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Effectiveness of personalized recommendations on e-commerce websites

Supervisor:

Prof.ssa Anna Spagnolli

Department of General Psychology

Candidate: Ali Kami Ayvat

Student ID number:1222474

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Abstract

The widespread use of the internet has driven rapid advancements in business-to-customer e-commerce**.** However, in order to survive in today's competitive environment where options are plentiful, e-commerce websites must solve the information overload problem and help their customers to make better decisions. The issue of information overload can be solved via recommendation systems. This paper is a Systematic Literature Review of articles published in the field of e-commerce recommender techniques and their effectiveness. It is found that CF and Hybrid models are dominant, cold-start, scalability, and sparsity are the key problems

addressed, new models tend to be more effective than those they are compared to, and the future of the field is diverse and complex.

Chapter 1: Introduction

In the modern era of the internet, e-commerce is a ubiquitous mode of business-to-customer (B2C) interaction (Alamdari et al., 2020). However, as customers have more and more products easily available at their fingertips, the wide choice makes selecting the right product more difficult. Recommender systems solve this problem of information overload.

The information gained from understanding recommender systems, how they function, and what works is significant to understanding human preferences and decision-making in a purchasing environment. Understanding the key features of products that make them suitable recommendations, as well as the characteristics of users that make them good sources for recommendations, sheds light on the nature of online shopping experiences.

In order to understand the psychological relevance, it is also important to understand recommender systems themselves, the context they are used in, and the algorithms that underpin them. This systematic review begins with explanations of what e-commerce is, the different recommender systems used, as well as summarizing some past literature reviews in the field. A detailed methodology of paper selection and information selection is described, followed by a breakdown of relevant findings and a conclusion based on these findings.

1.1 E-commerce

Electronic commerce, often known as E-commerce, refers to the purchasing and selling of products and services over the internet. Many business owners find e-commerce much more efficient than physical stores. Customers can select what they want or need from endless options anytime, anywhere in the world. E-commerce can take four different forms: business-to-consumer (B2C), business-to-business (B2B), consumer-to-business (C2B), and consumer-to-consumer (C2C). When people think about e-commerce, they often associate it with B2C transactions. Amazon, Shopify, and eBay are all examples of e-commerce websites.

There are many advantages that e-commerce offers to possible customers. First, as mentioned above, it removes the problem of place because both the vendors and customers can communicate in a virtual environment. The second advantage is that it eliminates the maintenance cost of the physical stores. Lastly, it saves time both for vendors and customers.

1.2 Recommender systems in e-commerce

E-commerce websites have become very common in our lives with the fast development of the internet. There are thousands of products on websites like eBay, and Amazon, and because of that it is difficult for customers to find the right item, and this obviously reduces the total sales. That is why a suitable recommender system is necessary because the system is able to offer the right products to customers that may not have found the correct product otherwise. The recommender systems provide users with suggestions for products, movies, and hotels.

Alongside solving the information overload problem, there are other reasons to introduce recommender systems as follows:

1. Increasing the conversion rate, which will increase the revenue per visitor, attract more customers, and overall grow the business
2. User satisfaction
3. Loyalty, which will increase the conversion rate.

Evidence shows that recommender systems (RSs) can improve important e-commerce metrics for businesses (Park et al., 2007). A good salesperson in a physical store uses their knowledge of customers' preferences to make recommendations and increase satisfaction, leading to higher profits. In a way RSs work in the same way, only online, curating the products that customers get presented with. Some researchers use social factors to enhance the accuracy of recommendations, like Li et al. (2013), as cited by Alamdari et al. (2017), who combined recommendation trust, social relation analysis, and preference similarity to suggest products in e-commerce. They found that this method outperformed traditional CF models and is just one example of research that is done in the field.

1.3 Related Work

Research into RSs has been going on since the mid-1990s (Karimova, 2016), roughly since e-commerce sites started to take off and about a decade after the internet itself was invented. Despite this being a comparatively young and developing field of research, several research reviews and surveys have been conducted that summarize the findings and developments of work on the subject. This section discusses a few of these reviews and how they relate to the analysis conducted here.

The article "Recommender Systems in E-Commerce" from 1999 by Schafer, Konstan, and Riedl, discusses the role of recommender systems in automating mass customization for e-commerce sites. Main inspiration for this paper is the book Mass Customization (Pine, 1993).

The five fundamental methods for achieving mass customization listed in Joe Pine's book can be realized through recommender systems, such as customized service and delivery, quick response, and customizable products. They discuss how the use of recommender systems will increase in the future as businesses focus on the long-term value of customers. However, ethical challenges will arise in balancing recommendations' value to the site and customer.

There are various techniques for implementing recommender systems, and the type chosen will depend on the degree of automation plus persistence desired. The optimal technology for e-commerce sites is likely to be persistent and partially automatic. In contrast, the optimal technology for customers may be fully automatic and entirely self-contained to one customer's individual browsing session.

However, those suggestions were made nearer the beginning of the field. One broad review of the field that is more contemporary is from Alamdari et al. (2020). In this paper, a comprehensive and systematic literature review (SLR) was conducted to examine the state-of-the-art e-commerce recommender systems. The five categories of recommender system algorithms were analyzed: Content-Based Filtering (CBF), Collaborative Filtering (CF), Demographic-Based Filtering (DBF), Hybrid filtering, and Knowledge-Based Filtering (KBF). The authors reviewed papers identified in search of the traditional methods' challenges and significant issues observed.

They also compared the selected papers based on which metrics they had focused on, such as accuracy, performance, scalability, security, and response time. The results showed that the writers of the papers they had selected for analysis focused mainly on enhancing accuracy and a shift towards novel approaches such as data and web mining algorithms. Alamdari et al. highlighted the lack of attention to response time, diversity/novelty/serendipity of suggestions. Security remains an overlooked issue in this work's findings as well.

All this considered, it was not recommended that these conclusions should be generalized as many articles did not meet the search criteria used for their sample, so they were excluded from the analysis. They also stated that the search technique used could not be considered exhaustive either, as articles sourced from google scholar were included. This is, of course, an engine that does not give complete sets of filterable results. So, while this review covered the developments in the literature from years 2008 until 2019, they did not intend for it to be a definitive source on all trends in the research at the time.

The study by Xiao and Benbasat (2014) aimed to review empirical papers on e-commerce product recommendation agents published from 2007 to 2012. 34 papers were selected and analyzed, focusing on various topics such as recommendation agent type, preference-elicitation, explanation, social aspects of recommendation agents, user perception variables, and modifying factors. The authors presented a refreshed conceptual model for recommendation agents, focusing mainly on user evaluation factors such as social presence, perceived usefulness, trust, satisfaction, and perceived ease of use. The use of the conceptual model was a key aspect of the research. That being their updated version of MISQ, which was first published in 2007.

Another study Lu et al. (2015) conducted a review of the application developments of recommendation systems (RSs) in eight fields: e-government, e-business, e-commerce/e-shopping, e-library, e-learning, e-tourism, e-resource services, and e-group activities. They analyzed RS techniques in regard to recommendation methods, RS software, real-world application domains, and application platforms. The authors sourced papers published between 2013 and 2015. This review provides valuable insight into the content and categorization of recommendation methods. They found that collaborative filtering was the most widely used recommendation method across all eight fields. Hybrid methods, combining multiple recommendation techniques, were also identified as a popular approach in some papers.

Karimova (2016), which reviewed 60 e-commerce RS technique reviews in journals and conference proceedings published between 2014 and 2016. She examined the developments of e-commerce recommender systems from the viewpoint of e-commerce providers or e-vendors. The main finding was that the traditional RS techniques of CF and hybrid methods played a dominant role in e-commerce and that researchers in the field have been focusing on improving personalized recommendations with high accuracy and decreasing computational complexity.

These papers provide an empirical backdrop and theoretical basis on which research into RSs has developed since their inception, with clear patterns emerging about the relative popularity of the various models and techniques used. In all the prior analyses used, CF or hybrid models were the dominant technique employed. This observation is corroborated in the Findings section of this thesis.

1.4 Types of recommender systems

It is important to define and summarize the main models of recommender systems that exist before discussing the empirical research performed. Different types of recommender systems are summarized in Figure 1

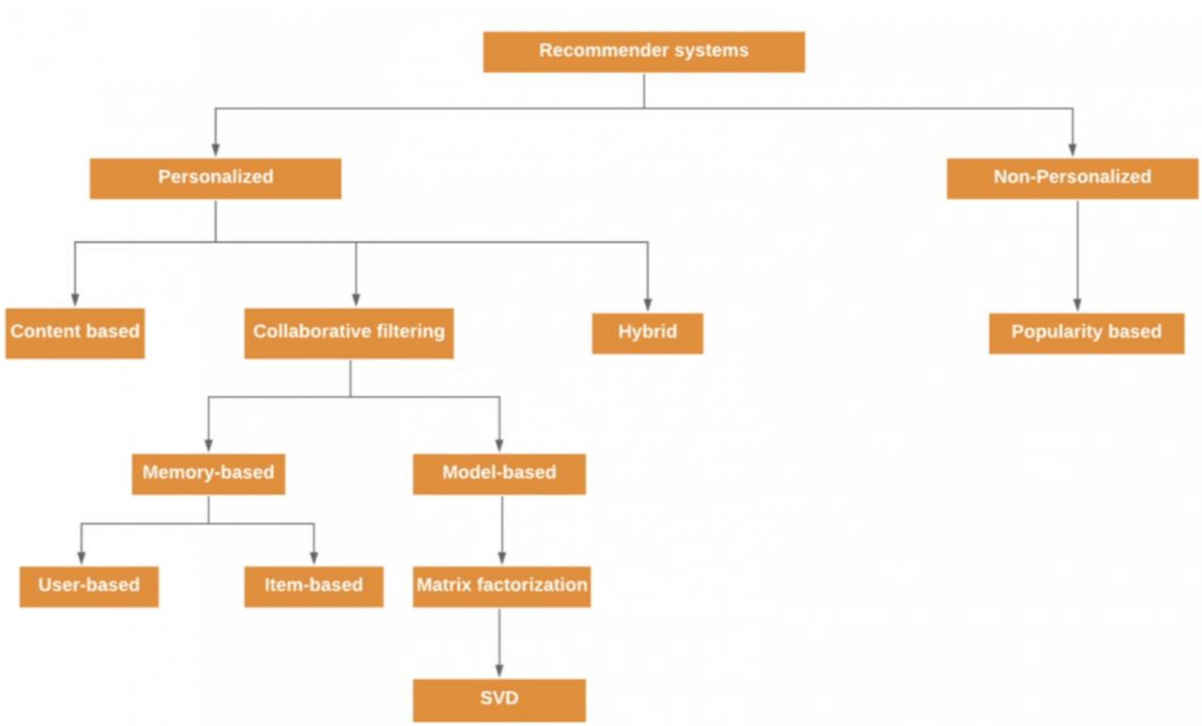

Figure 1: Types of recommender systems (Đorđević,2021)

1.4.1 Content-based filtering

People tend to selectively read specific pages or sections of a newspaper that interest them rather than reading all the pages. Their eyes are exposed to all the information in the newspaper, but their mind naturally filters the content and focuses on certain parts on the newspaper to read (Tewari & Barman, 2018). Details about the item and a profile of the user's preferences serve as the foundation for content-based recommendation (CBRs) systems. The user's buying history is analyzed. For instance, it is presumed that if a user has previously read a book by one author or purchased a product from a particular brand, they prefer that author or brand and are likely to do so again in the future. Assume that Tatiana really likes crime books and her favorite one is by her favorite author is Agatha Christie. If Tatiana reads the Murder on The Orient Express, then her suggested book will be Death on the Nile, which is also a crime book written by Agatha Christie.

Some limitations of content-based recommender systems include (Alamdari et al., 2020):

- Lack of diversity: Recommendations are limited to items that are similar to what the user has already liked, leading to limited diversity in the recommendations.
- Cold start problem: Cold start problem is a challenge in recommender systems where it may not be able to make recommendations for new users or items considering the limited information available it has about customers that have never used the site before, or items that have not been linked to other categories yet.
- Difficulty in capturing context: The system relies on item features and user preferences, which may not fully capture the context and nuances of a recommendation scenario.
- Scalability challenge: As the number of items increases, the system can become computationally expensive and difficult to scale because every time something new is added like a product it needs to be tagged and defined.
- Limited personalization: The system only considers the individual user's preferences, ignoring the preferences of other users that could lead to more diverse recommendations.

1.4.2 Collaborative filtering

Collaborative Filtering (CF) is a method for recommending items to users based on what other users with similar preferences have liked. The recommendation is referred to as collaborative since it is based on the preferences of other users. It was introduced by Dave Goldberg and his colleagues. There are two types of CF: memory-based and model-based (such as Matrix Factorization).

Memory-based CF can be further divided into item-based CF and user-based CF. Item-based CF recommends items based on what other users purchased after or as well as purchasing the same item as the target user ("Users who liked this item also liked…"), while user-based CF recommends items based on the preferences of similar users.

Model-based CF uses algorithms such as Singular Value Decomposition (SVD) to predict the best item for a user based on latent features of user ratings. This form of matrix factorization assists with many of the problems previously discussed, such as processing speed and scalability.

Unfortunately, CF systems suffer from many of the same issues as content-based models, including the Cold start problem and changing user preferences over time.

Another problem is data sparsity. The data sparsity issue arises when a dataset (matrix of user to product ratings) is lacking sufficient information, resulting in many entries missing or being equal to zero. This leads not only to decreased model accuracy but also increased computational costs.

1.4.3 Hybrid filtering

Hybrid recommendation systems instead combine two or more recommendation methods, such as content-based and collaborative filtering. Hybrid RS can overcome challenges like the cold-start problem and boost performance. There are various approaches to creating a hybrid system, including weighted, switching, mixed, feature combination, cascade, feature augmentation, and meta-level methods. These systems often use probabilistic techniques like neural networks, Bayesian networks, clustering or latent features (e.g., SVD). Although hybrid RS provide solutions to many issues faced by individual recommendation systems, they do require more effort and information to implement (Karimova, 2016).

1.5 Evaluating the performance of a Recommender Systems (RS)

With so many different models to compare it is important to have a well-established and agreed upon metrics to measure the quality of a RS model. This is a complex task and requires a variety of metrics. Common metrics include MAE (Mean Absolute Error), MSE (Mean Squared Error), RMSE (Root Mean Squared Error), recall, and evaluating the relevance of recommended items. Four key criteria for the quality of a RS model described as follows (Alamdari et al., 2020):

Accuracy: A higher level of system accuracy results in recommendations with higher quality and less errors, which can improve consumer satisfaction and increase sales in e-commerce. Accuracy is measured along with many different metrics, two most frequently used being recall and precision.

Privacy and Security: Privacy and security are important factors to consider in RSs as they collect personal information. Privacy is always a concern for general public. Additionally, RSs need to protect themselves from malicious attacks.

Scabality: Scalability is the ability of a system to meet the growing demands while still maintaining decent efficiency. A scalable recommender system technique should be able to handle large input data without compromising its performance.

Diversity/serendipity: The diversity and serendipity of recommended items are also important for improving user satisfaction. A higher variety of items in the recommendation list can lead to serendipity, which is the ability of the RS to surprise the user with unexpected but interesting items. Serendipity will keep recommendations from becoming monotonous.

Chapter 2: Methodology

In order to collect papers to use, articles on personalized recommendation on e-commerce websites were searched primarily in the Scopus database, with the later assistance of Google Scholar. All the outcomes were limited to those published in a journal and conference papers written in English. Considering the multidisciplinary nature of the topic, publications from fields different from Psychology, such as Economics, Computer Science, Mathematics and Decision Sciences were included.

To look for articles related to personalized recommendations and recommendation systems on e-commerce websites, 3 primary keywords are selected: “personalized recommendations”, “e-commerce website” and “effectiveness”, combined and queried on the Scopus database ("personalized recommend*" AND "e-commerce website*" AND "effectiveness"). 7 total results were returned.

Although the results were relevant, this query did not return adequate numbers of papers for further analysis, so subsequent query excluding the word “effectiveness” was used (“personalized recommend*" AND "e-commerce website*"), returning 47 results. Of these, 21 that were not already returned in the previous search were deemed to be relevant to the topic.

Papers were excluded based on irrelevance. Those that did not investigate the performance or effectiveness of a RS model were deemed irrelevant, as they were not related to the key research questions being investigated.

A further 13 papers were included from google scholar searches. Finally, 7 articles were removed due to the fact full access was not available. 2 of these were from the Scopus searches and the other 5 were google scholar. In the end there were 34 articles that were eligible to read in full.

At this stage 21 papers were selected for inclusion in the analysis. This did not include any of those found on Google Scholar as they were deemed redundant. However literature reviews and theoretical papers among these 8 were found to be valuable sources of background information.

A diagram depicting the full process of paper selection is shown in Figure 2.

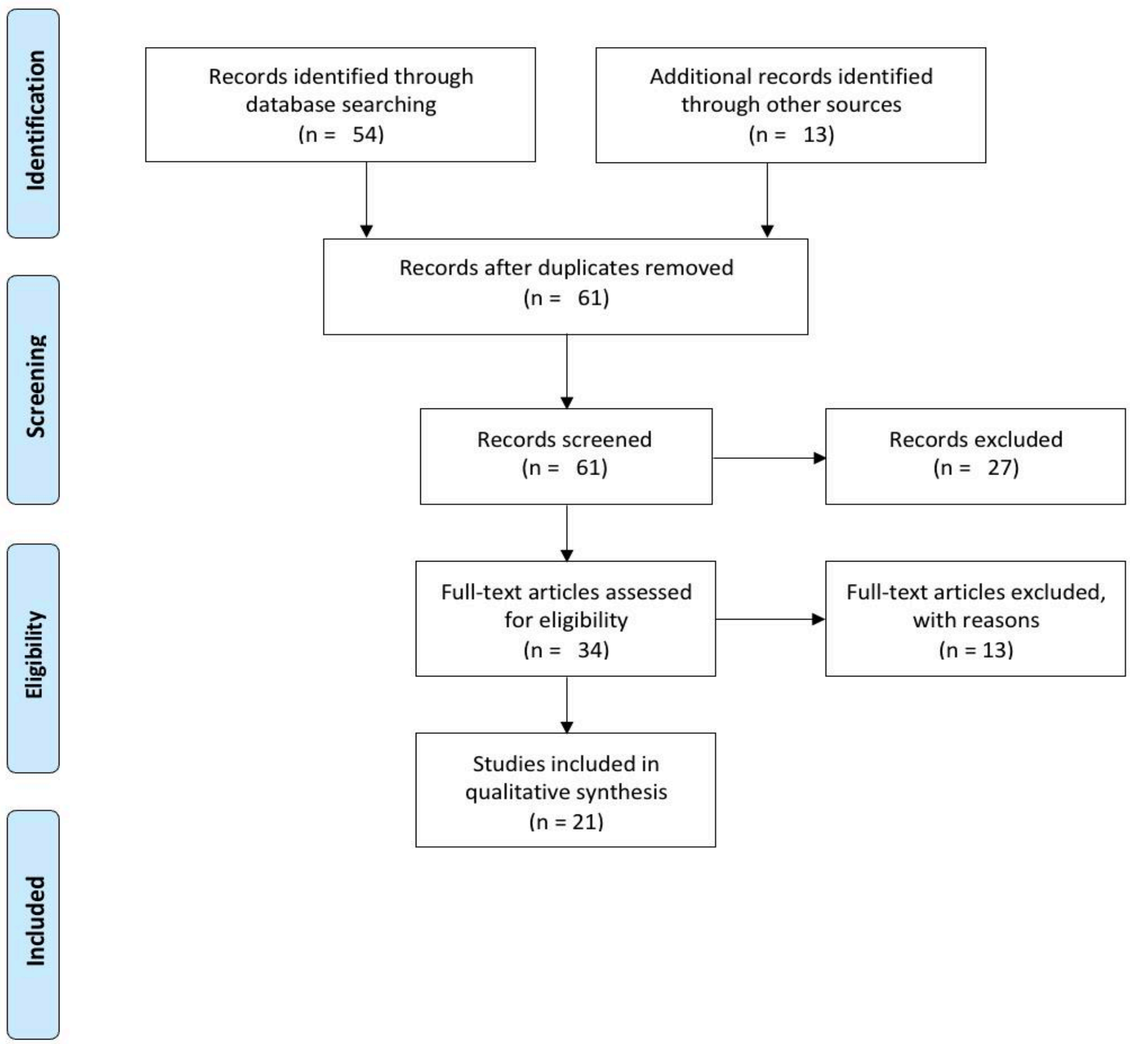

Figure 2: PRISMA Flowchart of paper selection process

Once selected, the 21 papers were reviewed, and relevant information was extracted into an excel spreadsheet for ease of analysis. The following information was specifically recorded:

- Bibliographic info (title, authors, year of publication...)
- Abstract
- Study method (questionnaire, observation, ...)
- Type of devices from which the recommender system is supposed to be used (smart phone, tablet, ...)
- Prototype or commercial (if the application is available for everyone to use it, or a research prototype)
- Content targeted by the recommender system
- length of the usage of the recommender system by the study participants
- type of participants/users (patients or not, age, sex...)
- study hypotheses
- independent variables
- dependent variables and related measurement strategy
- results for each hypothesis
- RQ1: What kind of recommendation technique is used, proposed in this paper?
- RQ2: How effective was the recommendation technique that is used?
- RQ3: What was the problem targeted using that specific recommendation technique?
- RQ4: Based on the results, what can be changed, improved about the new recommendation technique that is used?

As stated in the definitions section (1.4 Types of recommender systems), there are a number of different recommendation techniques that can be used (CF, Hybrid, CB, etc.). And as discussed in the related work section, prior research suggests that CF and Hybrid dominate the field. The answers to RQ1 were used to evaluate if this is the case among the sample reviewed. See 3.1 Distribution of recommendation techniques.

RQ2 addresses how well the models presented performed on the various industry standard metrics of evaluation (accuracy rate, recall, etc.). See 3.2 Effectiveness of recommendation techniques.

The motivation different authors had for their specific contributions and developments of new RSs was varied. The different challenges each author sought to overcome were extracted in the answers to RQ3. See 3.3. Problems targeted.

Of course, no model is perfect, so the answers to RQ4 provided by the authors give a picture of the direction research in the field will be going in the future. See the section 3.4 The future of recommender systems.

Chapter 3: Findings

3.1 Distribution of recommendation techniques

After analyzing the selected 21 papers, some key patterns were observed. The first of which is the distribution of which models were proposed and tested, which relates directly to RQ1.

Out of these 21 papers 10 papers used collaborative filtering (CF) models, 8 papers employed hybrid approaches combining multiple recommendation systems, 1 paper used content-based filtering, 1 paper proposed a novel approach and lastly 1 paper was not applicable. The breakdown is summarized in figure 3.

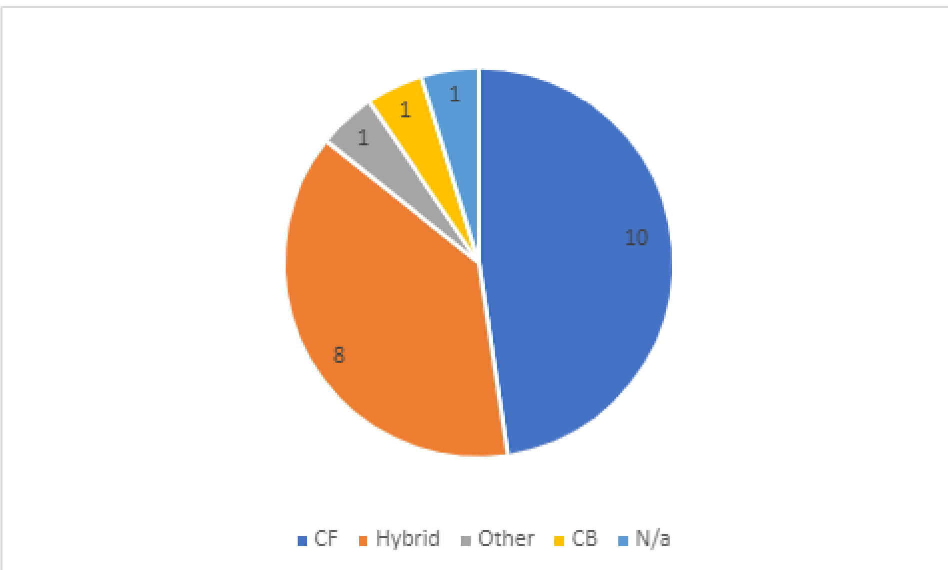

Figure 3: Breakdown of recommender systems used

It is clear from this that CF and hybrid are the dominant models proposed at least by those papers selected for this analysis, in line with prior work discussed in section 1.3 Related Work. The plurality of these being 10 CF models.

Among the 10 CF models used in the analysis, 5 used model-based CF, 4 utilized user-based CF, and 1 applied item-based CF. These findings suggest a diverse range of CF techniques being applied in the field. These findings are summarized in figure 4.

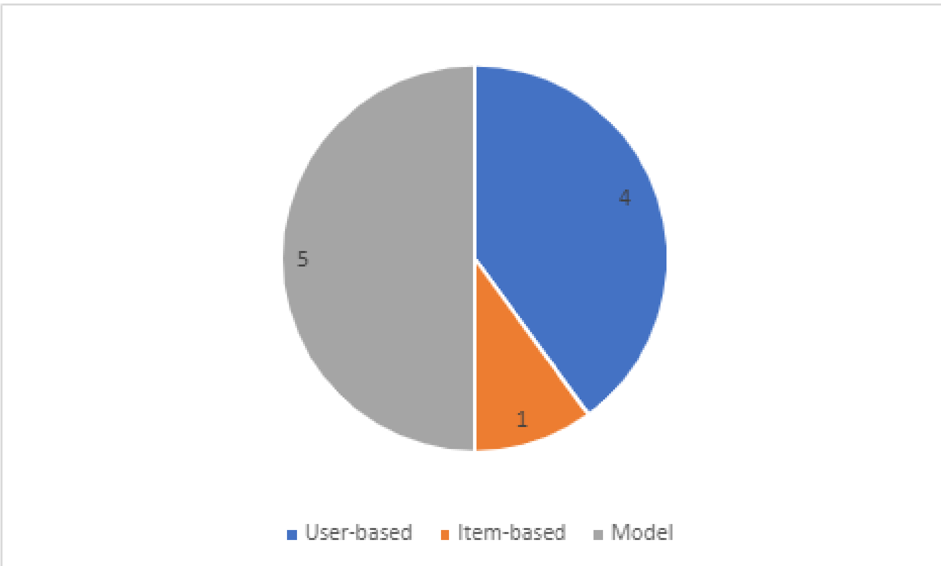

Figure 4: Breakdown of collaborative filtering subtypes

3.2 Effectiveness of recommendation techniques

In regard to RQ2, without exception, the papers selected showed that the model proposed was more successful than those it was compared to on the metrics used (recall, accuracy, computational speed, etc.). This is likely a outcome of the file draw problem, the tendency to publish only successful models.

However, it is still possible to extract comparative findings from the results. For instance, the results from the selected papers indicate that models from the hybrid category consistently demonstrated higher accuracy and recall compared to exclusively user-based CF, item-based CF or CB models, this is in line with theoretical predictions, as they can take the best aspects of the other models (Đorđević, 2021). This highlights the benefits of using a combination of techniques for tackling the product recommendations. With limited models proposed that did not fall into the hybrid or CF categories, it is hard to perform any more direct comparisons between categories.

3.3. Problems targeted

Another key trend investigated was the problems targeted by each model. I.e., what the authors were trying to solve by presenting a new model. The problems identified in the analysis are presented in table 1.

Table 1: Problems addressed by models proposed

Problem	Description	Papers
Cold start	There are new user problem and new item problem. The cold start of new user problem is that at begin the recommendations cannot be provided because of lack of user's historical transaction data, the personal buying behavior cannot be analyzed. The cold start of new item problem is that if an item has not been rated before, it cannot be recommended to users. (Huming & Weili, 2010)	(Huming & Weili, 2010; Jiao & Cao, 2007; Tewari & Barman, 2018; Yu & Sun, 2010; Zhang et al., 2015)
Display best practice	This refers to the process of presenting recommendations	(Sulikowski et al., 2021)

	in an effective and visually appealing manner to users, taking into consideration factors such as diversity and relevance. (Sulikowski et al., 2021)	
Early rater	This refers to a user who rates many items in a short amount of time and may cause the recommender system to over-weight their preferences. (Jiao & Cao, 2007)	(Jiao & Cao, 2007)
Grey sheep	This simply refers to a user who has unique or unpopular tastes that are not well represented in the data, this leads to difficulty in making accurate recommendations for them. (Tewari & Barman, 2018)	(Tewari & Barman, 2018)
Long tail phenomenon	This refers to the phenomenon where many niche items collectively make up a significant portion of total demand and is often encountered in recommender systems. (Pham et al., 2020)	(Pham et al., 2020)

Popularity bias	This refers to the tendency of recommender systems to favor popular items over less popular ones and can result in a lack of diversity in recommendations. (Pham et al., 2020)	(Pham et al., 2020)
Scalability	It is impossible for users to generate recommendations in practice if the users' and item' databases are very big. (Huming & Weili, 2010)	(Ait Hammou et al., 2019; Guo et al., 2016; Huming & Weili, 2010; Stefani et al., 2019; Su & Chen, 2015; Wang et al., 2019; Zheng et al., 2022)
Sparsity	Stated simply, that users do not rate on most items and hence resulted in a sparse user-item matrix. This problem often occurs when there has numerous items but too less rating values or taking place in the initial stage of recommendation system. (Huming & Weili, 2010)	(Ait Hammou et al., 2019; Ding et al., 2019; Huming & Weili, 2010; Sridevi & Rao, 2016)

As can be seen from table 1, the cold start, scalability and sparsity problems are the most pressing issues in the field, as the most papers focus on them. Solutions to these problems are described in the following passages.

The cold start problem is tackled in a variety of ways by the 5 papers that tried. One recurrent solution was including content-based features such as explicit tagging in Jiao & Cao, (2007) or the product feature extraction algorithm that analyses details in embedded reviews used by Zhang et al., (2015). Yu & Sun, (2010) suggested using web mining to overcome insufficient data problems.

Huming & Weili, (2010) implemented a rankboost algorithm to improve performance in low information scenarios whereas Tewari & Barman, (2018) used a dynamic content builder (DCB) to create profiles for every user actively based on their browsing activity.

The rankboost algorithm also helps with the scalability issue but the primary solution to scalability is more efficient clustering algorithms (Wang et al., 2019). Ait Hammou et al., (2019) used the self-adaptation multi-thresholding mechanism which allowed automatic and rapid convergence towards optimal recommendations. This is just one of the many computational algorithms employed to improve performance efficiency (see Guo et al., 2016; Stefani et al., 2019; Su & Chen, 2015; Zheng et al., 2022).

Sridevi & Rao, (2016) addressed the sparsity problem by employing 'expert opinions' into their collaborative filtering model. They did this by finding users that had profiles more concentrated on classes of items. They could then use the recommendation of these 'experts' to make suggestions for users with few ratings, overcoming the sparsity problem.

Other solutions to the problem involved more sophisticated algorithms such as multi-thresholding and gradient descent (Ait Hammou et al., 2019; Ding et al., 2019).

These three challenges to recommendation systems have been addressed through a mix of simple and complex solutions, including content-based features, novel or advanced algorithms, and ‘expert’ opinions. This diverse array of approaches shows the complexity of the topic and exemplifies how it can be developed in the future.

3.4 The future of recommender systems

Most of the papers included in the analysis were obviously imperfect and suggested ways in which research could be continued, either by themselves or for other authors to build off. Based on these recommendations, it is possible to build an idea of the future of recommender system research, and the trends that might be expected to be seen.

In recent years, several studies have been conducted to investigate the potential of various algorithms and models for use in recommender systems. One of the more original of these studies is "Buy It Again: Modeling Repeat Purchase Recommendations" (Bhagat et al., 2018), which proposed a new method for modeling repeat purchases and recommendations. This is an aspect of recommendations that is often neglected, with the focus mainly on just recommending products that a customer may like with no regard for recurrent patterns or consumable products.

Another pioneering study, "CFRS: A Trends-Driven Collaborative Fashion Recommendation System" (Stefani et al., 2019), aimed to develop a new recommendation system that takes into account fashion trends and utilizes customer data from a fashion online shop. This prevents the recommendations from becoming stale and out of date, keeping up with contemporary trends and preference.

These two papers both look at customer loyalty and what will keep them purchasing, but from different angles. Bhagat et al. looked at the best way to encourage repeat purchases and felt the best way to improve that would be to look into richer behavioral data, I.e., how shoppers interact with widgets on the site.

On the other hand, Stefani et al., planned to investigate more features of products that could better predict their “trendiness”. In this way both fresh and relevant suggestions can be made, thus encouraging customers to return.

The future of recommender systems holds much promise as researchers continue to investigate new methods and approaches to enhance the accuracy and effectiveness of these systems. For example, in "A Method for Discovering Clusters of e-Commerce Interest Patterns Using Click-Stream Data" (Su & Chen, 2015), a new approach was proposed to discover clusters of e-commerce interest patterns by utilizing the more comprehensive dataset of all user activity on a website, during browsing. This more detail rich source of information can provide more valuable insights, if an algorithm can be produced that interprets it properly. However, this has yet to be tested directly against traditional CF models, so this is an avenue the authors plan to pursue in the future.

In "Group-Buying Recommendation for Social E-Commerce" (Zhang et al., 2020), the authors pioneered research in the specific realm of group purchase scenarios. This opens the door for further elaborations and attempts to understand the specific dynamic, but it will first be necessary to address the issue of data sparsity and conduct a/b tests to more rigorously evaluate the model.

Other studies have focused on improving the scalability or issues with computation that are present in recommendation systems. "FRAIPA version 2: A Fast Recommendation Approach Based on Self-Adaptation and Multi-Thresholding" (Ait Hammou et al., 2019) introduced a self-adaptation and multi-thresholding techniques to vastly improve computational time. This also outperformed contemporary models in terms of accuracy and dealing with the sparsity problem, so it is a very promising innovation for the future of the recommender systems.

The authors plan to further develop and refine the model by introducing content-based features which will alleviate the cold start problem they also plan to consider the properties of complex social network and introduce the capacity to deal with nosy data.

The fact that Zhang et al. (2020) is also considering the value of social networks in their algorithms shows that this is a popular line of future research.

Deep learning models have also been explored for use in recommender systems. In "AICF: Attention-based Item Collaborative Filtering" (Lv et al., 2020), they incorporated neural networks into a traditional item-based CF model allowed for historical items to be weighted more appropriately. They found that this greatly improved performance. To further develop this new AICF model the authors wanted to add a fully connected layer or convolution layer on the item embedding layer to extract more information about the item, modeled higher-order relationships between items, and explored other deep learning models to improve recommendation performance.

There are numerous ways in which recommender systems have been developed, and there is still plenty of room for improvements in the future. Mainly it seems to focus will be on addressing the many problems discussed elsewhere as well as a particular emphasis on cutting edge algorithms to improve computation.

Chapter 4: Conclusion

This work has examined papers in the field of recommendation systems investigating the different algorithms used to make relevant and enticing suggestions to users usually customers of a shop in an e-commerce setting. The papers analyzed were drawn primarily from scopus.com with a few supplementary works taken from Google Scholar. Specific details were extracted and reviewed based on key research questions. Based on the information found, an analysis of the distribution of recommendation models used, the effectiveness of these models, the problems targeted by those models and flaws for future address was conducted.

The results showed that CF and hybrid models are the dominant form of RS used. This is in line with other reviews in the literature (Alamdari et al., 2020; Karimova, 2016). It was also found that these models typically outperformed contemporary and traditional counterparts, potential reasons for this were discussed.

The key problems facing the field (cold-start, scalability, and sparsity) and their solutions were discussed and finally the trends and directions the field is going to move in, going forward. the future of recommender systems is an exciting area of research with a wide range of opportunities for improvement. New algorithms, models, and techniques are being developed and evaluated, and researchers are exploring new ways to incorporate user data and behavior to enhance the accuracy and effectiveness of these systems.

Overall recommender systems are a crucial aspect in e-commerce that provide valuable insight into the preferences and behaviors of people as they go about their day to day and specialized shopping. Understanding the latent features of products and users that allows them to be appropriately grouped in clustering algorithms is a valuable resource, and can will become more so as the field and algorithms continue to advance.

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