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Research Trends of Recommendation Systems in Digital Libraries: Bibliometric Analysis and Literature Review

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Abstract

Objective: This study maps trends, approaches, challenges, and future research directions in digital library recommendation systems. **Theoretical framework:** The study focuses on recommendation systems in digital libraries, exploring *Collaborative Filtering* (CF), *Content-Based Filtering* (CBF), and hybrid approaches. It emphasizes algorithm optimization to address data sparsity and cold-start issues, and the integration of deep learning for improved accuracy and personalization. **Literature review:** The literature review tracks the evolution of recommendation systems from CF and CBF to hybrid and deep learning models, focusing on accuracy and cold-start issues. It highlights the growing use of advanced models and the challenges of algorithm optimization and data scarcity. **Methods:** A *Systematic Literature Review* (SLR) was conducted following the PRISMA framework. Literature was searched on Scopus using keywords related to recommendation systems. Data was analyzed using RStudio with Bibliometrix and VOSviewer for keyword network visualization. **Results:** This study shows a significant trend in the development of digital library recommendation systems, with publications increasing rapidly since 2014 and peaking in 2024. *Collaborative Filtering (CF)* remains the dominant approach, but hybrid approaches and deep learning techniques are increasingly being applied to improve accuracy and relevance. The main challenges faced include algorithm optimization, data scarcity, and cold starts, as well as the use of hybrid and deep learning techniques that require more resources. Further research is needed to develop more efficient and personalized algorithms in the digital library recommendation system. **Implications:** The research offers insights to improve recommendation system efficiency and relevance in digital libraries, addressing key algorithmic challenges. **Novelty:** This research provides a deeper understanding of recommendation system applications in digital libraries, identifying challenges, future directions, and solutions that combine various algorithms to enhance user experience.

Keywords: recommendation system, digital library, content-based filtering, hybrid filtering, collaborative filtering.

INTRODUCTION

Library services offer significant changes, directly proportional to the development of the digital world. Libraries in this era can create a new ecosystem in presenting literature collections. The services provided are not only in print, but are more modern by presenting a digital platform that provides a large collection of literature. Libraries are not only a passive repository of literature collections, but are able to transform into an active, interactive platform by offering a wider range of services from a variety of resources. The large amount of information accumulated from various sources can then cause classic problems, such as creating confusion in the search and collection of relevant information according to needs.

In the era of the development of artificial intelligence, which is in this period, the recommendation system is present as an offer of solutions to the problems mentioned above. This recommendation system has been very commonly applied to similar problems in various fields. There are many types of recommendation systems offered. The recommendation system is currently developed based on user preferences, so the benefit is that it can help in making better decisions without wasting a lot of time and energy [1].

The recommendation system has undergone further exploration to find which approach has proven to be able to provide the most accurate, efficient, and satisfying results for users. A number of studies have developed and offered new approaches, such as the application of *Collaborative Filtering* (CF) and *Content-Based Filtering* (CBF) hybrid approaches. This approach was developed to complement the shortcomings of each method, such as the problem of cold start in CF and the problem of CBF's limitations in managing diverse information. The development of a recommendation system with this approach has been proven to increase accuracy and personalized recommendation results [2].

Other research offers a hybrid approach of CF and CBF with Semantic Relationships to find out the relationships of each content as a knowledge-based book recommendation. The offer of this approach is based on the problem of several recommendation systems that sometimes provide unfair recommendations due to biased data, and the absence of a clear relationship between content and users. Another study designed a hybrid approach of CF, CBF, and Rule Association Rule (ARM) based on the ECLAT algorithm. CF is used to provide recommendations based on interactions with other users, CBF assigns similarity values to the content of books, while ARM is used to see hidden patterns in each book from the user's interaction history by extracting "if-then" relationships in each book. The result is a better recommendation than just using CF and CBF alone [3].

The topic of this recommendation system has attracted great interest. Many studies then focus on the development and optimization of recommendation systems using several approaches that have been proposed according to the case studies. Although research on this topic is growing rapidly, the publication of this research is still widely carried out by many researchers from various fields. Therefore, a systematic discussion is needed to map the development of the recommendation system in this digital library case study, to identify research trends, approaches applied, and challenges that exist in the development of this recommendation system.

This research aims to provide a clearer picture of the technological development of book recommendation systems in the context of digital libraries. Specifically, this study will answer three questions, namely: RQ1 What have been the trends in publication and distribution of research regarding the recommendation system in digital libraries over the past decade? RQ2 What type of recommendation system is most widely applied in the context of digital libraries? RQ3 What are some of the challenges identified in the literature, and what is the direction of future research in this area?

This research has important significance to provide a deeper insight into the trends and direction of the development of the recommendation system in the context of digital libraries. By mapping the various approaches that have been implemented, as well as the existing challenges, this research is expected to contribute to the development of a recommendation system that is more accurate, efficient, and relevant to user needs. In addition, the results of this research can also be the basis for further research in optimizing digital library services in the future.

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LITERATURE REVIEW

Digital Library Recommendation Systems

Digital libraries have evolved into active, interactive platforms that offer users a vast array of resources. To manage these extensive collections and assist users in finding relevant content, recommendation systems play a crucial role. These systems help alleviate information overload by enhancing the discovery process, suggesting personalized content based on user preferences. The development of recommendation systems has seen a range of approaches, from traditional keyword-based methods to more sophisticated algorithms that integrate machine learning and hybrid models.

Challenges of Traditional Systems

Traditional recommendation systems, such as those using *Collaborative Filtering* (CF) and *Content-Based Filtering* (CBF), often face significant limitations, including:

1. Low Personalization and Scalability: Traditional systems struggle to deliver personalized experiences on a large scale, primarily because they average user preferences and cannot efficiently handle dynamic or ambiguous user queries. Yang noted that traditional systems achieve only 45-55% accuracy due to their inability to personalize recommendations in real-time.
2. Data Sparsity and Cold Start: Collaborative Filtering, while popular, suffers from the "cold-start" problem, where new users or items without interaction history result in poor-quality recommendations. This issue is exacerbated in digital libraries with limited user-item interaction data.
3. Static Models: Traditional methods treat user preferences as static, failing to account for the dynamic nature of user interests over time.

Modern Hybrid Approaches

To address these limitations, researchers have increasingly turned to hybrid models that combine traditional techniques with more advanced methods:

1. Integration of Fuzzy Logic and Deep Learning: The Fuzzy Deep Learning-Based Intelligent Library Resource Recommendation Framework integrates fuzzy logic to handle uncertain user inputs and deep learning for analyzing user interaction data. This approach demonstrated a 14.6% improvement in recommendation accuracy over traditional methods.
2. *Channel Attention Neural Collaborative Filtering* (CA-NCF): Wang et al introduced the CA-NCF model, which incorporates attention mechanisms into collaborative filtering. This hybrid approach, which combines neural collaborative filtering, convolutional attention networks, and generalized matrix decomposition, achieved a recommendation accuracy of 92.08%, with a recall rate of 89.88%.
3. Disentangling Preferences via Borrowing Duration (DPBD): This framework models user preferences over time by analyzing the duration of library resource borrowings. By using a dual-path neural architecture, it captures item-level and feature-level transitions, resulting in significant performance improvements on university library datasets.
4. User-Centered Hybrid Systems: Modern systems go beyond explicit user ratings by incorporating implicit signals, such as bookmarks and reservations, to gather user preferences. When data is scarce, content-based filtering techniques are used to prioritize recommendations based on user-stated preferences.

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User Behavior Analysis

Recent studies highlight the importance of user behavior signals in enhancing recommendation accuracy:

1. Implicit Signals: User actions such as borrowing duration and interactions with items provide valuable insights into their preferences. Liao et al found that longer borrowing periods (≥14 days) increased the likelihood of sustained interest in the subject, with subject continuity reaching 70%.
2. Action-Based Signals: Adding bookmarks or making reservations can contribute to a points-based system, creating richer user profiles that, in turn, enhance the recommendation process.

Addressing Data Scarcity and Cold Start

The cold-start problem and data scarcity remain significant challenges in recommendation system development. Several strategies have been proposed to tackle these issues:

1. Matrix Factorization and Deep Learning: Techniques such as *Matrix Factorization* and *Deep Pairwise Hashing* are used to mitigate data scarcity. These methods rely on deep learning to map user-item interactions into binary vectors, improving recommendation accuracy even in data-scarce environments.
2. Cross-Domain Knowledge: Models like COAST and Graph Distillation leverage cross-domain knowledge to address the cold-start problem by utilizing information from other domains to align user interests.

Table 1. Summary of Literature on Digital Library Recommendation Systems

Author(s)	Year	Approach/Model	Key Findings	Challenges Addressed
Yang [4]	2025	Fuzzy Deep Learning Framework (FDLILRRF)	14.6% improvement in recommendation accuracy over traditional methods	Low personalization, unclear user queries
Wang et al. [5]	2024	Channel Attention Neural Collaborative Filtering (CA-NCF)	Accuracy of 92.08%, recall of 89.88%, integrates an attention mechanism for better efficiency	Data scarcity, low accuracy
Liao et al. [6]	2025	Disentangling Preferences via Borrowing Duration (DPBD)	Improved recommendation accuracy by modeling temporal patterns in user behavior	Data scarcity, static modeling
Troussas et al. [7]	2023	User-Centric Hybrid Systems	Enhanced CF with implicit user actions, better recommendations with limited data	Cold start, data scarcity

METHODOLOGY

This study uses the *Systematic Literature Review* (SLR) approach, which refers to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guide to obtain a comprehensive overview of the development, methods, and direction of research related to the recommendation system in digital libraries [8]. This approach was chosen because it provides a structured and transparent review of the literature, as well as allows for the identification of trends, methodologies, and gaps in research. The research process is carried out systematically, starting with the identification of relevant literature, selection

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based on the criteria that have been set, and continued with thematic and bibliometric analysis to ensure results that can be scientifically accounted for [9]. The following diagram illustrates the flow of the literature selection process used in this study:

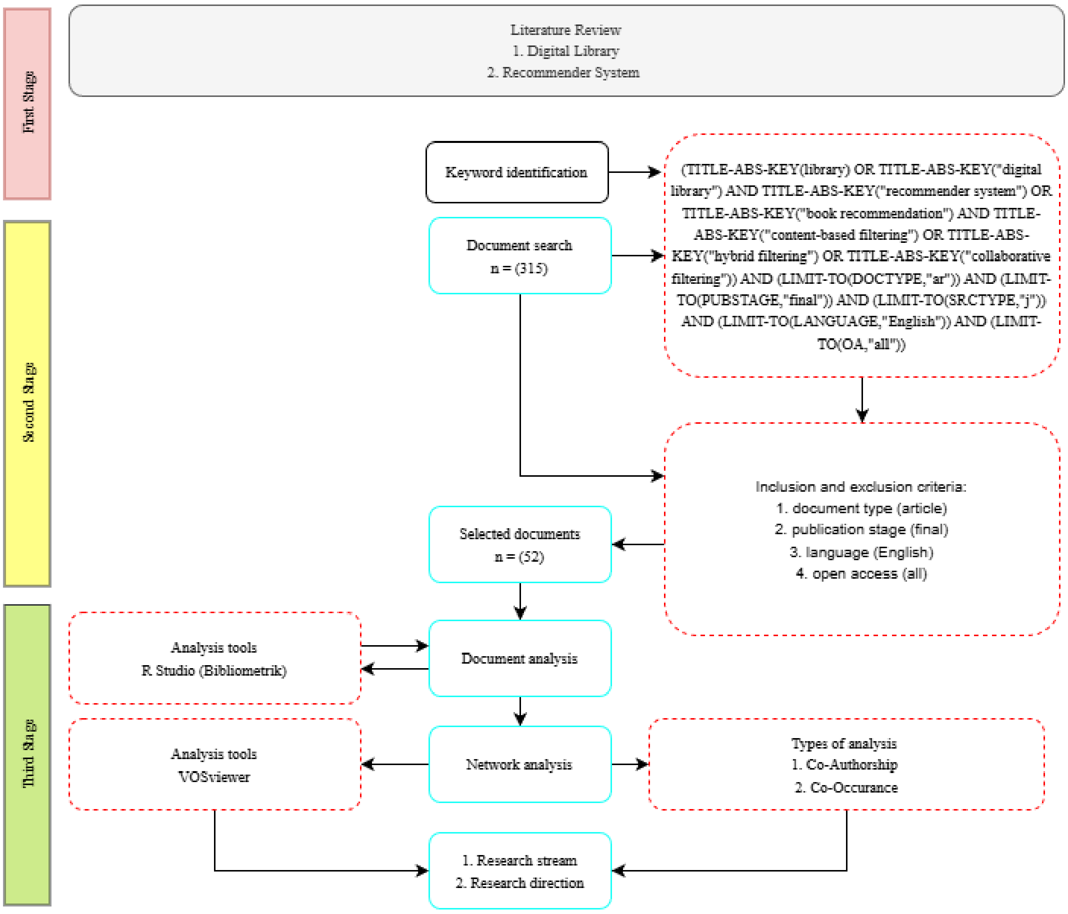

Figure 1. Systematic Review of Recommendation Systems in Digital Libraries Using the PRISMA Framework

Literature Search and Selection Process

The main data source in this study is taken from Scopus, one of the largest scientific indices that includes journals of international repute. The literature search was conducted on October 4, 2025, using a combination of keywords compiled based on Boolean logic. The keywords used include key terms in recommendation system research, such as *library*, *digital library*, *recommender system*, *book recommendation*, *content-based filtering*, *hybrid filtering*, and *collaborative filtering*. The purpose of this search is to identify relevant journal articles, published in English, that have been published finally, and are indexed in Scopus. The screening process is carried out with strict criteria, including document type (article), publication stage (final), language (English), and open access (all). This search yielded 52 articles that met the inclusion criteria and will be further analyzed.

Data Analysis

The filtered data was then analyzed using *RStudio* with *Bibliometrix*, which was used to conduct bibliometric analysis, including identification of publication trends, author collaboration, and keyword analysis, which was often used in this study. In addition, *VOSviewer* is used to visualize the network of keywords and relationships between articles, which helps in understanding the development and interconnectedness of key topics in the digital library recommendation system.

RESULTS AND DISCUSSION

Table 2. Summary of Data Information

Description	Results
MAIN INFORMATION ABOUT DATA	
Timespan	2004:2025
Sources (Journals, Books, etc.)	37
Documents	52
Annual Growth Rate %	6,82
Document Average Age	4,4
Average citations per doc	12
References	0
DOCUMENT CONTENTS	
Keywords Plus (EN)	393
Author's Keywords (DE)	458
AUTHORS	
Authors	153
Authors of single-authored docs	15
AUTHORS COLLABORATION	
Single-authored docs	15
Co-Authors per Doc	3,02
International co-authorships %	21,15
DOCUMENT TYPES	
Article	52

Table 2 presents the information processed using Bibliometrix. The data was analyzed on October 4, 2025, and the results of the analysis are shown in the table. A total of 52 articles published between 2004 and 2025 have been processed. These articles were written by 153 authors, which included 15 single authors, as well as 21.15% international collaborations. In addition, the documents do not include references, with an average citation per document of 12.

RQ1 What have been the trends in publication and distribution of research regarding the recommendation system in digital libraries over the past decade?

In this section, we will discuss the publication and distribution trends of research regarding recommendation systems in digital libraries over the past decade. The purpose of this discussion is to describe the dynamics of the development of this topic as well as the contributions of various parties in producing relevant literature. This analysis will cover several key aspects, namely: Annual Publication Trends, which identify fluctuations and developments in the number of publications over time; Reputable Publication Sources, highlighting major journals and conferences where this research has been widely published; Authors' Contributions, which explores the significant role of leading authors in this field; and State Scientific Production, which analyzes the contributions of various countries in the development of a recommendation system for digital libraries. Through this analysis, it is hoped that a deeper insight can be obtained regarding the direction and development of research in the field of recommendation systems in the context of digital libraries.

Annual Publication Trends

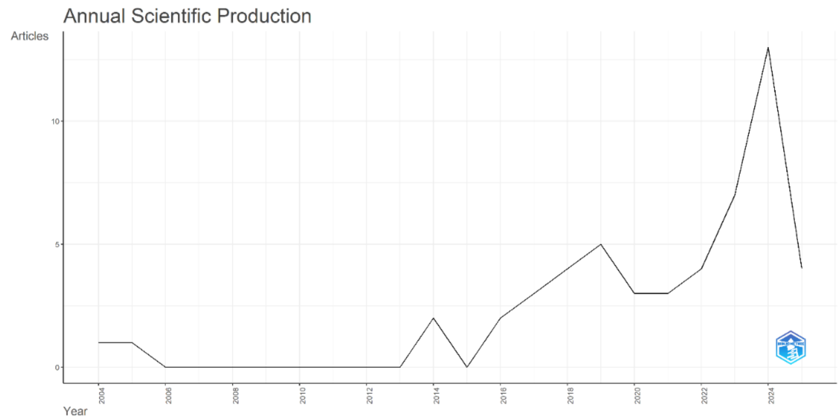

Figure 2. Annual Publication Trends

Figure 2 illustrates the trend of publication productivity related to the recommendation system in digital libraries from 2004 to 2025. The diagram shows that the first article was published in 2004 with only one document, which indicates that this topic began to be introduced in that year. However, there were no publications at all in the following years, especially between 2005 and 2013, which suggests that interest in this topic was still limited in the early period. In 2014, the publication reappeared with two articles, and there began to be a gradual improvement. A significant increase occurred in 2017, with the number of articles published reaching three, followed by five articles in 2019. Furthermore, 2020 and 2021 showed stability with three articles per year, while in 2022 the number of publications again increased to four articles. The highest peak occurred in 2024, with a total of 13 articles published, indicating a significant surge in interest and attention to the recommendation system on digital libraries. In 2025, although it is still in the early months, it is expected that the number of publications will continue. The increase in the number of publications reflects the growing interest and need for the application of recommendation system technology in digital libraries.

Leading Publication Sources

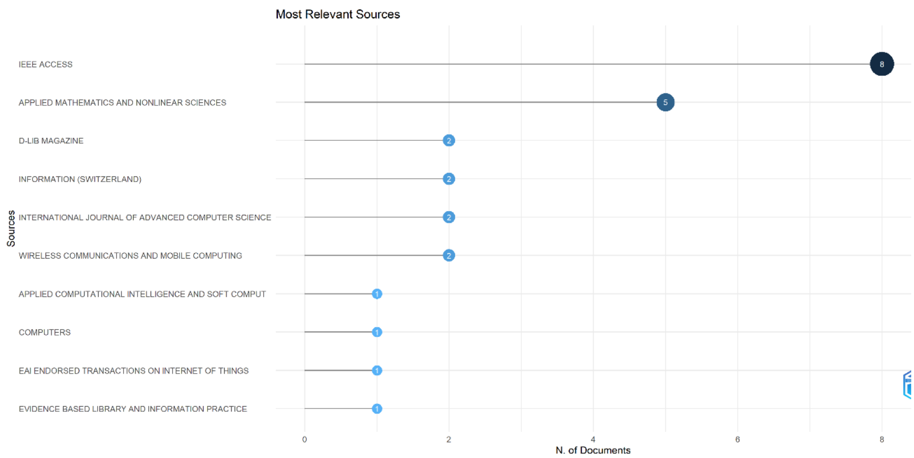

Figure 3. Leading Publication Sources

Figure 3 shows the ranking of the top ten sources or journals with the highest productivity in research related to the recommendation system in digital libraries. IEEE Access ranks first with a total of 8 published articles, making it the most prolific journal on the topic. Applied Mathematics and Nonlinear Sciences is ranked second with 5 articles, followed by several journals that publish two articles each, such as D-Lib Magazine, Information (Switzerland), International Journal of Advanced Computer Science and Applications, and Wireless

Communications and Mobile Computing. In addition, journals such as Applied Computational Intelligence and Soft Computing, Computers, EAI Endorsed Transactions on Internet of Things, and Evidence-Based Library and Information Practice each contributed with one article. This ranking shows that although IEEE Access dominates publications in this field, there are significant contributions from other journals, reflecting the diversity of reference sources in the research of recommendation systems in digital libraries.

Author's Contributions

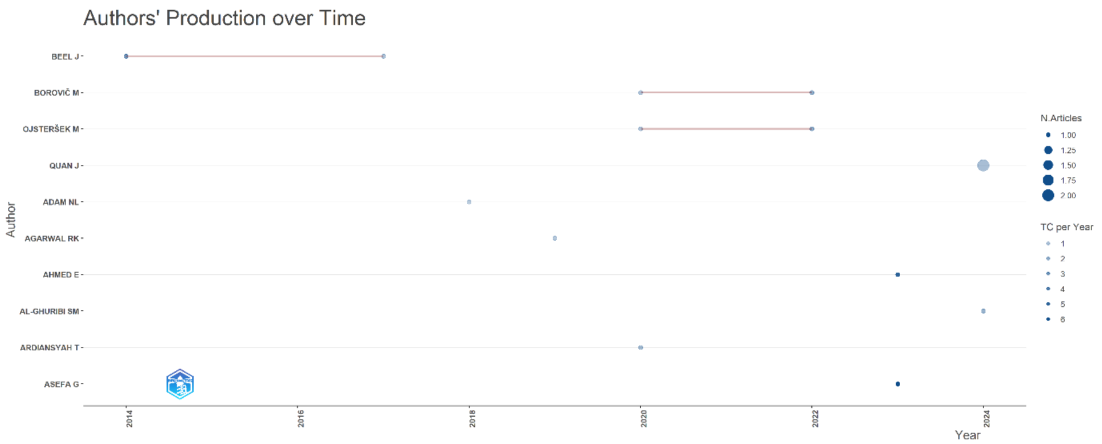

Figure 4. Author's Contributions

Based on the distribution of authors, the ten most relevant authors in the research of the recommendation system on digital libraries are shown in Figure 4. The image indicates that the most active authors are Beel J, Borovič M, Ojsteršek M, and Quan J, who each have two documents, demonstrating their significant contributions to this topic. Meanwhile, other authors, namely Adam NL, Agarwal RK, Ahmed E, Al-Ghuribi SM, Ardiansyah T, and Asefa G, each have one document. Although their number of publications is smaller, their contributions still play an important role in enriching the literature related to the recommendation system in digital libraries.

State Scientific Production

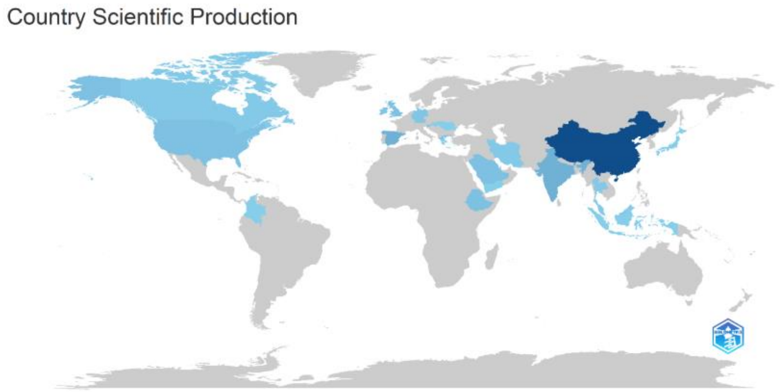

Figure 5. State Scientific Production

Based on Figure 5, "Country Scientific Production", China dominates with 34 publications related to the recommendation system in digital libraries, followed by India with 8 publications, showing the large role of Asia in this study. European countries such as Spain, the United Kingdom, Germany, Greece, and Ireland have smaller contributions, each with 3 to 8 publications, reflecting the focus on developing data-driven recommendation systems. Meanwhile, Ethiopia and Saudi Arabia, with 4 publications, reflect the growing efforts in Africa and the Middle East. Overall, this trend shows that Asia, particularly China, is leading the way in digital recommendation system research, while other countries are also contributing to developing this technology to improve library information access.

RQ2 What type of recommendation system is most widely applied in the context of digital libraries?

In this section, we will discuss the types of recommendation systems that are most widely applied in the context of digital libraries. Recommendation systems play an important role in making it easier for users to find information relevant to their preferences. This analysis will identify the dominant methods, such as *Collaborative Filtering*, *Personalized Recommendation Systems*, and *Hybrid Recommender Systems*. The purpose of this discussion is to provide an overview of the most commonly used approaches in improving the relevance and personalization of recommendations in digital libraries. The focus of the research on the types of recommendation systems in digital libraries can be seen in Figure 6, which is presented using the VOSviewer application with a threshold of 3, meaning that the keywords displayed have been used in at least 3 different documents.

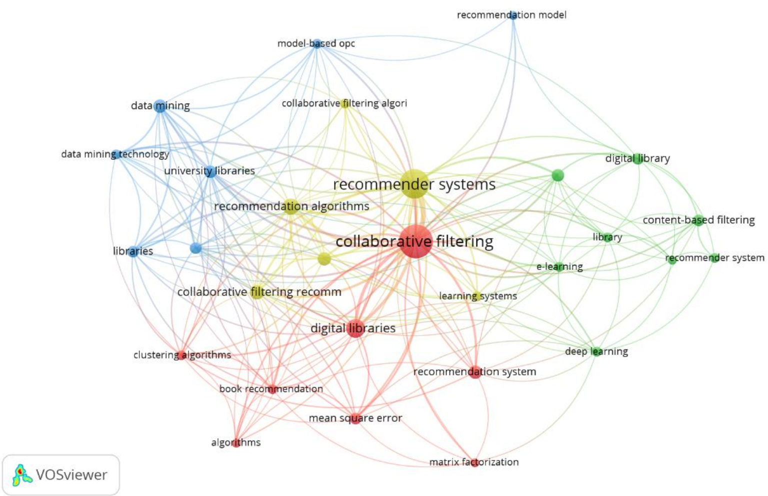

Figure 6. Network Visualization

Table 3. Keyword By Author

Rank	Keywords	Total Link Strength
1	Collaborative Filtering	168
2	Recommender systems	127
3	Digital Libraries	64
4	Recommendation Algorithms	47
5	Collaborative Filtering Recommendations	40
6	Personalized Recommendation Systems	40
7	Data mining	35
8	Recommendation System	22
9	University libraries	40
10	Hybrid recommender system	27

Based on Figure 6 showing the network visualization and keyword data analysis from VOSviewer, it can be concluded that the most widely applied recommendation system in the context of digital libraries is *Collaborative Filtering* (CF), with a Total Link Strength of 168.

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This shows that collaboration-based methods are becoming the dominant approach in various studies and applications in digital libraries. Research by Troussas et al supports these findings by developing a hybrid recommendation system that incorporates *Collaborative Filtering (*CF) with deep learning techniques to improve the accuracy of recommendations in the context of digital libraries [7]. This system shows that the integration of *Collaborative Filtering (*CF) with other methods can address challenges such as data scarcity and improve the relevance of recommendations.

Furthermore, the keywords *Recommender Systems* (127) emerged as a general term encompassing various types of recommendation systems, including *Collaborative Filtering*. Research by Sharma et al supports the results of this interpretation, which shows that *Recommender Systems* covers a wide range of approaches, including *Collaborative Filtering*. In the study, Sharma identified several well-known approaches in the recommendation system, such as *Content-based*, *Collaborative Filtering*, link-based algorithm (*Link-based*), a grounded approach, *Co-occurrence*, and global relevance (*Global Relevance*) [10]. The author emphasizes that *Recommender Systems* is a broad concept and can be applied in a variety of domains, including digital libraries.

In addition, several other keywords that indicate the approach in the recommendation system, such as *Recommendation Algorithms* (47) and *Collaborative Filtering Recommendations* (40), reflect the significant influence of algorithms used in the design of collaboration-based recommendation systems in digital libraries. The research by Na Lin is in line with the results of the interpretation of the significant influence of algorithms in the design of collaboration-based recommendation systems in digital libraries [11]. In the article, the author proposes the design of a personalized smart book recommendation system for university libraries, using algorithms *Item-Based Collaborative Filtering* (IBCF) algorithm. The system is designed to improve the accuracy and relevance of book recommendations based on user preferences and similarities between items. This research emphasizes the importance of the application of algorithms *Collaborative Filtering* algorithm in the context of digital libraries, especially in providing recommendations that are in accordance with the needs and interests of users.

Keywords *Personalized Recommendation Systems* (40) and *Hybrid Recommender Systems* (27) show trends in the use of recommendation systems tailored to individual preferences and incorporate several approaches, such as *Content-based filtering* and *Collaborative Filtering*. The research by P. Jomsri is in line with these findings, where the authors developed a hybrid recommendation system model for digital libraries that incorporates 80% *Collaborative Filtering* and 20% *Content-Based Filtering* to improve the accuracy and relevance of recommendations [12]. The study highlights the importance of a hybrid approach in improving the relevance and personalization of recommendations, supporting trends in the use of systems that combine various techniques.

Overall, these results show that collaborative filtering-based recommendation systems and *personalized recommendation systems* are most widely applied in the context of digital libraries. In addition, there is greater attention to the development of algorithms and hybrid approaches that can improve the user experience. Further research is needed to explore more sophisticated algorithm implementations and address the challenges in implementing recommendation systems in digital libraries.

RQ3 What are some of the challenges identified in the literature, and what is the direction of future research in this area?

In this section, the challenges faced in the implementation of the recommendation system in digital libraries will be discussed, as well as the future research direction in this field. Although the recommendation system has been widely implemented to improve the user experience in finding relevant information, there are still various challenges that need to be overcome, such as data scarcity issues, difficulties in handling dynamic user preferences, and

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the limitations of algorithms in providing accurate recommendations. In addition, as technology advances, research in this area continues to evolve, with a focus on developing more sophisticated algorithms, as well as more personalized and adaptive approaches. In this discussion, the main challenges contained in the relevant literature will be identified, as well as provide views on the direction of research that can improve the recommendation system and optimize its use in digital libraries in the future.

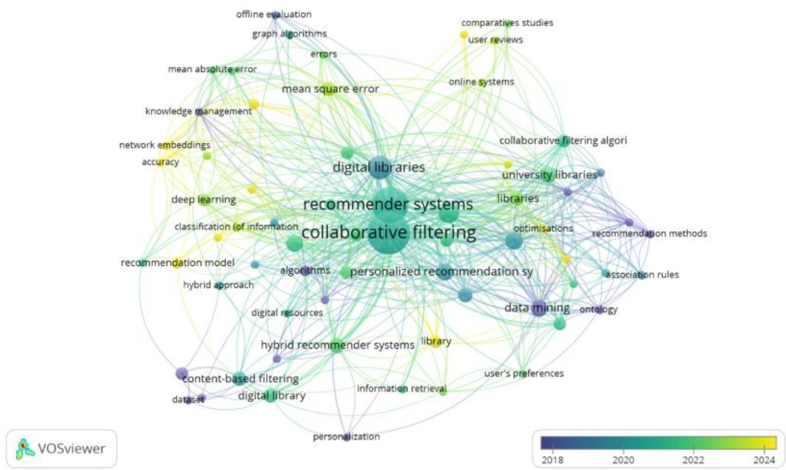

Figure 7. Overlay Visualization

Challenges in the Digital Library Recommendation System

Based on the literature analysis conducted, the challenges faced in the recommendation system in digital libraries include:

Algorithm Optimization (Optimization, Matrix Factorization)

The digital library recommendation system faces the challenge of optimizing algorithms to find which approach is the optimal approach for a library recommendation system. Therefore, optimization is also continuously carried out to improve and improve the performance of existing models. This is a major challenge because building a recommendation system using a single optimization model (e.g. *Transformers*) it is not enough, especially in dealing with the large and complex diversity of user needs, so it is necessary to combine it with other models, for example *Extreme Learning Machine* (ELM) as a collaborative approach to optimizing the recommendation system [13], [14].

Other research describes optimization approaches such as *Matrix factorization*, which is often used to improve recommendation accuracy by extracting latent features, still needs improvements to handle big data and provide more relevant recommendations. Previous research has shown that algorithm optimization is essential in improving the accuracy and efficiency of the digital recommendation system [15]. Some of the proposed solutions to this problem include *Magnitude Bounded Matrix Factorization* (MBMF) and *Double Regularization Matrix Factorization*, which significantly improve accuracy and reduce problems of *Cold Start* and *Data Sparsity*.

A study explained that algorithm optimization is necessary, but there are also problems in the optimization of the recommendation system's algorithm, such as the difficulty of determining initial parameters, such as determining values, *parameter neighborhoods*, and thresholds on traditional models. If the initial parameter selection is not correct, the recommendation results may not be optimal. In addition, there is the problem of computational complexity that can take up a lot of computer time and resources, so efficient algorithm optimization is needed without reducing accuracy [16]. This study introduces the *Distance optimization* and *Warhill algorithm* to overcome these problems. Nevertheless, the results of this study say that the threshold value *(threshold)* deep *Warhill algorithm* has not been adjusted properly, so that the algorithm built has not provided stable results. Further algorithm optimization is still needed to obtain an approach that is able to provide accurate and stable results.

Training Data (Dataset, Cold Start, Data Sparsity)

The variety of data types in large quantities or even vice versa is also a challenge in choosing the approach to be used. For example, the CF approach will encounter problems with the data, ranging from too large a dataset, scarcity of ratings (*Sparsity*), problems with *cold start*, and scalability issues as the data used continues to evolve and become more complex [17], [18]. Seeing these problems, a study proposed optimization using *Matrix Factorization* (MF), which is part of the *Singular Value Decomposition* (SVD), to optimize CF.

Other approaches are also proposed to address the problem, such as the use of *Deep Learning*. *Deep Pairwise Hashing* (DPH), for example, solves problems of *Data Sparsity* and *Cold Start* by mapping users and items into binary vectors in Hamming space, using item content information to learn more effective representations of items. This approach has been shown to improve the efficiency and accuracy of recommendations in sparse data environments. In addition, the *Wide and Deep Model of Multi-Source Information-Aware Recommender System* (WDMMA) that combines linear and non-linear interactions between users and items, as well as leveraging multi-source information, can improve recommendation performance in sparse data scenarios [19].

In addition to the *Deep Learning* Approach, *Cross-Domain* and graph-based approaches also show great potential in addressing this problem. For example, the COAST model uses knowledge from multiple domains to mitigate problems of *Data Sparsity* and *Cold Start* by building heterogeneous graphs across domains that unify user interests across domains [20]. In addition, graph-based models such as *Privileged Graph Distillation* (PGD) use heterogeneous graphical structures to model user-item interactions, addressing the problems of *Cold Start* by distilling knowledge from older users and items [21]. This approach shows how the incorporation of additional data sources, such as user reviews and social networks, can improve the accuracy of recommendations even though they require more complex modeling techniques and large computational resources.

Hybrid Approach & Deep Learning Model (Hybrid Recommender System, Deep Learning, Neural Collaborative Filtering)

One of the main challenges identified in the development of a digital library recommendation system is the use of hybrid approaches and models in *Deep Learning* to improve the quality of recommendations. A hybrid approach, which combines methods such as *Collaborative Filtering* and *Content-based filtering*, aims to solve the problem of *Data Sparsity* by utilizing the strengths of each method. However, these mergers often increase the complexity of the system in terms of system design, method integration, or data processing [22]. It also requires more computing resources, as well as extending model training time, which is an obstacle in practical application [23]. While this approach offers improved accuracy, the main challenge remains in the balance between the quality of recommendations and the efficiency of implementation [24].

Other research also explains that, in fact, a hybrid approach can improve system accuracy. However, a hybrid approach is sometimes not enough to provide a balanced and diverse recommendation result, for example, the CF hybrid approach with *Author & Category recommendations*. As a result, the final result of the recommendation becomes irrelevant and useless for the user. The main challenge identified in the study was how to determine the best way to combine multiple methods without creating systems or computational redundancy. In addition, hybrid techniques also require adjusting the system design in managing data inputs from different models and integrating them to be consistent and efficient. The complexity of this architecture will increase further as data increases and user preferences change [25].

Follow-up research describes the development of a recommendation system using *deep learning*. This model can overcome errors in the results of recommendations that are not capable enough to understanding the semantic meaning of the data. Although this model is a solution, other challenges also arise, namely the need to handle the high complexity of the architecture and the large computational needs to be able to understand the complex semantic meaning of the data. Application of *Deep Learning is* not only complex at the training stage, but also complicated at the stage of *Preprocessing*, especially in overcoming the problem of high dimensions *(high-dimensional)* and data scarcity *(sparsity)*. This research successfully conducted an experiment using the CNN architecture to overcome *High-dimensional* and *Sparsity*. However, the results of this study also make it clear that the approach taken makes the system more complex both in terms of architecture and computation [26].

Other deep learning models, such as *Neural Collaborative Filtering* (NCF) and the framework *Joint Neural Collaborative Filtering* (J-NCF), have shown great potential in improving recommendation performance by combining deep feature learning with user-item interaction modeling. These models can improve the quality of recommendations by capturing more complex relationships between users and items [27]. However, by utilizing the model of *Deep Learning*, increased complexity and greater resource requirements became a challenge. Therefore, to maximize the effectiveness of the system, it is important to optimize the model architecture and utilize additional relevant information, while considering the balance between accuracy and efficiency.

Metadata Integration (Ontology, Semantics)

One of the main challenges in a digital library recommendation system is the integration of metadata and semantic representations between data coming from various sources. To improve the accuracy of recommendations, data that is unstructured or has a different structure needs to be brought together using more sophisticated representation techniques. Ontology and semantics play an important role in bringing together different types of data, but their implementation requires technology that can connect and understand the meaning contained in the information [28], [29].

Recommendation systems need to combine metadata from different sources and metadata with different formats, so there needs to be an effective way to organize and manage metadata so that book information can be interconnected. Another challenge is when metadata uses different terms and structures even though it describes the same thing, so the recommendation system has difficulty finding semantic relationships if there is no uniform concept map. These challenges broadly illustrate the state of poor integration. If this happens, the system will have difficulty recognizing the relationship between the data, so the results of the recommendations will be inaccurate.

Metadata integration is also critical to addressing data sparsity issues, which are common on large datasets. For example, research by Do and Cao shows that the use of models such as *Metadata-dependent Poisson Factorization* can correct data shortcomings and improve the accuracy of recommendations [30]. However, another challenge is managing the complexity and uncertainty that arises when integrating data derived from different types of information, such as lexical and semantic information [31].

As a proposal to address this challenge, technologies such as knowledge graphs and RDF could be used to combine data from various sources. Research by Harrando and Troncy shows that the combination of manual metadata and automated annotation through knowledge graphs can improve the performance of recommendation systems without additional costs for training or data collection [32]. They also found that using automated information extraction techniques, such as entity recognition and topic modeling, could improve recommendation performance without the need for further user data. This approach

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is effective for improving the accuracy of content-based recommendations. However, automated solutions are needed to address difficulties in ontology matching and integration at scale.

Information Overload

Digital libraries face major challenges in dealing with *Information overload*, where an excessive amount of information makes it difficult for users to choose relevant information. This happens because of the ever-evolving growth of information, which poses challenges in dealing with excess information. This becomes complicated when traditional approaches, such as CF, are not sufficiently able to deal with these problems. As a solution, this study proposes an approach, *Matrix Factorization* (MF), to optimize CF. Other studies have also shown that to overcome *Information overload*, the recommendation system in a digital library should be able to filter and personalize content effectively. Li and Han explain that techniques such as CF and CBF can help by taking into account user preferences, although both techniques have drawbacks, so it is necessary to develop a hybrid model to improve the accuracy of recommendations [33].

Other techniques that are also effective for reducing *Information overload* include *Probabilistic Matrix Factorization*, which combines data about users' relationships, trusts, and their interests to provide more precise and personalized recommendations. Research by Li et al also shows that *Reinforcement Learning* can be used to manage the recommendation system, avoiding *Filter bubbles*, and provide more diverse content [34]. The system can adapt to user feedback to provide more relevant and diverse recommendations [35].

Evaluation and Accuracy (Offline Evaluation, Mean Squared Error, Mean Absolute Error)

The evaluation and accuracy of the digital library recommendation system face significant challenges. Traditional metrics such as *Mean Squared Error* (MSE) and *Mean Absolute Error* (MAE) are often used to measure the accuracy of recommendations. However, this metric focuses more on prediction accuracy and fails to capture other important aspects, such as user satisfaction and the impact of system usage. Henriques and Pinto, as well as Zangerle and Bauer, emphasize the need for a more comprehensive evaluation framework that goes beyond these traditional metrics [36], [37]. They suggest incorporating user behavior and user interaction with the system to provide a more holistic understanding of the effectiveness of the digital library recommendation system.

Another challenge occurs when recommendation systems are developed using *offline datasets.* The results of the evaluation conducted with the metrics *Root Mean Square Error* (RMSE) and *Mean Absolute Percentage Error* (MAPE) are not enough to display the real condition of the user. While metric values can show an increase in accuracy, they are only quantitative rather than qualitative of the user experience or changes in preferences in real-time [38]. This study proposes to integrate real-time learning mechanisms and adaptive feedback *(adaptive feedback loops)* into the development of the recommendation system [39]. This approach allows the model to study user interaction data directly, not just historical data, so that the results of the evaluation and accuracy can better reflect real conditions.

Other research also provides proposals in the form of integrating *heterogeneous network embedding* and *Cross-field data* to overcome the limitations of the traditional metrics mentioned earlier. By leveraging cross-field data *(cross-field recommendation)* and data representation, the model is not only much better in terms of accuracy, but also capable of recognizing latent patterns between different users and fields [40]. The study also said that although the accuracy value of the model has increased, a new challenge has arisen, namely, computational complexity.

Overall, these challenges underscore the complexity in the development and implementation of digital library recommendation systems. The development of a recommendation system in the future must pay attention to and overcome problems of algorithms, data, system complexity, metadata, excess information, as well as evaluation and accuracy, to provide recommendations that are relevant and useful for their users.

Future Research Directions for Digital Library Recommendation Systems

Analysis of the VOSviewer overlay revealed several key areas for future research in the development of the Library Recommendation System, which are reflected in the yellow and light green clusters. These clusters include keywords such as *network embeddings*, *accuracy*, *recommendation model*, *matrix factorization*, *recommendation accuracy*, *library*, *optimizations*, *deep learning*, and *mean square error*. These findings suggest that emerging topics and methodologies have great potential to improve the capabilities of recommendation systems, particularly in the context of digital libraries.

One of the key directions identified is engineering integration of *Network Embeddings* and *Deep Learning*. *Network embeddings* provide an effective method for representing complex relationships within digital libraries in lower-dimensional spaces, allowing data to be more manageable and interpretable. Application of *Deep Learning*, particularly through *Deep Neural Networks*, further refines the technique of *Network Embeddings* by studying more complex patterns from large data sets. This allows the system to capture non-linear relationships between users and items in greater depth, which were previously difficult to understand using conventional methods. Previous research by Hao et al and Jin et al showed that this approach is effective in improving the accuracy of recommendations by capturing intrinsic features in highly complex data [41], [42].

The focus on *the accuracy* and *recommendation models* in the identified clusters emphasizes the importance of continuous improvement in the accuracy of the digital library recommendation system. This is especially relevant in the context of university libraries, where user preferences are very diverse. Research conducted by Zhang et al and Ong et al shows that *deep learning* is able to improve precision by reducing prediction errors such as *mean square error* (MSE) and *mean absolute error* (MAE), which are critical to improving the effectiveness of recommendation systems in handling large and complex datasets. Therefore, further research is needed to develop algorithms that can further optimize these techniques to meet the needs of a diverse and dynamic user base.

Another promising area for research is the development and optimization of recommendation models. Technique *Matrix Factorization*, which is effective in *Collaborative Filtering*, can be further optimized by using advanced algorithms to capture complex interactions between users and items, especially in dynamic digital library environments. Research by Su et al and Shi et al supports that *Heterogeneous Information Networks* (HINs) can improve the performance of recommendation models by combining various existing sources of information [43], [44], and this can be applied to model-based optimization, *Matrix Factorization*. In addition, research on a hybrid recommendation system that incorporates *Collaborative Filtering* and *Content-based filtering* is very important. Research conducted by Huang et al shows that the combination of these two approaches can result in more accurate and personalized recommendations by integrating user behavior and item features more comprehensively.

The growing interest in optimization techniques signals the need for more efficient algorithms that can handle the big data that exists in digital libraries. As the size and complexity of data evolve, future research should explore ways to improve optimization strategies to handle large, dynamic datasets without sacrificing the accuracy of recommendations. Research by Xi et al shows that the application of techniques such as *Attention Mechanisms* and *neural networks* can better capture complex relationships and global impacts on user preferences, which can further improve recommendation accuracy [45]. Therefore, a more efficient recommendation system and higher personalization can be

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achieved through the use of user-specific data, which will increase user satisfaction and engagement with digital resources.

In conclusion, the direction of the research emerged, which focused on improving accuracy, algorithm optimization, and method application in *Deep Learning*, indicating that the future of digital library recommendation systems lies in the development of more sophisticated, personalized, and scalable models. Previous research, as described by Gao et al, suggests that this approach can overcome the major challenges of improving the accuracy and efficiency of recommendation systems [46], [47]. While there are challenges related to computing and data management costs, these advancements will significantly improve the ability of digital libraries to meet the diverse and ever-evolving needs of users.

CONCLUSION

This research reveals a significant trend in the development of digital library recommendation systems. Based on the results of RQ1, it was found that publications on this topic began to increase significantly in 2014, with a peak in 2024. This increase shows the increasing interest in the application of recommendation system technology in digital libraries. In addition, the study also highlights China's dominance in publication contributions, followed by India, with various European and Middle Eastern countries playing a role, albeit in smaller numbers. IEEE Access is the main source of publications, followed by several other leading journals such as Applied Mathematics and Nonlinear Sciences. Prominent authors such as Beel J and Borovič M have also made significant contributions to enriching this literature. Regarding the type of recommendation system used, RQ2 shows that Collaborative Filtering (CF) is the most dominant approach in digital libraries, with a Total Link Strength of 168. The use of deep learning techniques to improve the accuracy of recommendations is also growing in popularity, as shown in the research of Troussas et al. In addition, Personalized Recommendation Systems and Hybrid Recommender Systems are increasingly being implemented, with collaboration between Collaborative Filtering and content-based filtering to increase relevance. Overall, while Collaborative Filtering is still the mainstream, the development of hybrid algorithms shows growing potential to improve the accuracy and relevance of recommendations in the context of digital libraries. Based on the results of RQ3, the main challenges in implementing the recommendation system include algorithm optimization, data scarcity issues, and cold starts, as well as the use of hybrid and deep learning techniques that require more resources. Although recommendation systems have proven effective in improving the relevance of information, these challenges remain obstacles in improving accuracy and efficiency. More research is needed to develop more sophisticated algorithms, as well as apply techniques such as network embeddings and deep learning to handle big and dynamic data. The development of a more personalized and adaptive recommendation system in the future can allow digital libraries to provide more relevant and efficient recommendations for their users.

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Author's Contributions

Ishmah Afiyah and Hanif Amarudin are responsible for research methodology, data collection, and data analysis in manuscript writing. Shofwatul 'Uyun provided support throughout the research process.

Conflicts of Interest

All authors declare no conflict of interest.

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