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Trends in the AI-based Banking Conversational Agents Literature: A Bibliometric Review

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A B S T R A C T

Artificial Intelligence (AI) and the technologies powered by AI fuel the fourth industrial revolution. Being the primary adopter of such innovations, banking has recently started using the most common AI-based technology, i.e., conversational agents. Although research extensively focuses on this niche area and provides bibliometric understanding for such agents in other industries, a similar review with scientometric insights of the banking literature concerning AI conversational agents is absent till date. Furthermore, in the era following the pandemic, banks are faced with the imperative to provide solutions that align with the changing landscape of remote consumer behavior. As a result, banks are proactively integrating technology-driven solutions, such as automated agents, to effectively address the growing demand for remote customer support. Hence more research is needed to perfect such agents. In order to bridge these existing gaps, the present study undertook a comprehensive examination of two decades' worth of banking literature. A meticulous review was conducted, analyzing approximately 116 papers published from 2003 to 2023. The aim was to provide a scientometric overview of the topic, catering to the research needs of both academic and industrial professionals. Holistically, the study seeks to present a macro-view about the existing trends in AI based banking conversational agents' literature while focusing on quantity, qualitative and structural indicators that are effectively necessary to offer new directions for the AI-based banking solutions. Our study, therefore, presents insights surrounding the literature, using selected techniques related to performance analysis and science mapping.

Keywords: Bibliometric Analysis, Banking Conversational Agents, Performance Analysis, Science Mapping, Scientometrics

Ⅰ. Introduction

Artificial Intelligence (AI) and its manifestations such as AI-based conversational robots, are often illustrated as the drivers of the fourth industrial revolution (David et al., 2022; Mhlanga, 2022). Enholm et al. (2022) describe AI as the computerized stimulation of human intelligence. In other words, much

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like human intelligence, AI is intangible, yet embodied through systems such as robots (Kot and Leszczyński, 2022; Prentice et al., 2020). In this sense, AI is "*an applied discipline that aims to enable systems to identify, interpret, make inferences, and learn from data to achieve predetermined organizational and societal goals*" (Enholm et al., 2022, p. 1713).

Research surrounding the AI discipline has grown tremendously as it remains an attractive topic to stakeholders both in the industry and the academia (Rafiq et al., 2022). On the industrial side, over 80% of the organizations perceive AI as a strategic prospect, and 85% believe AI offers a competitive edge (Enholm et al., 2022), prospectively making the AI market worth USD 267 billion by 2027 (Mogaji and Nguyen, 2021). Consequently, academia has extensively conducted research concerning AI and its embodiments. For example, medical research presently focuses on embodying AI in the form of robo-advisors which may assist medical professionals (van de Sande et al., 2022; Rowe et al., 2022). Similarly, AI research in tourism focuses on information systems, like conversational agents, that reportedly provide insights to all stakeholders, such as personalized recommendations for customers (Solakis et al., 2022), and thereby, improving tourists' engagement and experiences (Rafiq et al., 2022).

As such, a trend can be observed in the AI literature in which the most common academic focus is on the intricacies of agents that disperse information to the user (Bawack et al., 2022; Goel et al., 2022; Hentzen et al., 2022; Tran et al., 2019). In this case, the user can be any entity seeking any information from an agent that can "*analyze inputs including human authored messages, communication history, personal information, or any other source of data. The agent may then suggest, augment, modify or produce messages to achieve an expected outcome*" (Hancock et al., 2020, p. 90). These agents, in some instances, may also deliver information unsought, but is personalized, strategically valuable, related to decision-making, actionable into outputs, etc. An example for such instances would be e-commerce conversational robots presenting unsought, yet personalized suggestions during shopping (Lim et al., 2022).

Considering this significant shift in the industrial and academic focus onto such AI agents in a short span of time, several researchers have provided industry-centric reviews to uncover evolutionary field nuances and emerging agents. For example, Xing et al. (2019) have conducted a bibliometric analysis on conversational agents in the health industry. Similarly, Yörük et al. (2023) have bibliometrically analyzed service robots in the hospitality industry. However, a chief adopter of such agents is banks (Hentzen et al., 2022; Trivedi, 2019) – which makes banks, a common theme for information system literature, like AI research (Adam et al., 2021). Yet, to the best of our knowledge, no study has analyzed such agents in banking, in a similar manner. Consequently, our research focuses on the AI agents that are exclusive to banks in a bibliometric discipline for the following reasons: *First*, the consumer reliance on virtual banking agents like chatbots has steadily increased since the covid-19 pandemic (Tut, 2023). The industry may find it necessary to embrace emerging trends and adapt existing agents to better align with consumer needs. This reliance on novel momentum could entail the implementation of new agents or further enhancement of existing ones, ensuring that they adequately cater to the evolving demands of consumers. (Sihotang and Hasanah, 2021). Moreover, while the integration of AI and banking has been a longstanding phenomenon (Kaya et al., 2019), the sudden spike in the usage of banking conversational agents post-pandemic warrants a need to quantify the trends. Analyzing and indexing the depth of such trends in banking research will contribute to future industrial research concerning the development and betterment of the agents. *Second,* we argue that focusing scientometric analysis on a particular industry will offer a highly accentuated outlook for stakeholders in academia and industry e.g., they may assist scholars evaluate the present literature depth and impact regarding the industry in question and address future research directions (Kim et al., 2021). *Third,* the lack of scientometric coverage on research investigating conversational agents exclusive to banking, creates a gap in the existing literature that requires researchers' attention.

To delve deeper into the subject matter, the study aims to address the following detailed research questions:

1. Within the domain of Banking Conversational Agents, how has research evolved over time? Specifically, what are the notable trends and advancements in terms of Performance Analysis and Science Mapping?
2. Based on this retrospective examination, what can be predicted about the future trajectory of research in this field?

To answer these questions, we utilize a range of quantitative techniques designed to analyze extensive datasets pertaining to the relevant literature, within the following scope: a) The review corpus includes 116 papers extracted from the Scopus and Web of Science databases, b) Using the corpus, the review contributes to the literature in two methods: i) Performance Analysis, and ii) Science Mapping.

i) The performance analysis reveals metrics related to publications and citations regarding the conversational agents in banking. Performance Analysis, referred to as the hallmark of bibliometric analysis, is a descriptive technique that presents the performance of different research constituents (e.g., authors, countries, and journals) through various measures such as, the number of publications from each author or country, number of citations, and the time-span of publications (Donthu et al., 2021a; Donthu, 2021b).

ii) The science mapping identifies the present themes, existing relationship among topics, and potential future topics within the banking conversational agent domain. Science Mapping, on the other hand, analyses the relationship between the research constituents through measures such as, the relationship among authors or countries, co-cited publications, etc. (Donthu et al., 2021a; Donthu, 2021b)

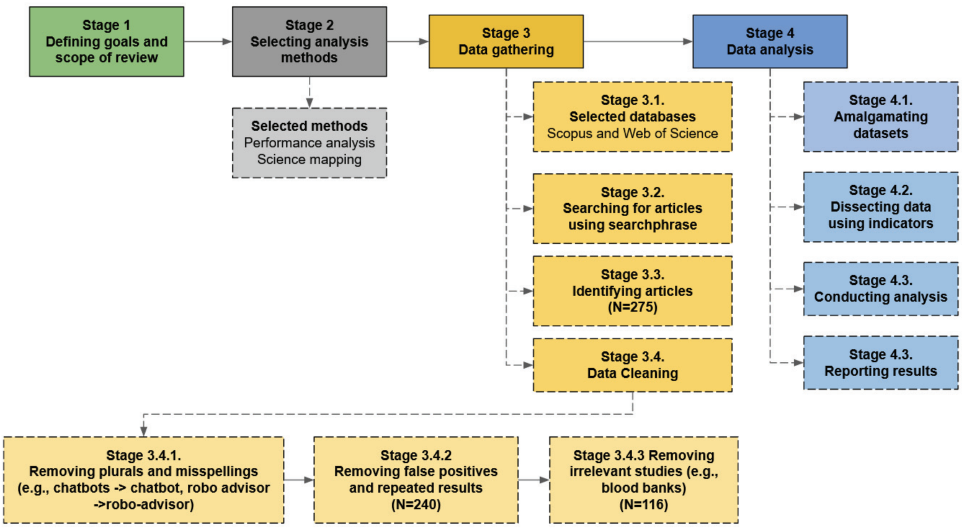
We have used the Clavariate Analytics Web of Science and Elsevier Scopus databases to generate the corpus for conducting the assessments above (Sana et al., 2023). In addition, our study also enriches the analysis further by visualizing the quantified findings using the VOSviewer version 1.6.19. With these assessments, the organization of this article is as follows: In the subsequent section, Section 2, we delve into the method employed for conducting this review and present the articles encompassed within. Section 3 is dedicated to discussing the results derived from the aforementioned methods. Moving forward to Section 4, we present the thematic clusters that have been identified along with their potential evolutionary trajectories. Section 5 entails a comprehensive discussion on the limitations of this review and offers suggestions for future research directions. Finally, we conclude the article with a section highlighting the implications drawn from the study.

Ⅱ. Data and Methods

Bibliographic information obtained from the identified databases is used in bibliometric procedures. A scientific research and comprehensive picture of any research field are made possible by the bibliometric analysis carried out using the aforementioned information. The number of bibliometric reviews in various fields of study has expanded as a result of the availability of bibliographical data (Ellegaard and Wallin, 2015). Likewise, the financial researchers have also produced numerous reviews based on bibliometric data related to the financial subfield considered for the review. Examples of such works include, Goodell et al. (2023), Gallego-Losada et al. (2022), Khan et al. (2022); Li and Xu (2022), Naeem et al. (2022) and Zhang et al. (2019). Accordingly, following Donthu et al. (2021)'s four-step process, our study analyzes the bibliometric information related to AI agents in banks. The steps include— (i) defining the goals and scope of the review, (ii) analysis method selection, (iii) data gathering, and (iv) analysis, and result summary (see <Figure 1>).

2.1. Stage 2: Selecting an analysis method

This study seeks to examine conversational agents with AI in the banking domain using bibliometrics as a research method. Bibliometric analysis is a qualitative research methodology that aids in revealing the intellectual framework, historical development, current state of knowledge, trending issues, and research implications for the future in relation to the area of interest (Donthu et al., 2021). As a general principle, this methodology analyzes large databases of extant literature statistically and mathematically to summarize research constituents, including the most influential authors, studies, sources, and countries (Adil et al., 2022; Donthu et al., 2021; Ellegaard and Wallin, 2015; Ellegaard, 2018; Narin et al., 1994; Wallin, 2005). Furthermore, existing patterns and focus of literature that may contribute to the better



<Figure 1> Research Flow Diagram

comprehension of a domain can also be uncovered with bibliometric analysis (Khan et al., 2022).

Although the possible outcomes of bibliometric analysis are numerous, application of the analysis to fit the purpose of the study often limits the researcher to consider only a handful of analytical approaches within the bibliometric discipline (Linnenluecke et al., 2020). Hence, as part of the performance analysis, we assessed publication metrics (such as, the total number of publications) and citation metrics (like, the total number of citations). The second step of the performance analysis involved evaluating the relationship between research constituents using citation analysis and co-occurrence analysis.

2.2. Stage 3: Gathering the Necessary Data

The third stage of our research involved gathering data for analysis. *First*, we selected the appropriate databases for obtaining the publication dataset. Researchers have repeatedly emphasized the suitability of the Web of Science and Scopus databases for synthesizing the extant literature (Adil et al., 2022; Dogra et al., 2022; Pranckutė, 2021; Zhu and Liu, 2020). Accordingly, researchers (such as Ertz and Leblanc-Proulx, 2018; Sana et al., 2023) have combined data from both the databases for their study. As such, since our topic of interest is still in its early stage, we chose both Web of Science and Scopus databases to obtain a comprehensive dataset.

Second, we created search phrases, as presented in <Table 1> to find the relevant publications, in the following manner. Due to the fact that the concept of conversational agents is still in its infancy, extant literature uses a variety of synonymous terms. Thus, to develop comprehensive search strings, we followed multiple steps. a) to identify and select the appropriate keywords to represent conversational agents, in-depth reviews of previous works of Agarwal et al. (2022), Ion and Lee (2017) and Bajwa et al. (2022), were conducted. b) the authors reviewed the selected keywords to identify and eliminate the irrelevant ones, such as “home assistants”, “big data” and “learning algorithm”, and considered the relevant ones. Our initial search, thus produced 275 results.

Third, any search engine is prone to providing inaccurate bibliometric and bibliographic data (Baker et al., 2021). As a result, direct processing of such results without data cleaning may result in improper assessment (Donthu et al., 2021). Hence, we cleaned the data as shown in Figure 1— a) in order to do an accurate topical analysis, we primarily removed

<Table 1> Data Collection

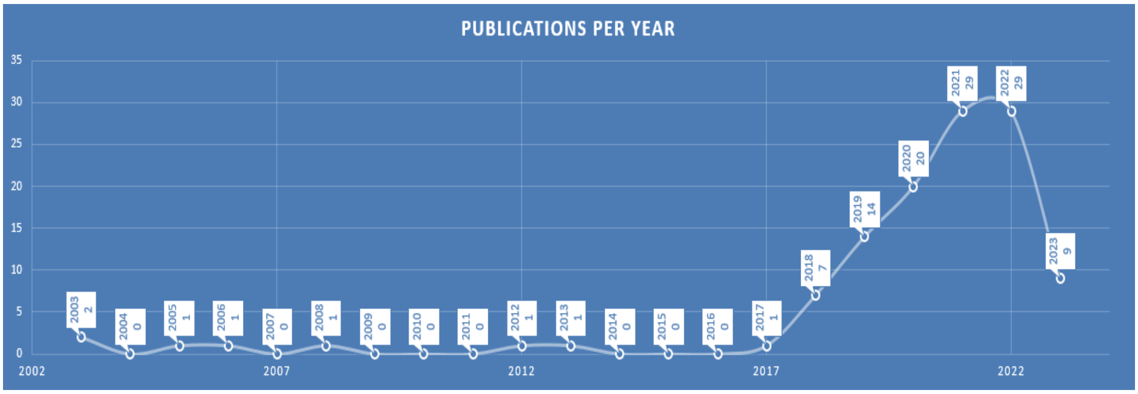
Search engines	Scopus and Web of Science
Search date	10th of March, 2023
Search phrase	Various combinations of the following phrases: i) to denote conversational agents: *“Chatbot*”*, *“Virtual assistant*”*, *“Conversational agent*”*, *“Natural language*”*, *“Virtual agent*”*, *“Personal assistant*”*, *“Dialogue system*”*, *“Robo$advisor*”* AND ii) to denote banks: “*bank**”
Document types	“Articles”, “Conference papers” and “Reviews”
Article languages	“English”
Content selection	Manually screen the “titles”, “abstracts”, and “keywords” sections of the publications to identify content relevant to the study
Initial number of identified publications	(132 from Web of Science) + (143 from Scopus) = 275
Publications selected for study	(49 from Web of Science) + (67 from Scopus) =116

many terms from titles, abstracts, and author-specified keywords. For instance, we changed several plural nouns to their single equivalents, such as “chatbots” to “chatbot(s),” “banks” to “bank,” “assistants” to “assistant”, etc. The phrases that have a similar meaning are also combined (e.g., “robo-advisor” and “robo advisor” were combined to get “robo advisor,” etc.). Next, we screened the abstracts of the collected data to eliminate repeated results and false positives—i.e., publications that contained the words from the search phrase in the “titles” or “author keywords” section, but were deemed irrelevant after the review of abstract. As such, papers which talk about “banks” irrelevant to our study, like “bio banks”, “blood banks”, and “tree banks” (e.g., Gandrud and Hallerberg, 2019; Li et al., 2021), publications related to data mining and related technologies that do not assist conversational agents (e.g., Cohen and Smith, 2010), publications that assess management information systems that provide humanly incomprehensible outputs for other systems (e.g., Carrasco et al., 2012 and Kawamura et al., 2019), and/or call routing systems (e.g., Zitouni et al., 2003), and so on, were dropped from any further consideration.

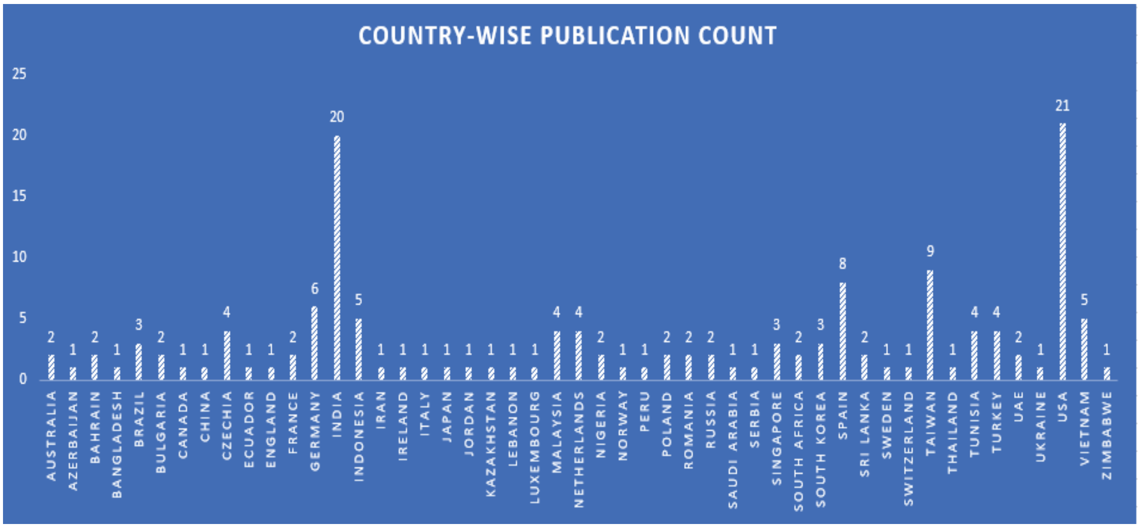
Additionally, we included publications that discuss the role of conversational agents in bank branding (e.g., Creelman, 2022), contributed to the development of modern artificial intelligence systems (Kuo et al., 2003), and evaluated conversational agents based on bank-specific datasets (e.g., Casanueva et al. 2020). In addition, we also considered publications that conduct co-industrial analysis with banking (e.g., Au et al., 2021), consider agents that provide highly contextual information like loan advisory (e.g., Stevenson et al., 2021), include banking conversational agents to their assessed list of technologies (e.g., Flavian et al., 2022), while focusing on the broader financial industry, provide implications specifically for banks, like Taylor et al. (2023), Huang et al. (2021) and Hwang and Kim (2021), and so on. As the study addresses an emerging topic and intends to present the topics evolution throughout the years, the researchers decided not to limit the research period. Therefore, after applying such stringent inclusion/exclusion criteria, our final dataset resulted in 116 records from two different databases (Web of Science and Scopus) published between 2003 and March 2023 (see <Figure 2>).

2.3. Stage 4: The Analyses

For the analysis, we first combined the datasets



<Figure 2> Growth of Publications over the Years



<Figure 3> Number of Publications Per Country

<Table 2> Performance Analysis

Metric	Value
Total publications (TP)	116
Number of sources	72
Number of keywords	404
Number of active years of publication (NAY)	12
Productivity per active year of publication (PAY = TP/NAY)	9.66
Number of contributing authors (NCA)	364
Average number of authors per publication (NCA/TP)	3.13
Sole authored publication count (SA)	12
Co-authored publication count (CA)	104
Academic publication count (TP-A)	96
Industrial publication count (TP-I)	9
Publications from academia-industry collaboration (TP-AI)	11
Total number of citations (TC)	1813
Average number citations per publication (TC/TP)	15.62
Average number citations per active year of publication (NAY/TC)	151.08
Collaboration index (NCA/TP)	3.38
Collaboration coefficient (1-(TP/NCA))	0.68
Number of cited publications (NCP)	81
Proportion of cited publications (PCP = NCP/TP)	0.69
i-index (*i*-10)	21

from the selected databases following Kumpulainen and Seppänen (2022) and Kasaraneni and Rosaline (2022). As such, the format of research constituents, such as “authors”, “references”, and “citation count” were amalgamated to produce a bibliographic database file in *.csv* format, to fit the Scopus-based data file analysis in the VOSviewer software.

Next, we dissected the dataset into the following indicators: a. quantity indicators to present the numerical data in the final dataset, b. qualitative indicators to present the academic influence of the identified dataset, and c. structural indicators to present the interplays between the factors (e.g., countries and authors) in the dataset. Using these indicators, we conducted the following analyses.

2.3.1. Performance Analysis

In this regard, under the performance analysis (see <Table 2>), first, we uncovered the following publication-related metrics: i) Total publications, ii) Number of sources, iii) Number of author keywords, iv) Active years of publication, v) Productivity per active year of publication, vi) Number of contributing authors, vii) Average number of authors per publication, viii) Number of sole authored publications, ix) Number of co-authored publications, x) Publications from academia, xi) Publications from industry, xii) Publications from industry-academia collaboration, xiii) Growth of publications over the years (refer to <Figure 2>), xiv) Top sources based

<Table 3> Source-Related Metrics

Most Productive Sources (Alphabetical Order)	Publications	Number of Publications	Source SJR (2021)	Rank based on SJR
International Journal of Bank Marketing	Eren (2021); Mogaji and Nguyen (2022); Northey et al. (2022)	3	0.886	4
Lecture Notes in Networks and Systems	Ivanova et al. (2020); Mane et al. (2022); Palomino-Navarro and Arbaiza (2022)	3	0.151	11
Advances in Intelligent Systems and Computing	Kaufman (2020); Tenemaza et al. (2020)	2	0.215	10
Computers in Human Behavior	Kim and Im (2023); Huang and Lee (2022)	2	2.174	1
Concurrency and Computation-Practice & Experience	Allegue et al. (2021); Kaushal and Yadav (2023)	2	0.309	9
Expert Systems with Applications	Carrasco et al. (2012); Pisařovic et al. (2022)	2	2.07	2
IEEE Access	Garcia-Mendez et al. (2020); González-González (2022)	2	0.927	3
Journal of Financial Services Marketing	Lappeman et al. (2022); Manshad et al. (2022)	2	0.511	7
Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)	Lothritz et al. (2021); Quah and Chuna (2019)	2	0.407	8
Sensors	Dang et al. (2021); Huang et al. (2021)	2	0.803	5
Sustainability	Au et al. (2021); Hwang and Kim (2021)	2	0.664	6

<Table 4> Countries with Most Publications

Top productive countries	Number of Publications
USA	21
India	20
Taiwan	9
Spain	8
Germany	6
Vietnam	5
Indonesia	5

on their number of publications (refer <Table 3>). xv) Top publications based on publication citation count (refer <Table 5>) and source quality (refer. <Appendix A>), and xvi) Country-related metrics (refer <Figure 3> and <Table 4>).

Second, the following metrics are related to citations: i) Total number of citations, ii) Average number of citations per publication, iii) Average number citations per active year of publication, and iv) Citation growth over the years (refer <Figure 4>).

Third, the following metrics are related to citations and publications (refer <Table 2>): i) Collaboration index, ii) Collaboration coefficient, iii) Number of cited publications, iii) Proportion of cited publications, and iv) *i*-index, where *i* is the number of publications at least cited *i* times (e.g., *i* = 10, *i* = 100, etc.).

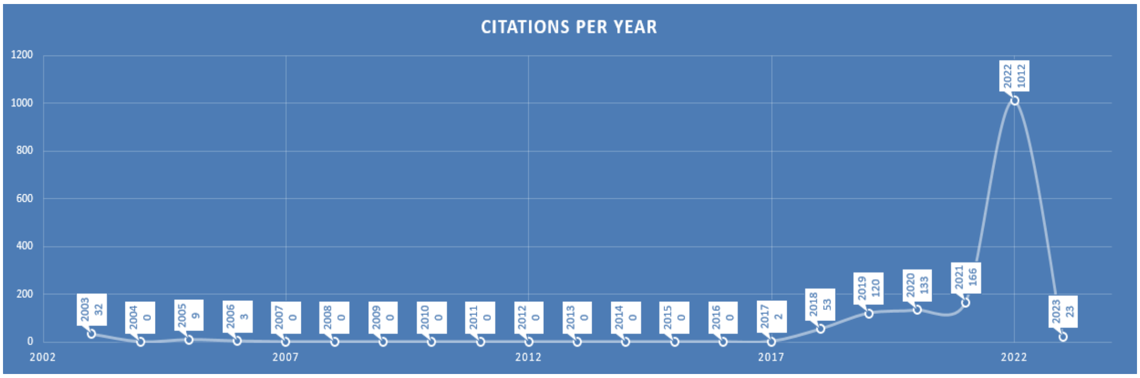
2.3.2. Science mapping

Under the science mapping analysis, we performed the following analyses:

i) *Citation analysis*: Citation analysis helps the study gain various insights in the domain of interest. *First*, as observed in <Table 5> and <Figure 4>, it helps the study identify the most influential authors and publications.

After identification, it sequences them based on their level of contribution and impact on the research field (Goodell et al., 2023). In other words, the number of citations received by a publication demonstrates its relevance and degree of contribution to the research field (Donthu et al., 2022; Khan et al., 2022) as presented in <Appendix A>.

ii) *Bibliographic coupling*: Bibliometric coupling is another kind of science mapping technique that functions under the assumption that publications with common references also present similar content (Khan et al., 2022; Rohm, 2018). The analysis thematically clusters publications based on common references with time



<Figure 4> Citation Count Per Productive Year

<Table 5> Authors with Most Publications

Authors	Number of Publications
Mogaji E	3
Nguyen N P	2
Cekic T	2
Chang Y J	2
Chen K	2
Cheng Y M	2
Darena F	2
Denizo O	2
Donder E B	2
Garcia-Mendez S	2
Kilic O F	2
Kim J	2
Kuo H K J	2
Lee C J	2
Li C H	2
Manav Y	2
Neerincx M A	2
Prochazka D	2
Sfenrianto S	2

parameters. Applying such parameters helps recent, niche and low-cited publications gain discernibility, unlike the co-citation analysis. Hence, this technique helps industrial scholars uncover the recent developments and trends in any given research field (Donthu et al., 2021; Goodell et al., 2023).

iii) *Co-word analysis*: Unlike the previous science mapping techniques, co-word analysis does not focus on publications and references. This technique establishes thematic clusters based on words shared by publications. Such words could be extracted from the "author keywords" section of publications (Goodell et al., 2023; Khan et al., 2022). In the case of keyword absence, the technique may rely upon the "title" or "abstract" or "full text" sections to extract the words needed for clustering. Similar to the co-citation analysis, co-word technique assumes that words appearing together are thematically similar (Donthu et al., 2021; Khan et al., 2022).

iv) *Co-authorship analysis*: As the name suggests, it is a science mapping technique that examines the collaborations among authors in any selected research field. Apart from the basic identification of co-authorship, this technique also categorizes the social relationships among the authors, such as countries. Co-authorship analysis remains an important science mapping technique as collaborations as it helps stakeholders in numerous ways, such as the identification of underrepresented countries (Burton et al., 2020; Donthu et al., 2021; Linnenluecke et al., 2020).

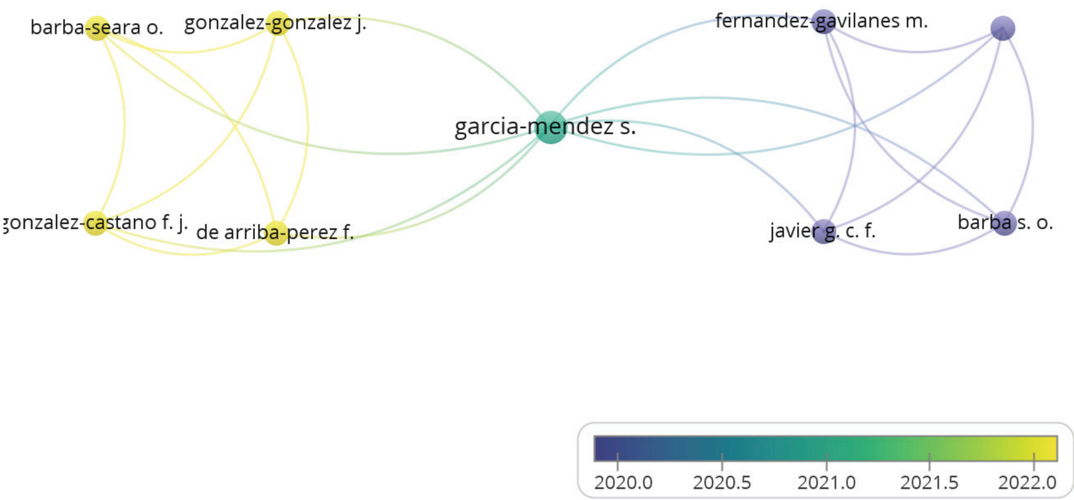
Ⅲ. Results

Our analysis produced the following results and implications for the field of AI conversational agents in banking

3.1. Performance Analysis

3.1.1. Publications, authors, countries and citations in the AI conversational agents in banking literature

Our analysis uncovered the following performance metrics (refer <Table 2>). *First*, in <Figure 2>, the publication count is plotted against the years in which they were published to show the publication trend of AI conversational agents in banking. This illustrates that conversational agents in banks are not a recent development and have been pondered upon



<Figure 5> Co-Authorship Analysis (Authors)

since 2003. Yet, the fourth industrial revolution's advent has recently led to a surge in this particular research stream within the financial domain. Accordingly, the recent years 2019 (14 publications), 2020 (20 publications), 2021 (29 publications), and 2022 (29 publications) have produced the largest output. Consequently, the exciting trend is likely to continue in 2023 as well as 9 articles (or 31% of total publication count in 2022) have been published during the first quarter of 2023.

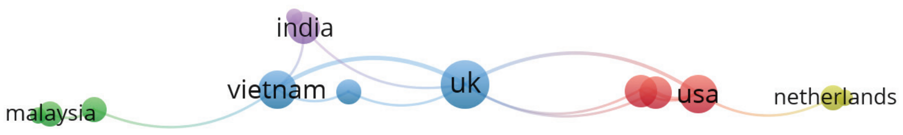
Second, using citation analysis, the prominent publications in the field of research ranked based on their citation counts are presented in <Appendix A>. Gomber et al. (2018) top the list with 1012 citations, followed by Trivedi (2019) (92 citations), and others. Likewise, Trivedi (2019), and Eren (2021) have published leading sole-authored publications with the most citation counts.

Third, based on SJR score, the publications of Gomber et al. (2018), Flavian et al. (2022), and Trivedi (2019) top the list as observed in <Appendix B>.

Fourth, using citation analysis we uncovered the leading authors based on publication count, as presented in <Table 4>. Out of the 19 identified authors with 2 or more publications, Mogaji E tops the list with 3 publications (Abdulquadri et al., 2021; Mogaji and Nguyen, 2022; Mogaji et al., 2021), followed by the others. Moreover, Cheng Y M has solely authored two publications (Cheng, 2023; Cheng, 2020), unlike others in the list. All of the aforementioned publications have majorly focused upon the acceptance of conversational agents either from the industry perspective or the consumer perspective. As such, we implicate that the present focus of literature is on exploring the intricacies of the acceptance of banking conversational agents by the industry and the consumer.

Fifth, we used the co-authorship technique, assessed based on authors, to identify the leading collaborators in our field of interest (refer. <Figure 5>). Garcia-Mendez S. tops the list with 8 collaborations, followed by the others with 4 collaborations each.

Sixth, as presented in <Figure 4>, the citation count grew along with the publications (refer. <Figure



<Figure 6> Co-Authorship Analysis (Countries)

2>) with an average citation count of 15.62 per publication and 151.08 per active year of publication (refer. <Table 2>).

Seventh, India (20 publications), USA (21 publications), and Taiwan (9 publications) have published the most articles, in our research field of interest. Given the sheer size and expected growth of Fintech markets in USA, China and India (Howarth, 2023), the results are not surprising.

Finally, <Figure 6> portrays the co-authorship analysis with countries as the control unit. Out of the 50 countries, 27 have collaborated with other countries. UK tops the list with 6 collaborations, followed by Vietnam (4 collaborations), USA, (4 collaborations), India (3 collaborations), and others (2 collaborations or less).

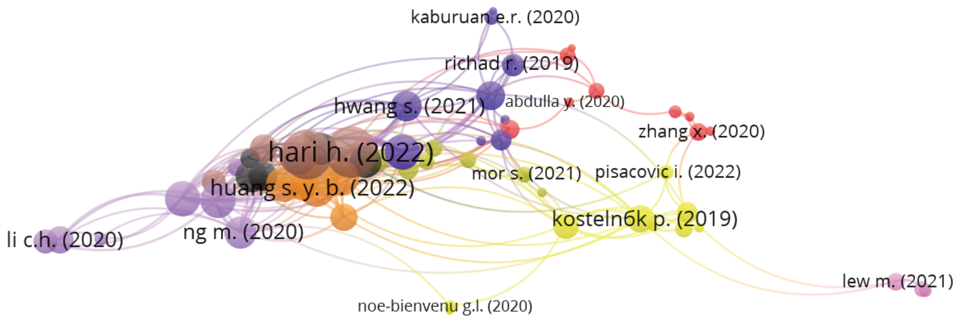
3.1.2. Prominent Sources of Identified Publications

We have presented the influential journals that have contributed to our field of interest in <Table 3>. *First*, the *International Journal of Bank Marketing* and *Lecture Notes in Networks and Systems* have published 3 articles each with a combined citation count of 50. Next, *Advances in Intelligent Systems and Computing, Computers in Human Behavior, Concurrency and Computation-Practice & Experience, Expert Systems with Applications, IEEE Access, Journal of Financial Services Marketing, Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), Sensors,* and *Sustainability* have published 2 articles each. *Second,* <Table 3> also presents the most prominent of these sources based on their SJR score. Accordingly, *Computers in Human Behavior, Expert Systems with Applications,* and *IEEE Access* are the top three productive high-ranking journals in the AI conversational agents in banking literature. In these publications, a pattern is observed where majority of the focus is on consumer acceptance of conversational agents (e.g., Eren, 2021; Huang and Lee, 2022; Kim and Im, 2023). Moreover, *Journal of Financial Services* and *Journal of Bank Marketing* are the core financial journals in this list. This surprising lack of financial journals in the list implicates another possible trend, which focuses on uncovering the convolutions of conversational agent acceptance among consumers and the industry with an intentional focus on banking. As banks are often regarded as the primary and largest adopters of any new technology (Hentzen, 2022; Trivedi, 2019), we assume that researchers expect a study sample who have used conversational agents to be easily available in the banking domain for their studies.

3.2. Science Mapping

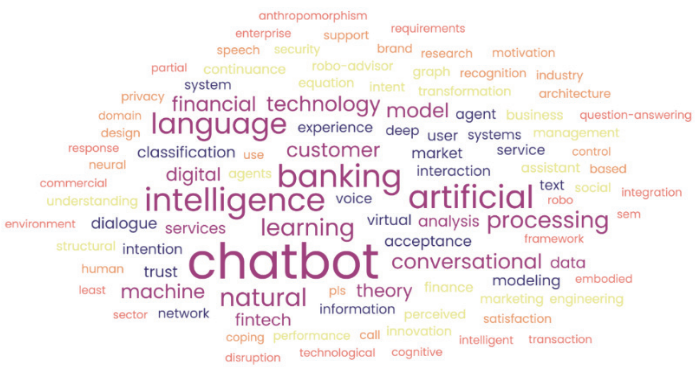
3.2.1. Identifying Themes Using Bibliographic Coupling

The study overlooks the co-citation technique which considers only seminal publications, unlike the bibliographic coupling technique. *First*, the biblio-



<Figure 7> Thematic Clusters

graphic coupling helps researchers understand the existing status quo of the literature under assessment by considering niche and recent publications along with the seminal ones (Goodell et al., 2021). In this sense, co-citation analysis becomes redundant for our scope of study. *Second*, the technique has become a standard for finance literature within the bibliometric discipline (Baker et al., 2021; Goodell et al., 2021; Rohm, 2018). Accordingly, using this technique we uncovered 6 thematic clusters as presented in <Appendix C>. *Technology Design, Language Processing, Banking Transformation, Technology Acceptance, Customer Service* and *Technology Personalization* are the foundational clusters identified as depicted in <Figure 7>. These clusters represent the extant knowledge foundations of the AI conversational agents in banking. Thematic cluster 1 contains 9 publications with 30 citations in total, under *Technology design*. The 12 publications in cluster 2, *Language processing*, were cited 21 times. Cluster 3 contains 15 publications under *Banking transformation* with 23 citations. The foundational cluster 4 under *Technology acceptance* contains 14 publications with 263 citations. Cluster 5 contains 7 publications with 43 citations in total under *Customer service*. Finally, cluster 6 under *Technology personalization* contains 5 publications with 4 citations. Among these foundational themes, the *Technology acceptance* cluster was cited the highest revealing that present research focuses upon the acceptance of conversational agents, more than other themes. In this regard, researchers like Eren (2021) and Trivedi (2019)

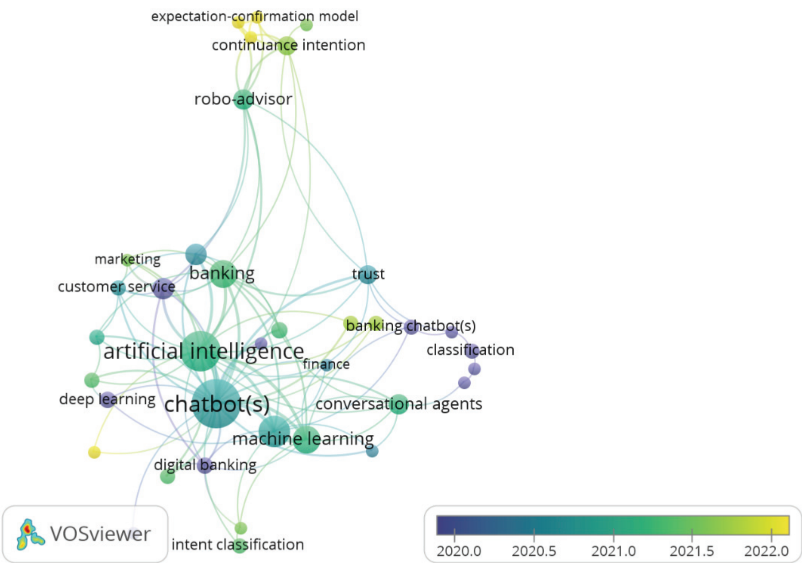


<Figure 8> Word Cloud (Authors Keywords)

offer insights for increasing the consumer acceptance of banking conversational agents. The second highest cluster based on citation count, *Customer service,* focuses on the employment of AI technologies like conversational agents in banking. Accordingly, researchers such as Li et al. (2020) and Ng et al. (2020) offer insights for the development and employment of banking conversational agents in customer service. The third highest cited cluster, the *Technology design* focuses on the design of conversational agents. Accordingly, researchers, such as Johari et al. (2022), and Lai et al. (2019) offer insights for designing chatbots that can appeal to the intended users. In this fashion, the rest of the studies listed in <Appendix C> represent the themes in extant AI conversational agents in banking literature.

3.2.2. Identifying Trends Using Co-occurrence Analysis

Building on the previous themes uncovered using the bibliographic coupling technique, we employed the co-occurrence analysis to understand how the themes have advanced. The co-occurrence technique gauges the "author keywords" section of the corpus in a temporal fashion to uncover the aforementioned advancement. Author keywords are the words that researchers choose, for a publication have a major influence on how it is portrayed and how it is communicated throughout scientific communities. First, we have presented a word cloud in <Figure 8> based on the keyword occurrence frequency. "Chatbots" tops the list of most frequently appearing keywords with 45 occurrences, followed by "artificial intelligence" with 29 occurrences, "banking" and "natural language processing" with 16 occurrences, "machine learning" with 11 occurrences, "financial services" and "fintech" occurring 7 times, and finally "continuance intention" and "trust" occurring 5 times. Second, the publication's primary topics of interest are identified using these keywords. We used the co-occurrence technique to detect keywords that



<Figure 9> Co-Occurrence Analysis (Author Keywords)

have occurred at least twice in the corpus. Accordingly, we have visualized the keywords matching our selection criteria, and the thematic relations between the keywords in a chronological manner in <Figure 9>. We have presented them in a chronological manner to understand their average publication year (APY), which can be formulated as

$$APY_t = \sum_{i,j} t_i j_y / \sum_i t_i$$

Here, if two articles discuss a topic *t* in 2020, then one article discusses *t* in 2022, and six articles, in 2023, then the APY value of *t* is [(2*2020) + (1*2022) + (6*2023)]/9 = 2022.2 (Goodell et al., 2021). The APY helps researchers understand how the trends in the literature of the selected field of interest have evolved over the years. The literature that supports conversational agents generally seems to be extensive. Therefore, we suggest that it is critical to analyze the existing literature on this subject in terms of the industry, like Yörük et al. (2023) and Xing et al. (2019). As such, using co-occurrence analysis we uncovered the current trends in our field of research interest, as presented in section 4. Furthermore, the next section seeks to clarify the current state of the conversational agents in banking, also to classify future research notions.

Ⅳ. Discussion on Present Thematic Clusters and Potential Research Trajectories

4.1. Language Processing

Before APY 2019.0, researchers such as Kuo and Lee (2003) and Zitouni (2007) have worked on systems using natural language processing. The researchers "*aim to gather knowledge on how human beings understand and use language so that appropriate tools and techniques can be developed to make computer systems understand and manipulate natural languages to perform the desired task*" (Chowdhary and Chowdhary, 2020, p. 1). Other research sub clusters exposed using the author keywords within this timeframe that directly contribute to the latest natural language processing systems, like *conversational agents* (APY 2021.1), are, *discriminative training* (APY 2005.5), *informational retrieval* (2012.5), *classification* (2016.6) and so on. All of these research clusters have helped the natural language processing systems advance over the years (e.g., Wilkie et al., 2005). While these systems were not artificially intelligent initially, they were seminal in developing the modern-day AI-based query handling systems such as AI-based chatbots. For instance, in the network visualization diagram presented in <Figure 9>, the *conversational agents*, which depend on *information retrieval* (2012.5) powered by *discriminative training* (2005.5), reveals how the systematic training (*discriminative training*) has enabled the system (*conversational agents*) to identify and retrieve information (*informational retrieval*), which is then presented to customers' questions, in the form of meaningful answers. After APY 2019.0, this trend happens to continue where keywords like *natural language processing* and *natural language understanding* (APY 2021.5) are linked to other sub clusters, like *machine learning* (APY 2021.2), *deep learning* (APY 2020.0), and *intent classification* (2021.3) signifying the shift of modern-day systems onto AI-powered trainings. When discussing avenues for future research, it is essential to provide comprehensive and detailed suggestions that can guide further investigation. In light of this, we recommend expanding the discussion to offer specific areas and aspects that merit exploration, potential research methodologies or frameworks to adopt, as well as the potential implications and benefits of undertaking such future research endeavors. To advance the knowledge in the "language processing" domain, future literature could consider narrowing down the agent training topics to specifically cater to the intricacies of the banking domain and the systems within it. This targeted approach would allow researchers to delve deeper into the specific challenges, requirements, and nuances associated with language processing in the context of banking. Furthermore, exploring the potential methodologies and frameworks that could be employed in investigating language processing for banking agents would greatly enrich the literature. Researchers could consider employing natural language processing techniques, machine learning algorithms, and semantic analysis approaches to develop advanced models and systems tailored to the unique linguistic requirements of the banking sector. By incorporating these methodologies, researchers can unravel the complexities of language understanding, sentiment analysis, and customer interactions within the banking domain. Such future research endeavors would yield several noteworthy implications and benefits. Firstly, it would lead to the development of more accurate and efficient banking conversational agents that can comprehend and respond to customer inquiries and requests effectively. Enhanced language processing capabilities would enable agents to provide personalized and context-aware solutions, ultimately enhancing the overall customer experience. Secondly, by delving into the nuances of language processing within the banking context, researchers can contribute to the advancement of the broader fields of natural language processing and artificial intelligence, offering insights and techniques that can be applied to various other domains and industries. We make this suggestion as other fields, like medicine, have produced tools and techniques for training their industrial agents (Richardson et al., 2021), while banking literature remains desolate in this regard.

4.2. Technology Acceptance

Keywords, such as *continuance intention* (APY 2021.6) and *customer satisfaction* (APY 2021.6) represent consumers' response to various stimuli, like *trust* (APY 2020.6), *externalities* (APY 2022), and *expectation-confirmation* (APY 2022). This represents a growing trend in research, which considers the consumer response to conversational agents. The response often confirms theories, like the *technology acceptance* (APY 2021.2), and *expectation-confirmation,* gained through positive *customer experience* (APY 2021.3) with *conversational agents* (APY 2021.1) in *banking* (APY 2021.2). In this regard, the existing trend in our research domain lacks comprehensive coverage of response-related variables, such as usage intention, actual usage, and attitude. Additionally, there is a need to incorporate stimulating variables derived from well-established theoretical frameworks, including the Unified Theory of Acceptance and Use of Technology, Innovation Diffusion Theory, Flow Theory, and the Task-Technology Fit. To address these gaps, future literature should consider incorporating a broader range of response-related variables in their studies. This would involve examining users' intentions to use banking agents, their actual usage behavior, and their attitudes towards these technological solutions. By including these variables, researchers can gain deeper insights into the factors that influence users' acceptance and adoption of conversational agents in the banking context. Understanding users' intentions, behaviors, and attitudes is crucial for developing effective strategies to promote the use of these agents and ensure their successful integration into banking services. Furthermore, it is imperative to draw upon established theoretical frameworks when investigating the adoption and usage of banking agents. The Unified Theory of Acceptance and Use of Technology provides a comprehensive perspective on users' acceptance and use of technology, encompassing factors such as performance expectancy, effort expectancy, social influence, and facilitating conditions. Incorporating this theory into research on banking agents would enable a more thorough analysis of the factors influencing users' acceptance and usage behavior. Similarly, the Innovation Diffusion Theory can offer valuable insights into the process of how innovations, such as conversational agents, spread and gain traction among users. Exploring the diffusion of banking agents and identifying the factors that facilitate or hinder their adoption can contribute to a more comprehensive understanding of their impact on the banking industry. Additionally, incorporating concepts from Flow Theory can shed light on users' experiences and engagement when interacting with banking agents. Understanding the flow state, characterized by focused attention, enjoyable experiences, and optimal challenge, can help researchers design conversational agents that enhance user satisfaction and overall experience. Lastly, considering the Task-Technology Fit perspective can provide insights into the alignment between the capabilities of banking agents and the tasks they are designed to support. Assessing the fit between the functionalities of the agents and the specific banking tasks can guide the development and implementation of tailored solutions that effectively meet users' needs. By incorporating these response-related variables and drawing upon established theories, future research can deepen our understanding of the adoption, usage, and impact of banking conversational agents. This would enable researchers to develop more robust models, theories, and practical guidelines that facilitate the successful implementation of these technologies in the banking industry, ultimately benefiting both users and service providers. Yet, confirmation of such theories and consideration of aforementioned responses are highly prevalent in literature considering conversational agents in other industries, like e-commerce (Wang et al., 2021) and education (Guggemos et al., 2020). Hence, we suggest the future scholars contributing to the conversational agents in banking literature to consider technology acceptance related theories such as the above.

4.3. Design

Another trend in the present conversational agents in banking literature centers on the design of said agents. Keywords like *anthropomorphism* (APY 2023) are generally used to represent the humanoid features demonstrated by the AI system. When the system exhibits such features, responses like trust get stimulated resultantly (Ogonowski et al., 2014). Accordingly, studies consider these aspects to assess various customer responses to several other factors pertaining to human-like features exhibited by AI systems. When examining the existing literature on conversational agents, it is noteworthy that studies conducted in other fields have explored design-related constructs, such as emotional support, appearance, and interactivity. Lee et al. (2022) focused on the emotional support provided by conversational agents, while Chong et al. (2021) emphasized the importance of appearance and interactivity. However, upon conducting a co-occurrence analysis within our corpus, we observed a dearth of such design-related keywords, suggesting a research gap that warrants attention in the context of conversational agents in banking. Therefore, future research endeavors in the banking domain should take into account the significance of design aspects when studying conversational agents. It would be valuable to investigate whether design-related features outweigh performance-related features or vice versa, particularly in environments perceived as risky, such as the banking sector. Understanding the role of design in shaping users' perceptions and experiences with banking conversational agents can provide crucial insights for developing effective and user-centric agent designs. By delving into the interplay between design and performance aspects, researchers can explore questions regarding the relative importance of these factors in influencing users' acceptance, trust, and satisfaction with banking conversational agents. Does a visually appealing and interactive design contribute more to user engagement and adoption compared to the performance capabilities of the agent? Alternatively, does the functionality and reliability of the agent outweigh design aesthetics in establishing user trust and confidence? Examining these trade-offs can help identify the key drivers that influence users' preferences and choices when interacting with conversational agents in the banking domain. Furthermore, investigating the impact of design-related features on users' perceived risk is of particular interest. Perceptions of risk can significantly influence users' willingness to adopt and engage with banking conversational agents. Research should explore how different design elements, such as visual design, interaction design, and conversational style, interact with users' risk perceptions in the context of banking services. Understanding the relationship between design and perceived risk can provide valuable insights for designing conversational agents that foster trust, mitigate risk perceptions, and enhance user acceptance in the banking domain.

4.4. Transformation

Transformation is a topic uncovered during the bibliographic coupling and co-occurrence analysis phases of our study. In the bibliographic coupling, publications like Abdulquadri et al. (2021) and Suhel et al. (2020) focus on the transformation of traditional banking through digitalization. In the same manner, the co-occurrence analysis exposed the relationship between keywords like, *digital transformation* (APY 2021.0), and *customer service* (APY 2020.6), demonstrating that another existing trend in research focuses upon the AI-backed transformation of various subdomains within banking, like *customer service* (APY 2020.6), *marketing* (APY 2021.5), *financial services* (APY 2020.0), and *roboadvisory* (APY 2021.1) using technologies like *chatbots* (APY 2020.7). When considering the ongoing digitalization of the banking sector, an area that merits attention in future research is the application of artificial intelligence (AI). The COVID-19 pandemic and subsequent lockdowns compelled numerous banks to expedite their digital transformation efforts, resulting in the adoption of AI-based technologies, such as customer service chatbots. However, the introduction of these novel and complex services can present challenges for customers (Kaur et al., 2021), necessitating further investigation into consumer acceptance and its impact on the broader banking transformation trend. Future research endeavors should delve into the factors that influence consumer acceptance of AI-driven banking services. Understanding how customers perceive and evaluate these digital innovations is crucial for their successful implementation and widespread adoption. Researchers can explore the determinants of consumer acceptance, including factors such as perceived usefulness, ease of use, trust in AI technology, privacy concerns, and the overall user experience. By examining these dimensions, a more comprehensive understanding of consumer acceptance and its implications for the digitalization of banking can be attained. Moreover, it is imperative to investigate the challenges and barriers that customers may encounter when interacting with AI-based banking services. These challenges can arise due to the novelty and complexity of AI technologies, as well as customers' familiarity with traditional banking practices. Exploring the specific difficulties faced by customers in their interactions with AI chatbots, such as issues related to communication, understanding responses, or obtaining accurate information, can provide valuable insights for improving the design and functionality of these services. Additionally, future research should address the impact of consumer acceptance on the broader banking transformation trend. As banks increasingly rely on AI and digital solutions, understanding how customer acceptance influences the pace and direction of this transformation is crucial. Researchers can investigate the relationship between consumer acceptance, adoption rates of AI-based banking services, and the overall success of banks' digitalization initiatives. This line of inquiry can shed light on the dynamics between customer preferences, technological advancements, and the strategic decisions made by banks in their pursuit of digital transformation.

Ⅴ. Limitations and Future Research Directions

The implications of our study should be considered with the following limitations in mind. First, the study considers only the Scopus and Web of Science databases to identify the corpus for analysis. We suggest future research to consider other growing databases like Dimensions and Google Scholar, to repeat our study. Second, during the dataset merging, the references format could have been compromised. However, since our study skipped the co-citation technique, the drawback exerts limited impact on our analysis. Yet, future researchers considering co-citation technique may carefully assess the reference section of the dataset to avoid inaccurate results. Third, we have merely quantified a growing financial research trend with minimal timespan. Hence, future researchers may repeat our research after the trend has experienced a considerable growth. Fourth, our research is quantitative in nature. Hence, we invite future researchers to analyze the same research field in a qualitative manner, such as the systematic literature review. In addition, the field of scientometric is witnessing the emergence of various review methodologies, including altmetrics, network analysis, text mining, and citation context analysis. Future researchers investigating conversational agents, irrespective of the domain, have the opportunity to leverage these methodologies to enhance their scientometric analysis. Finally, in the domain of conversational agents, several areas such as contextual understanding, multimodal conversations, personalization and adaptability, human collaborations, and continuous learning are gaining significant attention. To enhance existing literature through quantitative measures, we recommend future research to expand their scientometric reviews to encompass these domains.

Ⅵ. Conclusion

The corpus for the current study was developed by searching papers in the Elsevier Scopus and

Clavariate Analytics Web of Science databases using inclusion and exclusion criteria, then filtering procedures. The study's retrospective analysis of conversational agents in banking answered the suggested research questions. Accordingly, first, with corpus retrospection, we uncovered the publication metrics, citation metrics, and the research trends over the years in a quantifiable manner for our research field of interest. Second, we identified the most influential publications in the field through citation analysis technique, followed by the identification of leading authors using the same technique. Third, using the co-authorship analysis technique we revealed the top collaborators, and their collaborations, with countries as the unit of analysis. Fourth, we uncovered the publications and their significance in our field of interest. Next, the study revealed the extant themes in our research field of interest using the bibliographic coupling technique. Following this, we used the co-occurrence technique to understand how and whether the themes identified using bibliographic coupling have advanced over the years. Ultimately, the co-occurrence helped us present the future research directions for the scholars working on conversational agents in banking.

6.1. Academic Contributions

Our study offers the following implications for literature. Firstly, our findings provide researchers with a comprehensive understanding of the current boundaries and scope of research of the domain under review. Consequently, researchers can utilize these results to prioritize lesser-investigated and novel issues, thereby facilitating the broader adoption of conversational agents in banking domains. Secondly, researchers working in the area can benefit from identifying prominent publishers, researchers, and countries in this field, as they serve as potential collaborators and guiding forces for advancing research within this domain. Thirdly, the findings from the analysis of thematic clusters, achieved through bibliographic coupling and co-occurrence analysis, offer critical information regarding articles that form the foundation of this research field. Future researchers can leverage this information as a basis for conducting more nuanced research focused on specific issues identified through citation analyses. Fourth, the content analysis of the identified thematic clusters enables us to propose significant research agendas that can be addressed by future scholars. Lastly, our study can serve as a foundation for promoting methodological advancements in future studies, specifically through mathematical modeling and empirical investigations.

6.2. Practical Contributions

The findings of this study hold practical implications for industry-based researchers seeking to advance the existing knowledge base. Based on the analysis, we offer the following practical implications for managers and organizational policy makers to facilitate the implementation and adoption of conversational agents in the banking sector. Firstly, our research suggests that practitioners, including managers responsible for technological advancements within organizations, can utilize our study to grasp the broad scope of AI- based conversational agent applicability in managing business processes and operations across diverse sectors and managerial domains, specifically within banking. Secondly, industrial practitioners can apply the findings from the studies identified through science mapping to address design choices and transformations that may alleviate major implementation obstacles discussed in prior literature. Thirdly, the findings indicate the need for practical investigations into the societal, organizational, and environmental factors that influence the implementation of conversational agents in banking. Fourth, the results highlight the importance of considering language processing, acceptance, design, and transformational dimensions in the application of conversational agents for organizational customer management and related processes. Therefore, organizational managements and professionals involved in the information technology domains are urged to examine these factors. Lastly, we believe that industry-based practitioners can benefit from utilizing bibliometrics to delineate research boundaries within specific areas of interest, enabling a more nuanced application of conversational agents in different managerial domains, such as human resources, data management, and financial management.

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<Appendix A> Most Influential Publications Based on Citation Count

Type	Authors	Title	Year	Source	Citation Count	Source IF (2021)	Source SJR	Source SNIP	Quartile
Article	Gomber, P., Kauffman, R. J., Parker, C., and Weber, B. W.	On the Fintech Revolution: Interpreting the Forces of Innovation, Disruption, and Transformation in Financial Services	2018	Journal of Management Information Systems	1012	7.582	4.365	3.45	1
Article	Trivedi, J.	Examining the Customer Experience of Using Banking Chatbots and Its Impact on Brand Love: The Moderating Role of Perceived Risk	2019	Journal of Internet Commerce	92	7.73	1.719	1.99	1
Article	Jung, D., Dorner, V., Weinhardt, C., and Pusmaz, H.	Jung, D. and Dorner, V. and Weinhardt, C. and Pusmaz, H.	2018	Electronic Markets	55	6.017	0.847	0.847	1
Article	Baker, T., and Dellaert, B.	Regulating Robo Advice Across the Financial Services Industry	2018	Iowa Law Review	44	1.352	0.281	0.937	2
Article	Eren, B.A.	Determinants of customer satisfaction in chatbot use: evidence from a banking application in Turkey	2021	International Journal of Bank Marketing	38	5.083	0.788	1.335	1
Article	Abdulquadri, A., Mogaji, E., Kieu, T. A., and Nguyen, N. P.	Digital transformation in financial services provision: a Nigerian perspective to the adoption of chatbot	2021	Journal of Enterprising Communities	34	3.45	0.456	1.101	1
Article	Bhatia, A., Chandani, A., and Chhateja, J.	Robo advisory and its potential in addressing the behavioral biases of investors - A qualitative study in Indian context	2020	Journal of Behavioral and Experimental Finance	33	8.222	1.249	2.768	1
Article	Okuda, T., and Shoda, S.	AI-based Chatbot Service for Financial Industry	2018	Fujitsu Scientific & Technical Journal	32	0.293	0.161	0.401	4
Conference paper	Suhel, S. F., Shukla, V. K., Vyas, S., and Mishra, V. P.	Intention to use analytical artificial intelligence (AI) in services - the effect of technology readiness and awareness	2022	Journal of Service Management	29	7.47	2.658	2.537	1

Note: IF -impact factor; SJR - Scimago Journal Rank; SNIP - Source Normalised Impact per Paper

<Appendix B> Most Influential Publications Based on Source Quality (SJR score)

Type	Authors	Title	Year	Source	Citation Count	Source IF (2021)	Source SJR	Source SNIP	Quartile
Article	Gomber, P., Kauffman, R. J., Parker, C., and Weber, B. W.	On the Fintech Revolution: Interpreting the Forces of Innovation, Disruption, and Transformation in Financial Services	2018	Journal of Management Information Systems	1012	7.582	4.365	3.45	1
Article	Flavian, C., Perez-Rueda, A., Belanche, D., and Casalo, L. V.	Intention to use analytical artificial intelligence (AI) in services - the effect of technology readiness and awareness	2022	Journal of Service Management	29	7.47	2.658	2.537	1
Article	Trivedi, J.	Examining the Customer Experience of Using Banking Chatbots and Its Impact on Brand Love: The Moderating Role of Perceived Risk	2019	Journal of Internet Commerce	92	7.73	1.719	1.99	1
Article	Mogaji, E., Balakrishnan, J., Nwoba, A. C., and Nguyen, P. N.	Emerging-market consumers' interactions with banking chatbots	2021	Telematics and Informatics	19	9.14	1.567	2.912	1
Article	Carrasco, R. A., Munoz-Leiva, F., Sanchez-Fernandez, J., and Liebana-Cabanillas, F.J.	A model for the integration of e-financial services questionnaires with SERVQUAL scales under fuzzy linguistic modeling	2012	Expert Systems with Applications	19	8.665	1.368	3.079	1
Article	Bhatia, A., Chandani, A., and Chhateja, J.	Robo advisory and its potential in addressing the behavioral biases of investors - A qualitative study in Indian context	2020	Journal of Behavioral and Experimental Finance	33	8.222	1.249	2.768	1
Article	Jung, D., Dorner, V., Weinhardt, C., and Pusmaz, H.	Jung, D. and Dorner, V. and Weinhardt, C. and Pusmaz, H.	2018	Electronic Markets	55	6.017	0.847	0.847	1
Article	Eren, B. A.	Determinants of customer satisfaction in chatbot use: evidence from a banking application in Turkey	2021	International Journal of Bank Marketing	38	5.083	0.788	1.335	1
Article	Abdulquadri, A., Mogaji, E., Kieu, T. A., and Nguyen, N. P.	Digital transformation in financial services provision: a Nigerian perspective to the adoption of chatbot	2021	Journal of Enterprising Communities	34	3.45	0.456	1.101	1
Article	Baker, T., and Dellaert, B.	Regulating Robo Advice Across the Financial Services Industry	2018	Iowa Law Review	44	1.352	0.281	0.937	2

Note: IF -impact factor; SJR - Scimago Journal Rank; SNIP - Source Normalised Impact per Paper

<Appendix C> Thematic Clusters

Theme	Authors	Publication Title	Citations
Technology design	Doherty, D., and Curran, K.	Chatbots for online banking services	10
	Hwang S., and Kim J.	Toward a Chatbot for Financial Sustainability	6
	Johari, N. M., Nohuddin, P. N., Baharin, A. H., Yakob, N.A., and Ebadi, M. J.	Features requirement elicitation process for designing a chatbot application	0
	Kaburuan, E.R., and Kelvin, A.	Analyzing and designing conversational banking service architecture for banking company	0
	Kelly, S., Kaye, S.A., and Oviedo-Trespalacios, O.	A Multi-Industry Analysis of the Future Use of AI Chatbots	1
	Lai, S. T., Leu, F. Y., and Lin, J. W.	A Banking Chatbot Security Control Procedure for Protecting User Data Security and Privacy	10
	Patil, G. V., and Dhamdhere, V.	Research and Analysis on Voice Based System with Machine Learning	0
	Sharma, D., and Gupta, A.	Regression examination of factors influencing the chatbots usage in banking industry of India	0
	Tenemaza, M., Lujan-Mora, S., de Antonio, A., Ram¡rez, J., and Zarabia, O.	Ekybot: Framework proposal for chatbot in financial enterprises	3
Language processing	Ahmed, M., Ansari, M. D., Singh, N., Gunjan, V. K., Krishna, S. B. V., and Khan, M.	Rating-Based Recommender System Based on Textual Reviews Using IoT Smart Devices	1
	Dondar, E. B., Deniz, O., and Arslan, S.	A hybrid approach to question-answering for a banking Chatbot on Turkish: Extending keywords with embedding vectors	1
	Kim, S., Goh, J., and Jun, S.	The Use of Voice Input to Induce Human Communication with Banking Chatbots	8
	Kosteln¡k, P., PisaRovic, I., MuroN, M., DaRena, F., and ProchAzka, D.	Chatbots for enterprises: Outlook	6
	Lothritz, C., Allix, K., Lebichot, B., Veiber, L., Bissyand, T. F., and Klein, J.	Comparing MultiLingual and Multiple MonoLingual Models for Intent Classification and Slot Filling	3
	Noe-Bienvenu, G. L., Nouvel, D., and Mostefa, D.	Measuring the Polarity of Conversations between Chatbots and Humans: A Use Case in the Banking Sector	0
	Pisacovic, I., Darena, F., Prochazka, D., and Janis, V.	Preprocessing of normative documents for interactive question answering	0
	Van, T. D., Quang, T. M., Toan, P. M., Thien, V. M., Hung, L. M., and Quan, T.T.	A Human-like Interactive Chatbot Framework for Vietnamese Banking Domain	0
	Wicaksono, B. P., and Zahra, A.	Design of the use of chatbot as a virtual assistant in banking services in Indonesia	0
	Dondar, E. B., KiliC, O. F., CekiC, T., Manav, Y., and Deniz, O.	Large scale intent detection in Turkish short sentences with contextual word embeddings	2
	Kilic, O. F., Dundar, E. B., Manav, Y., Cekic, T., and Deniz, O.	Conversation management in task-oriented Turkish dialogue agents with dialogue act classification	0
	Lew, M., Obuchowski, A., Kacprzak, E., and Pluwak, A.	Conversation Clustering Adaptation for Intent Recognition	0

<Appendix C> Thematic Clusters (Cont.)

Theme	Authors	Publication Title	Citations
Banking transformation	Abdulla, Y., Ebrahim, R., and Kumaraswamy, S.	Artificial Intelligence in Banking sector: Evidence from Bahrain	3
	Bhattacharya, C., and Sinha, M.	Role of Artificial Intelligence in Banking for Leveraging Customer Experience	1
	Deepthi, B., Gupta, P., Rai, P., and Arora, H.	Assessing the Dynamics of AI Driven Technologies in Indian Banking and Financial Sector	0
	Hristova, G.	Topic modeling of chat data: A case study in the banking domain	3
	Khan, S., and Rabbani, M. R.	Chatbot as islamic finance expert (CaIFE): When finance meets artificial intelligence	1
	Mane, D., Patil, M., Chaudhari, V., Nayakavadi, R., and Pandhe, S.	A Survey on Chatbot in Devanagari Language	0
	Nair, K., Anagreh, S., Sunil, A., and Gupta, R.	AI-Enabled Chatbot to Drive Marketing Automation for Financial Services	2
	Thisarani, M., and Fernando, S.	Artificial intelligence for futuristic banking	1
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	Lappeman, J., Marlie, S., Johnson, T., and Poggenpoel, S.	Trust and digital privacy: willingness to disclose personal information to banking chatbot services	1
	Li, C. Y., and Zhang, J. T.	Chatbots or me? Consumers? switching between human agents and conversational agents	0
	Mogaji, E., and Nguyen, N. P.	Managers' understanding of artificial intelligence in relation to marketing financial services: insights from a cross-country study	7
	Palomino-Navarro, N., and Arbaiza, F.	The Role of a Chabot Personality in the Attitude of Consumers Towards a Banking Brand	0
Technology acceptance	Abdulquadri, A., Mogaji, E., Kieu, T. A., and Nguyen, N. P.	Digital transformation in financial services provision: a Nigerian perspective to the adoption of chatbot	34
	Al-Ababneh, H. A., Borisova, V., Zakharzhevska, A., Tkachenko, P., and Andrusiak, N.	Performance of Artificial Intelligence Technologies in Banking Institutions	0
	Mor, S., and Gupta, G.	Artificial intelligence and technical efficiency: The case of Indian commercial banks	9
	Mulyono, J. A., and Sfenrianto, S.	Evaluation of Customer Satisfaction on Indonesian Banking Chatbot Services During the COVID-19 Pandemic	1
	Quah, J. T., and Chua, Y. W.	Chatbot assisted marketing in financial service industry	19

<Appendix C> Thematic Clusters (Cont.)

Theme	Authors	Publication Title	Citations
Technology acceptance	Singh, G.	A Move Towards Intelligent Economy: Indian Evidence	0
	Suhel, S. F., Shukla, V. K., Vyas, S., and Mishra, V.P.	Conversation to Automation in Banking through Chatbot Using Artificial Machine Intelligence Language	31
	Toh, T. J., and Tay, L. Y.	Banking Chatbots: A Study on Technology Acceptance among Millennials in Malaysia	0
	Richad, R., Vivensius, V., Sfenrianto, S., and Kaburuan, E. R.	Analysis of factors influencing millennial's technology acceptance of chatbot in the banking industry in Indonesia	11
	Barakat, K. A., and Dabbous, A.	Factors affecting the sustained use of chatbots: An organizational perspective	0
	Eren, B. A.	Determinants of customer satisfaction in chatbot use: evidence from a banking application in Turkey	38
	Hari, H., Iyer, R., and Sampat, B.	Customer Brand Engagement through Chatbots on Bank Websites? Examining the Antecedents and Consequences	5
	Nguyen, D. M., Chiu, Y. T., and Le, H.D.	Determinants of continuance intention towards banks? chatbot services in vietnam: A necessity for sustainable development	23
	Trivedi, J.	Examining the Customer Experience of Using Banking Chatbots and Its Impact on Brand Love: The Moderating Role of Perceived Risk	92
Customer service	Andrade, I. M., and Tumelero, C.	Increasing customer service efficiency through artificial intelligence chatbot	1
	Fahn, V., and Riener, A.	Time to Get Conversational: Assessment of the Potential of Conversational User Interfaces for Mobile Banking	0
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	Li, C. H., Chen, K., and Chang, Y. J.	When there is no progress with a task-oriented chatbot: A conversation analysis	5
	Li, C. H., Yeh, S. F., Chang, T. J., Tsai, M. H., Chen, K., and Chang, Y. J.	A Conversation Analysis of Non-Progress and Coping Strategies with a Banking Task-Oriented Chatbot	15
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	Samuel, I., Ogunkeye, F. A., Olajube, A., and Awelewa, A.	Development of a Voice Chatbot for Payment Using Amazon Lex Service with Eyowo as the Payment Platform	4

<Appendix C> Thematic Clusters (Cont.)

Theme	Authors	Publication Title	Citations
Technology personalization	Alt, M. A., and Ibolya, V.	Identifying relevant segments of potential banking chatbot users based on technology adoption behavior	1
	Huang, S. Y. B., and Lee, C.J.	Predicting continuance intention to fintech chatbot	1
	Huang, S. Y. B., Lee, C. J., and Lee, S. C.	Toward a Unified Theory of Customer Continuance Model for Financial Technology Chatbots	2
	Kallel, A., Ben, D. M. N., Chaouali, W., and Danks, N. P.	Hey chatbot, why do you treat me like other people? The role of uniqueness neglect in human-chatbot interactions	0
	Manshad, M. S., and Brannon, D. C.	Gender-based conversational interface preferences in live chat systems for financial services	0

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