

Use of AI and ML enabled Chatbots in Banking Financial Services: A Bibliometric Analysis and Thematic Review Using SPAR-4-SLR

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Abstract: *This paper offers a systematic bibliometric review of how research on AI and ML driven chatbots has developed within the banking sector. Drawing on the Biblioshiny interface of the bibliometrix R package, we map the intellectual structure, conceptual evolution, and thematic development of this body of work through performance analysis and science mapping. Scholarly output has grown noticeably since 2020, which seems to track closely with the broader push toward digital transformation in financial services and the rising uptake of generative and conversational AI. The United States, India, and China stand out as the most prolific contributors, and a handful of high-impact journals bridge the gap between artificial intelligence, decision support systems, and financial applications. Thematic and factorial mapping point to machine learning and intelligent systems as the motor themes anchoring the field, with natural language processing (NLP) serving as the indispensable underlying technology. Sentiment analysis, generative AI, large language models, and advanced conversational architectures are all gaining traction as emerging research threads. Across these findings, a consistent pattern appears: the field has been moving away from rigid, rule-based automation toward adaptive, learning-capable chatbot systems now embedded in customer service, financial advisory, and operational decision-making. By charting the intellectual, conceptual, and thematic landscape of this field, the study pulls together scholarship that has so far remained scattered across disciplines, and puts forward a future research agenda built around explainability, responsible AI deployment, and interdisciplinary collaboration. The review should be of interest to researchers, practitioners, and policymakers who want to make sense of where conversational AI in financial services currently stands and where it might be headed.*

Keywords: Artificial Intelligence, Banking, Bibliometric Analysis, Chatbots, Conversational AI, Machine Learning

1. INTRODUCTION

Banking has changed dramatically over the past decade, and artificial intelligence is at the center of that shift. As financial institutions have moved away from branch-heavy models toward fully digital ecosystems, the way customers interact with their banks has changed just as fundamentally from call centres to AI-powered chat interfaces. Of all the technologies that have emerged from this transition, intelligent chatbots have perhaps been the most consequential, touching customer engagement, operational efficiency, and personalized financial services all at once (Belanche et al., 2019; Luo et al., 2019).

Despite the pace of growth in this area, the research landscape remains surprisingly fragmented. Work on AI and ML chatbots in banking is spread across information systems, marketing, computer science, and finance, with limited cross-disciplinary synthesis. Early studies were largely technical, focusing on system design and feasibility; more recent work has shifted toward user adoption, perceived service quality, emotional AI, trust, and strategic integration within digital banking (Adam et al., 2021; Belanche et al., 2019). Individually, these contributions are valuable but a consolidated view of how the field has evolved intellectually, which research clusters are emerging, and where the collaboration networks sit is still largely missing.

Bibliometric analysis provides a well-suited method for bringing some order to this fragmented picture. It allows us to identify influential authors, institutions, countries, and journals, and to map the conceptual structure of a field through co-citation, bibliographic coupling, and keyword co-occurrence techniques (Aria & Cuccurullo, 2017; Donthu et al., 2021). The SPAR-4-SLR framework (Paul et al., 2021) adds methodological structure, offering a clear and replicable process for scoping, planning, analyzing, and reporting systematic reviews in a transparent and replicable manner. Integrating bibliometric tools such as Biblioshiny within the SPAR-4-SLR protocol allows for objective mapping of intellectual trends and thematic structures in emerging research domains.

Against this backdrop, the present study sets out to provide a comprehensive bibliometric and thematic account of AI and ML enabled chatbot research in banking. More concretely, it aims to:

1. Examine the growth trajectory and intellectual influence of global research on AI-driven banking chatbots;
2. Identify dominant research clusters, methodological approaches, and technological paradigms; and
3. Map emerging themes such as large language models, explainable AI, multilingual conversational systems, and hybrid human–AI service frameworks in digital banking contexts.

2. METHODOLOGY

2.1 SPAR-4-SLR PROTOCOL

This study adopts the SPAR-4-SLR framework (Paul et al., 2021) to conduct a systematic, transparent bibliometric review of AI-driven chatbot research in banking. At its core, the SPAR-4-SLR protocol organizes a systematic literature review into three phases, which are Assembling, Arranging, and Assessing each of which is designed to make the process replicable and the findings defensible. This structure is particularly useful when working in a field as interdisciplinary as ours, where the risk of overlooking relevant scholarship is real.

2.1.1 ASSEMBLING

The Assembling phase is where we defined what the study was actually going to look at. We centered the scope on AI-driven chatbots within banking and financial services.

Scopus was chosen as the primary database given its broad coverage of peer-reviewed work in management, finance, and information systems. The search covered the period 2020 to 2026, using an advanced Boolean query.

Only English-language peer-reviewed journal articles and book chapters were included. Bibliographic metadata like titles, abstracts, keywords, author information, citations, and affiliations were exported in CSV format for analysis.

2.1.2 ARRANGING

The Arranging phase was primarily about cleaning and organizing the retrieved dataset. Records were screened against a set of inclusion and exclusion criteria to make sure the final dataset was actually relevant to AI-driven chatbot applications in banking.

2.1.3 ASSESSING

In the Assessing phase, we carried out bibliometric performance analysis and science mapping using the Biblioshiny interface of the bibliometrix R package (Aria & Cuccurullo, 2017). This phase covered both quantitative performance metrics and the broader conceptual architecture of the research field.

2.2 BIBLIOMETRIC PROCEDURE

The bibliometric component follows the framework proposed by Zupic and Éater (2015), which provides a systematic approach for conducting bibliometric research through sequential stages of research design, data collection, bibliometric analysis, and visualization and interpretation. This structured procedure enables a comprehensive examination of the intellectual, conceptual, and thematic development of research on Artificial Intelligence (AI)–driven chatbots in banking. The approach

ensures methodological rigor and transparency in identifying publication trends, influential sources, collaboration patterns, and emerging research themes within the domain of conversational AI in financial services.

3. RESULTS AND FINDINGS

3.1. DESCRIPTIVE ANALYSIS

3.1.1. ANNUAL SCIENTIFIC PRODUCTION

Figure 1 tracks annual scholarly output on AI-driven chatbot applications in banking from 2020 to 2026. Publications rose from just 12 in 2020 to a high of 145 in 2025 a trajectory that speaks to genuinely sustained and accelerating academic interest in this space.

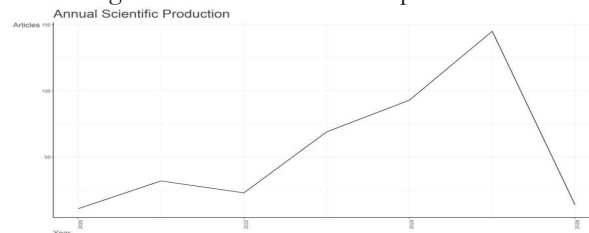


Figure 1: Annual Scientific Production (Source: Biblioshiny output)

The 2025 peak reflects the maturing status of this area as a recognized interdisciplinary field at the crossroads of AI, banking, human-computer interaction, and fintech. The apparent dip in 2026, however, should be treated with caution it almost certainly reflects indexing lag and incomplete database coverage rather than any genuine decline in research activity (Donthu et al., 2021)

3.1.2. MOST RELEVANT SOURCES

Among the identified outlets, *Studies in Systems, Decision and Control* emerged as the most productive source, contributing the highest number of publications (9 documents). This was followed by the *ACM International Conference on AI in Finance (ICAIF 2025)* with 7 publications and *Scientific Reports* with 6 publications.

The strong showing of conference proceedings especially ICAIF is telling. Conferences carry cutting-edge work before it reaches journals, and their prominence here suggests a field moving too fast for traditional publication cycles to capture fully. The presence of interdisciplinary journals like *Scientific Reports*, *PLOS ONE*, and *Sustainability* indicates the expanding relevance of chatbot research beyond computer science into broader domains including digital banking transformation, customer experience, and financial innovation.

3.1.3. Source Impact Indicators

The *Journal of Money Laundering Control* demonstrates the highest scholarly impact (h-index = 8, TC = 247, NP = 14), establishing its prominence in publishing research related to AI applications in financial crime prevention, regulatory compliance, and intelligent monitoring systems.

Knowledge-Based Systems records the highest total citation count (TC = 443, h-index = 6) unsurprising given its long-standing reputation in AI, expert systems, and machine learning. Alongside it, *Decision Support Systems* (h-index = 5, TC = 296) and *Research in International Business and Finance* (TC = 277) show substantial academic influence, highlighting the integration of AI-based decision technologies in financial services and banking environments.

Across these indicators, the picture that emerges is consistent: chatbot research in banking gravitates toward high-impact journals in AI, financial systems, and decision sciences, reflecting the dual technological and applied nature of the work (Aria & Cuccurullo, 2017; Donthu et al., 2021).

3.1.4. Country-Level Scientific Production over Time

Figure 2 maps country-level research output between 2020 and 2026. The results reveal a substantial increase in research output across multiple countries, with the United States and India emerging as the dominant contributors. The United States demonstrates the highest cumulative production, rising sharply from 6 publications in 2020 to approximately 285 publications by 2025 and maintaining a strong level of output through 2026. This leadership reflects the country's advanced technological ecosystem, strong presence of global financial institutions, and significant investments in artificial intelligence research and financial innovation.

India's trajectory is arguably more striking: output grew from just 3 publications in 2020 to nearly 290 by 2026, eventually rivaling the United States in total volume. This growth appears closely tied to India's rapid banking digitization, wide adoption of fintech platforms, and a strong government push on digital financial infrastructure. The emphasis on financial inclusion has also created a particular impetus for exploring AI-driven customer service tools at scale.

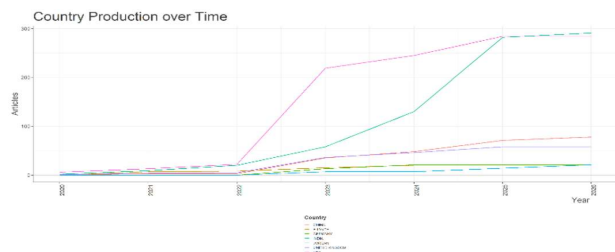


Figure 2: Country level production overtime (source: biblioshiny output)

3.2. SCIENTIFIC MAPPING OF LITERATURE

3.2.1. Trend Topic Analysis

Figure 3 traces how research topics in this field shifted between 2021 and 2025. The early phase of the analysis (2021–2022) is characterized by the prominence of foundational terms such as *financial services*, *text mining*, and *social networking (online)*, reflecting the initial exploration of digital communication technologies and data-driven approaches to enhance banking operations and customer engagement. These early topics highlight the role of text analytics and online interaction platforms as precursors to the development of intelligent conversational systems in financial environments.

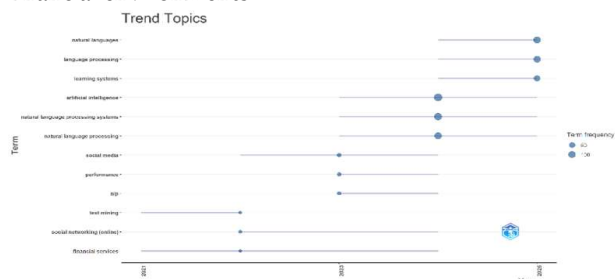


Figure 3: Trend topic analysis (Source: biblioshiny)

The most recent phase (2024–2025) is defined by advanced AI-related topics: *natural languages*, *language processing*, and *learning systems*, which appear with higher frequency and larger prominence in the visualization. This trend signifies a shift toward the development of more sophisticated chatbot architectures powered by machine learning, deep learning, and large language models. These technologies enable chatbots to perform complex conversational tasks, provide personalized financial recommendations, and support intelligent decision-making processes in banking services.

3.2.2. THEMATIC MAPPING

The thematic map in Figure X organizes research themes using Callon's dimensions of centrality (relevance to the field) and density (internal development). The four quadrants which are motor, basic, niche, and emerging or declining — each reflect a different combination of importance and maturity.

The **motor themes**, in the upper-right quadrant, are well-established and highly influential the themes that actively drive the field forward. Here, *machine learning*, *learning systems*, and *machine-learning* emerge as dominant motor themes, both show high centrality and density, confirming their role as the field's technological backbone. Nearly every other development in this space depends, at some level, on machine learning from adaptive learning and personalization to automated decision-making.

The **basic themes**, in the lower-right quadrant, include *natural language processing*, *natural language processing systems*, and *natural languages*. These themes show high centrality but comparatively lower density foundational to the field but still evolving. NLP is the technology that enables chatbots to make sense of human language; without it, none of the applied banking functionality discussed in this literature would be possible.

The **emerging or transitional themes** near the center and lower-left include *artificial intelligence*, *banking*, and *chatbots*, as well as *sentiment analysis*, *investments*, and *financial markets*. Moderate centrality and density suggest these themes are gaining momentum without having fully crystallized. Sentiment analysis signals growing interest in what chatbots can do with emotional context — not just processing queries, but reading between the lines. The financial markets and investment clusters point to expanding ambitions for chatbots beyond routine service.

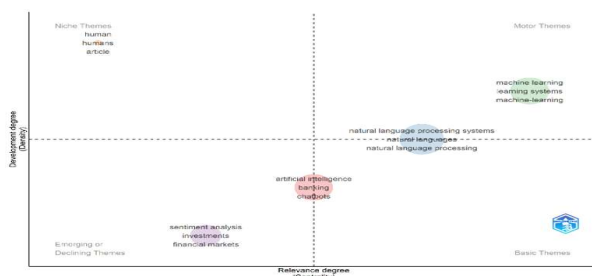


Figure 4: Thematic map (source: biblioshiny)

The **niche themes**, in the upper-left quadrant, include terms like *human*, *humans*, and *article*, which exhibit high density but lower centrality. High internal density alongside lower centrality suggests a coherent body of work that has developed somewhat independently covering

models. ChatGPT, sentiment analysis, and conversational analytics are now at the frontier, reflecting ambitions for smarter, more personalized, and more emotionally attuned chatbot interactions (Dwivedi et al., 2021).

4.1 IMPLICATIONS

4.1.1. ACADEMIC IMPLICATIONS

The emergence of large language models, sentiment analysis, and conversational intelligence opens up research directions that go well beyond traditional chatbot architectures. A particularly promising avenue is interdisciplinary work at the intersection of AI, behavioral finance, and human-computer interaction this is where questions of user trust, adoption, and sustained engagement are most naturally located (Adamopoulou & Moussiades, 2020).

The rapid diffusion of generative AI and transformer-based models into banking contexts creates an urgent need for more research on chatbot intelligence, explainability, and ethical governance particularly when these systems are involved in decisions with real financial consequences for customers (Dwivedi et al., 2021).



For practitioners, the findings reinforce what many financial institutions have already begun to discover in implementation: chatbots can meaningfully improve service efficiency, reduce operational costs, and lift customer satisfaction when deployed thoughtfully (Davenport et al., 2018).

ML-based systems allow banks to automate the routine inquiries, account management, basic advisory freeing human staff for more complex and judgment-intensive work. Sentiment analysis and conversational analytics add another layer, giving institutions insight into customer behavior and emotional responses in ways that can translate into genuine service improvements.

4.1.3. POLICY IMPLICATIONS

The policy implications of widespread chatbot adoption in banking are substantial and not yet fully worked out. Regulators face the challenge of ensuring that these systems handle sensitive financial information in ways that are private, transparent, and ethically sound without stifling the innovation that makes them valuable in the first place.

Like all bibliometric studies, this one carry limitations that should be read alongside its findings. The most important is database scope: restricting the search to Scopus means potentially missing relevant work indexed in Web of Science, IEEE Xplore, or Google Scholar. Whether this affects the conclusions in any material way is difficult to assess, but it is a constraint worth noting (Donthu et al., 2021).

Second, bibliometric methods work with metadata, titles, abstracts, keywords and cannot fully capture the technical depth or performance characteristics of individual studies. Qualitative review and experimental benchmarking would complement these findings in ways that bibliometrics alone cannot.

With these limitations in mind, future research might usefully pursue:

- Integration of multiple bibliographic databases (like WOS and many databases combined).
- Full-text natural language processing analysis (using python).
- Comparative studies across banking, fintech, and insurance sectors.
- Investigation of ethical, explainability, and trust issues in chatbot systems.
- Analysis of generative AI technologies such as ChatGPT in banking.

6. CONCLUSION

This study set out to map the bibliometric landscape of AI-driven chatbot research in banking, and what emerges is a coherent story. Scholarly output has grown substantially since 2020, not as a mere academic trend, but as a genuine reflection of how rapidly conversational AI has become embedded in financial services. The United States, India, and China account for the largest shares of research output, each reflecting distinct technological trajectories and the speed at which their financial sectors have embraced digital transformation.

At the conceptual level, machine learning and artificial intelligence anchor the field as its motor themes, well-developed and highly influential. NLP and conversational systems function as foundational enablers. Sentiment analysis, generative AI, large language models, and decision-support applications are all emerging themes, representing where research energy is beginning to concentrate and where the most interesting questions remain open.

By mapping the field's intellectual architecture and identifying where it is heading, this review hopes to offer something useful to researchers, practitioners, and policymakers navigating the evolving landscape of conversational AI in banking. The foundations are well established, the more pressing questions now concern reliability, ethics, explainability, and how to integrate increasingly autonomous systems into financial ecosystems responsibly and at scale.

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