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Review

Text-Based Chatbot in Financial Sector: A Systematic Literature Review

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Abstract: Text-based chatbots are implemented in the financial sector to enhance the relationship between the customer and services provided by the sector, and also to address external challenges and customer requirements. The chatbot technology in the financial sector serves to examine customers' frequently asked questions and the representation of the process using machine learning. In light of this, this study presents a comprehensive systematic literature review of articles focused on text-based chatbots in the financial sector. It describes the understanding of chatbots in the financial sector in terms of implementation, adoption intention, attitude toward use and acceptance; it also describes how people experience chatbots, specifically in terms of perception, expectation and trust, as well as how they are engaging and emotionally motivated; management of the security and privacy vulnerabilities of the chatbots; and identifies the potential strategies that can hinder the efficient, successful evolution of chatbots in the financial sector. Finally, the main findings regarding the use of text chatbots in the financial sector are presented; additionally, the open issues in current research are highlighted and a number of research opportunities that can be pursued in the future are suggested.

Keywords: text-based chatbot; systematic literature review; financial sector; human-computer interaction

JEL Codes: G20, O30

1. Introduction

In an earlier era, people interacted with the computer by using a command line or graphical user interface. But, as technology continues to advance in line with the latest trends and requirements, this type of interaction is also modernizing, which has given rise to tremendous advances such as artificial intelligence (AI), machine learning and natural language processing. Currently, among the various types of communication, speech and text forms are the main forms of communication between people and computers, and they take place through web-based information applications that play a vital role in communication between people. Given this evolving technology, a chatbot is an advanced technology that has been designed to answer user queries (Mondal, 2018).

Chatbot applications can provide a variety of effective interpersonal interactions and the ability to learn through interactive methods and easy-to-use interfaces; they can even be used as a personal consultation tool (Muniasamy and Alasiry, 2020; Poncette et al., 2020; Yamada et al., 2015). The most significant advantage of a chatbot is that it can reach a wide audience through a messaging system and automated custom messages (Ahmad et al., 2018). In addition, as the popularity of mobile technology grows, the absence of time and place restrictions, as well as the expansion of interactive teaching methods, open up the space for the use of chatbots (Zhou et al., 2020).

In this sense, chatbots are increasingly being used in the financial sector, which generates a huge amount of data, such as customer data, financial product logs and transaction data that can be used to support decision-making, along with external data via social media data and data from websites due to the routine actions and the limited number of repetitive tasks, which can increase speed and reduce cost. Finacle Connect lists the top 10 technologies for the financial industries, including blockchain for banking, the creation of cloud-based business technologies and the use of AI (Al Nasseri et al., 2015).

Research on chatbots in the financial sector is mainly focused on the study of specific conversational and technical aspects (e.g., chatbot–user interaction and algorithms for learning and development of chatbots) (Ciechanowski et al., 2017; Go et al., 2019), security aspects related to chatbot deployment (Lai et al., 2018), customers' conversation determining factors related to deploying chatbots (e.g., acceptance, customer satisfaction, trust) (Chung et al., 2020; van den Broeck et al., 2019), customers' and company perceptions (Araujo, 2018), thoughts and experiences of managers in the field of chatbots (Jang et al., 2021), customer engagement and support (Thompson, 2018), psychological factors (e.g., affective, behavioral and cognitive user experience) (Rodríguez et al., 2019) and emotional factors (Huang et al., 2021).

As per our literature review, the research gap regarding chatbot technology appears to be more in the form of a profound understanding of the conversation determining factors and technical challenges, in addition to a detailed description of the influential factors for effective implementation. Therefore, this article is intended to systematically review literature related to chatbots in the financial sector, to categorically highlight the main determinants of conversational and technical issues that have been addressed to date, as well as contained in the indexed database, in order contribute to the existing literature and help the financial sector to obtain a profound understanding of chatbots. Moreover, in addition to providing a reliable and up-to-date overview, it is also intended to serve as a one-stop repository for financial sectors and researchers interested in using chatbots, as well as provide insight into future research directions.

The remaining sections of the paper structured as follows: Section 2 presents published articles related to the proposed work; Section 3 presents the methodology for conducting the systematic literature review; Section 4 presents the synthesis of the data obtained from the current reviewed articles; Section 5 provides a summary and discussion of the results of the current study; Section 6 presents the conclusions and suggested topics for further research.

2. Related work

This study was designed to review literature related to text-based chatbots in the broad field of the financial sector. We have focused on 1) whether and why people accept chatbot technology, 2) how trust, engagement and satisfaction may impact user experience and 3) the influence of safety and security on the development of chatbots; this was achieved by conducting a systematic literature review from a conversational and technical perspective. In this case, the literature review can help to meet the aforementioned needs by synthesizing existing knowledge discoveries and identifying key areas for further research. Further, the literature review can provide a useful summary of current knowledge in the area of research and allows us to identify potential knowledge gaps that may indicate potential research directions (Aznoli and Navimipour, 2017). Some of the recent publications related to our proposed study, with their contributions and limitations, are presented in Table 1.

Table 1. Overview of related works.

Author	Contribution	Limitation
Miklosik et al. (2021)	• Identifies the business implications of using chatbots and discussed development, both inside the firm (internal environment) and regarding various external stakeholders, such as customers. • Identifies topics and applications that require further research. • Provides a comprehensive overview of the methods used in the field of chatbot research in the business context.	• Only journal articles were included in the study, while conference proceedings were omitted.
Vlačić et al. (2021)	• Provides a comprehensive overview of over 30 years of experience in AI development and marketing without any time limit or topic. • A more objective review of the development of AI and marketing were performed.	• The various impacts of AI on marketing are not discussed.
Hentzen et al. (2021)	• Provides an intersection of AI and financial services marketing in multiple ways. • Identifies the gaps in the literature and sets a comprehensive agenda for future research.	• The review focuses on AI in customer-facing financial services.
Bavaresco et al. (2020)	• Explores the role of chatbots over the last decade in business industry domains.	• The study only included search strings containing business terms.
Milian et al. (2019)	• Describes the main resolved problems regarding chatbots in the areas of financial technology activity by mapping and categorizing selected articles related to the aforementioned topic.	• The factors affecting the chatbot are not included in the review.

Although some of these works have reviewed the chatbot implementations and determining factors in enterprise and business contexts no study has explored the literature to evaluate how the determining factors are considered for chatbots applied in financial sector domains. Therefore, this article covers identifying, describing and synthesizing topics concerning chatbots in the financial sector and provides profound information that can be used as a guideline for researchers and financial institutions.

3. Methodology

A comprehensive systematic methodological review of the literature on the topic has been carried out on the basis of a two-step approach. Each step consists of several actions. In the first step, relevant keywords, synonyms and search strings were identified to search for relevant articles on the topic; then, relevant databases of journal articles were identified. Then, we collected research articles on chatbots from the selected databases. These activities were focused on gathering information about the topic. The next step involved article screening and analysis of the retrieved articles by categorizing the articles into subcategories based on five aspects of chatbots: understanding chatbot technology in the financial sector, experience with chatbots, emotional experience and expressions, the security of chatbots and chatbot development. A detailed description of the adopted methodology is shown in Figure 1. In the following sections, the detail descriptions of some of the steps are given.

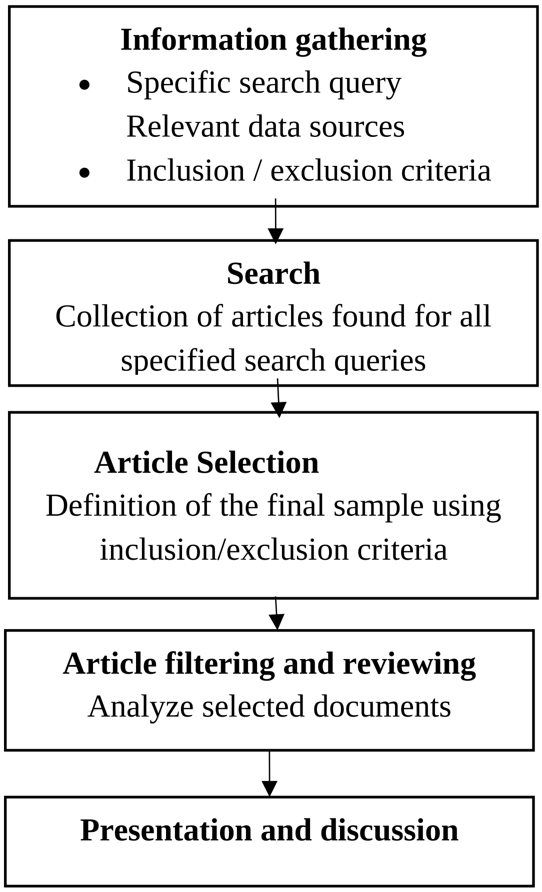

Figure 1. Schematic diagram of the steps followed during the literature review.

3.1. Step one: Information gathering

Searching strings and database identification. We used five electronic databases to identify relevant articles on text-based chatbots related to the financial sector. These were Science Direct, SpringerLink, Google Scholar, IEEEX plore and MDPI. The articles were collected from October to January of 2022 and limited to full-text, peer-reviewed journal articles and/or articles from international conference main proceedings written in English. These databases provide a good assortment of peer-reviewed articles in many fields. In addition, the methodology for collecting information is described as follows. Two keywords were obtained by decomposing the research questions to "chatbot" and "financial sector". It is important to mention that the first part of the query relates to the notion of chatbots and included synonyms that could point to text-based conversational agents. The second part refers, instead, to the aspects of the financial sector; particularly, they combine general and more specific terms that may capture a wide range of topics that may be relevant for exploring the financial sector with text-based chatbots. The list of search terms was compiled after several iterations and refinements; it is presented as follows. Synonyms were created for "chatbot" that correspond to the following terms: "chat bot", "chatterbot" and "virtual assistant". Also, the following terms were used for the keyword "financial sector": "financial services", "financial technology", "banking", "insurance" and "e-commerce". In addition, the keyword "security" was added to include the security aspects. Search strings were generated by using logical operators as follows: "OR" for synonyms and "AND" to combine keywords. Algorithm 1, which was used for article searching with search strings, is presented below. In this regard, the inclusion and exclusion criteria presented in Algorithm 1 were applied to refine the paper search.

ALGORITHM 1: SEARCH STRATEGY AND ARTICLE SELECTION FROM DIFFERENT DATABASES

```
Procedure Title (Text-Based Chatbot in Financial Sector)
Search Database ← Google Scholar, IEEE, Science Direct, SpringerLink, MDPI
Search year ←2016–2021
i ← 1
N ← 5
while i ≤ N do
    keyword ← chatbot, financial sector
    if Google scholar ε search database AND year ε search year then
        Search (allintitle: chatbot "financial sector" OR banking OR "financial technology" OR "financial
        services" OR insurance OR "e-commerce" OR "security")
    else if IEEE ε search database AND year ε search year then
        Search ((("chatbot") AND ("financial sector" OR banking OR "financial technology" OR "financial
        services" OR insurance OR "e commerce" OR "security")))

    else if Science direct ε search database AND year ε search year then
        Search (chatbot) AND ('financial sector' OR banking OR 'financial technology' OR 'financial
        services' OR insurance OR banking OR 'e commerce' OR 'security')
    else if SpringerLink or MDPI ε search database AND year ε search year then
        Search ("chatbot") financial sector OR "Banking" OR "Insurance" OR "          e commerce" OR
        "security".
    end if
end while
if Number of Paper > 0 then
    Refine paper
    Apply Inclusion Criteria ← IC1, IC2, IC3, IC4, IC5, IC6
    Apply Exclusion Criteria ← EC1, EC2, EC3, EC4
end if
```

3.2. Step two: Article selection

After the search keywords were identified, the initial search resulted in a total of 283 papers being retrieved via the aforementioned technique: 62 via Google Scholar, 64 via IEEEXplore, 24 via Science Direct, 110 via SpringerLink and 23 via MDPI. It is important to mention that we have limited the retrieved articles to a publishing time between 2016 and 2021 to keep the number of articles to a manageable number for the synthesis of data. After the first round of screening, article titles and abstracts were further checked based on the inclusion and exclusion criteria presented in Table 2. At this stage, 283 articles were included. The titles and abstracts of the 283 articles were screened against the eligibility criteria for inclusion in the review. Then, the full texts of the articles that were considered to be eligible were further evaluated to determine inclusion. At this phase, we identified 48 articles to be included in our collection; three additional papers were found by examining the reference lists of the articles included in our study. In the final step, we collected 51 articles to be included in the review. Further, the detailed article selection procedure is presented in Figure 2.

Table 2. Inclusion and exclusion criteria for paper selection.

Inclusion criteria (IC)	Exclusion criteria (EC)
IC1: The papers focus on the financial sector and are related to banking, insurance and e-commerce.	**EC1**: Papers that did focus on text-based chatbots in the financial sector.
IC2: The papers focus on chatbots that are exclusively text-based.	**EC2**: Publications not peer-reviewed or correspond to the abstract of a full book, an editorial or a letter.
IC3: The study should be published in recognized international journals or international conference proceedings with a potential research review.	**EC3**: Papers published in the additional proceedings of conferences (such as MSc and PhD papers, posters, seminar reports and late-breaking result papers).
IC4: The studies should be written in English.	**EC4**: Studies that were published earlier than 2016.
IC5: Published between 2016 and 2021.	
IC6: Journals in which the papers were published must be either Scopus or Web of Science indexed.	

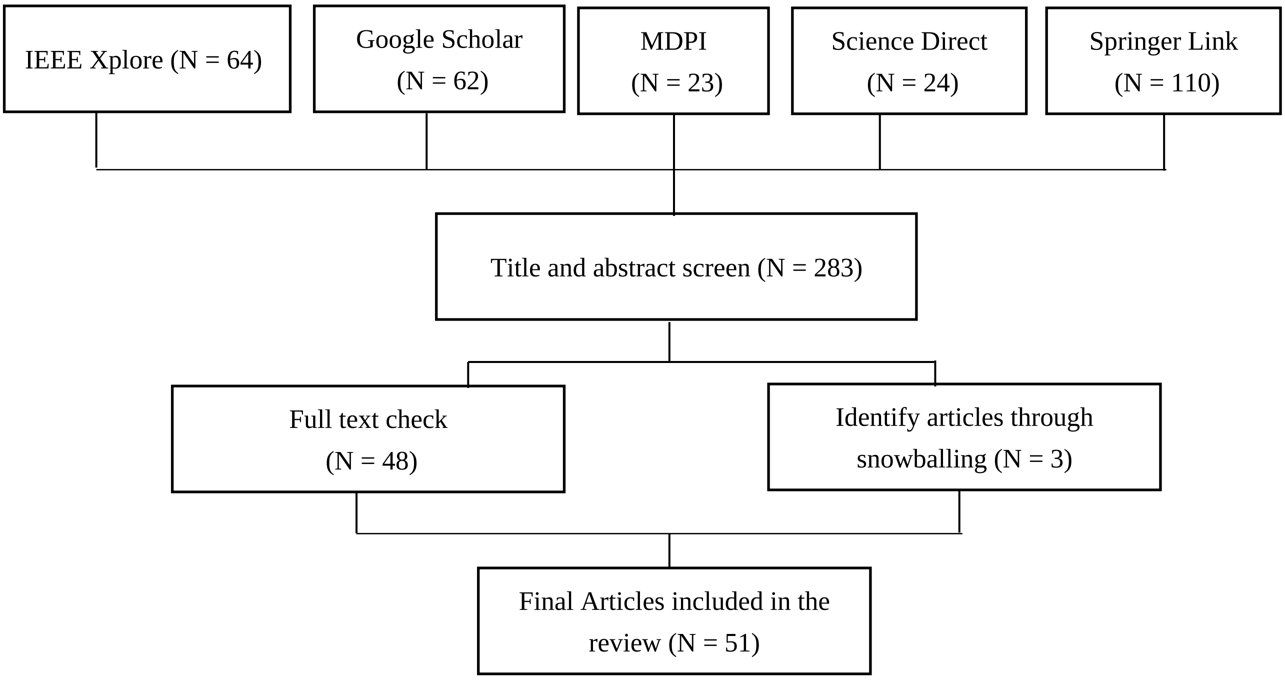

Figure 2. Block diagram of database searches and paper screening procedure method.

4. Synthesis of data

In this section, the following main categories of text-based chatbots in the financial sector are outlined to raise the discussion points based on the final dataset of 51 articles in the literature review, which are as follows: 1) understanding chatbot technology in the financial sector, 2) interaction with chatbots, 3) emotional experience and expressions, 4) security in chatbots and 5) chatbot development.

The data from our findings following the literature review have been synthesized in such a way that summaries of articles related to the topic and the sub-topics that make up the topic are presented in a table; additionally, the main findings underlying the topic are discussed.

4.1. Understanding chatbot technology in the financial sector

Of all of the 51 articles, 19 articles contributed to these themes. Also, four sub-themes were identified within the current theme and related to the notion of understanding chatbot technology, particularly in terms of implementation, adoption intention, attitude toward using chatbots and acceptance. Each of the sub-themes is described in detail in the following subsections.

4.1.1. Implementation

Text-based chatbots are used in various financial sectors, such as banking, insurance and e-commerce services, to improve the existing quality of customer service, user satisfaction, human productivity and workload, etc. In our collection, articles related to implementation are presented in Table 3. Suhel et al. (2020) revealed that implementing chatbots in banking and financial sectors can increase the quality of user service, productivity and proportion of satisfied users, as well as reduce human workload. Also, Illescas-Manzano et al. (2021) reported that implementing chatbots can help clients living in remote areas receive proper service and bring modernity, efficiency and intimacy. Gondaliya et al. (2020) studied the various factors influencing risks, including the type of service and its pricing plans, infrastructure, quality level and number of users prior to chatbot implementation. Allal-Chérif et al. (2021 pointed out that chatbots can solve complex customer problems that were previously unsolvable. Hwang and Kim (2021) reported that chatbot services for existing products have a positive impact on banks' net income. Stoeckli et al. (2020) presented a new perspective on how to balance emerging digital technologies, such as chatbots, with traditional systems, the relationship between agility and flexibility and control and stability, exploration with use and flexibility with discipline. Nayak et al. (2021) showed that health insurers are pursuing new technological opportunities to improve innovative products, backed by a strong knowledge base. Chatbots can help with process automation, decision-making, information gathering vendor integration, performance monitoring, resource management, contracting and administration. In conclusion, this study highlights the key benefits of implementing chatbots in the financial sector, such as improved decision-making, customer service, productivity, efficiency, resource management, etc. Moreover, important influential factors have been identified that can serve as a guideline for the future implementation of chatbots. Further, detailed descriptions of the articles included in the current theme are presented in Table 3.

Table 3. Articles related to chatbot implementation.

Author	Method	Approach	Result	Limitation
Suhel et al. (2020)	Case studies	• Ontology-based dialog handling in the area of banking and finance.	• Implementation of chatbots can enhance the quality of user services and reduce human workload.	• Limited number of tests considered in the study.
Illescas-Manzano et al. (2021	Survey	• Leads generated approach	• Chatbot implementation will help link brands and offer value proposition. • Chatbot implementation leads to immediate response customer query. • Lead achievement increased by 25%.	• Chatbot application deployment platform privacy restriction.
Gondaliya et al. (2020)	Privacy data protections layers checklist	• Risk evaluation framework, survey of service-level agreements (SLAs) for real chatbot providers	• Performs attacks on the third-party infrastructure, so the chatbot can be monitored by the proposed SLA.	-
Allal-Chérif et al. (2021	Qualitative survey based on multiple case studies	• Synertrade automated international purchasing system • Silex matching system • SAPAriba decision support • Jaggaer supplier relations management	• It was found that chatbot technologies can simplify buyers' needs.	• Most firms were not included in the study since most of the firms adopted AI for their purchasing because they lack relevant experience.
Hwang and Kim (2021)	Quantitative survey based on empirical analysis of personal data	• Automatic response service (ARS) analysis of covariance (ANCOVA)	• The percentage of products sold through the ARS was less than 5% of the bank's total sales. Of these, sales via the chatbot were insignificant, i.e., less than 10%; hence, it may be unreasonable to closely associate them with bank profits.	• The data were developed through trial and error at the time of initial settlement. The stability of the sample was poor.
Stoeckli et al. (2020)	Qualitative study to inductively derive rich contextual insights of affordances and constraints	• Explorative approach, using Q-methodology study	• The results revealed 14 lower-level affordances and 14 constraints of chatbots within enterprises.	• The study cannot guarantee and provide verified theory. • Small number of datasets used in the study.
Nayak et al. (2021)	Qualitative method using interviews and modified Delphi technique in sequential combination	• Inductive approach was used, where expert opinions were the basis for developing thematic patterns	• It was found that the operational costs of insurers can be optimized with better technological proficiencies and also facilitate the exploration of customer perceptions.	• The model was developed based on the market forces and industry structure only in India.

4.1.2. Adoption intention

Table 4. Articles related to chatbot adoption intention.

Authors	Method	Approach	Result	Limitation
Abdulquadri et al. (2021)	Theoretical model to investigate chatbot adoption	• Search-access-test (S-A-T) model	• The study found that most Nigerian banks adopted chatbots linked with the WhatsApp platform.	• The study was only performed for emerging markets and communities of Nigeria.
Jang et al. (2021)	Semi-structured interviews with managers.	• Core–periphery analysis of social representations.	• The technological level of chatbots was found to be insufficient for meeting customer expectations. The managers did not have specific and sufficient knowledge about chatbot services, and their organizational capability was found to be insufficient.	• The study only considers the financial sectors present in South Korea. • The study was conducted with a limited number of participants. • The study only includes the manager perspective, ignoring customer intention.
Kumar et al. (2021)	Managerial interviews, existing literature and popular press discussions	• Managers' concerns and questions about the implications of new-age technology response analysis.	• It was revealed that the adoption of new-age technologies requires intermediaries to identify ways to leverage their advantage.	• The study only focuses on a limited number of new-age technologies.
Adam et al. (2021	Randomized online experiment	• Empirical examination	• The study demonstrated that humans acknowledge conversational software agents as a source of persuasive messages.	• The study was performed in an experimental setting with a simplified version of an instant messaging application.
Quah & Chua (2019)	Quantitative and qualitative interviews and qualitative user tests	• Quantitative study and empirical analysis	• 6% of participants did not use chatbots; 40% did not have access to the technology to use the chatbot; 76% of the interviewees were not satisfied with the bank chatbot technology; 24% of the interviewees were satisfied with the bank chatbot.	• Limitation of published works regarding chatbots in the banking sector due to non-disclosure policy.
Følstad & Taylor (2021)	Collaborative research, innovative project framework development and case study	• Design science research approach	• It has been pointed out that chatbots can predict the intent reflected in user messages and respond to them for most user requests.	• The case study was performed with a small sample of customer-service chatbots within a specific time and place.
Rodríguez et al. (2019)	Qualitative and quantitative survey	• Sequential exploratory design	• Relative advantages and insurance sector infrastructure were identified as the most important ambivalent positive and negative socio-technical factors for the adoption and diffusion of chatbot technology.	• The study did not cover the deeper socio-psychological factors that influence the perception of financial, psychological and privacy risks associated with the use of chatbots.

Adoption intention refers to the adoption process of text-based chatbots in the financial sector, driven by factors such as the surrounding conditions, leading to positive outcomes. Regarding our collection, the articles related to adoption intention are shown in Table 4. Abdulquadri et al. (2021) reported that chatbots in the Nigerian banking system were branded with female gender identification and are less responsive beyond their pre-defined purposes. It was also reported that the chatbots work in the English language, and that there are no chatbots working in the local language. Jang et al. (2021) suggested the three main barriers to chatbot adoption in the Korean financial sector: organizational factors, management factors and technological factors. Kumar et al. (2021) discussed the outcome of the adoption of AI technologies such as chatbots from the manager's perspective in terms of customers, developers, firms and regulators. Adam et al. (2021 reported that, while cost and time savings opportunities have led to the widespread adoption of chatbots, they still often fall short of customer expectations, which could lead to users being less likely to fulfill requests made by the chatbot. Rodríguez et al. (2019) revealed that "relative advantage" and "Information systems infrastructure" are the most important ambivalent socio-technical factors for adoption and dissemination. Regarding chatbot technology in Germany, Følstad and Taylor (2021) discussed how chatbots can predict and respond to the intentions reflected in user messages for most user queries. Quah and Chua (2019) provided a gauge of the user adoption of chatbots and discussed whether a chatbot can provide better value-added services than bank employees in the Singapore banking sector. To summarize, the articles included in our collection emphasize that the adoption intention for a chatbot is highly dependent on language, value-added, managerial, organizational and technological factors; a summary of the literature is presented in Table 4.

4.1.3. Attitude toward using chatbots

The attitude toward using a chatbot can be seen as a user's willingness to use and interact with chatbots in the financial sector. Regarding our collection, the articles related to attitudes toward using a chatbot are depicted in Table 5. Kasilingam (2020) revealed that parameters such as perceived ease of use, perceived enjoyment, perceived usefulness, price consciousness, personal innovativeness and perceived risk significantly influences the attitude toward chatbots. Additionally, trust, attitude and personal innovativeness directly influence the intention to use. Sowa et al. (2021) reported on an increasingly positive attitude toward chatbots in intellectual work, but also significant fears associated with full automation, including among the younger and tech-savvy generation. Alt et al. (2021) reported that perceived compatibility and perceived usefulness are the determining factors for predicting customer intentions to use a banking chatbot. In summary, this study pointed out that the perceived ease of use, perceived enjoyment, perceived usefulness, price consciousness, personal innovativeness, perceived risk, trust, personal innovativeness, automation and perceived compatibility are the determining factors of the attitude toward using chatbots.

Table 5. Articles related to the attitude toward using chatbots.

Authors	Method	Approach	Result	Limitation
Kasilingam (2020)	Quantitative survey	• Response analysis using partial least squares (PLS) structural equation modeling.	• The study demonstrated that more than 72% of the variance associated with adoption; variables can differ over time as people begin to adopt and use the technology.	• Absence of empirical validation for developed markets due to cultural and economic variation.
Sowa et al. (2021)	Qualitative methods (scenario-based design combined with semi-structured interviews) and online experiment	• Study of preferences using 10-item Likert scale.	• It was demonstrated that 62% of respondents were satisfied with the performance of chatbots.	• Small number of participants were considered. • The characteristics of the participant groups were not specified.
Alt et al. (2021)	Quantitative survey	• Hypotheses testing using PLS-structural equation modeling (PLS-SEM).	• Perceived usefulness, ease of use and compatibility were found to have a significant positive effect on customer intention to use the banking chatbot.	• The study sample is not representative, which leads to non-generalizable findings. • The research was not limited to a specific banking chatbot application.

4.1.4. Acceptance

Table 6. Articles related to chatbot acceptance.

Authors	Method	Approach	Result	Limitation
Thusi and Maduku (2020)	Survey using questionnaire	• Innovative multi-perspective framework (UTAUT2).	• It was suggested that millennials will have a positive intention to adopt mobile banking apps if they believe that the technology benefits their banking activity.	• The study followed a convenience sampling technique. • The study used a single cross-sectional research design.
Brachten et al. (2021)	Online survey via the service online consumer panel (via Prolific).	• Decomposed theory of planned behavior; Smart 3.2.8 was used as PLS software with a bootstrapping technique.	• It was found that trusting relationship with the chatbot technology coincides with the simplified usage and maximal acceptance.	• The user intention of employee insights is not provided. • The results are demonstrated using a small dataset. • The study was only conducted using native English-speaking participants.

This sub-theme focuses on acceptability, which refers to the perceived judgment and attitude toward technology that will be implemented in the future (Distler et al., 2018). Basically, a study of acceptability is often related to a study of the motivation of users to use a particular technology artifact in order to accept the technology or maintain its use over time; this is because people must be motivated (Fessl et al., 2011). Thusi and Maduku (2020) reported that customer support helplines are the determinants of chatbot acceptance in mobile banking. Brachten et al. (2021) indicated that the intrinsic motivation of employees has a strong positive impact on acceptance, while extrinsic influences have less impact. In conclusion, the customer support helpline and awareness play important roles in the acceptance of chatbots in the financial sector. A summary of the literature is presented in Table 6.

4.2. Interaction with chatbots

The results for this theme reflect the research on user perceptions related to using chatbots, as well as user satisfaction, trust and the quality of the user experience. This theme has three sub-themes related to perception, expectation, satisfaction, trust and engagement.

4.2.1. Perception, expectation and satisfaction

Table 7. Articles related to chatbot perception, expectation and satisfaction.

Authors	Method	Approach	Result	Limitation
Brüggemeier & Lalone (2022)	Experimentation using custom framework running on Mechanical Turk.	• Bespoke data collection interface to generate speaking chatbots.	• It was revealed that the conversational privacy has a positive influence on user perception of privacy and security.	• The participants did not have a real stake in their interaction data. • The study only covers the English language.
Chung et al. (2020)	Survey using a questionnaire	• Hypotheses testing using structural equation modeling.	• It was showed that online service agents provide convenience and quality communication that positively affect customer perceptions of marketing efforts.	• In the study, live feed for participant interaction was not considered.
Kushwaha et al. (2020	Live-channel customer experience organization	• Diffusion of innovation theory, trust commitment theory, information systems success model.	• Suggested that customers are likely to enjoy interacting with chatbots and have a better customer experience.	• The study was conducted using only English tweets from Twitter social media data.
Eren (2021)	Survey of customer experience and data analysis	• PLS-SEM, SPSS 21 and Smart PLS programs	• Customer expectations and confirmation of customer expectations have no direct impact on customer satisfaction, but customer expectations positively affect perceived performance.	• The study conducted with a small number of participants of Turkey's entire population.

In our collection, four papers were examined with the aim of understanding and investigating user perceptions, expectations and satisfaction when interacting with a chatbot. In general, the reviewed articles attempted to identify the factors that can influence user perception and satisfaction, as well as the relationship between user expectations and resulting level of satisfaction. The articles related to the current sub-theme are shown in Table 7. Brüggemeier and Lalone (2022) reported that the privacy of conversations has a positive effect on users' perceptions of privacy and security. Chung et al. (2020) pointed out that customer satisfaction with luxury brand e-service retailers requires perceptions of having received quality communication. It was also pointed out that chatbots can improve customer satisfaction, communication between the company and customer and shopping experiences. Kushwaha et al. (2021) reported that customer satisfaction is significantly influenced by factors such as information system success (customer satisfaction and service quality), trust (transparency, privacy and trust), innovation (predictability and innovation), system characteristics (time distortion, visual appearance and engagement rate), customer design (challenge, skill and ability) and perceived risk (sensory appeal and brand credibility). Eren (2021) confirmed that customer expectations, confirmation of customer expectations, perceived trust, perceived performance and corporate reputation are determining factors for customer satisfaction. It was also found that perceptions of chatbot usage has a positive effect on customer satisfaction, and that productivity efficiency plays a crucial role in customer satisfaction. In summary, this study highlights that user expectations influence the actual perception of chatbots during interaction, which can affect overall user satisfaction. Further, user privacy, performance and trust appear to be the significant factors affecting customer satisfaction, and user expectations are focused on the shortcomings of the chatbot technology.

4.2.2. Trust

Table 8. Articles related to chatbot trust.

Authors	Method	Approach	Result	Limitation
Toader et al. (2020)	Conceptual model, research hypothesis development and experimental Study	• Social information processing theory, media equation theory, CASA paradigm and a quantitative survey using Amazon's Mechanical Turk	• The study indicated that the influence of trust should be considered when developing chatbots that can provide customers with a compelling, error-free experience.	• A limited sample of respondents was taken, resulting in non-generalized customer segments in the online environment.
Hildebrand and Bergner (2021)	Online survey via the service Prolific.	• Analysis of variance to manage dependent variable and robo-advisor condition.	• Participants in the conversational robo-advisory interface were found to be associated with significantly greater levels of effective trust as compared to the non-conversational robo-advisory interface.	• Specific pre-designed personality traits related to a brand or firm were not used.
Lee et al. (2021)	Qualitative study (interviews, focus group, observations)	• Usability testing data with descriptive statistics.	• It was demonstrated that the Brokerbot could be used as a mediator between user trust and cryptocurrency.	• Comparison of developed Brokerbot to other available bots is not presented.
Rodríguez Cardona et al. (2019)	Qualitative quantitative study, including semi-structured expert interviews and a web-based cross-sectional survey.	• PLS-SEM	• It was found that trust has a significant positive influence on the intention to use.	• The study used a small data size and was limited to inexperienced individuals to evaluate the relationship between trust and intention to use.
Nordheim et al. (2019)	Quantitative and qualitative study	• Quantitative analysis using linear regression on an IBM SPSS statistics 25 platform; a thematic analysis using the free-text data.	• It was revealed that 28.1% of the participant responses strongly suggested that the correctness and relevance of the chatbots' answers were important for trust. • Further, the factors related to trust of chatbots were explored.	• The sample only covered individuals who already felt comfortable with interacting and sharing information online.
Nguyen et al. (2021)	Quantitative survey and data analysis	• Structural equation modeling	• It revealed that system quality is the strongest predictor of trust.	• A limited number of chatbot users selected for a convenient sampling technique; results were not generalized.

Trust can be viewed as a cognitive assessment (Mayer and Davis, 1999) that depends on subjective moods and satisfaction of the psychological needs for security (Frison et al., 2019).

Regarding our collection, the articles related to trust are depicted in Table 8. Hildebrand and Bergner (2021) pointed out that increased effective trust not only influences the perception of the firm (in terms of generating goodwill or a more positive adaptation experience). Toader et al. (2020) studied the impact of social presence and chatbot errors on digital marketing trust. In addition, the perceptions of social presence and competence have been demonstrated to play a critical role in the development of strong trusting feelings. Lee et al. (2021) reported that cryptocurrency chatbots pose challenges for users and developers. Rodríguez et al. (2019) reported that trust has a significant positive impact on users' willingness to interact with a chatbot system. It was also reported that privacy concerns have a significant negative impact on the credibility of insurance chatbots. Nordheim et al. (2019) reported that perceived experience, responsiveness, user-related factors, such as inclination, and environment-related factors, such as brand perception, are important for user trust in customer-service chatbots. Nguyen et al. (2021) indicated that information quality, system quality, service quality and confirmation of expectations had significant effects on three drivers of continuance intention in different ways. From this, it can be concluded that trust is an important factor in the willingness of users to interact with a chatbot system to serve customers in the financial sector.

4.2.3. Engagement

Engagement refers to the quality of the user experience, which describes the phenomena associated with technology (Attfield et al., 2011). Moreover, engagement is seen as an affective, behavioral, and cognitive association between a computer and user (Goethe et al., 2019; Lukoff, 2018); engagement seems to indicate subjective experiences in the form of absorption, engagement and pleasure (Boyle et al., 2012; Liu et al., 2017). Engaging applications are supposed to keep users' attention over the long term by encouraging them to spend time with the applications (Debeauvais, 2016; Doherty et al., 2018). Regarding our collection, the articles related to engagement with chatbots in the financial sector are presented in Table 9. Bajdor (2021) pointed out that experience and time experience in online shopping requires both the satisfaction levels and ratings. Lo Presti et al. (2021) found that digital assistants can change the context of online shopping by increasing the perception of hedonic values. It was also found that decision-making time can be shortened by increasing the utilitarian perception of the value of utilitarian and hedonic products. Cheng and Jiang (2021 showed that chatbot marketing efforts have a significant direct impact on the quality of communication with chatbot agents and indirectly affect customer–brand relationships and customer feedback. Hsu et al. (2021) demonstrated a methodology to understand the complexity of customer feedback and provided insight into e-commerce managerial services for chatbots. Zhang and Watson (2020) identified emergent trends for each of the five macro factors in the marketing ecosystem. Li et al. (2019) developed a model that is more efficient than the existing Ubuntu Dialogue, e-commerce and Douban Conversation Corpuses. Finally, it can be concluded that analyzing customer engagement across multiple channels can help the financial sector to provide some personalized offerings.

Table 9. Articles related to engagement.

Authors	Method	Approach	Result	Limitation
Bajdor (2021)	Quantitative survey	• Data encoding using Excel spreadsheet and Statistical 13 software for statistical analysis.	• It was indicated that the perception of online shopping depends on the feedback received from the shopping experience.	• In the study, specific products concerning the experience acquired and the assessments and attitudes of e-commerce customers were not considered.
Lo Presti et al. (2021)	Online shopping laboratory experiment	• A mono-factorial experimental design using website and chatbot interaction.	• The study showed that interaction with chatbots can facilitate the purchase intention process. • It was also shown that chatbots can stimulate the buying process, irrespective of the familiarity with the brand.	• The choice of cruise sector may not be fully consistent with the target used for the study. • The study does not include participation of consumers belonging to other age groups. • The research was only conducted in a single country.
Cheng & Jiang (2021	Quantitative survey	• Data analysis using structural equation modeling on an Mplus 7.4 platform.	• Chatbot marketing efforts we found to have significant direct effects on the quality of communication with chatbot agents and indirectly affect customer–brand relationships and customer response.	• The study focused only on the USA market; this study did not compare chatbot marketing efforts between industries.
Hsu et al. (2021)	Qualitative and quantitative survey, conceptual model and hypothesis testing.	• Five-point Likert scale ANOVA test and post-hoc test.	• It has been reported that factors such as the perceived failure of the self-service technology service, the execution of co-creation activities in the process and the interdependent effect caused by a combination of factors lead to customers choosing to continue using the self-service technology.	• The paper does not discuss emerging concepts related to the proposed topic.
Zhang & Watson (2020)	Marketing strategy formulation	• Holistic and structured perspective in the view of outside-in marketing.	• Provides insight into obtaining an accurate prediction of the changing preferences of consumers and formulated appropriate strategies to engage with new technological trends.	• The sole determined success through the technological trends cannot be predicted by the proposed research.
Li et al. (2019)	Banking institution chatbot conversation analysis	• Conversation analysis based on the natural use of a task-oriented banking chatbot.	• The study identified specific factors that are more likely to cause users to stop using a chatbot, the most common of which is the chatbot's inability to understand additional words from users in messages they have previously sent.	• The analysis of the text entered did not distinguish between the text that users typed themselves and the predefined answer buttons that they could press.

4.3. Emotional experience and expressions

Here, we discuss the articles related to emotions, as shown in Table 10, which are a fundamental aspect of human-machine interaction; particularly, any interface that ignores the user's emotional state or does not display the corresponding emotions can be perceived as cold, socially incompetent, unreliable and incompetent (Brave, 2007). In our collection, three articles highlight the importance of emotion in human interaction with a chatbot. For instance, Go and Sundar (2019) presented the influence of psychological, attitudinal and behavioral outcomes associated with agents of online e-commerce online chatbots; they noted that the influence of message interactivity and agent performance would be different. Rajaobelina et al. (2021) studied the influence of customer service and support, accessibility, perceived security/privacy and design on the emotions experienced by banking customers when using chatbots. Huang et al. (2021) reported that cognitive and emotional aspects influence the growth of users' positive attitudes toward chatbots in financial technology, which, in turn, positively influences the intention to continue working overtime. In summary, it can be concluded that positive emotions that arise during a conversation with a chatbot can be an indicator of the success of interaction; negative emotions that lead to miscommunication must be eliminated.

Table 10. Articles related to emotional experience and expressions.

Authors	Method	Approach	Result	Limitation
Go & Sundar (2019)	Subjective online experiment	• Identification of cues and assessment using 7-point Likert scale.	• It was revealed that participants with high message interactivity showed greater social presence, perceived similarity, contingency and dialogue than those with low message interactivity.	• The study was conducted online, with each participant completing the study in his or her own preferred environment, thus introducing noise.
Rajaobelina et al. (2021)	Quantitative survey using a web-based panel	• Items measured using a 7-point Likert scale and theoretical framework testing using structural equation modeling.	• It was found that the negative and positive emotions experienced when using the live chat service impact positive word of mouth.	• This research examined the impact of emotions on positive word of mouth; others might wish to consider the addition of the impact on negative word of mouth.
Huang et al. (2021)	Quantitative survey	• Latent growth curve modeling for surveying Taiwanese users of financial technology chatbots.	• It was reported that cognitive and emotional factors can affect customer attitudes and the predictive power for continuance intention.	• In the study, emotion- and cognition-based factors in different regions/countries were not considered.

4.4. Security of chatbots

This theme deals with the articles presented in Table 11, which were related to security patterns, as well as those custom strategies that could potentially fix the security and privacy vulnerabilities of chatbots in the financial sector. Lai et al. (2018) analyzed e-commerce security strategies and integrated AI security principles to plan a chatbot security control procedure (CSCP); they reported that a bank chatbot with a CSCP can reduce security risk and, in particular, protect customer data security and personal privacy data. Bhuiyan et al. (2020) integrated chatbots into blockchain technology to improve the security concerns of financial chatbots. Specifically, proof-of-concept development, performance evaluation and analyses of various security and privacy issues were performed using a blockchain-enabled chatbot. Ye and Li (2020) studied the security and privacy vulnerabilities of an existing conversational system and suggested that a developer should conduct a security analysis before deploying a chatbot to avoid significant damage. Ng et al. (2021) reported that the social-emotional characteristics of chatbots in the financial sector may indicate inconsistency between privacy and trust. To summarize, it can be concluded that the appropriate precaution and analysis regarding the security and privacy vulnerabilities of a chatbot in the financial sector should be performed before deployment.

Table 11. Articles related to the security of chatbots.

Authors	Method	Approach	Result	Limitation
Lai et al. (2018)	Designing and planning of chatbot security control procedures	• E-commerce security strategies and AI security principles.	• Developed security precautions based on e-commerce security strategies and AI security principles to perform continuous monitoring activities to effectively identify security deficiencies.	• The study does not indicate whether the developed security strategies can be applied to other financial sectors such as insurance.
Bhuiyan et al. (2020)	Development of a chatbot using blockchain technology	• Formulation of a set of requirements based on rigorous threat models for financial chatbots.	• The study provided a proof-of-concept prototype and described its protocol flow to show applicability. • Performance evaluation and security and privacy issues were studied.	• A proof of concept does not facilitate the transactions between multiple banks; the study utilized a small dataset to train the chatbot with only limited query language.
Ye and Li (2020)	Survey of existing dialogue system vulnerabilities	• Communication, response generation and database module of chatbot architecture.	• Study analyzed possible security and privacy vulnerabilities in the chatbot architecture and found that the chatbot community has not yet developed comprehensive standards for securing chatbots.	• The study discovered security attacks with limited modules of the chatbot architecture.
Ng et al. (2021)	Between-subject online experiment	• Vignette-style methodology as an induction protocol.	• It was observed that social presence has a negative effect on privacy concerns.	• The study did not use real chatbot prototypes and socio-emotional cues integrated with financial solutions.

4.5. Chatbot development

Chatbot development in the financial sector refers to a set of activities devoted to the process of designing, creating and deploying chatbots that can improve efficiency and potentially solve specific problems in the sector. The articles related to chatbot development that were included in our collection are presented in Table 12. Li et al. (2021) explored efficient deep-context modeling to study the various strategies related to response selection for retrieval-based chatbots for e-commerce; they also provided an in-depth comparison. Ciechanowski et al. (2017) pointed out that honesty, transparency, predictability, benevolence and control need to be considered for chatbot development in business or commercial environments. Weerabahu et al. (2019) proposed a chatbot system for the Sri Lankan banking sector that has the ability to retrieve questions, identify meaning, display knowledge bases and answer customer queries. Nuruzzaman and Hussain (2020) proposed a dialogue-based chatbot called IntelliBot that uses several strategies to generate a response. Banu and Patil (2020) developed a fast, accurate, secure and high-performance chatbot for web applications that responds to a user request within seconds and authenticates the user. Virkar et al. (2019) introduced an approach designed to improve the efficiency of a chatbot or artificial conversational entity that can be used in various commercial and banking sectors. Khan (2020) developed an e-commerce sales chatbot that provides customer support and increases sales by offerig cheaper and more satisfying customer service. Khan & Rabbani (2020) proposed an interactive AI-based chatbot for the Islamic finance and banking sector; it allows users to communicate with a robot. Tran and Luong (2020) employed a deep neural network to study the useful features of the intent implied by user utterances, consequently extracting useful contexts. In conclusion, chatbot development has been approached from different perspectives to fill research gaps related to efficiency, customization, ease of use and customer satisfaction.

Table 12. Articles related to chatbot development.

Authors	Method	Approach	Result	Limitation
Li et al. (2021)	Deep context modeling framework for multi-turn response selection via the application of various strategies and comprehensive comparisons	• BERT as the context encoder; dataset comparison experiment using previous works.	• Proposed a multi-turn response selection system with better performance than the existing promising models.	• Topic flow modeling and an investigation of logical consistency across multi-turn conversations were not performed.
Ciechanowski et al. (2017)	Quantitative survey using questionnaires and objective-based psychophysiology measures	• Condor Tribe finder system based on a machine learning classification engine.	• It was found that most chatbot and user interactions are of the journalist personality type rather than indicative of deceitful language.	• In the study, only journalist and politician personality types were considered.
Weerabahu et al. (2019)	Question extraction, meaning identification, knowledge base mapping, answer generation, quantitative survey and model experiment	• Pre-processing techniques, bag-of-words classification module, pattern-matching template-based system and verification.	• Proposed an online assistant to clarify customer queries, focusing on question extraction and meaning identification, knowledge base mapping and answer generation to simplify traditional banking using chatbots.	• The proposed system did not give the correct answer and misinterpreted the question.
Nuruzzaman & Hussain (2020)	Deep learning techniques such as recurrent neural networks, deep neural networks and convolutional neural networks	• Seq2seq, word2vec, term frequency-inverse document frequency, end-to-end attention mechanism for model training.	• Developed IntelliBot, which can generate intelligent responses and have decent conversations with users on both general and specific insurance-related issues.	• The handling of coherent texts in generative tasks was not explored.
Banu and Patil (2020)	Chatbot architecture development and advanced language understanding intelligent service training	• Microsoft Azure bot service	• Development of a secure chatbot with an accurate and precise response to user requests within a few seconds for an enterprise application.	• The developed chatbot does not work for voice speech.
Virkar et al. (2019)	Natural language processing and natural language generation techniques	• Tokenization, parts-of-speech tagging, word reinstatement, sentence semantic similarity and sentence encoder architecture.	• The proposed model can generate a more accurate similarity score for calculating semantic similarity for a given sentence (as compared to the word embedding score).	• There is some variability in the results.

Continued on next page

Khan (2020)	Natural language understanding	• Web-based natural language training, micro service-based text classification, entities extraction and request to specific controller framework.	• The developed system can improve customer relationships, which can lead to more sales and make customer service cheaper and more satisfying.	• The study used a limited number of datasets.
Khan & Rabbani (2020)	Natural language processing technique	• IBM Watson framework	• Developed a chatbot for Islamic financial institutions that can understand complex sentence structure and respond to direct and non-ambiguous responses to the users.	• The developed bot cannot solve numerical issues related to Islamic financial institutions.
Tran & Luon g (2020)	Identification of the intent implied by Vietnamese language user utterances and parsing of the content to extract useful contexts by performing experimentation	• Convolutional neural networks and bi-Long short-term memory for detecting intent; using Keras libraries to extract context.	• When detecting intent, their system achieved the best statistical (F-measure) score of 82.32%. Further, when extracting context, the proposed method yielded promising F-measures ranging from 78% to 91% depending on the types of context.	• The study was carried out only to extract deeper semantic features.

5. Discussion

The present article highlights the characteristics of empirical studies on chatbots in the context of the financial sector. From acceptability and user interaction to engagement, satisfaction, customer service, security, customer and company perception, trust and implementation of a chatbot that, these factors allow the financial sector to transform their activity and operations. However, the financial sector faces several challenges that can obstruct the successful adoption and implementation of chatbot technologies. These range from potential employee skill, user know-how about chatbots, adaptability, privacy breach concerns, restrictive implementation costs and intention to use. Interestingly, most of the peer-reviewed articles in our collection were published quite recently, i.e., since 2016. This shows that chatbots have been supporting the financial sector for the past few years, and it signals a growing interest in this technology in academia. Regarding our collection, the reviewed articles quantified user interactions with chatbots through surveys and experimental research based on specific hypotheses. The review also reveals a lack of research focused solely on chatbot development, which can be useful for gaining in-depth information on chatbots. Further, based our findings, we hereafter emphasize an overview of research characteristics such as the publication sources, research design, study domains, publication year and paper indexing; we also summarize the context or types of chatbots used in the financial sector; finally, we recommend future research directions.

5.1. Research characteristics

5.1.1. Publication sources

In this section, we present the publication sources for selected article datasets in the current analysis. The publication sources for the reviewed papers were Google Scholar, IEEE Xplore, Science Direct, SpringerLink and MDPI. The distribution of the articles in each publication source is shown in

Table 13. According to the review, a total of 35% (N=18) of papers were published in Science Direct. It can be concluded that Science Direct is the most common source of the articles reviewed.

Table 13. Summary of selected article database sources.

Database	Search results	Duplicate articles	Relevant articles
Google scholar	62	-	6
IEEE Xplore	49	1	10
Science Direct	-	2	18
SpringerLink	-	2	11
MDPI	-	2	6
Total	-	9	51

5.1.2. Research design

This section presents the research design methodologies used by the chatbots in the financial sector. Table 14 presents a closer view of the research designs used in these financial sector chatbots. Among them, there were 23 (45%) using survey methods (qualitative and quantitative), followed by 10 (19.6%) using mixed methods, nine (17.6%) using experimental methods and nine (17.6%) performing a case study. It can be seen that most of the researchers used a survey research method to study the issues related to financial sector chatbots and answered the research questions through the collection and analysis of quantitative data. In addition, we note that, even though various chatbots have been developed, this technology is not mature and there are still gaps in the application and study of chatbots in the financial sectors.

Table 14. Research design methodologies.

Research method	Number of papers
Survey (qualitative or quantitative)	23
Experiment	9
Case study	9
Mixed	10
Total	51

5.1.3. Publication year

This section discusses the distribution of the selected articles used in the current study by year of publication, as presented in Figure 2. It can be observed in the figure that the selected articles fall within the range of 2018 to 2021 in all of the databases, indicating that financial chatbot studies are trending. It can also be seen that the majority of reviewed articles from Science Direct were published in 2021 (N=9), followed by MDPI (N=5) and SpringerLink (N=4).

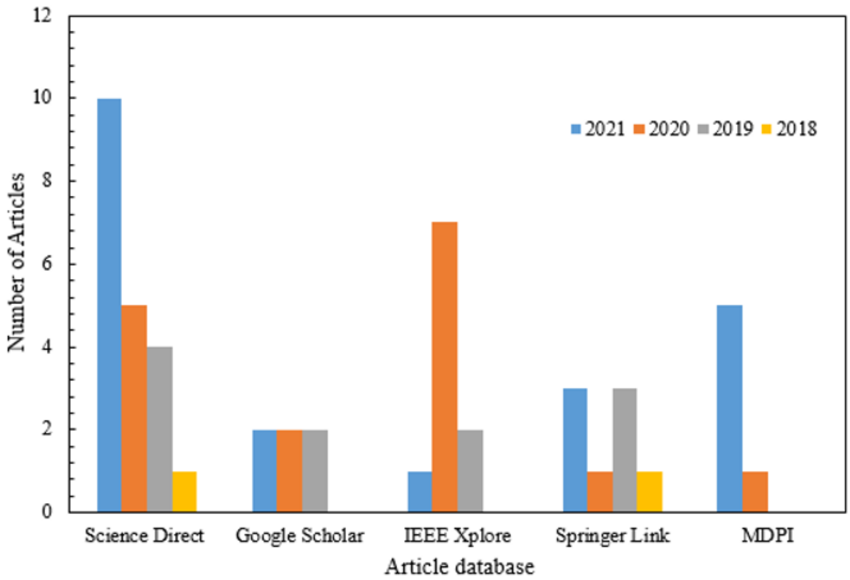

Figure 3. Distribution of selected articles by year of publication.

5.1.4. Study application domains

In this section, the most frequent application domains of chatbots in the financial sector are presented and discussed. The classification of selected articles by the application domains are presented in Figure 3. From the figure, it can be seen that 19 (37.25%) of the 51 articles were devoted to research that can be applied in the general financial sector, followed by e-commerce, banking, and insurance. The higher percentage of e-commerce applications compared to insurance and banking is due to the widespread adoption of online commerce platforms in recent years.

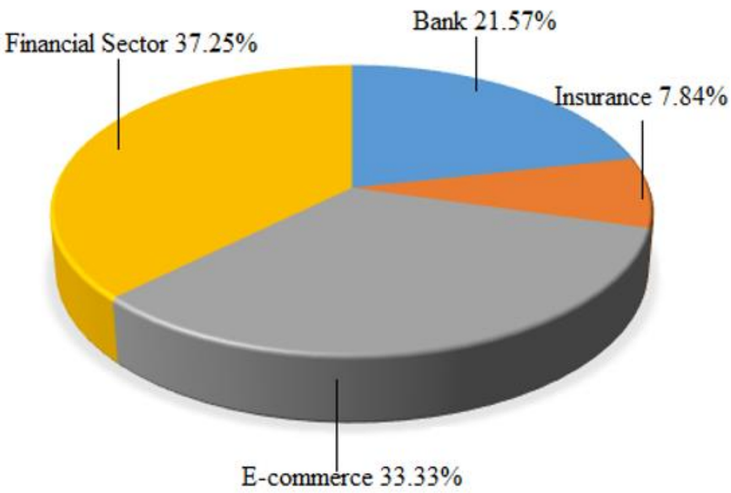

Figure 4. Classification of the selected articles by application domain of chatbots in the financial sector.

5.1.5. Paper indexing

Articles included in the current analysis were indexed in both Web of Science and Scopus, showing that our systematic literature review covers the most influential and accessible articles from the scientific community and the financial sector.

5.2. Overview of the context of the reviewed articles

This section presents and highlights the general context of the articles reviewed in our collection, considering the identified five main themes. In general, the reviewed articles in our collection highlight theoretical research questions and provide theoretical knowledge about how people interact with chatbots in the financial sector. A significant number of articles cover theoretical perspectives that have been developed as general theories for chatbot integration into financial technology. This review shows that there is significant interest in evaluating a chatbot's design in terms of its user experience. However, this also suggests that there is a limited amount of research related to the design and development of chatbots in the literature, and that there are relatively few articles that seriously address these issues. In particular, there is a lack of studies related to the speech interface domain e.g., Abdulquadri et al. (2021). The lack of development design research shows that there is still no clear understanding of what pressing design problems need to be addressed for chatbots in the financial sector. In doing so, the financial sector must find design research methods that work better with chatbots, which is a technology that relies heavily on written text and therefore requires consideration of different languages. It is not enough to discuss a chatbot in the financial sector in terms of its usefulness, effectiveness and ability to satisfy, attract and engage people. There may be times that improving the user experience might not be worthwhile, or when encouraging chatbot sympathy might be questionable. Thus, a systematic literature review provides a broader understanding of various conversational and technical aspects of chatbots in the financial sector, which suggests the usefulness and implementation of chatbots. We argue that this area offers many unexplored but fruitful areas for further research. We invite researchers to use the proposed research topics as a guide for developing and empirically testing assumptions and hypotheses, while others may wish to consider developing a theory.

5.3. Limitation

In general, the articles included in this study focused primarily on the conversational aspects of chatbot usage in the financial sector. Further research could be done to include articles on technical aspects. Moreover, only journal articles and conference proceedings were considered in the current analysis. Future reviews can be done by including research published in posters, workshops and supplementary materials. Finally, the current research only includes chatbot communication via written language. Future reviews may compare the current findings in greater depth with those of other reviews with speech interfaces.

6. Conclusions

In this study, a literature review of relevant works focused on the subject was carried out and the current state-of-the-art technology was highlighted in terms of their implementation, adoption intention, attitudes toward using chatbots, acceptance, perception, expectation, satisfaction, trust, engagement, emotional experience and expressions, security and chatbot development. Further, the study indicates the limitations, current challenges and several lines of future research that could be interesting to explore for the financial sector. Finally, some important findings from the literature review are presented below:

- The current study highlights the key benefits of implementing chatbots in the financial sector, such as improved decision-making, customer service, productivity, efficiency, resource management and more. Significant influential factors have also been identified when implementing a chatbot.
- The study also highlights that user expectation influences the actual perception of chatbots during interaction, which can affect overall user satisfaction. The users privacy, performance and trust appear to be the significant factors affecting customer satisfaction; additionally, user expectations are focused on the shortcomings of the chatbot technology.
- It was shown that chatbot adoption intention is highly dependent on language, value-added, managerial, organizational and technological factors.
- It was pointed out that the perceived ease of use, perceived enjoyment, perceived usefulness, price consciousness, personal innovativeness, perceived risk, trust, personal innovativeness, automation and perceived compatibility are the determining factors for attitude toward using chatbot.
- It was revealed that analyzing customer engagement across multiple channels can help the financial sector to provide some personalized offerings.
- It was also noted that the security and privacy vulnerabilities of chatbots in the financial sector should be considered and analyzed before deployment.

7. Future works

The current work briefly discussed topics related to text-based chatbots in the financial sector, such as the understanding of chatbots, their implementation, their adoption intention, attitude toward use, acceptance, trust, engagement and security and privacy vulnerabilities, based on existing literature. In the future, the described topics related to text-based chatbots can be studied empirically in detail to determine the extent to which they influence the implementation and development of chatbots in the financial sector.

Conflict of interest

All authors declare no conflicts of interest regarding this study.

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