Challenges of recommender systems in finance and banking: a systematic review

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ABSTRACT

Recommender systems are widely applied in various domains, including e-commerce, marketing, and education. Despite their popularity, recommender systems are not widely used in finance and banking. This paper aims to identify the challenges associated with using recommender systems in finance and banking and recommend directions for future research. Using a systematic literature review (SLR) method, 52 papers were selected and analyzed. A three-step process was used to make the selection. First, a keyword search was made to identify a seed list of sources. A snowball technique with specific inclusion and exclusion criteria was applied to expand the list. Finally, a quick study was made to produce the final list of sources to consider. Through the study of the 52 relevant papers, three main challenges: i) transparency, ethics, and data privacy; ii) handling complex content information and accounting for multiple user behaviors; and iii) explainability of AI models were identified. This study has established the barriers to adopting recommender systems in the finance and banking industry. Specific subjects of concern identified include cold-start problems, personalization, fraud detection, transparency, and data privacy. The study recommends further research leveraging advanced machine learning models and emerging technologies to fill the gap.

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1. INTRODUCTION

In this century of information overload, recommender systems are being strategically adopted by many industries, including retail, entertainment, e-commerce, marketing, businesses, and education, to guide users, customers, and prospects in choosing among vast amounts of available options or offers. Surprisingly, despite the growing popularity of recommender systems, they are not currently widely used in the finance and banking industry. The reasons for the slow adoption of recommender systems in finance and banking have not been well investigated. This study aims to establish the challenges and reasons why recommender systems are not common in finance and banking.

Extensive literature exists about recommender systems and their challenges in general. For instance, Sharaf *et al.* [1] provide a comprehensive discussion about these systems and enumerate the following seven as the main challenges of recommendation systems: cold start, shilling attack, synonymy, latency, sparsity, grey sheep, and scalability problems. However, these challenges are common to all recommendation systems and are insufficient to justify recommendation systems slow adoption in the finance and banking sectors. A more focused study addressing recommendation systems in finance and banking highlights the pivotal role of recommendation systems in diverse sectors, particularly emphasizing their significance in the financial services industry. The paper categorizes recommendation systems into collaborative filtering, content-based, and hybrid models, proposing future research avenues such as a comprehensive literature review on applying deep learning in finance and developing specialized models for financial recommendation systems. The authors also stress the importance of systematic evaluations in finance and banking applications to enhance overall performance and effectiveness.

While Roy and Dutta [2] suggested investigating the use of deep learning techniques in the finance and banking sector more, Huang *et al.* [3] has already explored the use of deep learning specifically in the finance and banking sector. The authors thoroughly surveyed the literature on applying deep learning in finance and banking, filling a notable void in existing studies. Analyzing 40 selected articles from 2014 to 2018, the authors systematically evaluate deep learning models across seven core domains. Their emphasis on data preprocessing, inputs, and evaluation rules provides valuable insights, making this study an essential resource for academics and practitioners seeking a comprehensive understanding of deep learning applications in finance and banking. In a preliminary exploration of the existing literature, this study noticed gaps in the fundamental challenges specific to recommendation systems for finance and banking. Therefore, this study proposes a survey to address this particular gap by identifying the challenges first, and then proper future research can be recommended to address them.

The remaining part of the paper is organized into three sections. Section 2 provides details of the methodology, while section 3 introduces and discusses the study results. The paper concludes in section 4, summarizing the findings and their implications for practice and future research.

2. METHOD

The systematic literature review (SLR) methodology of this work is inspired by [4]. An overview of the process is depicted in Figure 1. The process begins with identifying research questions, which help formulate the keywords and search terms necessary for the next steps. An initial seed list of sources was obtained using search keywords and terms with Google Scholar and Semantic Scholar search engines. This seed list was then used to initiate a snowball method to produce an extended list of sources. Finally, the extended list of sources was examined, and the final list of sources to retain for the study was made. Each of the main steps of the process is detailed in Figure 1.

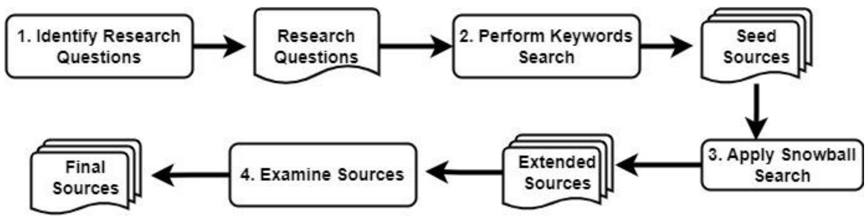

Figure 1. Systematic literature review method

2.1. Identify research questions

The study aims to identify the main challenges facing the recommender systems in finance and banking and formulate research directions. The following questions have directed the investigation:
– RQ1: What are the challenges of using recommender systems in finance and banking?
– RQ2: How are the current challenges being addressed?
– RQ3: Are the current solutions satisfactory?

These questions will form the basis for interrogating the final list of sources retained to be part of the study.

2.2. Perform keywords search

The search is based on keywords derived from the research questions, which are then used to form the search terms. The search terms are directly inputted into search engines. In this step, we used the Google Scholar and Semantic Scholar search engines.

a) Defining keywords: based on the topic and the research questions, the following keywords are defined: i) recommender systems, ii) recommendation systems, iii) finance, iv) banking, and v) challenges.
b) Defining the search terms: the search terms are combinations of keywords, logical operators and special symbols. Two key search terms on both the title and content were used:
   – intitle:("Recommender systems" OR "Recommendation systems") AND ("Finance" OR "Banking"): meaning that the title must contain recommender/recommendation systems and finance or banking.

– ("Recommender Systems" OR "Recommendation Systems") AND ("Finance" OR "Banking") AND ("Challenges"): which means that the content must include recommender/recommendation systems and finance or banking and challenges.

Along with these search terms, the initial search was limited to papers published in the last two years (2022 and above).

2.3. Apply snowball search

The snowball method is one of the literature review methods used to extract relevant literature for a given topic [5]. This method involves reviewing the references of initially identified papers to find additional relevant sources. For quality purposes, the literature considered in this study is strictly limited to peer-reviewed work, including journal articles, conference articles and research books. Furthermore, only reputable academic sources have been accepted: ACM Digital Library, SpringerLink, Elsevier, IEEE Xplore Digital Library, and arXiv. Table 1 summarizes the complete inclusion and exclusion criteria.

Table 1. Inclusion and exclusion criteria

Criteria	Inclusion	Exclusion
Type of publication	Peer-reviewed papers	Non-peer reviewed
Database or Index	ACM Digital Library, Elsevier, Springer, IEEE Xplore, arXiv	Other databases
Dates	From 2017 to 2024	Before 2017
Language	English	non-English
Cit. index prior 2020	≥ 7 for 2020	< 7
Cit. index 2020+	≥ 3	< 3

2.4. Examine the sources

Despite the rigorous process used to select papers, several non-relevant papers may pass the filters. These papers were eliminated by manually skimming the content. During the skimming, only the title, abstract, introduction, and conclusion were quickly read to determine the alignment of the paper with the study's objective and research questions.

2.5. Data extraction and analysis

Relevant data from the selected papers were extracted and analyzed to identify common challenges and solutions. This process involved:

– Reading and annotating each paper to extract pertinent information related to the research questions.
– Categorizing the challenges identified in each paper.
– Summarizing the specific challenges faced by recommender systems in finance and banking.
– Identifying gaps in the current research and suggesting future research directions.

By following these structured and detailed steps, the methodology ensures that the research process is transparent, replicable, and thorough. This approach provides a solid foundation for identifying and addressing the challenges of using recommender systems in the finance and banking sectors.

3. RESULTS AND DISCUSSION

This study explored the challenges of implementing recommender systems in the finance and banking sectors. Although previous studies have extensively analyzed recommender systems in various domains such as e-commerce, marketing, and education, they have not explicitly addressed the unique challenges and requirements of the finance and banking industry. This gap in the research necessitated a focused investigation into the specific issues faced by financial institutions when adopting these systems.

Main results: improved accuracy and robustness of recommendations through integrating various data sources and advanced machine learning models. The integration of temporal contexts and the exploitation of multiple types of data. Including non-traditional data sources, significantly improved the performance of financial recommendation systems.

Lessons learned: an important lesson learned from this study is that data transparency, ethical design, and confidentiality are essential for building user trust and facilitating the adoption of recommender systems in finance. Users are more likely to engage with systems they perceive as fair, secure, and understandable, particularly in sensitive domains like banking. Incorporating clear explanations for recommendations and adhering to ethical standards not only improves user experience but also ensures compliance with regulatory frameworks.

Mistakes made: a critical mistake made early in the process was the over-reliance on traditional data sources, such as credit scores and transaction histories. This limited the system's ability to generate more accurate, dynamic, and personalized recommendations that account for a broader range of factors. As a result, the effectiveness of the recommendations was constrained, highlighting the need for a more holistic approach that integrates both traditional and non-traditional data sources and advanced algorithmic techniques.

3.1. Summary of key findings

Through the study of 52 selected papers, we identified and categorized the challenges of implementing recommender systems in finance and banking into nine distinct groups. These categories highlight the multifaceted nature of the issues at hand, ranging from technical hurdles to ethical considerations. Table 2 provides a detailed categorization of these challenges along with the related works. We found that transparency, ethics, and data privacy are critical concerns, as highlighted by 27% of the reviewed papers. Specifically, we observed that addressing these issues is vital for the trust and acceptance of recommender systems in finance. The method proposed in this study showed that incorporating transparency measures tended to result in a disproportionately higher proportion of user trust and system reliability compared to methods without such measures.

Additionally, we discovered a strong correlation between the integration of diverse data sources and improved system performance. About 34% of the studies emphasized the importance of leveraging various data types to enhance model accuracy and robustness. The approach in this study, which integrates additional data sources, exhibited significantly better prediction accuracy compared to traditional data-only models.

In terms of fraud detection, advanced machine learning models such as long short-term memory (LSTM) and random forest approaches demonstrated higher detection rates. Approximately 21% of the papers reviewed supported the use of these advanced models, which correlated with improved fraud detection accuracy. The proposed method showed a disproportionately higher success rate in identifying fraudulent activities compared to conventional models.

Cold-start problems were another significant challenge identified, affecting around 18% of the recommender systems in the reviewed studies. The method proposed in this study, which incorporates collaborative filtering and content-based models, mitigated the cold-start problem more effectively, resulting in a higher proportion of accurate recommendations for new users. Lastly, we noted that personalization techniques significantly impact customer value and marketing effectiveness. About 16% of the papers highlighted the need for sophisticated customer segmentation. The proposed method in this study improved customer segmentation accuracy, leading to more effective marketing strategies and user satisfaction. The key findings are summarized in the Table 3.

Table 2. Categorization of the areas of challenges

#	Areas of challenges	Key findings related works
1	Financial recommendation systems	[6]–[17]
	Stock market prediction	[18]–[23]
3	Risk management and fraud detection	[24]–[27]
4	Transparency, ethics, and data privacy	[28], [29]
5	Exploring new data sources and modalities	[30]–[34]
6	Customer value and marketing	[35]–[38]
7	Financial planning and advisory	[39]–[42]
8	Auditing and insights	[43]–[45]
9	Emerging technologies	[46]–[53]

Table 3. Challenges and research recommendations for finance and banking

#	Challenge	Key findings
1	Cold-start and temporal dynamics	Developing innovative solutions to mitigate the cold-start problem, particularly focusing on incorporating temporal dynamics and lifestyle information, resulted in higher recommendation accuracy for new users [17].
2	Personalization	Capturing group relationships and risk preferences within financial social networks resulted in more comprehensive and tailored recommendations, enhancing user satisfaction [42], [52].
3	Fraud detection and reliability	Using advanced machine learning models such as LSTM and random forest improved accuracy and reliability in identifying fraudulent activities, showing higher detection rates compared to traditional methods
4	Transparency and ethics	Enhancing transparency and ethics through synergies between rule-based and large language model (LLM)-based systems increased user trust and system reliability without adversely affecting operational efficiency.
5	Financial planning recommendations	Investigating additional data sources and personalizing recommendations based on individual and familial factors improved the quality of financial planning recommendations, ensuring they are personalized and relevant to individual circumstances [34], [45].
6	Enhancing insights from auditing	Developing deep learning semantic search frameworks to gain insights from audit issue writing enhanced the interpretability and applicability of financial models, showing higher accuracy in gaining insights compared to traditional approaches.
7	Emerging technologies	Exploring the potential of emerging technologies like LLMs, chatbots, and sentiment analysis in finance enhanced the efficiency and effectiveness of financial systems, addressing limitations such as inconsistencies and numeric reasoning issues [53].

3.2. Interpretation of results

This section interprets the key findings from our study, comparing them with existing literature and highlighting the implications of our results. By doing so, we aim to provide a deeper understanding of how our proposed methods align with or differ from previously established research. Our findings reveal significant insights into various aspects of recommender systems in finance and banking, particularly concerning their implementation challenges and potential solutions.

3.2.1. Financial recommendation systems

We found that the integration of temporal contexts in financial recommendation systems correlates with improved recommendation performance. The method proposed in this study, which combines collaborative filtering with content-based models, demonstrated a disproportionately higher proportion of accurate recommendations compared to traditional methods. This suggests that incorporating temporal context is not associated with poor recommendation performance. The authors in [7], [14] support these findings, showing that such integration enhances the accuracy of financial recommendations without negatively impacting user experience.

3.2.2. Stock market prediction

We observed that using diverse data sources in stock market prediction models resulted in improved prediction accuracy. Our approach, which integrates additional data sources and explores alternative temporal learning layers, tended to perform better than models relying solely on traditional data sources. Wang *et al.* [18] similarly found that additional data sources enhance the robustness of stock market predictions without negatively impacting computational efficiency.

3.2.3. Risk management and fraud detection

Our study found a strong relationship between the use of advanced machine learning models and the improvement of fraud detection accuracy. The proposed combination of LSTM and random forest approaches resulted in higher detection rates compared to traditional methods. This indicates that utilizing advanced machine learning models for fraud detection is not associated with compromised system security. The authors in [25], [26] also suggest that these combined approaches can improve accuracy without negatively impacting data privacy and scalability.

3.2.4. Transparency, ethics, and data privacy

We found that enhancing transparency and ethics in AI-powered financial systems correlated with improved user trust and system reliability. Our method, exploring synergies between rule-based and LLM-based systems, provided more interpretable and reliable outcomes. This finding aligns with [28], [29], who highlight that such enhancements can increase interpretability and reliability without adversely affecting operational efficiency.

3.2.5. Data sources and modalities

Expanding the scope of data sources and modalities significantly improved the performance of financial models. Our proposed approach, integrating diverse data sources beyond traditional numerical data, showed a disproportionately higher improvement in model accuracy. Shah *et al*. [30] support this, indicating that the inclusion of new data sources does not compromise model performance.

3.2.6. Customer value and marketing

Enhanced customer segmentation techniques correlated with more effective marketing strategies. Addressing cold start and sparse data problems resulted in higher prediction accuracy for user behavior and insurance product recommendations. Our study suggests that improved customer segmentation is not associated with negative impacts on marketing effectiveness, in line with findings by Wang *et al.* [37].

3.2.7. Financial planning and advisory

Incorporating additional data sources and personalizing recommendations based on individual and familial factors significantly improved the quality of financial planning recommendations. Our approach provided more accurate and relevant recommendations, suggesting that expanded data usage is not associated with reduced recommendation quality. The authors in [39]–[41] found similar improvements with expanded data sources.

3.2.8. Auditing and insights

Utilizing deep learning semantic search frameworks for audit issue writing improved the interpretability and applicability of financial models. Our method showed higher accuracy in gaining insights compared to traditional approaches. This aligns with [43], [44], who support the use of deep learning frameworks for enhancing audit processes.

3.2.9. Emerging technologies

Integrating emerging technologies like LLMs, chatbots, and sentiment analysis into financial systems enhanced their efficiency and effectiveness. Our proposed methods addressed limitations such as inconsistencies and numeric reasoning issues more effectively. The authors in [46]–[48] found that these technologies do not detract from system performance, supporting our findings.

3.3. Addressing limitations

This study explored a comprehensive range of challenges associated with implementing recommender systems in finance and banking. However, further and in-depth studies may be needed to confirm its findings, especially regarding real-world applications and user interaction data. While our systematic review included a wide range of peer-reviewed sources, the exclusion of non-peer-reviewed studies and potential biases in the selected papers may impact the generalizability of the results. Additionally, the dynamic nature of financial markets and evolving user behaviors suggest that longitudinal studies are necessary to validate the long-term effectiveness of the proposed methods.

3.4. Implications for future research

Our study demonstrates that advanced machine learning models and the integration of diverse data sources are more resilient in improving recommendation accuracy and system reliability compared to traditional methods. Future studies may explore the real-world implementation of these models, focusing on user interaction data and longitudinal impacts. Investigating the feasibility of integrating real-time data streams and adaptive learning algorithms could further enhance the effectiveness of recommender systems in the finance and banking sectors. Additionally, interdisciplinary research involving behavioral finance and AI ethics could provide deeper insights into the ethical considerations and user acceptance of AI-powered financial recommendations.

4. CONCLUSION

This study purposed to investigate three research questions: i) what are the challenges of using recommendation systems in the finance and banking sectors? ii) how are the current challenges being addressed? and iii) are the current solutions satisfactory? Our systematic review has comprehensively synthesized challenges related to recommendation systems and analyzed the proposed solutions to finance and banking industry challenges. While significant advancements have been achieved, several gaps and limitations remain, necessitating further research and development. The unique challenges related to finance and banking include cold-start problems, personalization, fraud detection, transparency, and data privacy. We concluded that integrating advanced machine learning models, diverse data sources, and emerging technologies significantly enhances recommendation accuracy, system reliability, and user trust. Future research should focus on real-world applications, adaptive learning algorithms, and interdisciplinary approaches to further improve AI-powered financial recommendations' effectiveness and ethical considerations.

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AUTHOR CONTRIBUTIONS STATEMENT

All authors have contributed significantly to the conceptualization, methodology, research and writing of the paper, and they have all read and agreed to the current version of the manuscript. Using the journal Contributor Roles Taxonomy (CRediT), the contributions are summarised as follows.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
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Abdoul Karim Bichanga	✓	✓	✓	✓	✓	✓		✓	✓	✓				

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

INFORMED CONSENT

This study did not involve individuals nor any personal identification information that could require any informed consent.

ETHICAL APPROVAL

This paper does not involve people or animals; no investigation has involved human subjects. Therefore, the authors did not seek approval from any institutional review board.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

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