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A decade perspective of recommender systems research: a systematic review

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Abstract

The amount of data and information created daily has made it nearly impossible for users to find what they are looking for without the help of a recommender system. A recommender system supports and simplifies selection processes by filtering for and recommending the most relevant information to its users. This systematic literature review (SLR) process critically examines past SLRs to identify recent developments and advancements in recommender systems and algorithms. Results show a sharp increase in SLRs focusing on recommender systems over the past decade, accelerating in the past few years. Additionally, the field has evolved to include more specific filtering techniques. It is crucial for researchers, practitioners, and users to understand the evolution of recommender system research, including how use of large language models may improve future SLR development.

Keywords: Information systems, recommender systems, SLR, artificial intelligence.

Introduction

By 2025, global data creation will grow to more than 180 zettabytes (Total Data Volume Worldwide 2010-2025, 2023). The sheer amount of data and information available to organizations does not mean it will be used effectively for decision-making. A significant problem many organizations face is an abundance of information, leading to information overload, data use complexity, and a reduction in decision-making performance (McCumber, J., 2005).

A recommender system is an information filtering system that searches for and identifies relevant information for users. The two main types of recommender systems, or filtering techniques, are content-based and collaborative-based systems. Content-based systems apply user input to user-defined data sets to find and highlight information that is most highly related to the user input, usually via a pre-defined scoring system (Gupta, Bindal & Prasad, 2023). Content-based systems, therefore, are classified as supervised machine learning products. In contrast, collaborative-based systems primarily employ unsupervised machine learning techniques to select and group content that is potentially relevant to a user's queries based on similarity to others' searches (Kim, Kang, Choi, Kim, Yang & Park, 2024). Hybrid systems use popular algorithms to blend different components of content-based and collaborative-based filtering techniques.

Given the current acceleration of artificial intelligence (AI) and large language models (LLM) and these technologies' potential to dramatically increase the speed, accuracy, and scope of recommender systems, understanding the current state-of-the-art is especially important at this time. Previous systematic literature reviews have mixed results as to which information filtering technique is most studied. Beel et al. (2016)

found that content filtering was the most researched recommendation method. However, a few years later, Da'u and Salim (2020) showed that collaborative filtering is studied more. In 2020, Dehdarirad et al. found that the three classes, content-based, collaborative-based, and hybrid recommender systems, have been studied almost equally, prompting the call for more research to identify the prominent class of recommender systems (Dehdarirad et al., 2020). The absence of a thorough analysis categorizing these systems and identifying the most extensively researched types has shaped the following guiding research questions for the systematic literature review.

RQ1: *"What type of recommender system is most researched in the literature?"*
RQ2: "*How has recommender system research evolved over the past decade?"*

To identify gaps in the literature and suggest future areas of research, the research questions are answered by categorizing the articles included in the review by the following:

1. The foci of the literature into different classes of recommender systems
2. The method of the SLR
3. Future research areas

The field of recommender systems is dynamic, with rapid technological advancements and changing user needs. Understanding how research trends have evolved over the past decade can highlight shifts in focus and areas that may require further exploration.

Background and Related Work

Due to the competitive advantage an effective recommender system provides to businesses, it is not surprising that this field is constantly evolving, and researchers frequently propose new processes and methods to improve the accuracy of recommendations. The most common types of recommender systems are collaborative-based, content-based, and hybrid recommender systems, each with its benefits and limitations.

Collaborative-Based Recommender Systems

Collaborative-based recommender systems make predictions for users in response to those users' inputs. The predictions are based on previous ratings of an item by either the user's own ratings or those of other, similar users. The assumption is that users get the best recommendations from other users with similar attributes and make recommendations by collecting similar users' preferences in the recommender system (Najafabadi & Mahrin, 2016). These types of systems can be classified by two main approaches: memory-based and model-based.

Memory-Based

The memory-based approach makes recommendations based on similarity. This approach can further be classified into user-based collaborative filtering (calculated by Euclidean distance or cosine distance), and item-based collaborative filtering using KNN (k-Nearest Neighbors) or stochastic gradient descent).

Model-Based

The model-based approach uses Singular Value Decomposition (SVD) or matrix factorization, with matrix factorization being more common in actual practice because the matrix should not include empty values.

Building an effective collaborative recommender system is not as simple as using a predefined scoring system to match strong or weak data sources to search criteria. Although some researchers have found collaborative filtering to be the most used technique (Da'u & Salim, 2020), this technique frequently suffers from rating sparsity (Najafabadi & Mahrin, 2016) and cold-start items and cold-start users (Assuncao et al., 2022). Cold-start problems occur when no adequate information about an item or a user is available to make predictions. Data sparsity occurs when there needs to be more information in the system.

Such issues are common in unsupervised machine learning because it is difficult for a data model to learn if it does not have adequate positive and negative exemplars to learn from within the data (Rodríguez, Chicaiza, Sánchez, & Escaño, 2023). Due to these issues, collaborative filtering techniques can make recommendations unreliable when there is a lack of user rating data. Many collaborative-based systems mitigate such issues by employing implicit or contextual data, such as users' buying behavior, login times, and history of viewed or purchased products.

Content-Based Recommender Systems

Content-based recommender systems predict new but similar items to a user. Recommendations are made based on pre-determined features for a product to build an item profile and a collection of vectors that comprise a user profile. Based on product ratings from other users, algorithms can calculate user vectors and preferences. This type of system works well to help avoid problems with cold-start items, but not with cold-start users, when user feature vectors are unknown.

In addition, content-based approaches recommend items based on content descriptions and therefore may not recommend diverse items making them less ideal for making recommendations to new users, though remaining effective for new items (Da'u & Salim, 2020). There are two main approaches used in content-based recommender systems: cosine distance and classification (i.e., Bayesian or Decision Tree).

Hybrid-Based Recommender Systems

Hybrid recommendation systems use a combination of both content and collaborative-based filtering techniques. The assumption is that integrating these methods will "improve and provide more enhanced recommendations than applying a single technique" (Da'u & Salim, 2020, p. 2714). The most common types of recommender systems and their algorithms are listed in Figure 1.

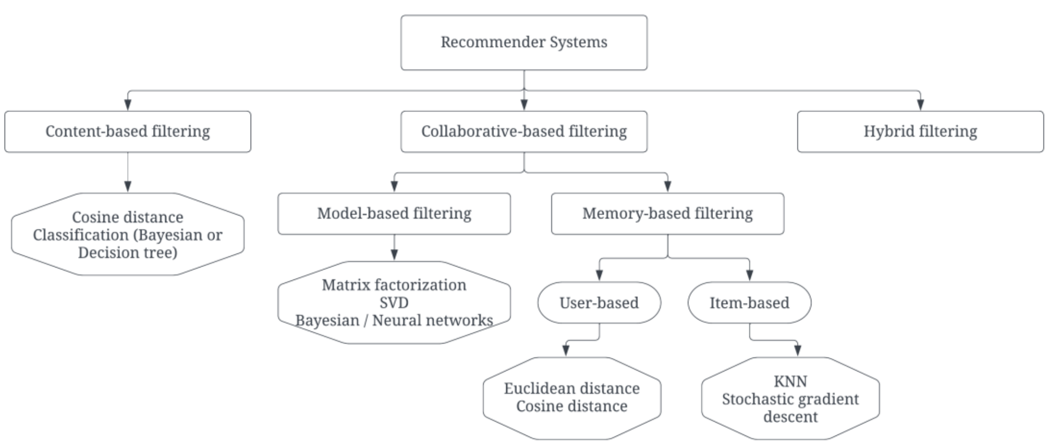

Figure 1: Common Recommender Systems

Two more specific types of recommender systems are knowledge-based and context-based recommender systems. These systems typically offer more tailored and accurate recommendations by incorporating explicit knowledge and situational factors.

Knowledge-Based Recommender Systems

A knowledge-based recommender system is one type of recommender system that recommends items based on knowledge about how the item's characteristics meet the needs and preferences of the users (Aguilar et al., 2017). This system requires users to provide input preferences, such as rules or guidelines, before suggesting a recommendation. A knowledge-based recommendation approach is helpful as other recommendation techniques, such as content-based and collaborative recommender systems, may not have enough data to make accurate predictions initially, also known as the cold start problem (Di Tommaso, 2018). Knowledge-based recommendation approaches are beneficial until enough data has been collected to apply collaborative or content-based methods.

Context-based Recommender Systems

Context-based recommender systems have also been a more recent focus of the field (Assuncao et al., 2022). Contextual information may include demographic information (i.e., user’s gender, age, nationality, job, education, and income level) or social information (i.e., contacts and interactions between users, followers, reputation, trust, social tagging, and credibility) or cognitive information (i.e., user's goal, mood, and current state of user’s mind) (Etemadi et al., 2023).

Current research shows that the integration of Artificial Intelligence (AI) into recommender systems is accelerating. Large language models (LLMs) are of great interest and are likely to become a significant factor in the evolution of recommender systems (Kim et al., 2024). Research on adding AI and LLM technologies into recommender systems finds that substantial improvements have already been achieved relative to the speed and accuracy of systems’ results (Tran et al., 2018). Recent publications have proposed and tested methods for integrating and applying AI and LLMs to enhance recommender systems (Roczey & Szenasi, 2023; Tahla Iqbal, 2024). Although AI-specific technologies and enhancements are beyond the scope of this paper, it is important to recognize that these technologies will be transformational to future recommender systems development, and research regarding their costs, benefits, and risks will likewise be essential.

This paper summarizes the state of research and practices in recommender systems over the past decade. By examining the literature to find which type of recommender system has been studied most we can better understand evolutions and trends in this area (Dehdarirad et al., 2020). The findings may afford practitioners and researchers with insight and future research directions.

Methodology

Systematic literature reviews (SLRs) are essential for summarizing literature in a structured process to ensure accuracy and reliability (Liberati et al., 2009). Additionally, SLRs have the potential to identify research trends and gaps as well as propose new areas of research. SLRs must follow well-established processes to ensure that the literature gathered and identified as relevant to the topic is exhaustive, complete and replicable. Thus, this SLR follows a prominent SLR approach in the IS field: Kitchenham and Charters

(2007). Additionally, it follows the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines (Liberati et al., 2009).

Data Sources & Search Strategy

A systematic review should find as many primary studies relating to the research question as possible using an unbiased search strategy (Kitchenham & Charters, 2007). To help answer the research questions and to identify all relevant publications, these search terms were used: "Recommender System" and "Systematic Literature Review." The search was narrowed by identifying these terms in title or abstract only from the past ten years (2013-2023) in peer-reviewed journal articles and conference proceedings from the following databases: ABI/Inform, Science Direct, IEEE, Web of Science, and ACM. Slight adjustments were made to each search query based on the design of the advanced database search queries, as shown in Table 1.

Table 1: Academic Database Search Queries

Database	Count	Search Terms
ABI/INFORM	**5**	noft(slr systematic literature review) AND noft(Recommender recommendation system)
Science Direct	**27**	("systematic literature review" OR "systematic review") AND ("Recommender System" OR "recommendation system" OR "Recommender Systems" OR "recommendation systems")
IEEE	**24**	("Publication Title":"systematic literature review" OR "Publication Title":"systematic review") AND ("Publication Title":"Recommender System" OR "Publication Title":"recommendation system" OR "Publication Title":"Recommender Systems" OR "Publication Title":"recommendation systems") OR ("Abstract":"systematic literature review" OR "Abstract":"systematic review") AND ("Abstract":"Recommender System" OR "Abstract":"recommendation system" OR "Abstract":"Recommender Systems" OR "Abstract":"recommendation systems")
Web of Science	**11**	slr systematic literature review AND Recommender recommendation system (Title) or slr systematic literature review AND Recommender recommendation system (Abstract)
ACM	**4**	"query": {Title:(("systematic literature review" "systematic review") AND ("Recommender System" "recommendation system" "Recommender System" "recommendation system")) OR Abstract:(("systematic literature review" "systematic review") AND ("Recommender System" "recommendation system" "Recommender System" "recommendation system"))} "filter": {E-Publication Date: (01/01/2013 TO 12/31/2022)},{ACM Content: DL}

Inclusion/Exclusion Criteria

Studies for review were complete SLR studies from the past decade focusing on recommender systems research. Publications identified as literature reviews, but not complete SLR publications were excluded. During the identification phase, seventy-one articles were identified in the five previously mentioned IS databases. Four duplicate articles were removed. The articles were reviewed first by title and abstract and then via a complete textual analysis during the screening process.

Articles were removed based on the inclusion/exclusion criteria. Publications in the full textual analysis were excluded if the SLR was not directly related to recommender systems such as privacy concerns (Beg et al., 2022), decision support tools or algorithms (Nindito et al., 2020; Khalid et al., 2022; Yadav et al., 2019; Amin et al., 2020). Three articles were not accessible (Colombo-Mendoza et al., 2020; Murad et al., 2018; Gao et al., 2021), and two were not available in English (Brunialti et al., 2015; Oliveira & Frango, 2021) and thus excluded from the analysis.

There were 67 publications sought for retrieval, as no additional articles were removed after the initial title and abstract exclusion process. However, after the full textual review, only 38 articles were identified as meeting the criteria and remained for the analysis. Because the process of performing a systematic review must be transparent and replicable (Kitchenham & Charters, 2007), the PRISMA guidelines (Liberati et al., 2009) report the search and exclusion process shown in Figure 2.

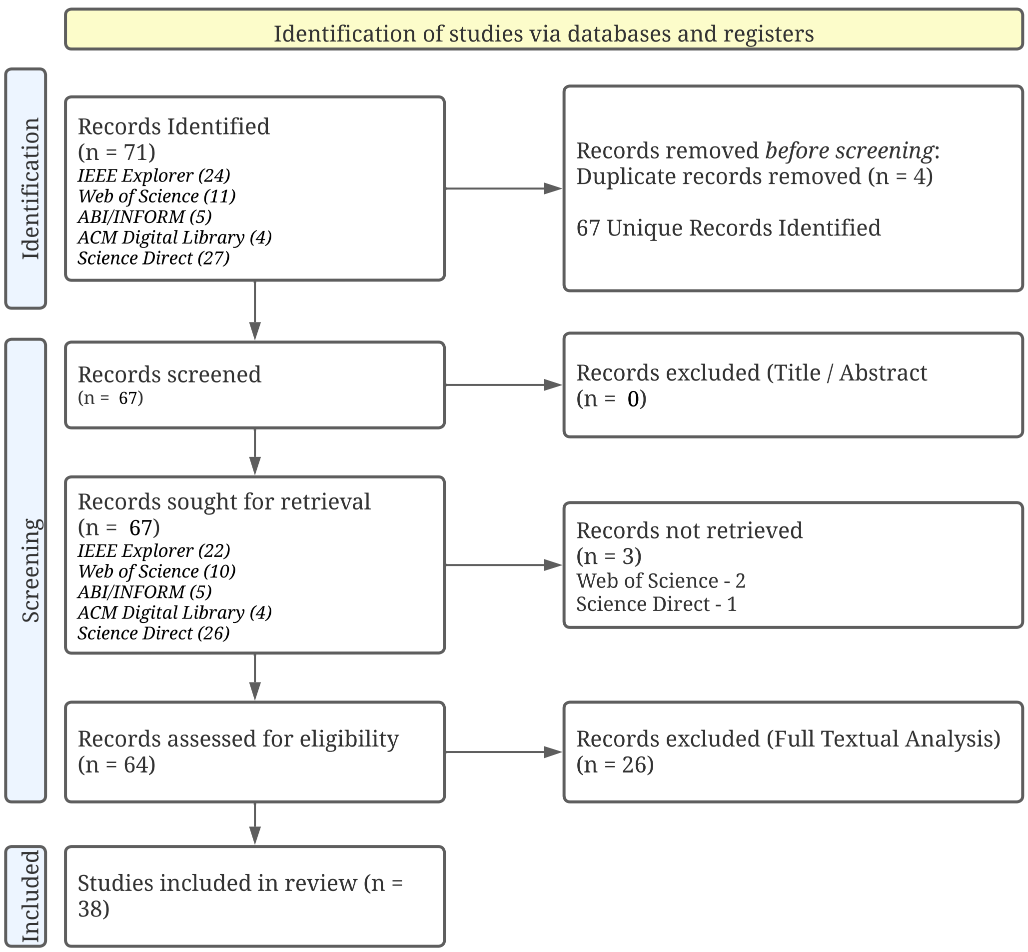

Figure 2: PRISMA Chart

Results

No SLRs were identified in the search for the year 2013, and only one in 2014. After 2014, the number of SLRs began to increase rapidly. As shown in Figure 3, 19 articles have been published since 2022.

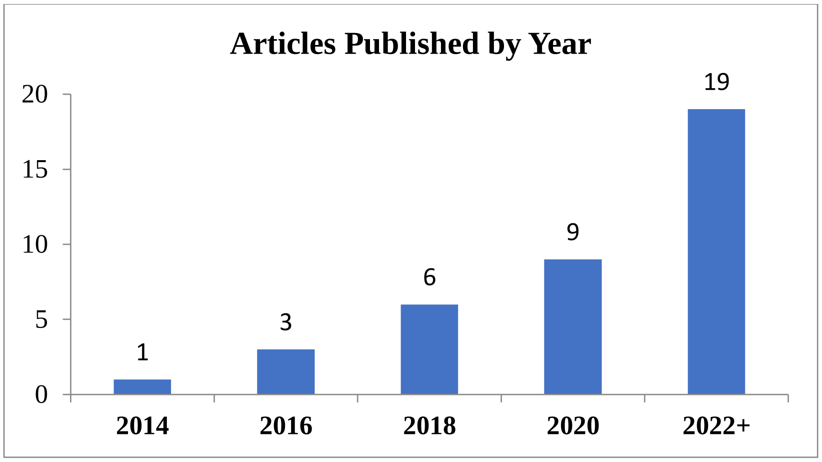

Figure 3: Histogram of Articles by Year

The majority of articles used Kitchenham and Charter’s (2007) methodology (n=23) for conducting the SLR. Kitchenham and Charter's methodology is commonly used in software engineering and information systems. Three studies followed Moher’s (2007) methodology for conducting an SLR. Other methodologies in the review were used only once, which include Barbara and Stuart (2007), Keele (2007), Webster and Watson (2002), Levy and Ellis (2006), and Page et al. (2021). Six reviews did not list a specific methodology, as shown in Figure 4. Surprisingly, six publications identified as an SLR did not reference any methodology but did show some form of SLR methodology approach.

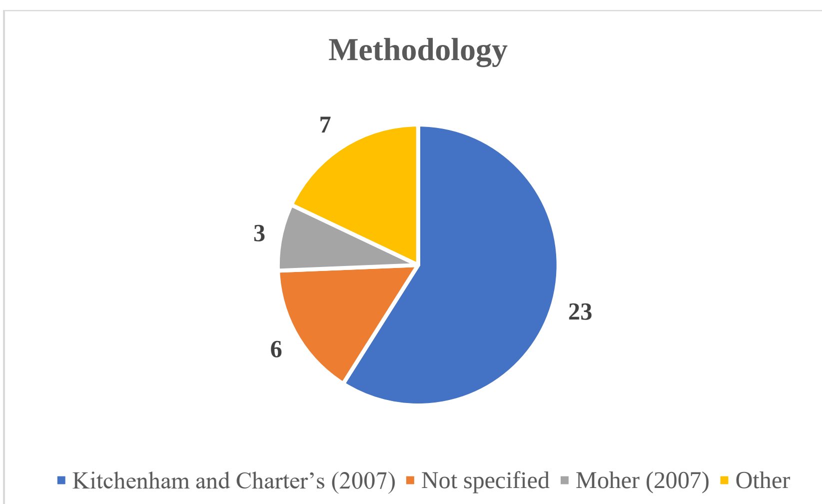

Figure 4: SLR Methodology

The article's recommendation system filtering types were documented during the full textual review. The collaborative-filtering technique was used extensively and included in 32 of the 38 papers reviewed. Content-based filtering was included in 27 papers, followed by a hybrid approach (22), knowledge-based, context-based, graph-based, demographic-based, and suitable-based, as shown in Figure 5. Other less common filtering techniques included utility-based, temporal-based, community-based, ontology-based, conversation-based, feature-based, profile-based, peer-based, diagnostic-based, metadata-based, and personalized-based.

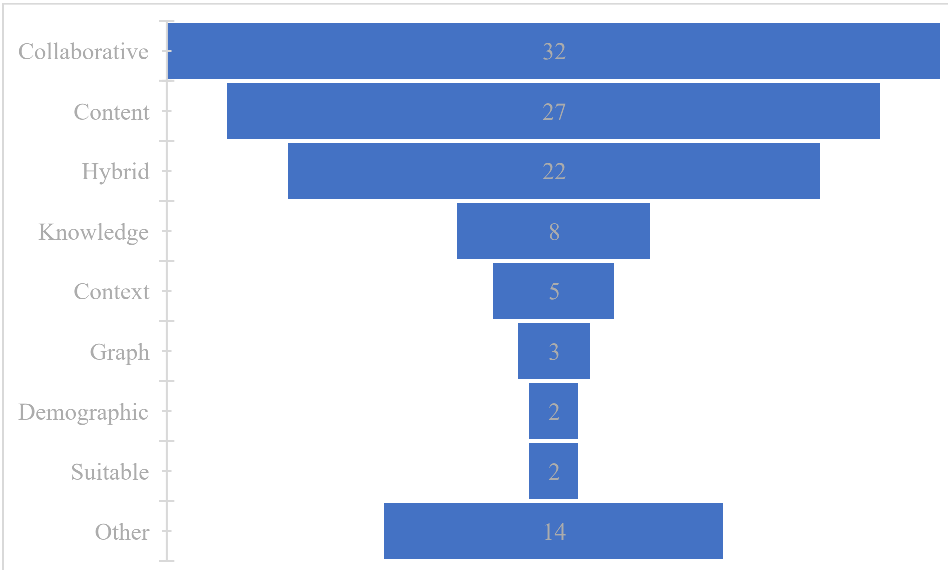

Figure 5: Recommender System Method

Discussion

Unsurprisingly, the number of SLRs focusing on recommender systems has increased rapidly over the past decade. As data and information grow, new methods of filtering information will continue to evolve. This SLR shows that recommender system research has evolved from traditional filtering methods to more specific techniques that can be combined with frequently used techniques to make better predictions. This diversity of filtering techniques explored reveals the innovation and adaptability of the field to new data types and user requirements.

The most researched recommender system filtering technique identified in this study was collaborative filtering, consistent with Da'u et al.'s (2020) findings. Additionally, this finding supports other recent studies such as those in healthcare that reveal most research in in this field uses a collaborative-based approach (Etemadi et al., 2023). Many specific types of recommender systems may be due to redundancy in the types of recommender systems cited in the papers. This phenomenon, mainly due to overlapping definitions, indicates a need for standardized terminology in the field and a common language to define these systems.

The research results also reveal the amount of research relating to recommender systems has increased over the past decade. The three most common types (collaborative-based, content-based, and hybrid) to more specific types, including context-based, domain-specific, ontology-based, and more. Two of the most frequently researched recommender systems included with collaborative and content-based were knowledge-based and context-based recommender systems.

Earlier this year, researchers Etemadi et al. (2023) conducted an SLR to identify, taxonomically classify, and systematically compare current HRS research. In addition to studying content-based, collaborate-based, and hybrid recommender systems, the researchers included knowledge-based and context-based recommender systems. The researchers found that a significant fraction of research in health care recommender systems was conducted using a collaborative-based approach (27%), followed by a knowledge-based approach (22%), hybrid approach (19%), content-based approach (17%), and then context-based approach (15%). This is also consistent with this paper's five highest recommender systems, which explore the research across all domains.

The comprehensive use of Kitchenham and Charter’s methodology across numerous studies indicates a strong adherence to a well-established SLR protocol. However, six studies did not specify their methodology, which raises concerns about the rigor and reproducibility of these reviews. Additionally, the variation in methodologies used, and in some cases, the lack of specified methodologies, suggests inconsistency in how SLRs are conducted in this field, which can lead to variability in the results.

Future Research

As part of this SLR, future research areas were identified in the articles examined. Researchers Pinho et al. (2019) published an SLR to provide an analysis of the current research efforts in educational recommendation systems. These researchers looked at various techniques, including collaborative, content-based, hybrid, knowledge-based, context-based, utility-based, demographic, and community-based. The researchers found that the hybrid approach has been the leading strategy for recommendation production, however, no frameworks satisfy the needs of the educational context.

In addition to more research establishing a framework, there are calls for more research in application fields other than e-commerce and movie recommendations (Najafabadi & Mahrin, 2016) and other fields of specialization (Dehdarirad et al., 2020). Other researchers have called for more studies looking at other factors that affect recommendations, such as user activity, satisfaction, feedback, cold start problems, cognitive load, learning, personality, and user preferences (Assuncao et al., 2022). Finally, more research is needed to identify the architectures and critical mechanisms that generalize to most recommender models (Wu et al., 2022) and methods of classifying filtering based on the user's perspective (Rahayu et al., 2017).

Limitations

This study has limitations. Five bibliographic databases were used for retrieving the relevant studies; however, these are not exhaustive and may limit the validity of the study. Future studies could include additional databases to broaden the findings of this research. Additionally, some articles found were excluded due to the inability to access them.

When articles did not explicitly list the methodology used in the SLR, the studies were coded as if they did not follow a specific process. This is a limitation as some studies may have followed specific guidelines, even though they needed to be clearly specified. Another limitation is the threat of misclassification of the articles that may occur during the data extraction phase. Although the data extracted is relatively sufficient, coding is based on the researcher's perspective, and there is the potential for other researchers to discover other findings and research trends. Future research could replicate the study to determine the accuracy of the categorization of the articles and discover other findings.

Conclusion

Recommender systems can provide organizations and consumers with relevant information in a timely manner to support decision-making. Research on recommender systems in the past traditionally focused on three main types of systems: content-based, collaborative-based, and hybrid methods. However, as this research shows, there has been more research, specifically in the last year, focusing on other methods, such as knowledge-based and context-based filtering. Practitioners should be aware of this evolving landscape of recommender systems and consider integrating newer techniques to enhance the accuracy and relevance of recommendations. The steep increase in research studies is not surprising considering the topic of the research. The rapid acceleration of AI-based or AI-enhanced recommender systems necessitates much additional research in this area. Future research focusing on the user's preferences and contextual factors will continue the evolution of recommender system research and support practitioners in building effective systems.

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