International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 4
***Article Received:** 25 January 2023 **Revised:** 12 February 2023 **Accepted:** 30 March 2023*

Personalized E-Commerce Recommendations Using Hybrider Recommender Systems

Vaghani Divyeshkumar
divyeshvaghani96@gmail.com

Chandra Raparla

Raparlamani@gmail.com

Rahul singh

singhrahulbrijesh@gmail.com

Gannon University, 109 University Square, Erie, PA 16541, USA

Abstract

In the rapidly evolving landscape of e-commerce, understanding customer preferences and product features is paramount for enhancing user experience and driving sales. This research presents a comprehensive exploration of hybrid recommender systems, which effectively combine various algorithms to provide personalized product recommendations. By integrating collaborative filtering and content-based filtering methods, we demonstrate how these systems can leverage user behavior and item characteristics to improve recommendation accuracy. The study highlights the challenges of combining different algorithms, emphasizing the importance of careful selection and adjustment to ensure optimal performance. Furthermore, we explore the role of smart technology in understanding customer desires through keyword analysis, moving beyond traditional purchase history methods. Our findings underscore the significance of user modeling processes in content-based filtering, which utilize diverse data-mining techniques to learn about customer preferences from online activities. This research contributes to the ongoing discourse on enhancing the transparency and effectiveness of hybrid recommender systems, addressing the complexities of user trust and data privacy in sensitive domains such as healthcare and finance. Ultimately, this work aims to provide valuable insights for researchers and practitioners seeking to optimize recommendation systems in e-commerce environments.

Keywords: Hybrid Recommender Systems, E-commerce. Collaborative Filtering, Content-Based Filtering, Personalized Recommendations, Machine Learning.

I. INTRODUCTION

Whenever we go to a shopping website like Amazon or a music or video site like Spotify or YouTube, we see new things for sale that we didn't know we wanted until we saw them. When we look at a product or rate something we've bought before, the next time we visit the website, we see products that are similar to what we bought or new ones that other people like us have bought. This is done using recommendation systems that use Machine Learning. These systems learn from what we've done before and guess what we might do next (Choi et al., 2012; Ji et al., 2013). These systems are used by almost all big online stores to bring their customers back. Unlike regular shopping, where a person sells items in person and tells customers about new products, E-Commerce, and recommendation systems have made it easier to buy things and find new products.

The growing amount and complexity of digital data have led to the development of many recommendation systems (Balabanović, 1997; Isinkaye et al., 2015). Recommendation systems help businesses by showing their customers products or services that they are likely to be interested in (Schafer et al., 1999). There are different kinds of recommendation systems, such as collaborative filtering, content-based, and knowledge-based systems. These systems help create personalized suggestions for customers (Burke, 2007). For instance, if someone has shown interest in buying sneakers before, a recommendation system might suggest similar sneakers or other sporty shoes.

However, not all algorithms work well in every situation. They can also be weak because of their built-in limits, which can make them less effective in some cases. These problems, which can be different for each method, usually

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 4
***Article Received:** 25 January 2023 **Revised:** 12 February 2023 **Accepted:** 30 March 2023*

involve issues with not having enough data, starting new projects, and finding it hard to understand what customers like.

To deal with these challenges, combining different methods has become an effective way to use various algorithms together. This helps to fix the problems that each individual algorithm may have (Patel & Dharwa, 2016). Hybridization means combining different algorithms and using various methods to weigh them in order to reduce the weaknesses of each algorithm (Sharma et al., 2019; Ma & Jiang, 2020). It is used in many areas like E-Commerce, streaming videos, music suggestions, social media, and others, often helping business owners succeed (Lu et al., 2015). For example, a hybrid recommender system can find users who are alike using collaborative filtering. Then, suggestions can be improved by looking at the details of the items based on content.

Recommendation systems are important for E-Commerce, helping to boost sales and improve the experience for users (Schafer et al., 1999). For companies like Alibaba, eBay, and Amazon, using a mix of different recommendation methods is a key part of how they do business. This shows how important and effective this strategy can be (Ren et al., 2018; Jannach et al., 2020; Hung & Le Huynh, 2019). These benefits have encouraged business owners to put money into recommendation systems. They have also motivated researchers to do a lot of studies in this area, especially in E-Commerce (Lu et al., 2015). Many research studies look specifically at hybrid recommendation systems (HRS) that are made for or can be used in E-Commerce.

Even though there are many individual studies (Çano & Morisio, 2017), there has not been a thorough research work on personalized e-commerce recommendations using hybrider recommender systems, this is what this research work aims to achieve.

II. BACKGROUND

In this part, we look at the basics of recommendation systems and share some popular algorithms that we will talk about.

2.1 Recommendation Systems

A recommendation system is a tool that suggests products or services to users based on what they have bought before, their interests, and other important information. It is used in many areas like E-Commerce, social media, and video streaming services. (Lu et al., 2015) Its main aim is to make the user experience better by giving personalized suggestions (Konstan & Riedl, 2012). Recommendation systems help online store owners get more visitors to their websites and turn shoppers into buyers (Ding, 2018).

In every industry, recommendation systems are used to suggest things to customers based on what they liked before. There are two parts to the recommendation problem. The ability to guess what a user likes about a product and to make a list of the best products for them. There are three kinds of recommendation systems. One type of system helps make suggestions to users based on what they do. This can be based on what they have rated before or even on their comments. Content-based recommender systems suggest items that are similar to what users liked before. Figure 2 shows the different kinds of recommendation systems. These methods are often used together to fix the problems that each one has on its own.

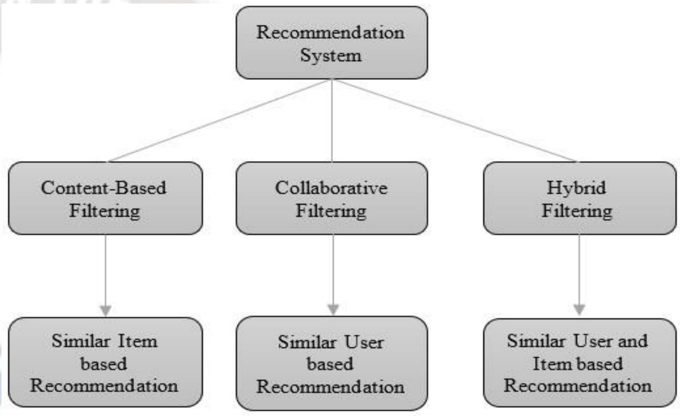

Figure 2: Types of recommendation systems

1) **Collaborative filtering**: This recommendation method looks at what users like, finds users with similar tastes, and suggests items based on how those similar users rated them. You often find this type of recommendation system on websites like Netflix and Amazon (Song, 2021). Collaborative filtering is a method used to collect information based on what the user likes. It involves using different strategies and working together with various people and sources of information. We use team-based filtering methods for large datasets (Jin et al., 2021). Sensing and monitoring data in financial services includes various financial resources and E-Commerce or web apps, focusing mainly on the user's information.

2) **Content-based Recommendation System**: This type of recommendation system uses what users like and the details about items to suggest new things to them. These systems use filters to find items that match what a person likes based on things they liked before and then give suggestions based on that (Gigimol & John, 2016). An example of this is the music app Spotify. When you listen to music on Spotify, it notices what kind of songs you like, like the style, speed, and singers or bands.

3) **Knowledge-based Recommendation System**: This system suggests products to users based on what they need and like. It uses information about the products to meet the

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 4
***Article Received:** 25 January 2023 **Revised:** 12 February 2023 **Accepted:** 30 March 2023*

user's preferences. These kinds of recommendation systems do not need personal user information because their choices do not depend on each person (Gigimol & John, 2016). A great example of this kind of recommendation system is an online learning site like Coursera. They look at the user's education, the classes they have completed, and their job goals, along with other things, to suggest courses that match what they want to achieve (Agarwal et al., 2022).

4) **Typicality-based Recommendation System**: This system finds similar users by looking at how common their interests are within groups. Items are arranged into groups, and users are categorized based on how similar they are. A matrix showing how similar users are to each other is created to find and choose nearby users. The system guesses what rating a user would give to an item by looking at the ratings from similar users for that item. LinkedIn uses a common method to recommend jobs to people (Kumalasari & Susanto, 2020).

For businesses that want to grow, a strong recommendation system has many advantages, like higher sales and a better experience for users. These benefits make it worth investing in a strong architectural recommendation system. There are some key problems facing recommendation systems, such as not having enough data, difficulties with new users, low accuracy, problems with being precise, too much information, and others (Fayyaz et al., 2020; Schedl et al., 2021). Using one regular method to suggest products while adjusting to changing user habits is very difficult. To solve the problems with traditional methods like collaborative filtering and content-based filtering in a complex setting, hybrid recommendation systems (HRS) have been created.

Hybrid Recommendation System

Recommender systems are important for E-Commerce websites. They help give personalized suggestions to improve user experience and increase sales. Traditional recommendation systems, like collaborative filtering and content-based filtering, have some problems that make their recommendations less accurate, less varied, and harder to scale. To fix these issues, hybrid recommendation systems, which use a mix of different methods, have become popular in recent studies. In this review, we will look at the most recent studies on hybrid recommender systems for E-Commerce. We will highlight what has improved and what is currently being researched in this area. The author (Monti, 2021) suggests a new recommendation system for energy-saving mobile devices. This system mixes two methods: one that looks at what similar users like (collaborative filtering) and another that focuses on the specific features of the items (content-based filtering). It also takes into account how the device is used and how much energy it uses to give tailored suggestions for better energy-efficient settings on mobile devices. The hybrid recommender system considers what users like and the situation they're in to suggest things. This helps make mobile devices use less energy.

A hybrid recommendation system (HRS) uses two or more methods to give better, more personalized suggestions that adjust to how customers' preferences change. Combining two or more methods smoothly creates suggestions that are very accurate and can easily adjust to changing customer preferences. This flexible method makes sure that the suggestions given are not only personalized but also closely match the constantly changing actions of users. A hybrid recommendation system has many benefits compared to traditional ones. While we have only talked about a few, they are very important. Here, we talk about the main benefits of using an HRS.

2.2 Benefits and Challenges of Hybrid Recommender Systems in E-Commerce

Benefits of HRS Compared to Old Recommendation Systems

The benefits of hybrid recommender systems in e-commerce are:

Better Recommendation Accuracy: Hybrid recommender systems combine different methods, like collaborative filtering, content-based filtering, and context-aware filtering, to give more accurate and useful recommendations than using just one method alone (Zhang, 2021).

Table 1: A comparison of different Hybrid methods

Methods	Advantages	Disadvantages
Weighted Hybrid	Can be easily changed to fit different recommendation situations. Finding the best weights can be difficult and might need some careful adjusting or trying out different options. It lets you use the best parts of different methods by putting them together.	Depends on correctly guessing weights, which isn't always easy. Needs careful work on choosing and combining features to make sure they work well together and are useful.
Feature Combination	Can understand how different methods work	Might need more computer power and time

	together in complicated ways. Can help make recommendations better by using different types of information together. Might not effectively show how different methods work together or influence each other.	to work with the combined features. It might not always improve performance if the different methods don't work well together or if they add confusion or extra information.
Cascade	Lets you use the results from one method to help improve the suggestions from another method. Can help make recommendations more accurate and relevant, one step at a time. Can be easily updated to add more methods or to deal with complicated recommendation situations.	You need to choose and arrange the methods carefully in the series to make sure they work well together. This may add extra work and time for processing because each step in the process needs to be done one after another.

Better Variety and Chance Surprises: Hybrid recommendation systems can provide a wider range of suggestions by using different methods that consider various user likes and item features. This can lead to a wider variety of surprising suggestions, showing users new and unexpected things. It helps prevent the filter bubble effect, which happens when users only get recommendations similar to what they liked before. (Ricci, 2015)

Hybrid recommender systems use different methods together to fix the problems of each method alone and offer better, personalized suggestions to users.

Strong against Little Data and New Users: Hybrid recommender systems can handle challenges like having little data and new users better, which are common issues in E-Commerce recommendations. Hybrid systems use different methods together to deal with the problem of not having enough data (Son et al., 2018). This means they can still give suggestions, even if there is not much information about some users or items.

Challenges of Hybrid Recommender Systems in E-Commerce

Mixing different recommendation methods in one system can be hard and needs careful planning. Some of the challenges when using different methods together include merging data, combining different algorithms, picking the right algorithm, testing them, and dealing with new situations where there is no prior data.

1) **Combining data**: Different recommendation methods might need various kinds of data, and mixing these can be tricky. For example, collaborative filtering needs data on how users interact with items, while content-based filtering needs information about the items themselves. There can be problems with using data together, getting the data ready to use, and making sure the data is good. To fully understand what customers like and the features of products, it is important to combine data from different methods effectively (Sharma & Gera, 2013).

2) **Combining different algorithms can be difficult because they might work under different rules and use different settings**. It's important to choose and adjust the algorithms carefully so they can work well together. This can be achieved using methods like weighted averaging, stacking, or hybrid ensemble techniques. The challenge is to figure out the best way to combine the results of each algorithm so that they work well together.

3) **Choosing the right method**: There are many different ways to make recommendations, and it can be hard to pick the best one for a specific problem. It is important to consider things like what kind of data is available, how big the dataset is, and what the goals of the recommendation system are. This means looking at things like what users like, the features of the items, and the situation they are in. Choosing the right algorithm might need methods like machine learning or decision-making models to pick the best one for each recommendation request.

4) **Evaluation**: Checking how well a hybrid system works can be difficult because there might not be one measurement that shows everything about its performance. It is important to choose the right ways to measure success that fit the specific problem.

5) **Cold-start problem**: The cold-start problem happens when there is not enough information about new users or items to give good recommendations. This can still occur in hybrid systems. It is important to think about ways to fix this problem, like using helpful suggestions based on knowledge or including feedback from users. However, it's still hard to make good suggestions when starting from scratch.

Using different recommendation methods together in a hybrid system can greatly enhance how well the

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 4
Article Received: 25 January 2023 Revised: 12 February 2023 Accepted: 30 March 2023

recommendations work. However, careful thinking is needed about the difficulties and factors when bringing together different methods and algorithms.

Problems with Using Recommender Systems in E-Commerce:

Here are the main difficulties when trying to use recommender systems on shopping websites.

Data sparsity: This means that there isn't much information about how users interact with items. Many users have only rated or used a small number of the items available. Data sparsity can make recommender systems work poorly because there may not be enough information about what users like. This makes it hard to give good recommendations (Zhang S. et al., 2021).

Scalability: Scalability is a problem for big E-Commerce websites that have a lot of users, products, and activities happening at the same time. As more data comes in, it takes more computer power to make recommendations. This can make it hard to provide quick recommendations (Chen, W., et al., 2020).

Cold Start: Cold start is when there isn't much or any information available about new users or items in a recommendation system. A cold start can be hard for E-Commerce websites because new products or users don't have enough past information to give good recommendations (Huang Y. et al., 2022).

Privacy and Security: Keeping information private and safe is very important for E-Commerce. This is because users' personal details, like what they like and how they act, can be sensitive. Keeping user data safe and private while using recommendation systems can be difficult. It needs strong protection methods, following privacy laws, and making sure there are no security problems (Yao, J. et al., 2021).

Real-time Recommendations: Giving recommendations in E-Commerce can be difficult because people's preferences change, items may not always be available, and various situations can affect choices. To make sure that the suggestions we give are up-to-date and useful for the e-commerce platform, we need effective computer programs, good data handling, and strong system design (Li et al., 2020). Recent studies have given us information about the problems with not having enough data, handling large amounts of data, starting with no data, privacy and security issues, and making quick recommendations in e-commerce. They also suggest some solutions and ways to deal with these problems.

Challenges of understanding hybrid recommender systems: Understanding how recommendations are made is very important for these systems. It helps users trust the suggestions they receive. Hybrid recommender systems use different methods to suggest things, but they can be hard to understand. Here is a summary of the difficulties in understanding how hybrid recommender systems work:

Black-box Models: Hybrid recommender systems often use complicated machine learning techniques, like deep learning or combined methods, which can be hard to understand. These models can be hard to understand, which makes it tough for users to see how suggestions are made and to trust them (Monti D. et al., 2021).

Model Fusion: Hybrid recommender systems use different methods to suggest items. Mixing these methods can make it harder to understand how the suggestions are made. It can be difficult to understand how different methods are mixed and balanced in the hybrid system because it might use complicated rules or processes (Lu W. et al., 2020).

Feature Combination: Hybrid recommender systems usually mix different types of information, like details about the content and user preference data, to create suggestions. It can be hard to understand how these features work together because it involves creating, choosing, and weighing different features, which can influence the final suggestions (Jamali M. et al., 2021).

Understanding vs. Balance between Understanding and Performance: There might be a balance between how easy it is to understand hybrid recommender systems and how well they work. Easier-to-understand models might not work as well, while more complicated models can perform better but are harder to understand. It is often tricky to find a good balance between making recommendations easy to understand and ensuring they are accurate in hybrid recommendation systems (Adomavicius, G. et al., 2020).

Understanding how things work can be different based on the type of e-commerce platform: For example, in areas like healthcare or finance, being able to understand how decisions are made is very important for following rules and gaining people's trust. But getting clear explanations in these areas can be harder because of specific rules in the field, worries about data privacy, and complicated user choices (Wang F. et al., 2021). These findings highlight the difficulties of understanding how hybrid recommender systems work and suggest possible ways to make these systems easier to understand. Understanding how recommender systems work is a current focus of research. Scientists are always finding new ways to make these systems easier for users to understand and see how they make their suggestions.

Measuring how well hybrid recommender systems work is important to understand their effectiveness and to decide if they should be used in E-Commerce sites.

III. RELATED WORK

The main problem with recommendation systems is figuring out how users will rate and buy items based on predictions. Find users with similar interests by looking at the people they recommend. Manual setups are mainly used for recommendation systems, such as collaborative filtering, content-based filtering, and hybrid methods.

Collaborative filtering algorithms (Al Fararni et al., 2021) work on the idea that users with similar tastes will like new things too. This means they suggest popular items that are believed to match the user's interests. This adds more details about new products that are similar to ones the user has liked before. The main issue is figuring out what the user likes based on their feedback about previous items. Binary classification tasks are done using different methods like support vector machines, K nearest neighbors (K-NN), neural networks, and logistic regression (Baheshti et al., 2020).

A recommendation system for an E-Commerce platform is used here to give personalized suggestions based on what other people have liked. A new behavior record module has been created (Abbasi-Moud et al., 2020). The module has been analyzed, and a recommendation algorithm module is being looked into. A special recommendation system is used to give suggestions to users in a way that works well for everyone. A recommended method can find better matches for users more accurately than other existing methods (Liu & Lee, 2009).

A good way to improve recommendations is to include information from social networks. This is done by gathering users' ratings and their social media connections from a social media site (Yang et al., 2017). Next, to check how well collaborative filtering works, we look at different groups of friends and nearby neighbors together.

A new method is created to improve how well collaborative filtering recommendations work. This is done by combining limited rating data collected from users with a small social trust network among the same group of users. Stereotyping is one of the earliest methods for understanding users and making recommendations. Rich used it for the first time in the Grundy recommendation system, which recommended books. Rich's users had mental shortcuts that helped researchers quickly judge people (Sreedhara et al., 2022). Rich talks about stereotypes, which he calls "facets." These are groups of traits based on very unique features. Grundy assumed that male users in this situation know English very well (Taurus et al., 2017; Walek & Fojtik, 2020), can handle suffering and violence, enjoy suspense and excitement, and do not like stories that are too slow. Grundy then suggested some books. These were carefully organized by their different parts.

One of the most common and widely researched types of recommendations is called content-based filtering (CBF) (Liu & Lee, 2009). The user modeling process, which figures out what users like based on the things they use, is an important part of CBF. Usually, "items" are things that are written, like emails (Garcia-Sánchez et al., 2020) or web pages (Ranjbar Kermany & Alizadeh, 2017). "Interaction" usually happens when people download, buy, create, or label something. A content model is used to show the important parts of an object. Word features, like single words, sentences, or groups of words, are commonly used. Some recommendation systems also look at things other than just text. They consider the way something is written, how it is arranged, and special coding tags called XML tags (Bauman et al., 2017). Users and features are often rated, and usually, only the most important features are used to create a model of an object.

Hybrid recommendation algorithms use both collaborative filtering and content-based filtering together. According to Kanwal et al. (2021), this combination works better than using either method alone. One important exception here can be used in other areas to help make predictions in the recommendation system. Customers can share their likes to add new items when new products are out, helping to boost sales. People are looking into how to find information using this method in different fields, such as online education and E-Commerce (Jin et al., 2022; Adomavicius & Tuzhilin, 2005; Zheng et al., 2022; Huang et al., 2022). The main job is to define what the user wants, what they eat, and what they like. Recommendation systems help make websites and online experiences better by showing users content based on their interests. They also act as tools for communication in many different areas. A personalized view means showing things that match what each user likes in order of importance. Many different artificial intelligence (AI) methods are used, such as machine learning, understanding user behavior, and meeting certain requirements. Suggestions are needed for ADA-boost machine learning algorithms (Liu & Lee, 2010). An Ada-Boost method is used to predict what users liked and did not like in the past (Dai et al., 2020). The comparison is made using strong and adaptable methods to train the classifiers. The results from the Ada-Boost classifier go through a process called k-fold cross-validation. A new method was created to help recommend tourist spots by looking at what users like and providing suggestions just for them (Wu et al., 2019). The reviews collected from social media about travel give a lot of useful information about what people like. Also, all the comments that have been cleaned up and checked for feelings are prepared to find out what tourists like (Wei et al., 2019; Yang et al., 2020). In the same way, the characteristics of these topics are taken from all the collected reviews. We might make detailed profiles for each user and come up with a way to suggest things for groups. Instead of using item preference profiles like in previous studies, this is based on adding up all the group numbers for detailed profiles.

A hybrid method that uses fuzzy multi-criteria collaborative filtering for suggesting movies (Walek & Fojtik, 2020) considers people's personal information and the meanings of items. A way called neuro-fizzy inference is used to understand how each standard relates to the overall ranking. Cosine and Jaccard similarities are used to see how similar people or movies are to each other. They also consider how the number of items people or movies have in common affects the accuracy of the similarity measures. A look at the system that suggests items based on text. Collects information from online sources published between 2010 and 2020 based on existing research. According to the author, this survey mainly shows four parts of text-based recommendation systems (RS) found in previous research. The four parts included are datasets, methods for extracting features, computer techniques, and evaluation metrics. A system that involves human input (Jin et al., 2022) focuses on controlling city traffic using an agent-based design. For this process, a local dispatcher is set up to assign workers to do different tasks whenever "operation on demand" is needed. A daily method for managing traffic at a specific location finds out what is needed (Dhelim et al., 2021; Baral et al., 2019).

A product recommendation system that understands personalities is created by finding Meta paths and looking into what users like (Dhelim et al., 2021). Even if the user's past doesn't show any interest in certain topics or things, the Meta-Interest predicts that the user might still like them and related items. A fuzzy tree structure learning activity method and a learner profile technique help to clearly explain complex learning experiences and the students' profiles. Two ways, fuzzy category trees, and similar measures, are used to understand the meanings of learning activities or what the learner needs. To provide a summary of recommender systems (Adomavicius & Tuzhilin, 2005) and explain the current types of recommendation methods, they are divided into three main categories. These classes focus on the content and work together with a mixed recommendation system. This system uses context information to make suggestions and supports different ratings. It also offers more flexible and less annoying ways to give recommendations. A simple recommendation system that uses matrix factorization (Zheng et al., 2022) helps keep users' information private by using a method called local differential privacy. According to this method, the rating data from regular users is changed to make it less affected by changes. Before sending the sensitive data to the aggregator, some extra random noise is added. Now, the MF algorithm helps predict ratings using scattered data.

A messy but reversible method for changing data, used for keeping information private while finding patterns in data within recommendation systems. Using this method, the RDT parameter results will be made locally, so there is no need to share the results about the recovery method earlier. This method can be used instead of the regular RDT algorithm (Huang et al., 2020) when memory and bandwidth are very important. An e-commerce system has many products available for thousands of visitors (Ma et al., 2017; Sreedhara et al., 2022). This system has several problems, including issues with personalizing content, protecting privacy, and starting up when there's little information available. A semantic recommendation model helps the system give suggestions. The accuracy of recommendations is improving, and they are performing well. Semantic technology includes the preferences that help create important connections based on their different likes. The way meaning is organized works very well for the active node to connect with a node that does not have meaning. Some problems with the current recommendation techniques can be fixed to improve how recommendations work. This will help make recommendation systems more popular in different areas (Wei et al., 2019). U2CMS is a recommendation system that suggests things based on what people like and what similar items share, using a method called Markov chains. U2CMS (Yang et al., 2020) has data about what things are and the order they appear to help figure out how objects are connected. A system is set up for making recommendations based on data, knowledge, and thinking. These are called Recommender Systems (RS) for cognitive recommenders. A cognitive recommender is a smart system that understands what users like and gives them better suggestions. It aims to improve on the weaknesses of current methods.

A new approach called the group recommendation model with two-stage deep learning (GRMTDL) has been created to solve the problem of not having enough interactions between groups and items. This algorithm has two steps: first, learning about how groups are represented (GRL), and second, learning about the preferences of those groups (GPL). Here, two new methods of attention for the recommendation system are proposed. The contextual item attention module collects information about the situation, which helps change the patterns and items to match what the user likes. The multi-head attention method helps to widen the range of choices for users to keep up with changing preferences. Recommendation systems have been used to improve performance because of new deep-learning methods and knowledge graphs (Zhou et al., 2022). Most of the recommendation systems available today work in one direction. A new method called GRMTDL has been developed to address the issues of a few interactions between groups and items. The GRL and GPL stages of this method happen one after the other. This section introduces two advanced attention methods for the recommendation system (Schafer et al., 1999). The design and items change to fit what the user likes because the system collects information about the context. The multi-head attention method helps to understand different user preferences better, especially as they change. When used online, skilled computer programs can figure out what their users like best, leading to very personalized recommendations (Hwang & Park, 2022; Mahmood et al., 2014). It is assumed that the user's behavior has been accurately shown by past data and that it will stay the same in the future.

Jianfeng (2012) suggested a way to recommend products using a method called collaborative filtering. This method focuses on finding customers who have bought and rated similar items as the ones that the target user has bought. The algorithm combines items that similar customers liked and the ratings from other similar users to guess what this user will rate. In user-to-user collaborative filtering, items are recommended based on how similar customers are to each other. It begins by identifying a group of customers who have bought and rated items that are similar to what the target user has purchased.

Schafer et al. (1999) suggested a system that gives recommendations based on people's demographics. This looks at how people have bought things in the past and their personal information to guess how they will shop in the future. The good thing about this method is that it can work for different areas and different kinds of customers. However, looking at how users bought things in the past could cause privacy problems. Not having the old data might cause more problems.

Steven et al. (2010) suggested that a smart system be used to recommend products based on knowledge. Smart technology uses information from processing systems and feedback from customers to suggest products. With this method, we find out what customers want by looking for keywords instead of just checking their purchase history.

Cho et al. (2002) proposed a way to give personal recommendations. This method can improve the effectiveness of the recommendations. The method in this paper uses various data-mining techniques, like web usage mining, decision trees, association rule mining, and product categories. It automatically learns about what customers like and how products are related based on their online activity, which is tracked in something called click-stream or weblogs. It looks at how people buy things and how often they visit stores to suggest products. It prevents bad suggestions by using decision tree ideas. Marketers update the product recommendations using clear information. This method is clear and works well for getting the correct results.

Hwang, et al (2008) researched how to choose Web services in situations where failures can occur. Their goal was to find a group of Web services to use during operation so that they can successfully work together as a combined service. The matching service can be one service or a combination of different services that are registered. This system personalizes websites automatically, making each customer's experience unique based on their background information.

Guia *et al*. (2019) introduced a new way to recommend things, which is called the Ontology-based recommendation system. This method mixes the easy-to-use neighborhood model of collaborative filtering with effective ontology-based recommenders. Ontology is a way to show knowledge using a group of ideas related to a specific area and how those ideas connect to each other.

Shilu *et al*. (2017) introduced a new recommendation system called Clustered Content Boosted Collaborative Filtering (CBCF). This system mixes the best parts of content-based filtering and collaborative filtering by using KNN (k-nearest neighbors). Using grouping makes the results better. The Naive Bayesian algorithm is used to sort data based on ratings, and then a classifier is used to understand a user's profile. The learned profile is used to create a rating. The K-Mean algorithm is used to find groups that are similar by repeatedly adjusting the center of each group. Next, a k-nearest Neighbor (KNN) method is used to find better matches by using weights. A fake user rating is made by mixing the results from both recommendation systems. The fake ratings get better by changing the real user ratings step by step to make the results nicer.

Darvishy *et al.* (2020) suggested a mixed recommendation system for personalized news. This system uses two methods: one that looks at the content of the news articles and another that considers what other people like. A new method called ordered clustering, which does not need supervision, is used with a similarity matrix to group news articles together. The new plan seeks to make news recommendations more accurate by addressing problems that come from dealing with a lot of news articles, improving user profiles, clearly showing the features of news stories, and suggesting a variety of news items. This recommendation system begins by gathering user information using clear methods and keeps that information saved. Collaborative filtering creates a detailed profile for each user over time. Then, it groups similar user profiles together into specific categories. Labels are made for all the news articles using content-based filtering, and similar articles are put into groups. Then, the HYPNER method is used to put the results together. The results are sorted by rating, and we focus on the best X items by removing the ones that scored lower. The new hybrid HYPNER recommendation system gives you a list of suggestions in order of how relevant they are.

Jayathilaka *et al.* (2018) suggested a new recommendation system that uses two methods: content-based (CB) and collaborative filtering (CF). It works by using these methods separately, then combining their results and improving them by giving different importance (weights) to each method. The weights are changed all the time to improve the model

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 4
Article Received: 25 January 2023 Revised: 12 February 2023 Accepted: 30 March 2023

and get better results. It also uses a hidden factor model and a bias hidden factor model to improve the results.

Hidayatullah *et al*. (2018) suggested a mixed recommendation system that uses a special method called the multi-objective ranked Bandits algorithm. The Bandit algorithm is commonly used for scheduling tasks, where each option gives a suggestion based on a certain chance. In this recommendation system, every time a user clicks, it keeps track of that click and uses it to make better recommendations. It does not need any past information to do this. The RS will give a list of ready-made suggestions for users to choose from.

IV. EVOLVING TRENDS AND WHAT THEY MEAN FOR THE FUTURE

Recent improvements in HRS show that accuracy, flexibility, and the use of different algorithms together have gone up. To solve problems like not having enough data and the cold start issue, there's a trend of combining deep learning with older methods like collaborative filtering and content-based filtering. This approach is showing good results. This change means that future HR systems will likely use more advanced AI and machine learning to provide better and more personalized experiences for users. To stay competitive and meet the changing needs of users, these systems will be very important in the fast-changing world of E-Commerce.

In this article, we look through existing research to find the best studies in this field. Our goal is to stay updated on the latest developments in Hybrid Recommendation Systems (HRS) for both academic and practical uses.

FUTURE WORK

Over the years, recommendation systems have been widely used on shopping websites, but they still have problems. These include how to handle large amounts of data, giving suggestions that focus on what consumers want, dealing with users who do not share their identities, and linking recommendations to buying trends. They are used on big websites like Amazon, where millions of products are available. They suggest items to many users right away. The things we check include how quickly recommendations are made, how many requests are being handled at the same time, how many users there are, how many products are available, and the large amount of ratings and reviews. To help with this problem, we use different methods from data mining, such as reducing dimensions and working in parallel. A challenge when trying to grow using data mining methods is that there are not enough ratings available (Wei et al., 2001). The recommendation system is helpful when users haven't given ratings to many of the products. If different groups of people give ratings to different types of products, it is less likely that the products they rate will be the same. This makes it harder to use their ratings to suggest new products to them. Dimensionality reduction methods are used to solve this problem, but they do not work well with very sparse data and need to be adjusted for recommendation systems (Schafer et al., 2001). Having too much data can make the system slow, but not having enough data can also make it hard to give good recommendations.

As we get more information, the ways we use it and the methods we apply need to change, too. Until now, suggestions have been based on one piece of information instead of looking at various kinds of data together. New machine-learning methods are being developed to fix this problem by creating models that use different product characteristics and user details (Schafer et al., 2001). However, there is a big problem with seasonal and temporary data. A snow blower is helpful in winter if someone looks for it, but it does not matter for swimmers. Temporal associations are a new issue that needs more study (Schafer et al., 2001). Many recommendation systems are made for just one person to use, and there aren't many social recommenders. For example, there aren't many systems that suggest movies to see in a theater. We need new methods that consider the different views and likes of different users. Another problem is giving suggestions that the user likes and finds helpful because it can be hard to know if the suggestion was actually helpful. One way to do this is to explain to the user why they got a certain recommendation based on their likes or actions and then get their thoughts on it (Schafer et al., 2001). It is very hard to give suggestions when the user has been looking at and buying things without showing their identity (Regi & Sandra, 2013). A method was suggested to address this issue by looking at how people buy things and trying to guess how likely they are to buy new products (Suh et al., 2004). To study buying habits, we can use the user's weblog along with details like their IP address, cookies, and other session information. This information can help find products the user has looked at before. The chance of buying something is figured out using rules that find connections between products to see what the user might like. However, the problem with this method is that it only lasts for a short time. Someone using a different browser might not see the same recommendations as they would in the same browser. Recommender systems are like virtual salespeople because they only suggest new products but do not really promote them actively. The system should consider the price and value for the user, as well as the company's profits. When recommending new prices by looking at how users act, there are ethical concerns because different users may be charged different prices. It is hard to keep users loyal and trusting when recommendations are made just to increase company profits.

V. CONCLUSION

Recommender systems make it possible for online stores to be tailored to each user and buyer. They help companies learn about their customers and offer tailored experiences, and this leads to happier customers who keep coming back.

They are used by taking different data mining tools and changing them to fit what we need now. Common methods include using association rules, collaborative filtering, content-based filtering, and a mix of both (hybrid filtering).

Recommendations are made based on past purchases that the user has shown interest in. Collaborative filtering helps users find recommendations for products by looking at what other people with similar interests have bought and liked. It also takes into account the user's past ratings and purchases to suggest new products that are similar. Content-based filtering looks at what a user likes and their profile to find products in the database that match their interests and show them those options. Recommendations can be tailored to individuals or be based on what the community prefers, and they can offer many different options. The suggestions are being updated because search history, ratings, and new products are always changing. This also brings many difficulties, such as starting from scratch, dealing with users who do not have profiles, building a recommendation system for multiple users at once, managing different types of data, and keeping up as the amount of data grows.

References

1. Abbasi-Moud, Z., Vahdat-Nejad, H., & Sadri, J. (2021). Tourism recommendation system based on semantic clustering and sentiment analysis. *Expert Systems with Applications*, *167*, 114324.
2. Adomavicius, G., & Tuzhilin, A. (2005). Toward the next generation of recommender systems: A survey of the state-of-the-art and possible extensions. *IEEE transactions on knowledge and data engineering*, *17*(6), 734-749.
3. Adomavicius, G., et al. (2020). Context-Aware R ecommender Systems: A Comprehensive Survey and Analysis of Current Research Challenges. A CM Transactions on Intelligent Systems and Tech nology, 11(4), 1-40.
4. Agarwal, A., Mishra, D. S., & Kolekar, S. V. (2022). Knowledge-based recommendation system using semantic web rules based on Learning styles for MOOCs. *Cogent Engineering*, *9*(1), 2022568.
5. Ahmad Hidayatullah (2018). A recommender system for e-commerce using multi-objective ranked Bandits algorithm, *4th International Conference on Computing, Engineering and Design* (ICCED).
6. Al Fararni, K., Nafis, F., Aghoutane, B., Yahyaouy, A., Riffi, J., & Sabri, A. (2021). Hybrid recommender system for tourism based on big data and AI: A conceptual framework. *Big Data Mining and Analytics*, *4*(1), 47-55.
7. Balabanović, M. (1997, February). An adaptive web page recommendation service. In *Proceedings of the first international conference on Autonomous agents* (pp. 378-385).
8. Baral, R., Iyengar, S. S., Zhu, X., Li, T., & Sniatala, P. (2019). HiRecS: A hierarchical contextual location recommendation system. *IEEE Transactions on Computational Social Systems*, *6*(5), 1020-1037.
9. Bauman, K., Liu, B., & Tuzhilin, A. (2017, August). Aspect based recommendations: Recommending items with the most valuable aspects based on user reviews. In *Proceedings of the 23rd ACM SIGKDD international conference on knowledge discovery and data mining* (pp. 717-725).
10. Beheshti, A., Yakhchi, S., Mousaeirad, S., Ghafari, S. M., Goluguri, S. R., & Edrisi, M. A. (2020). Towards cognitive recommender systems. *Algorithms*, *13*(8), 176.
11. Burke, R. (2007). Hybrid web recommender systems. *The adaptive web: methods and strategies of web personalization*, 377-408.
12. Çano, E., & Morisio, M. (2017). Hybrid recommender systems: A systematic literature review. *Intelligent data analysis*, *21*(6), 1487-1524.
13. Chen, W., et al. (2020). Scalable Collaborative Fi ltering for Recommender Systems: A Review.AC M Computing Surveys, 53(6),1-38
14. Cho, Y. H., Kim, J. K., & Kim, S. H. (2002). A personalized recommender system based on web usage mining and decision tree induction. *Expert systems with Applications*, *23*(3), 329-342.
15. Dai, W., Wang, Y., Ma, J., & Jin, Q. (2020). BTR: a feature-based Bayesian task recommendation scheme for crowdsourcing system. *IEEE Transactions on Computational Social Systems*, *7*(3), 780-789.
16. Darvishy, A., Ibrahim, H., Sidi, F., & Mustapha, A. (2020). HYPNER: a hybrid approach for personalized news recommendation. *Ieee Access*, *8*, 46877-46894.
17. Dhelim, S., Ning, H., Aung, N., Huang, R., & Ma, J. (2020). Personality-aware product recommendation system based on user interests mining and metapath discovery. *IEEE Transactions on Computational Social Systems*, *8*(1), 86-98.
18. Ding, Y. (2018). Post-click conversion rate predictive model on e-commerce recommender system.
19. Fayyaz, Z., Ebrahimian, M., Nawara, D., Ibrahim, A., & Kashef, R. (2020). Recommendation systems: Algorithms, challenges, metrics, and business opportunities. *applied sciences*, *10*(21), 7748.
20. Gigimol, S., & John, S. (2016). A survey on different types of recommendation systems. *International Research Journal of Advanced Engineering and Science*, *1*(4), 111-113.

21. Guia, M., Silva, R. R., & Bernardino, J. (2019). A hybrid ontology-based recommendation system in e-commerce. *Algorithms*, *12*(11), 239.
22. Hu, J., & Zhang, B. (2012). Product recommendation system. *CS224W Project Report*.
23. Huang, Y., et al. (2022). Addressing Cold Start Ch allenges in Recommender Systems: A Survey.Infor mation Processing & Management, 59(1),1-20.
24. Huang, Z., Liu, Y., Zhan, C., Lin, C., Cai, W., & Chen, Y. (2021). A novel group recommendation model with two-stage deep learning. *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, *52*(9), 5853-5864.
25. Hung, P. D., & Le Huynh, D. (2019, February). E-commerce recommendation system using mahout. In *2019 IEEE 4th International Conference on Computer and Communication Systems (ICCCS)* (pp. 86-90). IEEE.
26. Hwang, S. Y., Lim, E. P., Lee, C. H., & Chen, C. H. (2008). Dynamic web service selection for reliable web service composition. *IEEE Transactions on services computing*, *1*(2), 104-116.
27. Hwang, S., & Park, E. (2021). Movie recommendation systems using actor-based matrix computations in South Korea. *IEEE Transactions on Computational Social Systems*, *9*(5), 1387-1393.
28. Isinkaye, F. O., Folajimi, Y. O., & Ojokoh, B. A. (2015). Recommendation systems: Principles, methods and evaluation. *Egyptian informatics journal*, *16*(3), 261-273.
29. Jamali, M., et al. (2021). Hybrid Recommender Sy stems: A Systematic Review. Information Processi ng & Management, 58(4), 1-21.
30. Jannach, D., Kallumadi, S., King, T. H., Luo, W., & Malmasi, S. (2020, July). ECOM'20: The SIGIR 2020 Workshop on eCommerce. In *Proceedings of the 43rd International ACM SIGIR Conference on Research and Development in Information Retrieval* (pp. 2459-2460).
31. Jayathilaka, D. K., Kottage, G. N., Chankuma, K. C., Ganegoda, G. U., & Sandanayake, T. (2018, September). Hybrid Weight Factorization Recommendation System. In *2018 18th International Conference on Advances in ICT for Emerging Regions (ICTer)* (pp. 209-214). IEEE.
32. Ji, H., Li, J., Ren, C., & He, M. (2013, July). Hybrid collaborative filtering model for improved recommendation. In *Proceedings of 2013 IEEE International Conference on Service Operations and Logistics, and Informatics* (pp. 142-145). IEEE.
33. Jin, J., Guo, H., Xu, J., Wang, X., & Wang, F. Y. (2020). An end-to-end recommendation system for urban traffic controls and management under a parallel learning framework. *IEEE Transactions on Intelligent Transportation Systems*, *22*(3), 1616-1626.
34. Jin, J., Rong, D., Pang, Y., Ye, P., Ji, Q., Wang, X., ... & Wang, F. Y. (2022). An agent-based traffic recommendation system: Revisiting and revising urban traffic management strategies. *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, *52*(11), 7289-7301.
35. Kanwal, S., Nawaz, S., Malik, M. K., & Nawaz, Z. (2021). A review of text-based recommendation systems. *IEEE Access*, *9*, 31638-31661.
36. Kermany, N. R., & Alizadeh, S. H. (2017). A hybrid multi-criteria recommender system using ontology and neuro-fuzzy techniques. *Electronic Commerce Research and Applications*, *21*, 50-64.
37. Keunho Choi, Donghee Yoo, Gunwoo Kim, Yongmoo Suh (2012) A hybrid online-product implicit recommendation system: rating-based collaborative filtering and sequential pattern analysis "ScienceDirect".
38. Konstan, J. A., & Riedl, J. (2012). Recommender systems: from algorithms to user experience. *User modeling and user-adapted interaction*, *22*, 101-123.
39. Kumalasari, L. D., & Susanto, A. (2020). Recommendation system of information technology jobs using collaborative filtering method based on LinkedIn skills endorsement. *Sisforma*, *6*(2), 63-72.
40. Li, Y., Zhang, J., Ma, Z., & Zhang, Y. (2020). Clustering analysis in the wireless propagation channel with a variational Gaussian mixture model. *IEEE Transactions on Big Data*, *6*(2), 223-232.
41. Liu, F., & Lee, H. J. (2010). Use of social network information to enhance collaborative filtering performance. *Expert systems with applications*, *37*(7), 4772-4778.
42. Lu, J., Wu, D., Mao, M., Wang, W., & Zhang, G. (2015). Recommender system application developments: a survey. *Decision support systems*, *74*, 12-32.
43. Ma, D., Li, S., Zhang, X., & Wang, H. (2017). Interactive attention networks for aspect-level sentiment classification. *arXiv preprint arXiv:1709.00893*.
44. Ma, M., & Jiang, Y. (2020, December). A meta-level hybrid recommendation method based on user novelty. In *Proceedings of the 3rd International Conference on Information Technologies and Electrical Engineering* (pp. 616-625).
45. Mahmood, M. A., El-Bendary, N., Platoš, J., Hassanien, A. E., & Hefny, H. A. (2014). An Intelligent Multi-agent Recommender System. In *Innovations in Bio-inspired Computing and Applications: Proceedings of the 4th International Conference on Innovations in Bio-Inspired*

Computing and Applications, IBICA 2013, August 22-24, 2013-Ostrava, Czech Republic (pp. 201-213). Springer International Publishing.

46. Monti, D., et al. (2021). Explainable Recommend er Systems: A Survey and New Perspectives. AC M Transactions on Information Systems,39(1),1-3 3.
47. Patel, A. A., & Dharwa, J. N. (2016, November). An integrated hybrid recommendation model using graph database. In *2016 International Conference on ICT in Business Industry & Government (ICTBIG)* (pp. 1-5). IEEE.
48. Regi, A. N., & Sandra, R. (2013). A survey on recommendation techniques in E-Commerce. *International Journal of Engineering Research & Technology*, *2*(2), 1586-1590.
49. Ren, Z., He, X., Yin, D., & de Rijke, M. (2018, June). Information Discovery in E-commerce: Half-day SIGIR 2018 Tutorial. In *The 41st International ACM SIGIR Conference on Research & Development in Information Retrieval* (pp. 1379-1382).
50. Ricci, F., et al. (2015). Recommender Systems Ha ndbook.Springer International Publishing.
51. Rupal J. Shilu, Tejas & P. Patalia (2017). A Hybrid Recommender system in ecommerce using clustered content boosted collaborative filtering. *Journal of information, Knowledge and research in computer engineering*.
52. Schafer, J. B., Konstan, J. A., & Riedl, J. (2001). E-commerce recommendation applications. *Data mining and knowledge discovery*, *5*, 115-153.
53. Schafer, J. B., Konstan, J., & Riedl, J. (1999, November). Recommender systems in e-commerce. In *Proceedings of the 1st ACM conference on Electronic commerce* (pp. 158-166).
54. Schafer, J. B., Konstan, J., & Riedl, J. (1999, November). Recommender systems in e-commerce. In *Proceedings of the 1st ACM conference on Electronic commerce* (pp. 158-166).
55. Schafer, J. B., Konstan, J., & Riedl, J. (1999, November). Recommender systems in e-commerce. In *Proceedings of the 1st ACM conference on Electronic commerce* (pp. 158-166).
56. Schedl, M., Knees, P., McFee, B., & Bogdanov, D. (2021). Music recommendation systems: Techniques, use cases, and challenges. In *Recommender systems handbook* (pp. 927-971). New York, NY: Springer US.
57. Sharma, L., & Gera, A. (2013). A survey of recommendation system: Research challenges. *International Journal of Engineering Trends and Technology (IJETT)*, *4*(5), 1989-1992.
58. Sharma, R., Rani, S., & Tanwar, S. (2019, May). Machine learning algorithms for building recommender systems. In *2019 International Conference on Intelligent Computing and Control Systems (ICCS)* (pp. 785-790). IEEE.
59. Shaya, S. A., Matheson, N., Singarayar, J. A., Kollias, N., & Bloom, J. A. (2010). *U.S. Patent No. 7,809,601*. Washington, DC: U.S. Patent and Trademark Office.
60. Son, J, et al. (2018). Hybrid Recommender System s: Survey and Experiments. Information Processing & Management,54(2),274-300.
61. Song, M. (2021). A comparative study on over-the-tops, netflix & Amazon prime video: based on the success factors of innovation. *International journal of advanced smart convergence*, *10*(1), 62-74.
62. Sreedhara, S. H., Kumar, V., & Salma, S. (2022). Efficient big data clustering using adhoc fuzzy C means and auto-encoder CNN. In *Inventive Computation and Information Technologies: Proceedings of ICICIT 2022* (pp. 353-368). Singapore: Springer Nature Singapore.
63. Suh, E., Lim, S., Hwang, H., & Kim, S. (2004). A prediction model for the purchase probability of anonymous customers to support real time web marketing: a case study. *Expert Systems with Applications*, *27*(2), 245-255.
64. Tarus, J. K., Niu, Z., & Yousif, A. (2017). A hybrid knowledge-based recommender system for e-learning based on ontology and sequential pattern mining. *Future Generation Computer Systems*, *72*, 37-48.
65. Walek, B., & Fojtik, V. (2020). A hybrid recommender system for recommending relevant movies using an expert system. *Expert Systems with Applications*, *158*, 113452.
66. Wang, F., et al. (2021). Interpretability of Machine Learning Models: A Survey of Recent Advances. I EEE Transactions on Big Data, 7(1),1-24.
67. Wei, W., McElroy, C., & Dey, S. (2019). Towards on-demand virtual physical therapist: Machine learning-based patient action understanding, assessment and task recommendation. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, *27*(9), 1824-1835.
68. Wu, D., Lu, J., & Zhang, G. (2015). A fuzzy tree matching-based personalized e-learning recommender system. *IEEE transactions on fuzzy systems*, *23*(6), 2412-2426.
69. Yang, B., Lei, Y., Liu, J., & Li, W. (2016). Social collaborative filtering by trust. *IEEE transactions on pattern analysis and machine intelligence*, *39*(8), 1633-1647.
70. Yang, Y., et al. (2020). Trust-Aware Hybrid Rec ommender Systems: A Survey. IEEE Transaction s on Computational Social Systems,7(5),1169-11 82.
71. Yang, Y., Jang, H. J., & Kim, B. (2020). A hybrid recommender system for sequential

recommendation: combining similarity models with markov chains. *IEEE Access*, *8*, 190136-190146.

72. Yao, J., et al. (2021). Privacy-Preserving Collabo rative Filtering: A Survey. ACM Computing Sur veys, 54(1),1-35.
73. Zhang, S., et al. (2021).Addressing Data Sparsity in Collaborative Filtering-Based Recommender Syste ms: A Survey. ACM Transactions on Management Information Systems, 12(1),1-34.
74. Zhang, Y., Feng, F., He, X., Wei, T., Song, C., Ling, G., & Zhang, Y. (2021, July). Causal intervention for leveraging popularity bias in recommendation. In *Proceedings of the 44th international ACM SIGIR conference on research and development in information retrieval* (pp. 11-20).
75. Zheng, X., Guan, M., Jia, X., Guo, L., & Luo, Y. (2022). A matrix factorization recommendation system-based local differential privacy for protecting users' sensitive data. *IEEE Transactions on Computational Social Systems*, *10*(3), 1189-1198.