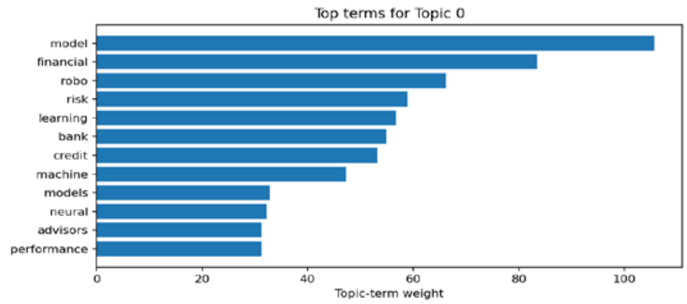

Figure 1. Top terms for Topic 0 derived from LDA

Note. The figure shows the relative weights of the top terms for Topic 0.

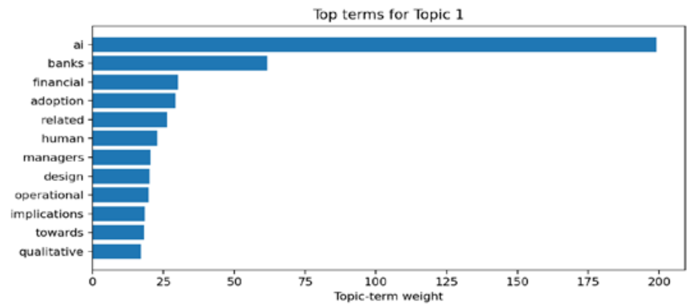

Figure 2. Top Terms For Topic 1 Derived From LDA

Note. The figure shows the relative weights of the top terms for Topic 1.

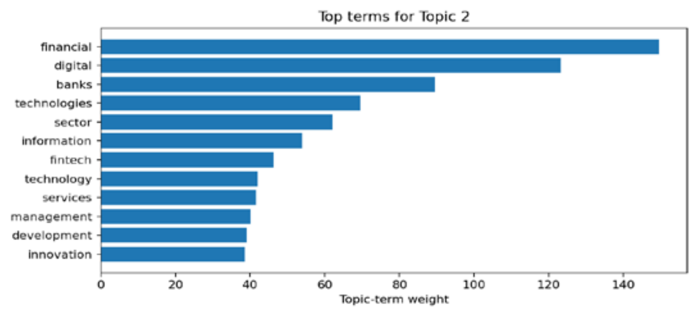

Figure 3. Top Terms For Topic 2 Derived From LDA

Note. The figure shows the relative weights of the top terms for Topic 2.

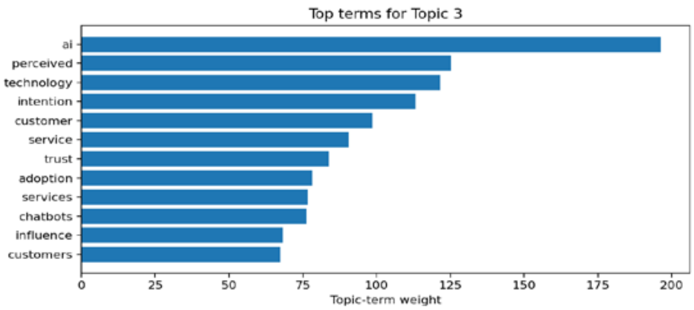

Figure 4. Top Terms For Topic 3 Derived From LDA

Note. The figure shows the relative weights of the top terms for Topic 3.

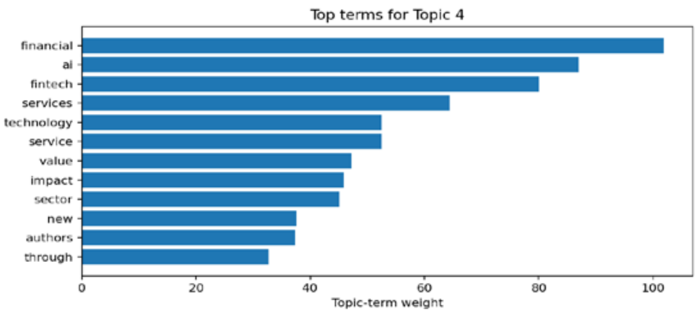

Figure 5. Top terms for Topic 4 derived from LDA

Note. The figure shows the relative weights of the top terms for Topic 4**.**

Figure 1-5 have represented the weight of the leading terms to the latent topic in a relative way. Figure 1 shows the critical role of operational risk management in AI-based banking by the abundance of such words as fraud, credit risk, and compliance. On the other hand, clusters in Figures 3 and 4, where the focus is on trust, explainability, and transparency, show that the academic community is becoming more concerned with human-related and ethical issues concerning AI use. Figure 5 continues this line by adding references as ESG and sustainability, which suggests a gradual diversification of AI studies in the direction of research areas with long-term policy implications. All these numbers give a readable map of intellectual terrain of the field between the technical and social issues (Schoenmaker and Schramade, 2019) and (Busch and Friede, 2018).

Table 2 presents the dominant topic assignments and reveals the thematic structure of AI research in banking.

Table 2: Sample Document-To-Topic Assignments from LDA Analysis

Title (shortened)	Year	Dominant topic	Probability
The analysis of critical success factor ranking...	2025	3	.65
A study on adoption of artificial intelligence...	2023	3	.85
Transforming banking: Examining the role of AI...	2024	2	.99
An empirical study on the use of artificial...	2025	3	.49
AI in banking: Socio-economic aspects	2024	2	.54
...	...	...	...

Note. The table shows the first 20 documents with their dominant topics and probabilities. The full dataset is provided in the supplementary material. Additional rows omitted for brevity; see Appendix for the full dataset.

Additional LDA results, including the complete topic-to-document assignments, are provided in Appendix A.

The example given with Table 2 represents document-level topic allocations. The example highlights the probabilistic association of individual studies to various dominant themes. It illustrates the heterogeneous nature of AI research in banking. For example, a few papers align closely to the fraud detection and KYC/AML clusters, while other papers demonstrate a more generalized form of literature through topics of explainability, ESG, or sustainability-related reporting. The spread of publication topics clearly suggests literature does not sit in silos, but instead highlights literature that overlaps, suggesting researchers are increasingly recognizing the overlap and interplay between operational efficiency, regulatory compliance, and ethical or socially responsible accountability. Literature rounds that cut across these imperatives recognize that because data and financial services are intertwined, they have implications across domains and raise both ethical and financial efficiency concerns. Thus, it appears in recognition of these overlaps and understandings across different domains that researchers have increasingly articulated and suggested multi-methods, cross-disciplinary studies focused on AI in financial services. Regarding the integration of technology adoption frameworks, it has been a topic of considerable discussion over the past few years.

The topic clusters based on LDA indicate shifts in themes from technical enablers (ML, big data, blockchain) to behavioral and ethical concerns (trust, explainability, ESG). These shifts are consistent with recent conceptualizations (or frameworks) of adoption and innovation. Like the work of Davis and his TAM, perceived usefulness and perceived ease of use are established as important indicators to drive adoption (please see the cluster related to efficiency and automation in AI). Similarly, UTAUT Framework uses performance expectancy, facilitating conditions, and social influence. While ostensibly consistent with Davis and Venkatesh work, clusters aligned with customer trust, regulatory support, and organizational readiness, respectively, represent similar constructs but with respect to socio-institutional forces. The relationship between the bibliometric trend analysis and these theoretical constructs illustrates that academic discourse can do more that build knowledge but delineate on long-established frameworks or behavioral models. Davis, (1989) and Venkatesh et al., (2003).

The integrated findings help to maximize the explanatory potential of the results and suggest a next step may include a research project that investigates the simultaneous effects of technology affordances and related socio-institutional forces to the adoption of AI in banking.

RESULTS

In this section, the main results of the bibliometric study on AI and banking literature are presented. The results produced are organized around four areas: keyword co-occurrence, author collaboration, contributions of countries, and citation impact. Each of the sub-sections provide data on the intellectual, conceptual, and geographical structure of the field, supported by VOSviewer visualizations.

The analysis identifies core topics, major contributors, important studies, and shows the evolution of research topics, collaboration, and geographical spread over the past 15 years, providing the complete picture about the development of the field.

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The analysis identifies core topics, major contributors, important studies, and shows the evolution of research topics, collaboration, and geographical spread over the past 15 years, providing the complete picture about the development of the field.

Keyword Co-occurrence Analysis (Author Keywords)

The analysis of author keywords has been shown to help reveal the thematic structure of the research field via co-occurring terms. This analysis is a valid approach for tracking emerging topics, methodological shifts, and emergent areas within an academic discipline. In this study, a keyword co-occurrence map was created using VOSviewer with a threshold of 5 occurrences for each keyword.

The result is a network showing conceptual connections and a host of thematic clusters, including predominant trends such as machine learning, trust and fintech, as well as incipient niche areas of research. And through its mapping of the conceptual landscape, the co-occurrence analysis provided a base understanding of how AI is framed and employed within banking.

Figure 6 illustrates the top 15 author keywords in the AI and banking literature, highlighting the dominant research themes.

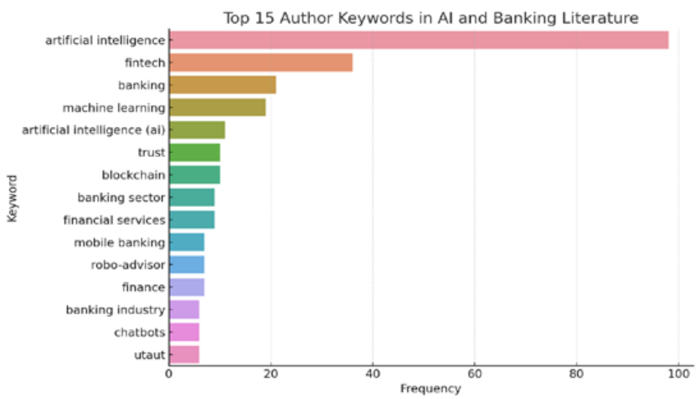

Figure 6. Keyword Co-occurrence Map of Thematic Clusters in AI

and Banking.

As shown in Figure 6, five main thematic clusters emerge from the keyword co-occurrence analysis, indicating that the literature remains broadly structured around technical AI methods, fintech applications, risk analytics, and human-centered adoption factors.

Figure 6 presents an analysis of keywords used by the authors and represents an overview of the keywords used in literature in AI and banking. Such data indicates that most authors generally use keywords associated with both the technical underpinning and developing behavioral-financial themes. “Artificial Intelligence” gives separate yet equal indication of emphasis in the degree of centrality in the author's keywords analysis as it has emerged as a keyword employed frequently in published literature. Artificial intelligence is directly related, but unique from “fintech” and “banking” keywords and indicate that AI is just as relevant in the digital transformation of finance. 'Machine learning' surfaced as also important to the field, representing a great methodological basis in both predictive analytics, financial fraud detection, and automated algorithmic decision making. More recent behavioral-financial themes associated with emerging subjectivity, such as “trust”, “chatbots”, “mobile banking”, and “UTAUT”, demonstrate an interest in digital interaction, user adoption, and emergent behavioral models. Related, 'robo-advisor' and 'financial services' appeared frequently in the literature indicating an emerging interest in AI assisted investing strategies and client personalization.

The minor differences in keywords like “artificial intelligence” and “artificial intelligence (AI)” are similar to the bibliometric normalization issues that we've discussed above, but it is evident that there are methodological and technical issues in the terms that were the rationale for the differences and relations, in the articles.

By including languages like "blockchain," "banking sector," and "banking industry," we are highlighting the infrastructural nature of AI's impact on traditional financial systems. The existing literature is largely focused on technology, although this is evolving to include behavioral dimensions. There is also a range of coverage on topics that include investment services, regulations and customer experience.

When looking at the co-occurrences of key words, machine learning and blockchain such as trust and user acceptance are of considerable priority, now relatively established as an academic subject. The interdisciplinary research has a bright future as revealed by the integrated nature of technology and human-centered research. The map however shows that the films are highly disproportional in terms of creativity. Many point out topics such as governance, explainable AI (XAI) and sustainability to have emerged less than other models suggest would be appropriate in contemporary literature. Such omissions indicated that future research should focus on similarities and differences between advanced and emerging economies; of incorporating ESG principles into AI in banking; and on further analysis of trust and user experience using more ethnographic, qualitative or mixed methods. Addressing such omissions will allow AI to be better used and more effectively contribute to how the financial services develop.

Co-authorship Analysis

Co-authorship analysis has provided a view of the collaborative landscape of a research discipline in terms of academic collaborations of co-authors. The emphasis of this article has been to discover the ways in which knowledge is constructed through local and international research networks. With regard to AI and banking, co-authorship analysis helps to reveal where new research teams are located, which players are developing banking technology, and where collaborative activities are situated.

As shown in Figure 7, the co-authorship network was visualized in VOSviewer with a minimum threshold of one publication on record for any author. The visualization provides an outline of clusters of researchers that co-published together, which illustrated intellectual partnerships, research productivity, and social influence established within the academic community.

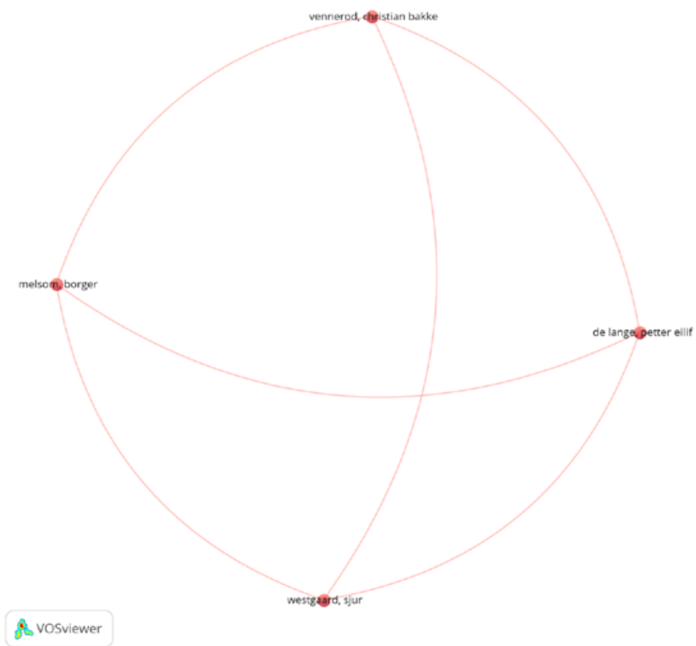

Figure 7. Author Co-authorship Network Revealing Emerging but Fragmented Collaboration

The co-authorship structure shown in Figure 7 suggests that academic collaboration in this field remains fragmented, with a few central authors and several isolated research groups.

The researchers conducted a co-authorship evaluation of metadata of the authors to evaluate the collaboration pattern between AI and banking research. Since the aim of the research was to maximize the number of contributors, they selected a threshold of one per author to pull out the fragments of the collaboration network and to define small clusters of collaboration. The collaboration network was formed using VOSviewer and the result is as shown in Figure 7.

This ego network has developed around a close and professional circle of five authors, namely Vennerod, De Lange, Westgaard, and Melsom; at least the group presumed a center of interest, there should be intersectional themes, like financial risk modelling with AI and machine learning. In spite of the fact that the degree of the co-authorship concentration is less than anticipated even in the fields mentioning the entirety of the work provided, this visualization instrument has also provided demonstrations which illustrate that the small-scaled partnerships are rising. The fact that this network is not dense also suggests that interdisciplinary and inter-institutional collaborations are also rather under researched, which gives room to develop.

The way the author co-authors indicates that research collaboration is relatively new in this area but obviously a pro-organizational process and having some fragmentation. Despite the observations of several key micro-clusters by some of the experts in the field, e.g., Vennerød, De Lange and Westgaard, the society itself shows an unclear density or meaningful connections, or relationships between disciplines and organizations. The abundance of isolated nodes and infrequent transnational connections shows how the development of this field is still limited in narrow academic silos, which indicates perhaps there is potential yet to be realized towards a more interdisciplinary and international research network. Similarly, the low numbers of interconnected large-scale collaborative ecosystems indicate systemic barriers, like funding imbalances and institutional silos, which may deter scholars from diffusing knowledge. Possibly the diversification and multiplication of the academic exchange programs, intercontinental consortia, and joint research funding can be a stimulus in transforming the monolithic and narrow formats of academic production in this field.

Country Analysis

Conducting an analysis at the country level is a useful way to gain insight into geographic signals in research productivity and international collaboration. While studying AI and banking, innovation can have rather different propensities at various worldwide systemic levels. A country-level analysis will help showcase countries that occupy the upper-right of the cohort of countries and reveal regional research trajectories.

Using a minimum threshold of one publication and one citation per country, a collaboration map was created in VOSviewer. The study exposes geographic clusters and institutional linkages, framing and evolving the study of AI regionally.

As shown in Figure 8, it identifies India, USA, England and Malaysia as central nodes that display considerable research productivity and growing cross-country interaction across the global AI and banking space.

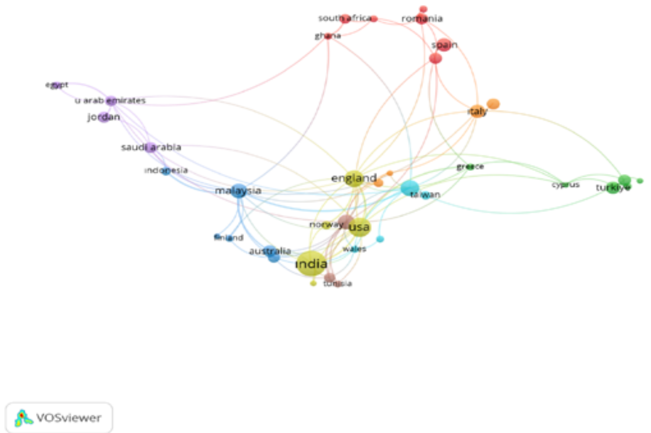

Figure 8. Country Collaboration Map Highlighting Partnerships.

As illustrated in Figure 8, research activity is dominated by collaborations among high-income countries, while emerging economies show weaker research connectivity.

To examine collaborative research activity in AI and banking at the national level, a co-author map was created in VOSviewer at the country level, with at least 1 document. Like what we noticed at the author-level networks, the co-author map, revealed clusters of collaboration across countries.

The following figure indicates what we would refer to as prominent central nodes for collaborative effort at the international level, namely an international collaborative effort from countries such as India, the USA, England, Malaysia, and Spain. Both India and the USA are notable for their significant publication output, and more importantly their output of co-authored documents, as they contribute to the conversation at the international level. England also shows strong connectivity with Malaysia and Australia that resembles a collaborative triangle. Finally, Spain, Romania, and South Africa demonstrate strong collaborative effort in a Euro-African triangle.

In the context of the green cluster, Türkiye clusters closely with Greece and Cyprus indicating a multi-country interest in regional research on the Eastern Mediterranean region. It also reveals regionally clustered outputs and increasing participation from emerging economies in the global AI-banking conversation.

The mapping serves as a comprehensive overview of the research landscape internationally within this area and highlights the importance of cross-border collaboration and the increasing focus of researchers, practitioners, and other stakeholders on participation by both developed and developing countries. It is apparent from the country-level collaboration map that the research ecosystem is asymmetrical; some countries such as India, the United States, and England are prominent in multiple bilateral and trilateral collaborations. Other areas of the world such as Türkiye, Jordan, Bangladesh, and some areas of Sub-Saharan Africa, show strong digital banking activity (evidence of technology) but are either on the peripheral edges of the network of countries represented or are not even represented. These disparities highlight the possible reasons for the need to be more supportive of peer-reviewed research from countries and regions that have been previously excluded. Being excluded from international funding opportunities, language barriers, limited research capacity, and lower levels of data and research management may all be reasons for the isolated position of some countries. Future work may explore the reasons peer-reviewed academic work is either facilitated or limited by focusing specifically on the effects of AI on cross-border financial transactions.

An extensive analysis of the country level data demonstrates that a high level of publication output does not necessarily correlate with a high citation impact. For example, even though India has the highest number of publications, the average citations per publication are more moderate than those from the US or the UK, in which the average number of publications are generally cited more often. Both variations reveal dissimilarities in visibility of the research, variations in journal quality, and differences in levels of international collaboration. In the event of university based academic publication, it would be probable that countries that have lower publication counts but have higher levels of citation and visibility of their publications are benefiting from academic connections through a network of researchers, or through access to high impact journal publications. Conversely, research produced at a markedly higher volume of publication that does not achieve visibility or high citation impact may struggle to achieve visibility amongst a global audience. An awareness of this opportunity gap is critical to support both productivities, as well as scholarly impact across the disciplines of AI and banking.

The country-level collaboration map indicates the existence of a few global research hubs, including India, the US, and England. It further illustrates the relatively peripheral position of many developing and middle-income countries, such as Türkiye, Jordan, Bangladesh, and parts of Sub-Saharan Africa.

Research contributions that are hampered in the manner described will often involve some underlying systemic barrier, like the absence of funding for AI related research and the presence of barriers to high-quality data sets and/or a set of regulatory conditions that make profound experimentation with AI extraordinarily difficult for academia and industry researchers - a condition that creates no shortage of frustration and uncertainty in these conditions. In addition, countries, and especially countries that are not primarily research-oriented, suffer further constraints, like an absence of a national strategy for AI development, weak digital infrastructure, and weak coordination mechanisms or linkages between academia and industry. By way of heritage these conditions will ideally lead to many researchers in these contexts completely disenfranchised from the global information and knowledge network. It is no wonder that the absence of visibility, citation profile, and connections through cross-border consortia leave marginal researchers with little to no opportunity for inquiry and contribution to global AI related research. Addressing these factors, at the level of funding, capacity, and policies will require not just financial investments in establishing research capacities and funding models but may also entail some recruitment of new funding and funding frameworks that facilitates we'll think researchers to share ethically, support regional collaborations, and enable some participation in international obligations for governing AI activities and development.

Analytical Evaluation of Türkiye's Position in AI and Banking Research

The recognition of Türkiye in the global context of AI and banking research is limited. In a regional bibliometric mapping in Figure 8, Türkiye is displayed within a modest regional cluster with Greece and Cyprus which signal some level of activity in that Eastern Mediterranean region. However, this appears to be lacking in density and international connectivity, compared to major research topics like India, the USA or England. The overall lower level of contribution and citations may be the result of several contextual and structural factors. There is limited support for research funding in the field of advanced digital finance, limited involvement in AI consortia funded by the European Union during the pandemic, and uncertainty in data governance and fintech innovation regulatory environment.

Furthermore, many academic institutions in Türkiye operate in disciplinary silos, inhibiting the interdisciplinary cooperation that is needed for research in AI-finance. Addressing these issues requires countries to develop a national strategy for AI research, engagement in international research programs, and allocate funds for support in human resourcing. Since Türkiye is positioned between Europe and the Middle East, there are numerous opportunities for ethical and inclusive AI to have a firm foothold in banking.

Figure 9 shows the 15 authors with the most productive in AI and banking literature by the number of publications.

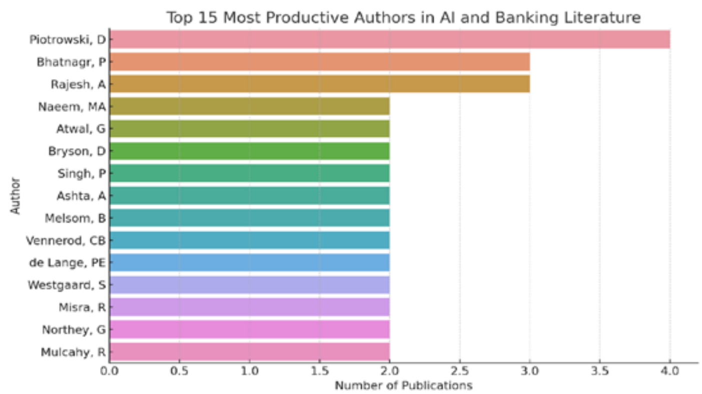

Figure 9. Top 15 Most Productive Authors in AI and Banking

Figure 9 identifies the most active authors in the domain, highlighting a concentration of productivity within a limited group of researchers.

These authors are established scholars and represent potential collaborators in future multi-disciplinary research. The author with the highest publication count is Piotrowski, D. with four publications which indicate there is the development of a longer-term research themes (risk modelling, automation and digital transformation). Bhatnagr, P. and Rajesh, A. are second with three each which indicates they have sustained engagement for a period and are building an authorial impact. The authors with collaborative papers who each authored two articles are Naeem, M.A. Atwal, G., Bryson, D., Singh, P., Ashta, A., Melsom, B. and Vennerod, C.B. The co-authored papers published by these authors are centered around topics of AI adoption, ethics in finance, credit analytics, and consumer trust.

Some authors shown in Figure 9, de Lange, P.E., Westgaard, S. and Vennerod, C.B., are also prominent in the earlier citation analysis and co-authorship research previously referenced as possible suggestions of a connection between collaboration and research productivity. In the context of this thesis, while there are many authors interested in AI in banking, there does not seem to be a clear dominant author, indicating that this area of research is still emerging and fragmented. As mentioned earlier, fragmentation suggests opportunities are available for emerging researchers to also contribute to the discourse and for stronger cross-institutional collaboration and networks to emerge.

Country-Level Analysis

Identifying global research movements is imperative to contextualize revolutions in AI and banking. Country-level analysis will tell us which countries the most significant contributors to AI and banking research and where global knowledge circulation occur across borders.

To help us visualize this knowledge circulation, we used VOSviewer to perform a country-level co-authorship analysis, designating a minimum threshold of one publication and one citation to confirm that country participation was relevant. The result is a collaboration map that exposes participant countries with interaction via the example of publications and citations. This map enables us to identify active and academic-new entrants to the AI and banking studies research landscape and identify amounts of participation from countries and institutions.

The top 15 countries with the most publications in this area of research are seen in Figure 10.

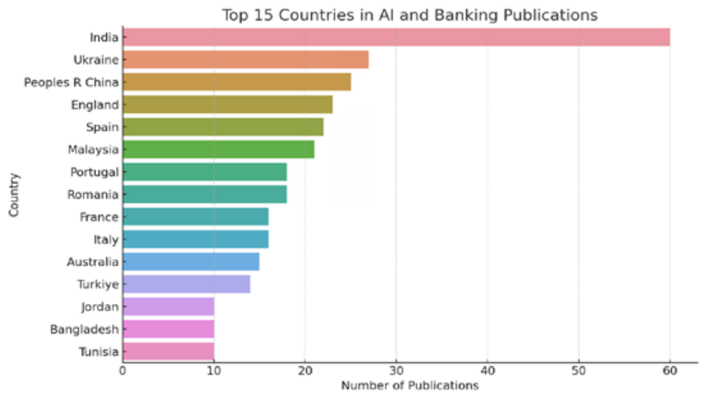

Figure 10. Country-Level Distribution of AI and Banking Publications

According to Figure 10, AI in banking research is geographically skewed, with the highest publication volume originating from the United States, China, and the United Kingdom. The geographical distribution of AI & Banking knowledge production and case studies of the 15 leading countries in AI & Banking is presented in Figure 10. India has the most publishers. This likely reflects the country rapidly gaining experience with digital financial inclusion and fintech startups, accompanied by some government support with the development of AI (Demirguc-Kunt et al., 2022).

It is reasonable to conclude that India's preeminence can be attributed to the importance of academic-industry linkages and the digitization of the economy.

It is also possible that Ukraine and China will follow India. Ukraine's contributions are grounded in the strength of its academic clusters and interest in digital financial transformation (Kolodiziev et al., 2024). As for China, its use of AI in banking relates to the areas of credit scoring, surveillance, and facial recognition coupled with significant national investment (Li et al., 2021).

Other notable contributors included England, Spain and Malaysia. The fintech ecosystem in the UK, along with its supporting regulation, and the regional networks and digital banking strategies of Spain and Malaysia contributed to their research output.

European countries like Portugal, Romania, France and Italy provided a steady source of contributions, particularly related to the ethical and regulation of AI. Contributions from Malaysia and Romania related to Islamic banking and ethical issues of AI stand out for their implications for ethical banking.

These contributions were in addition to a number of emergent contributors (e.g. Türkiye, Jordan, Bangladesh, Tunisia), that could be seen as an improvement of equity in global research output. These demographics focus largely on the issues of AI transformation in banking and regulation of Fintech.

Overall, while contributors from countries around the world have increased, issues with imbalances in published work creates opportunity for collaboration and improvement of capacity building in countries with produced less work overall.

Citation Analysis

Citation analysis is an essential mechanism for assessing intellectual influence of publications in a research field. It allows us to detect influential research papers, researchers and institutions that provide knowledge advancements to the AI and banking domain. Citation data for this research study were sourced through the data generated from the Web of Science core collection and visualized using VOSviewer. A limit of 10 citations per document to aid in highlighting major contributions to the AI and banking literature in the present document was applied. The citation network produced allows for structural representation of knowledge diffusion and knowledge clustering.

Figure 11 shows the top 15 most cited papers in the area of AI and banking research. The articles that demonstrate the highest level of citation are focused on AI adoption, fintech evolution - development, and customer experience; knowledge advancement of those themes reflect not only thematic priorities, but also the conceptual and cognitive evolution of the domain.

Figure 11. Most Cited Articles in AI and Banking: Citation Impact and Intellectual Anchors.

The preceding Figure 11 presents the Top 15 Most Cited articles in AI and banking based on the Web of Science Core Collection. Citation counts are a means of illustrating the academic impact and influence of the articles which comprise the literature base on AI and banking overall. The most cited article entitled, "Intention to use analytical AI in services" examines users' behavioral readiness to embrace AI and represents a transition to user-oriented research. Significantly, included among them, the author of "Genetic algorithms applications in the analysis of insolvency risk" has a multitude of other highly cited technical works. "Genetic algorithms applications in the analysis of insolvency risk" is a pioneering work that illustrates the importance of AI within both predictive modelling and risk management.

A further illuminating piece of work entitled "Exploring banking chatbots customer experience" articulates connections between consumer psychology and service innovation in conjunction with AI, particularly on trust and quality in digital services. A similar type of conceptual contribution also resides in "Fintech: what's old, what's new?", which synthesizes broad overviews connecting AI to broader trends in financial innovation. The same may be said for "AI customer service: The papers "Task complexity, problem solving ability, and usage intention" and "Determinants of customer satisfaction in chatbot use" incorporate another emphasis on personalization and automation in banking applications.

There are several highly cited works that explore organizational change, value co-creation, and strategic impacts of AI, including "Digital servitization value co-creation framework" and "Adoption of AI for talent acquisition."

An overall review of the most commonly used literature in this area shows that there is an interdisciplinary research agenda, a blend of the technical, behavioral, and managerial approaches, and evidence of the transformative effect of AI through financial institutions.

The citation network map of the major publications establishing the major themes of the AI research in the banking area contains a distinct pattern. The majority of the studies that are frequently cited focus on the novel algorithmic approaches, credit risk evaluation and approaches to integrating new services by users. It translates to the fact that individuals are acting and operating technology intensively. Hence, this primary topic trend means that such issues like explainable AI, sustainability and dynamics of cultural trust are not yet well-developed in the books on AI. The connection between the concept of ethics, regulations and the essence of AI seldom exists significantly.

This observation provides an auspicious starting point for future research that will include previously ignored perspectives. Expanding the scope of citation influence beyond technical contributions may provide legendary intellectual diversity in the field, and produce a more balanced, contextually sensitive knowledge base.

VOSviewer Visualizations and Network Mapping

To provide a visual representation of the intellectual structure and thematic development within the AI and banking literature, VOSviewer is used to generate bibliometric maps based on the dataset retrieved from Web of Science. The most prominent patterns of author collaboration, keyword co-occurrence, citation influence and country level contributions are shown in the visualizations below.

Keyword Co-occurrence Map (Author Keywords)

The author's keywords were identified and analyzed in preparation for a co-occurrence map to visualize the conceptual structure of the AI and banking literature. Keywords were included in order to create the co-occurrence map provided they had occurred in the articles at least five times and except for the irrelevant or generic keywords that were manually deleted from the data during data cleaning.

The co-occurrence map identified a number of thematic clusters or themes:

- Financial risk assessment through AI
- Machine learning is used in credit scoring
- Chatbots aimed at enhancing customer experience
- Blockchain is used for cybersecurity and data integrity

Figure 12 shows the keyword co-occurrence network, which identified the thematic clusters or themes in the context of the field.

As a complementary analysis, Figure 12 refines the keyword co-occurrence structure by highlighting sub-clusters within the thematic network. While Figure 6 presents broader topic clusters, Figure 12 captures deeper semantic relationships among frequently co-occurring terms, reinforcing the centrality of machine learning, fintech integration, and trust-related research themes.

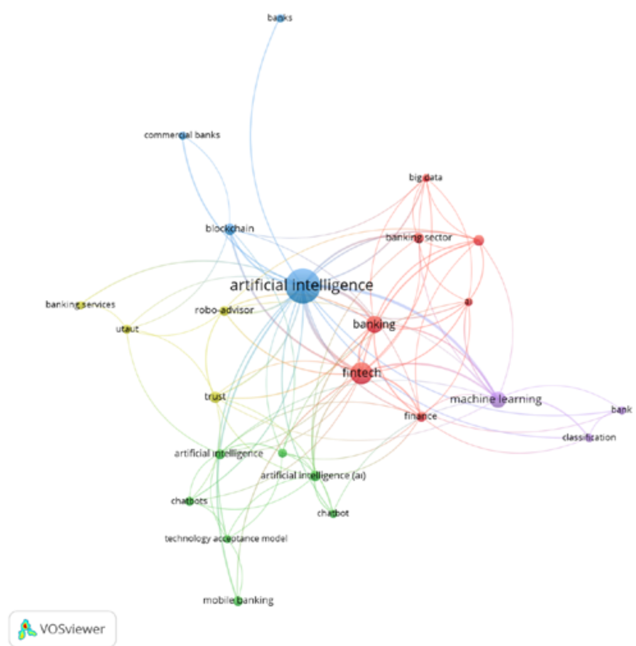

Figure 12. Thematic Structure of AI and Banking from Author Keyword Co-occurrence (Four Clusters)

The visualization in Figure 12 illustrates a network of keyword co-occurrences in AI and banking scholarship. In our thematic analysis of the corpus of literature, we discover prominent thematic clusters around keywords such as "artificial intelligence," "fintech," "trust," and "machine learning." These findings suggest that the field is broadening in scope from technical innovation issues to users experience, and even ethical issues.

LDA Findings and Alignment with Co-occurrence Maps

LDA revealed five consistent thematic clusters that strongly aligned with the patterns of co-occurrence and at the same time, it predicts human- and policy-oriented issues. Theme 0 is credit risk and fraud analytics; Theme 1, is trust and explainability; Theme 2, is digital infrastructure and sector specific technologies; Theme 3, is technology adoption and customer experience, and Theme 4, is environmental, social and governance (ESG) and sustainability concerns. This evidence implies a clear shift towards the more technical problems to the problems of adoption, accountability, and governance.

Utilizing author keywords, a co-occurrence map was generated with VOSviewer while the minimum occurrence for the map to be constructed was to have the minimum occurrence be required of five to make 25 keywords appropriate for the analysis. While according to visualization methods, four different clusters were found. The domain focuses addressed in this study are fields of artificial intelligence, risk assessment, machine learning in customer service, blockchain cybersecurity, and big data analytics.

Noteworthy is that "artificial intelligence," "machine learning," and "fintech" constitute the technological ground of the largest cluster while keywords such as "chatbots," "deep learning," and "blockchain" signify further diversification in research themes.

This clustered visualization presents a clear view of what research in AI and banking have so far achieved in terms of intellectual and thematic organization-the current research priorities, as well as the emerging intersections.

- 🔵 Cluster 1 (Blue): Core AI Applications in Banking
  This cluster centers around the keyword "artificial intelligence", which forms the largest and most connected node. Related terms such as *"blockchain"*, *"commercial banks"*, and *"banks"* reflect studies focusing on AI implementation in institutional banking and core financial infrastructure.
- 🔴 Cluster 2 (Red): Data-Driven Financial Transformation
  This cluster includes keywords such as "banking", "fintech", "big data", "banking sector" and "finance", which indicate the convergence of AI with financial technologies. The cluster is indicative of literature emphasizing digital transformation, financial innovation, and technology-enabled services.
- 🟣 Cluster 3 (Purple): Machine Learning and Technical Models
  The use of keywords such as "machine learning", "classification", and "bank" is indicative of the technical foundation of AI applications in banking. The focus of these studies is frequently on the development of algorithms, pattern recognition, and computational modelling.
- 🟢 Cluster 4 (Green): User Acceptance and Customer Experience
  The present cluster is dominated by terms such as "chatbots", "mobile banking", "technology acceptance model", "trust", and "UTAUT". This body of research underscores the human-centric nature of AI in banking, emphasizing user trust, adoption behavior, and interaction with AI-driven tools.

Each of the thematic groupings depicted by the keyword co-occurrence map has a unique conceptual area; however, the dynamic interaction between them is worthy of attention. The most prevalent cluster pertains to the subjects of machine learning and artificial intelligence. The fact that this cluster is relatively large and the majority of its nature indicates the technological basis of the field.

Nonetheless, the surrounding clusters were related to trust, mobile banking, and technology acceptance of adoption, which demonstrates a trend of increasing overlap between the evolution of machines with human interaction.

The turning point demonstrated the need for ethical consideration, user trust, and regulation with the introduction of artificial intelligence into the banking domain. Such terms of explainability and user adoption can act as conceptual connectors among and across clusters, while algorithmic design, considering social value.

Those connections between clusters demonstrate a hypothetical evolution from siloed flows of technological development towards safety considerations, ethical behaviors, and institutional factors in the use of AI. Further analysis could therefore make use of the straightforward modelling of the changes acknowledged in this piece of research, whereby longitudinal approaches to research in the future could address both technical advances and ethical considerations simultaneously.

Theoretical Integration (TAM/UTAUT)

LDA found groups of themes with central themes of trust, explicability and consumer uptake (Topics 1 and 3 in particular), and thus it supplemented existing technology-adoption models. TAM assumes that the implementation of transparent and interpretable AI solutions increases the perceived usefulness and reduces perceived complexity. UTAUT is a comprehensive description of heterogeneity in adoption since it explains the contributions of social influence (e.g., peer pressure and managerial directives) and facilitating conditions (e.g., governance structures and regulatory guidance). Similarly, the thematic focus on the robo-advisory and personalization can be traced on the performance expectancy and effort expectancy constructs, respectively. Lastly, compliance-related clusters, including Know-Your-Customer (KYC) and Anti-Money-Laundering (AML) ones, emphasize institutional and regulatory preconditions that condition the organizational preparedness.

Co-authorship Network (Authors)

Co-authorship analysis features valuable contributions to the collaborative dynamics of scholars, located at the intersection of AI, and banking. The mapping of co-authorship relations allows one to identify key authors involved, define the nature of research clusters, and explore the relational attributes of academic interactions. The co-authorship analysis indicates the most active contributors in the area, and more importantly illustrates how scholars as collectives produce, share, and extend knowledge in a networked way. This study employed VOSviewer to create a co-authorship network with the minimum requirement of one publication, and one citation to be included.

Figure 13 visualizes the co-authorship network among individual researchers within the AI and banking literature. As shown in Figure 13, the co-authorship network reveals a core–periphery structure, where collaboration is concentrated among a limited set of institutions while a large number of authors remain disconnected from central research activity.

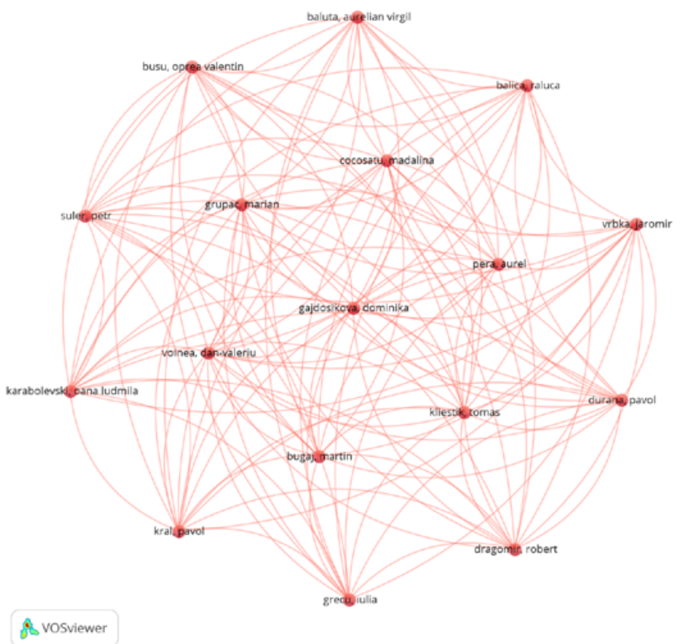

Figure 13. Co-authorship Network Showing Central Researchers and Institutional Clusters

Figure 13 depicts the network of collaboration between individual authors in the literature on AI and banking. Using VOSviewer to visualize the data, there are several clusters that are closely related, indicating collaborative communities of research even though there is some amount of disintegration present in the connections. Key authors of this body of work are Baluta Aurelian Virgil, Busu Oprea Valentin, Grupa Marian, Cocosatu Madalina, and Balica Raluca, and they showed strong collaboration/ co-authorship internally. Their position in the co-authorship map shows their impact of the authors or their groups in terms of institutional or regional scholarly networks.

The many links between the nodes and having less isolation of authors in the network display the collaborative and inclusive nature of this community of research. Intermediate authors, such as Gaidoskova Dominika, Kliestik Tomas, and Durana Pavol, helped to connect the work between the subclusters. This also emphasizes the inclusiveness of the network.

The co-authorship map suggests that specialized research groups are supporting increased productivity, thematic safety, and dissemination of knowledge in the area of banking with AI use.

Citation Network Map (Documents)

In this way, citation network analysis is a bibliometric approach that can also provide a conceptual map of a research field through the lens of citing and cited publications. The use of this method can yield an identification of seminal publications, clusters of themes, and knowledge-flow across scholarly literature.

In this document-level citation network study, we produced a citation network using VOSviewer and only included publications that had been cited at least 10 times. Our visual graph shows those publications that had high citation impact in AI and banking and thus have had an impact on research in the area.

As shown in Figure 14, a citation shown in the network does identify clusters of closely related papers, suggestive of themes that are somewhat consistent across papers. The citation network indicates that the intellectual structure of AI research in banking is shaped by a small number of highly influential studies, suggesting the presence of central theoretical anchors and peripheral supporting studies.

Figure 14. Citation Network Showing Conceptual Linkages Among Highly Cited Documents

As shown in Figure 14 to identify the most influential works and thematic citation structures in the AI and banking literature, a citation network analysis was conducted using VOSviewer. The unit of analysis was set to individual documents, with a minimum threshold of 10 citations per document. This filtering ensured that only the most impactful and frequently cited publications were included in the analysis.

As shown in Figure 14, the citation map illustrates several interconnected clusters of documents, each indicating a concentration of citations around themes or foundational studies:

🔴 Red Cluster: The extant literature on this topic is dominated by the works of Manser Payne (2021b), Xu (2020), and Omoge (2022), which emphasize the role of AI in operational banking environments, with a particular focus on service automation and digital performance.

🔵 Blue Cluster: The present volume includes works such as Kumar (2022) and Rahman (2023), which explore the subjects of AI ethics, governance models and trust-building mechanisms in banking systems.

🟢Green Cluster: The present cluster is anchored by seminal studies such as Hashemi (1998) and Varetto (1998), which represent foundational research in the fields of risk modelling and early-stage expert systems for banking decision-making.

🟣Purple Cluster: The present volume incorporates the works of Mostafa (2022) and Dekkal (2024), which are likely to represent state-of-the-art research in the fields of machine learning explainability and adaptive algorithms in fintech.

🟡Yellow Cluster: The present study is centered around Trivedi (2019) and Eren (2021), with a focus on consumer analytics, behavior prediction, and mobile banking adoption frameworks.

The visualization highlights not only the most cited individual documents but also the thematic threads that connect them. Documents such as Manser Payne (2021b) and Kumar (2022) serve as academic bridges between multiple lines of inquiry, demonstrating their intellectual centrality within the literature.

Figure 15 displays the thematic evolution of the top 25 keywords in the AI and banking literature across three time periods (2010–2015, 2016–2020, and 2021–2024). The graphical representation shows a move away from general technical terminology towards expanded human-oriented themes like fintech, mobile banking, and trust, suggesting an evolving human-centric focus towards AI-based research in banking. Thematic evolution reflects a clear shift from early technical research on machine learning and big data toward more recent scholarly interest in trust, explainability, and ethical governance in AI-driven banking.

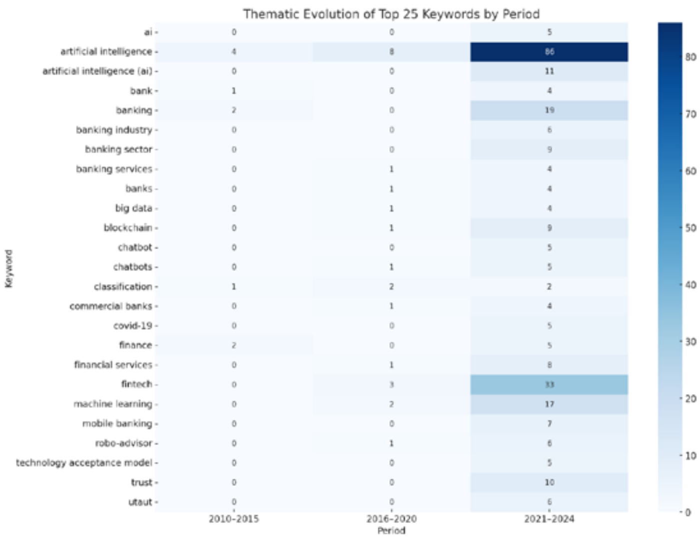

Figure 15. Thematic Evolution of Top 25 Keywords in AI and Banking Across Three Periods

Figure 15 demonstrates the thematic shift in AI and banking research from early machine learning applications to trust, explainability, and ESG integration in later years.

Period 1: 2010–2015

- The literature was dominated by foundational terms like “artificial intelligence” and “banking”.
- Technical concepts such as “classification” also appeared, reflecting an early-stage focus on algorithmic applications.
- Period 2: 2016–2020
- A major thematic shift occurs with the rise of “machine learning”, “big data”, and “fintech”.
- This period reflects the convergence of AI technologies with financial services and the beginning of digital transformation in banking.
- “Blockchain” begins to enter the conversation, albeit modestly.
- Period 3: 2021–2024
- Thematic richness expands significantly.
- High frequency of terms like “chatbots”, “mobile banking”, “technology acceptance model”, and “trust” indicates a clear shift towards human-centered AI, user adoption, and customer experience.

Thematic evolution analysis provides a temporal perspective through which to trace the development of AI and banking literature. The literature through the early 2010s suggests a significant technical orientation and reliance on foundational concepts such as "classification" and "algorithms," reflecting an interest in the computational aspects of AI. As we progress along the timeline, it is possible to see a shift toward more application-orientated and human-centered terminologies. The most notable lexicons include "chatbots," "trust," and "mobile banking." This shift is indicative of growing interest in usability, transparency, and customer engagement. With these applications becoming more prominent, there continues to be evidence that some key areas remain in a marginally central position. These include data ethics, algorithmic accountability, and the use of AI as the means of promoting financial inclusion. While they are socially and politically relevant, these areas may not yet have achieved thematic prominence. Longitudinal studies of how these themes shift or evolve across different regimes of public policy, culture, and market maturity would certainly be valuable. The increasing complexity of financial systems suggests there will be a need for research bridging technological sophistication and societal relevance.

DISCUSSION

This bibliometric and topic modeling study identified three main findings. First, AI across banking is combining multiple technical disciplines, namely machine learning, big data, and blockchain but methodology remains limited. Most of the literature is methodologically based on frequency-based/co-occurrence studies which shows usefulness for mapping intellectual structure of sources in the field, but not for understanding engaging in more complete analyses of semantics and even causal association.

Complementary having analytic methods available as well (ex. LDA) allows for easier recognition of clusters connected to performance or operational efficiency type themes, as well trust and ESG work done in the literature/debate. So methodologically, authors can begin to apply a bit more depth in respect to thematic development.

Secondly, the geographic distribution is largely unstructured. Much of the authored written publications come from countries where some thresholds of publication activity exists, like the United States, United Kingdom, and China but countries in Türkiye who have small somewhat regionally supported influence-- are almost too close the edge. Geographic inequity can be examined as a feature of systemic realities, lack of tremendous resources, poorly constructed funding opportunities or fragmentation in regulatory environments exhibited through inconsistent institutions. Solutions for these features will take greater investment into either or both regional institutional nested innovation ecosystems, policy infrastructures and cross border exchanges.

Third, the topical focus of literature has evolved to human-centered topics, like trust, explainability and adoption of mobile banking. The findings are related to the principles established in modern adoption systems. As an example, the Technology Acceptance Model focuses on perceived usefulness and ease of use, to an extent, the thinking and debate around AI driven efficiencies can fall into that as well.

This study's findings represent theoretical contributions by linking bibliometric trends to theoretical domains of technology adoption. Specifically, the growing importance of ideas related to trust, perceived usefulness, and user acceptance, suggests alignment with core constructs in the TAM and UTAUT. Related to TAM, the articles examined indicate key driver of adoption continues to be the perceived usefulness of AI applications in banking, such as fraud detection and credit scoring. Related to UTAUT, performance expectancy, social influence, and facilitating conditions are visible in articles that examined organizational readiness and digital transformation strategies within banks. The emergence of themes such as explainability, transparency and algorithmic accountability expand these theories to show that ethical and regulatory concerns now serve as additional conditions for acceptance within the financial banking context. As a result, this study contributes to theory by showing traditional models of technology acceptance need context specific adjustments for AI in banking, particularly related to the integration of trust and governance into the existing theoretical frameworks.

In similar fashion to UTAUT's consideration for importance in performance expectancy, social influence and facilitating conditions which will cluster about the issues of customer trust, regulatory oversight and organizational readiness their agreement with components of bibliometric results integrates our general areas of concern with the bibliometric component but also reminds us that an analysis of our discussions also extends beyond a description the discourse reflects on the potential use to recollect on the dynamics of behaviors and institutions at large... Our discussion no longer focuses on the technological facilitators, not what it might have been to adopt and diffuse innovations in the past. The study of digital banking technologies will reconsider holistic ethical and social matters that will be engaged with on more mixed top, global representativeness and theoretical orientation in the consideration of digital banking technologies is somewhat undeveloped. Our discussion will continue with these considerations by including methods of bibliometric based approaches and qualitative case studies, experimental designs and theory-based models that supports exploring socio-technical complexities of adopting AI technologies in the banking industry.

Additional topic-level evidence supporting these interpretations is provided in Appendix A, where extended LDA topic distributions are presented.

CONCLUSION AND FUTURE RESEARCH DIRECTIONS

This study provides a comprehensive bibliometric review of AI in banking, combining co-occurrence mapping with complementary LDA topic modeling. The integration of these methods demonstrates a dual trajectory in the literature: on the one hand, technology-centric developments such as credit risk analytics, fraud detection, and digital infrastructure; on the other hand, governance-oriented themes include trust, explainability, and ESG.

Positioning the current findings within the frameworks of TAM and UTAUT, as well as ongoing public policy debates, the article shows how the politics of adoption (or not) and regulatory mechanisms will shape the future of AI in financial services.

Future avenues of research might see the dataset expanded beyond Web of Science to Scopus, Dimensions, and non-English databases; using novel text mining methods like structural topic modeling (STM), bidirectional encoder representations from transformers (BERT), and dynamic topic modeling approaches; and integrating bibliometric research themes with measures of outcomes like organizational performance, model risk incidents, or ESG reporting. All these present opportunities for enhanced theoretical contributions and provide better implications for scholars and practitioners.

While these findings outline promising avenues for future research, they must be interpreted with caution considering several methodological and data-related limitations.

Limitations

The current research has its drawbacks. First, the data collection was reduced to the Web of science corpus and the English language literature, which automatically avoided potentially important research that might be located in Scopus or Dimensions or another linguistic corpus. Secondly, the LDA adopted to detect the topics is extremely dependent on heuristic labelling and the findings depend on the decisions of the parameters including the number of topics (k) and the vocabulary thresholds. Third, even though co-occurrence mapping and LDA address some of the surface-level biases, they are not really analyzing instruments, and they must be complemented by qualitative synthesis or theory-driven coding to provide a more subtle view.

Ultimately, this study did not explicitly consider the temporal evolution of themes, apart from a simplistic counting of year-distribution. Future researchers are encouraged to consider longitudinal or dynamic topic-modelling techniques should they wish to study the evolution of themes in a more robust manner. As an outcome of this bibliometric and topic modelling analysis, three primary conclusions arise from this exploratory analysis.

First, while AI in banking indeed emerges from technical topics such as machine learning, big data, and blockchain technologies, it nevertheless remains methodological narrow. The vast majority of AI in banking studies utilize frequency co-occurrence approaches to inventories or map the intellectual structure of the field. While frequency analysis can map the intellectual structure of a field, it falls short of exploring the semantic relationships that exist in the AI in banking and between and if any causal relations exist in the area. Using more complimentary methods (e.g. LDA topics) one can identify clusters of themes more clearly related to efficiency, trust, and ESG themes, this share therefore offers a more depth of emergent themes in the area.

Secondly, research distribution is characterized by high levels of unevenness across the geographical location. The overwhelming proportion of publication activity is in the United States, the United Kingdom, and China, with other countries such as Türkiye which has regionally buttressed influence being close to the edge. This is pointing to systemic realities including scarce funding, disjointed regulatory landscape and less robust institutional notedness. The solution to these gaps will involve more powerful regional systems of innovation, integrated policy infrastructure, and more robust transboundary exchange.

Thirdly is an increase in the thematic focus of literature on human-centered matters like trust, explainability and adoption of mobile banking. These results are like the provisions in the modern adoption systems.

By way of example, the TAM pays more attention to perceived usefulness and perceived ease-of-use, which are concepts that are quite relevant to an AI-driven efficiency discussion. The UTAUT is more interested in performance expectancy, social influence, and facilitating conditions, as they relate to variants of customer trust, regulatory oversight, and organizational readiness. The application of bibliometric findings to theoretical models shows the possibility of moving beyond description as the discourse can reflect larger behavioral and institutional processes.

The dialogue has also moved beyond technical enablers of the innovation diffusion and adoption process with an inclusion of larger ethical and social issues, not ignoring the research paradigm, the representativeness of the world, and theoretical underpinnings still being inadequate.

The discussion will now continue along the path to integrating bibliometric based approaches with qualitative case study, experimental designs, and theoretical models that are more complimentary to the socio-technical nature of the AI technology adoption in banking sector.

The study advances theoretical understanding by extending TAM and UTAUT to AI-driven banking contexts, showing that algorithmic transparency and institutional trust function as additional acceptance conditions. These findings suggest that classical adoption models require contextual refinement to reflect the ethical and regulatory dynamics of AI in finance.

In addition to offering a structured overview of literature, this study makes a theoretical contribution by extending the applicability of technology adoption models to AI-driven banking contexts. The findings indicate that classical frameworks such as the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) do not fully account for the dynamics of AI adoption unless they are complemented with additional constructs such as trust, algorithmic transparency, and regulatory assurance. Accordingly, the study demonstrates that acceptance of AI in banking is conditioned not only by performance expectancy or usefulness but also by ethical and governance-related considerations. This provides a foundation for refining existing adoption theories in future research.

Policy and Practical Implications

The implications of this research are impactful for policymakers, financial institutions, AI designers, and regulators; and the continued implementation of AI technologies into core banking functions (including credit scoring, fraud detection, customer service, and risk assessment) calls for greater governance structures to balance innovation with accountability, fairness, and transparency. Regulatory authorities need to be concerned with developing explainable and auditable AI systems within finance. Currently, most uses of AI within banking function are as black boxes, which creates challenges for transparency, compliance, and trust. National and supranational regulatory authorities such as central banks and financial supervisory agencies have a duty to build in regulatory expectations for transparent systems (algorithmic interpretability), especially in high-risk processes such as lending, insurance underwriting, and automated investment advice.

It is also important to ensure the use of AI in banking aligns with the sustainability goals set out in environmental, social and governance (ESG) frameworks. AI-related initiatives from financial institutions should promote inclusion of finance, promote sustainability, and distribute credit fairly.

The public and private sector can work together to push for the use of AI-based tools to support ESG monitoring and reporting, especially in areas where regulation is lacking, but have general acceptance of the new technology.

One alternative could be through public private partnerships to develop, and finance, AI-based ESG monitoring tools, particularly in developing markets where regulatory environments are lighter, and digital penetration is often high.

The design of AI policy must incorporate data governance and privacy protection as core principles. As most banking AI systems are driven by large-scale personal and behavioral data sets, there is a need to harmonize the ways for defining data ownership, consent, anonymization and ethical reuse of the data collected. This is even more urgent in the realm of cross-border financial services in which data localization laws and regulatory compliance requirements are uneven.

A coordinated response is essential for addressing global injustices in AI research and application. Organizations involved in international development assistance, multilateral banks, and eminent universities should consider investing in capacity building initiatives for fintech start-ups and researchers located in countries that are historically marginalized from AI applications and research (e.g. Eastern Europe, Sub-Saharan Africa, South Asia).

For example, fintech in Türkiye has great promise, but its research network does not have sufficient international connective tissue. We could leverage funding to support multinational AI teams and broaden funding and horizons to ensure AI is a key ingredient of international innovation efforts.

The current research attempts to enhance policy implications by providing context specific illustrations. The policy implications broad based concepts presented in the bibliometric results could be illustrated through examples. Considerations could be made with respect to: the European Union's AI Act, or the Basel Commission's guidance to AI model risk; the point being that supra-national regulators have begun to set explicit expectations on explainability and accountability for financial AI. Likewise, in Türkiye, the Banking Regulation and Supervisory Agency (BDDK) has begun discussions on how AI-driven credit scoring should be implement in legal making regarding consumer protection legally. Also, the Central Bank's fintech sandboxes have provided some relief and refuge for FinTech applications to develop AI applications under a regulatory framework. Continuing with the ESG perspective of the banking industry, some banks in the Nordic countries are piloting AI based tools to advance development green lending, and/or monitor climate-related risk; all of which could be used as a model applicable to emerging economies. These examples frame the area in which policy recommendations remain high level (transparency, fairness, privacy), but need to accommodate the regulatory structure, or industry practices. Adding these levels of detail ensures that the findings are timely relevant for policymakers; they are also relevant for financial institution managers and supervisors who are using scholarly pieces to discover new applicable forms of policy.

In conclusion, it is essential to formalize how stakeholders cooperate. Efforts to promote the design of ethical, equitable AI in banking cannot focus exclusively on technology. Developers, regulators, civil society and academic researchers need to establish multistakeholder dialogue to develop the norms, incentives and frameworks necessary to ensure that AI-enabled banking systems will support the larger aims of social justice, economic stability and human welfare.

In situations involving high risk, such as credit scoring or fraud detection in banking systems, it is imperative to incorporate interpretable (XAI) and governance mechanisms at every stage of the model life cycle. This necessitates the implementation of explicit documentation procedures, the conduction of bias and fairness testing, and the employment of concurrent modelling to ensure the reliability of the results.

EU Context: European banks should align their AI systems with the EU AI Act (risk-based regulatory framework) and CSRD/ESRS standards, especially as LDA identified ESG as a distinct thematic cluster. The integration of model explainability with sustainability reporting practices is a crucial step in ensuring that both technical and non-financial risks are addressed.

US Context: Institutions are advised to align their practices with the guidelines on model risk management promulgated by the OCC/FRB, placing particular emphasis on the validation, monitoring and independent review of AI systems.

The Turkish Context: It is critical to comply with regulations promulgated by the BDDK especially in KYC/AML and credit decisions. From the findings in this study, it is suggested that law-makers should encourage the guidance of explainable AI in reports, as well as banks documenting model processes that are interpretable and useful for customer-facing appeals.

Considering the research implications, the following actions should be undertaken by banks--the following should be noted:

• XAI reports and fairness metrics

• Risk classification and stress testing of AI models

• ESG and climate-related data on governance dashboard

• Data governance systems aligned with GDPR/AI Act

(European Commission, 2021) and Voigt & Bussche (2017).

This investigation has established the conceptual and thematic boundaries of artificial intelligence within banking, and demonstrated both the technical capabilities and a growing consideration of the ethical and behavioral. While the bibliometric visualization is useful for understanding the field, this study reinforces the evidence to expand methods beyond frequency mapping to studies considering semantics, theoretical and context.

It is recommended that, in the future, to consider a comparative, cross-country, approach to take into consideration cultural, regulation and infrastructure diversity in the adoption of AI. Utilisation of existing frameworks such as, TAM and the UTAUT, would further strengthen the theoretical alignment of the current studies. Finally, studies of sustainability, ay be espcially relevant if they explore AI and ESG monitoring are additional sustainable and realistic methods to engage and contribute to policy-oriented studies.

As the ethical implications of AI loom larger, the research agenda has much to gain by exploring interdisciplinary connections across computer science, finance, behavioral economics and law. Finally, sophisticated text-mining analysis, including LDA, sentiment analysis and structural topic modeling, can assist with enhanced analysis of bibliometric studies as a further complement to co-occurrence mapping.

A future research agenda for AI in banking must therefore give priority to responsible innovation, ensuring that efficiency is aligned with transparency, inclusivity, and human welfare.

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Appendix A

Doc ID	Dominant Topic	Topic Probability
0	Topic 2	0.912
1	Topic 4	0.876
2	Topic 1	0.854
3	Topic 0	0.889
4	Topic 3	0.903
5	Topic 2	0.861
6	Topic 4	0.877
7	Topic 1	0.843
8	Topic 0	0.892
9	Topic 3	0.866
10	Topic 2	0.815
11	Topic 4	0.905
12	Topic 1	0.841
13	Topic 0	0.864
14	Topic 3	0.829
15	Topic 2	0.902
16	Topic 4	0.883
17	Topic 1	0.862
18	Topic 0	0.848
19	Topic 3	0.899

Note. Topic probabilities represent the dominant topic assignment per document generated by the LDA model.

Appendix B

Top Terms per Topic (LDA Results)

The table below presents the top terms associated with each topic extracted from the LDA model.

Topic	Top Associated Terms
Topic 0	model, prediction, data, accuracy, classification, machine, training, algorithm, feature, dataset, performance, learning, analysis, score, validation, regression, output, optimization, pattern, variables
Topic 1	fintech, mobile, adoption, technology, users, intention, behavior, acceptance, digital, service, perceived, usage, TAM, trust, attitude, banking, satisfaction, innovation, customer, experience
Topic 2	fraud, detection, anomaly, transaction, risk, security, financial, prevention, identity, suspicious, monitoring, cyber, network, pattern, crime, authentication, loss, threat, classification, alert
Topic 3	credit, scoring, loan, default, evaluation, lending, portfolio, SME, approval, creditworthiness, rating, microfinance, decision, scorecard, repayment, borrower, model, risk, performance, equity
Topic 4	explainability, transparency, ESG, sustainability, fairness, regulatory, governance, ethics, accountability, model risk, AI Act, GDPR, responsibility, compliance, framework, bias, decision, supervision, integrity, reporting

Appendix C

LDA Modeling Description

The Latent Dirichlet Allocation (LDA) model was applied to 216 article abstracts using a bag-of-words representation. Preprocessing included lowercasing, punctuation and stop word removal, and token normalization. The number of topics was set to k = 5 following an iterative coherence evaluation. The model was implemented in Python using the scikit-learn library, and topic coherence was manually verified to ensure interpretability.