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Recommender systems: models, challenges and opportunities

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ABSTRACT

The purpose of this study is to provide a comprehensive overview of the latest developments in the field of recommender systems. In order to provide an overview of the current state of affairs in this sector and highlight the latest developments in recommender systems, the research papers available in this area were analyzed. **The place of recommender** systems in the modern world was defined, their relevance and role in people's daily lives in the modern information environment were highlighted. The advantages of recommender systems and their main properties are considered. **In order to formally** define the concept of recommender systems, a general scheme of recommender systems was provided and a formal task was formulated. **A review of different** types of recommender systems is carried out. It has been determined that personalized recommender systems can be divided into content filtering-based systems, collaborative filtering-based systems, and hybrid recommender systems. For each type of system, the author defines them and reviews the latest relevant research papers on a particular type of recommender system. **The challenges faced** by modern recommender systems are separately considered. It is determined that such challenges include the issue of robustness of recommender systems (the ability of the system to withstand various attacks), the issue of data bias (a set of various data factors that lead to a decrease in the effectiveness of the recommender system), and the issue of fairness, which is related to discrimination against users of recommender systems. **Overall, this study** not only provides a comprehensive explanation of recommender systems, but also provides information to a large number of researchers interested in recommender systems. This goal was achieved by analyzing a wide range of technologies and trends in the service sector, which are areas where recommender systems are used.

Keywords: Recommender system; machine learning; neural networks; deep learning; classification; information filtering system; information system.

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INTRODUCTION, FORMULATION OF THE PROBLEM

Recommender systems (RS) have become an indispensable tool in our daily lives due to their effectiveness in finding and discovering relevant, interesting, and useful objects for us. These systems help us choose music [1], movies [2], and even partners for social interactions [3]. Recommender systems learn to understand our interests and preferences by collecting information both through our own choices and data inputs and by analyzing our activity in the system.

These systems don't just display recommendations; they create individualized experiences for each user. They work to understand our preferences, predict our needs, and tailor content and recommendations to our unique interests.

Recommender systems provide us with personalized access to information and content, helping to improve our experience on various platforms and services. They allow us to efficiently discover new opportunities that meet our individual needs and enhance the quality of our online lives.

Data mining is an integral part of the data domain and is widely used in data and reporting activities. Data mining techniques, such as classification, clustering, and association rule discovery [4], are essential to data science activities and provide important insights and decision-making capabilities.

Recommender systems play a key role in a large number of areas where they help users find and select products or content that meet their individual needs and tastes. These systems use different filtering methods, such as collaborative, content-based, and hybrid, to create effective recommendations [5]. For example, after buying a book on a website, a recommender system can offer the user other books by the same author or in the same genre category.

There are numerous advantages to using recommender systems for businesses. They can help increase revenue by helping to increase the number of sales and optimize product selection for users [6]. In addition, recommender systems increase customer satisfaction by providing personalized recommendations and making it easier for customers to navigate the site. They also contribute to customer retention and loyalty, as users feel that their needs are understood and taken into account. Personalization in recommender systems provides users with an individualized approach, similar to recommendations from friends [7].

This creates a connection between the user and the platform, improves interaction, and increases the efficiency of resource use. In addition, recommender systems help to open up new opportunities for users by expanding their interests and supporting them in their searches. They also provide reports and analytics that help improve business strategies and make informed decisions.

Delivering reports is an integral part of a personalization strategy. Providing customers with accurate and up-to-date reporting allows them to make informed conclusions about their own website and traffic management. These reports open opportunities for product offers that can boost sales, particularly for slow-moving products. Today, the whole world is improving technologies and software for processing large amounts of data that are growing every day [8]. Working with big data requires comparing and combining results between different tables in a database with high performance. Various methods are used for this purpose, such as map reduce[9], hive [10], spark, and others. These methods are becoming key to the further development of recommender systems.

Thus, reporting and working with large amounts of data are important aspects of the effective functioning of recommender systems in the future. These tools can improve system performance and ensure user satisfaction, as well as increase business profitability.

All in all, while recommender systems have been a great success, they still need to be improved and problem-solved to maximize their usefulness and user experience.

Thus, **the purpose of this study** is to analyze the latest achievements and challenges facing recommender systems.

1. RECOMMENDER SYSTEM FRAMEWORK

Recommender systems can be formally defined by the following model: consider the set of all users, denoted as U, and the set of all items that can be recommended, denoted as I. Let a utility function f measure the utility of a particular item i for a user u, i.e. $f: U \times I \rightarrow R$, where R is an ordered set.

Then, for each user $u \in U$, the recommended items $i' \in I$ are those that maximize the utility for this user. In other words, this can be expressed as follows: $\forall u \in U, i'_u = argmax_{i \in I} f(u, i)$.

Recommender systems can be divided into two main categories: personalized and non-personalized [11]. Personalized recommender systems consider the individual history and behavior of the user to provide recommendations, while non-personalized systems provide general recommendations without taking into account the individual interests of the user.

Recommender systems can be used to make predictions and create recommendation lists of the top n choices, where n is an integer [12].

A schematic diagram of a recommender system is shown in Fig. 1. A recommender system collects data from users using additional software, filters this data using recommendation algorithms, and returns recommendations to users by ranking the filtered items.

2. RECOMMENDER SYSTEMS OVERVIEW

The issue of information overload, which may become a challenge for users, is addressed by recommender systems, which play a significant part in the solution development process.

They give a forecast of the category of things that may be of interest to the user, they construct a ranked list of suggestions for each user, and they provide the capability to propose products that are suitable for the user's requirements [13].

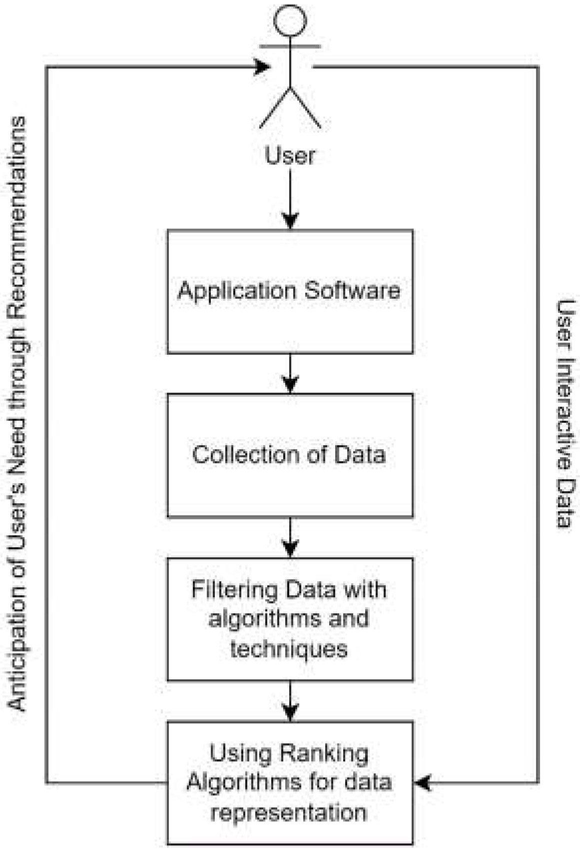

Fig. 1. **Framework of recommender system**
Source: **compiled by the authors**

Numerous services make use of recommender systems in order to provide proactive recommendations of customized items that are tailored to the needs of the customer. In order to do this, they use a variety of recommendation filtering models and data mining approaches [14].

Within the scope of this paper, we examined several data mining strategies that are used in recommendation models for recommender systems and assessed the efficacy of these strategies based on research articles. Fig. 2 is a table that provides a summary of the many recommender models that were used in research papers. An overview of the overall progression of the examination of recommendation models and recommendation approaches is shown in the chart that can be seen in Fig 3.

2.1. Content-based filtering

There have been many different models of information filtering that have evolved since 1992, beginning with the study that was conducted by Loeb et al [15]. One of these models is called content-based filtering, and it is used to propose things to consumers that have qualities that are

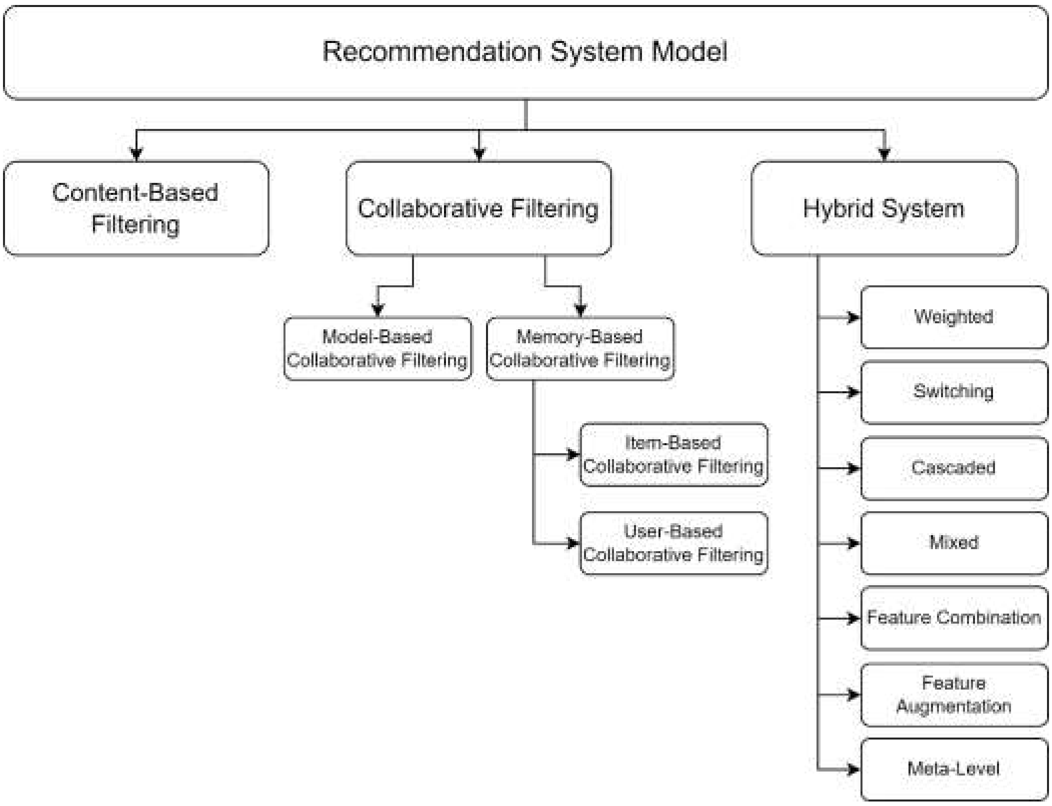

Fig. 2. **Overview of recommendation models**
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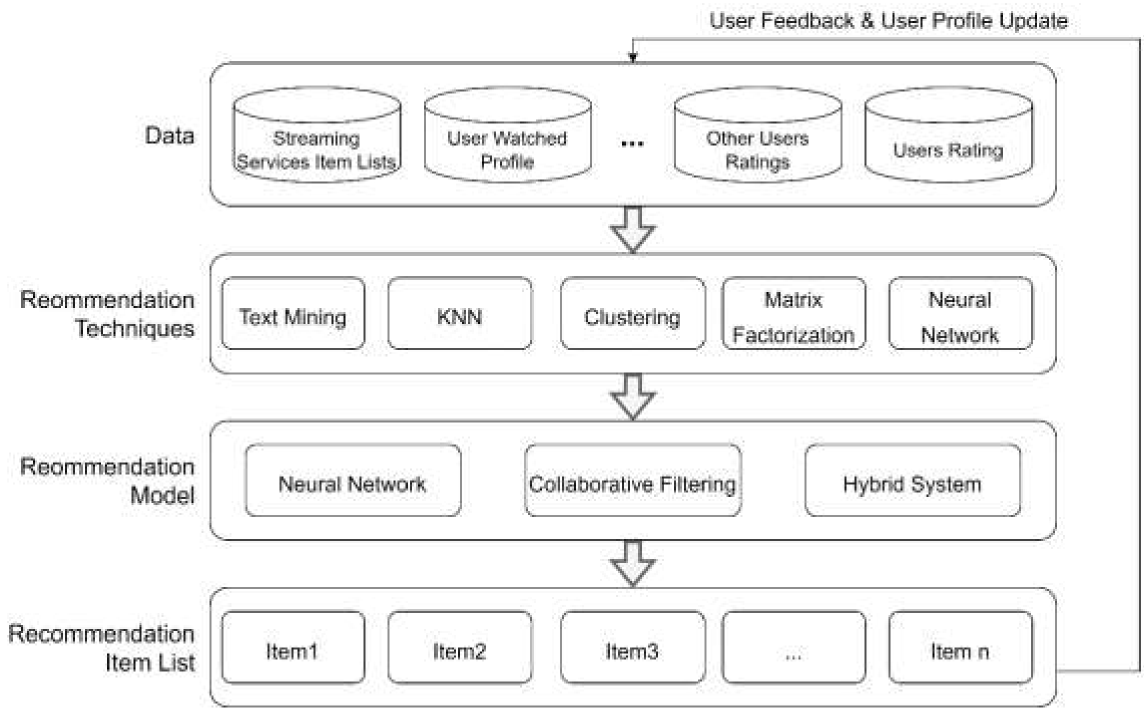

Fig. 3. **Overall flow of recommendation models and recommendation techniques**
Source: **compiled by the authors**

comparable to those that already exist in their collection. The suggestions that are generated by this approach are derived from the information that is gathered about the characteristics of the goods. Generally speaking, this is a rather straightforward method that was used in the early stages of recommender systems.

On the other hand, it is important to point out that research carried out by Salter and colleagues [16] has clearly shown the shortcomings of this approach. The only items that are recommended by content-based filtering are those that have attributes that are comparable to those of things that the user has evaluated in the past. Because of this, the algorithm is unable to provide accurate recommendations for new items, and it has restricted access to a wide range of information. For the most part, this approach was used in domains where suggestions were made based on information about the characteristics of objects, such as in the case of educational materials, movies, music, and things sold via online retailers.

For the purpose of information analysis, content-based filtering makes use of a number of different technologies, including semantic analysis, TF-IDF (Term-Frequency Inverse Document Frequency), neural networks, naive Bayes, and support vector machine (SVM) [17]. Several different strategies for content-based filtering have been developed over the course of several years.

The use of content-based filtering alone, on the other hand, has been less popular after the year 2012, when research on hybrid recommender models began to emerge. A great number of recommender systems make use of hybrid techniques, which integrate several methodologies in order to give consumers with suggestions that are both more accurate and wide-ranging.

Although content-based filtering is a significant tool in recommender systems, its limits should be taken into consideration when selecting a strategy to developing a recommender system. In the broader context, content-based filtering is an important mechanism.

2.2. Collaborative filtering

The decade of the 1990s saw the emergence of a model of information filtering known as collaborative filtering, which went on to become an important stage for subsequent research in the area of recommender systems [18, 19]. This strategy seeks to establish a database of user preferences by making use of the ratings that users have provided in order to forecast and propose products that are suitable for the user's tastes [20]. Memory-based collaborative filtering and model-based collaborative filtering are the two primary subtypes that may be distinguished under the more general category of collaborative filtering [21].

Both user-based collaborative filtering and object-based collaborative filtering are subtypes of memory-based collaborative filtering. Memory-based collaborative filtering is separated into two kinds. Comparing commonalities across users is accomplished via user-based collaborative filtering by examining the ratings that users have given to the same things. Based on the ratings of other users who have preferences that are comparable to the user's own, a list of the N best things that are a good fit for the user's preferences is generated. Through the usage of the user's rating history, collaborative filtering based on an object makes predictions about things by utilizing the similarity between individual objects.

The implementation of collaborative memory-based filtering may be accomplished via the use of a variety of techniques, including Pearson correlation, cosine vector similarity, and the closest neighbor approach (KNN) [22, 23]. It has been shown that this strategy is successful in domains where item suggestion is of utmost importance, such as e-commerce, where it helps to reduce the loss of customers and makes sales more successful [24].

On the other hand, collaborative memory-based filtering is not without its drawbacks, including problems with gray sheep, cold start, and sparsity effects. When there is insufficient information to formulate suggestions, an issue known as sparsity arises on the scene [25]. New users are said to have a cold start when they do not have any rating history [26]. “Gray sheep” is a phenomenon that arises when a small number of users have preferences that are comparable to those of a certain person [27].

Clustering, single-variable decomposition (SVD), and principal component analysis (PCA) are some of the approaches that have been used in the development of model-based collaborative filtering models [28]. These models have been created in order to address the constraints noted above. Research has been intensively focused on improving the effectiveness of collaborative filtering in recent times. This includes the improvement of techniques for assessing similarity, the use of customer input, the increase of the quantity of data on user preferences, and other factors [29, 30], [31].

As a consequence of this, collaborative filtering is an essential component of recommender systems, and it is continuously developing and finding applications in a wide range of sectors. However, in order to attain better outcomes, researchers in this field are actively working on finding solutions to the obstacles that occur while employing this technique with the goal of improving the results.

2.3. Hybrid Systems

The hybrid recommender system is a novel technique that was developed with the intention of overcoming the constraints that are associated with both content-based and collaborative filtering approaches. Both of these models are based on the analysis of information about things that are of interest to the user. The first model employs user ratings to produce suggestions, while the second model uses metadata to analyze objects. The hybrid recommender model was developed with the intention of overcoming these constraints and enhancing the overall performance of the system [32].

In accordance with the manner in which filtering models are combined, the hybrid recommender model may be classified into seven distinct types: weighted hybridization, switching hybridization, cascade hybridization, mixed hybridization, combination of features, feature augmentation, and meta-level [33]. In order to increase the accuracy of suggestions and compensate for the absence of rating data, these techniques make it possible to combine several filtering algorithms inside the system (Table 1).

The issue of sparsity, which is one of the most significant challenges in the process of constructing recommender systems, is the primary objective of the study that is being conducted in relation to the hybrid recommender model. A number of approaches are now being developed in order to achieve this objective. Some of these approaches include the utilization of Bayesian probabilistic matrix factorization to enhance taste data [34], the utilization of autoencoders to learn nonlinear user and item activity [35], and the incorporation of different parts of side information together with explicit item evaluations [36]. Every single one of these investigations is geared toward enhancing suggestions and expanding the quantity of data that is already accessible.

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Table 1. **Types of hybrid systems**

Hybrid Method	Description
Weighted Hybridization	It is a technique in which the weight is progressively modified in accordance with the degree to which the user's rating of an item agrees with the evaluation that is anticipated by the recommendation system
Switching Hybridization	A strategy for modifying the application of the recommendation model in accordance with the circumstances
Cascaded Hybridization	After using one of the models of the recommendation system to generate a candidate set that has preferences that are comparable to those of the user, the approach combines the model of the recommendation system that was used earlier with another model in order to arrange the candidate set in the order of things that are most suitable for the user's preferences
Mixed Hybridization	When there are a large number of recommendations being made at the same time, Content-Based Filtering is able to suggest things based on the description of the products without requiring the user to evaluate them. However, there is a difficulty with getting started with it since it is unable to propose new items that have inadequate information. In order to find a solution to this issue, the Mixed Hybridization approach makes suggestions to the user by using the user's previous history data, which is gathered when the recommendation system service is initiated
Feature-Combination	When it comes to highlighted data and example data for items, a collaborative filtering strategy is used, while a content-based filtering model is utilized for augmented data
Feature-Augmentation	A Hybrid approach in which one Recommendation System Model is used to categorize the preference score or item of an item, and the information that is obtained is then included into the subsequent Recommendation System Model
Meta-Level	A technique that involves using the full model of one recommendation system as the data that is used to populate the model of another recommendation system. The user's preferences are condensed and articulated via the usage of Meta-Level, which makes it simpler to run the Collaborative Mechanism in comparison to the situation in which raw rating data are utilized as single-input data

Source: **compiled by the authors**

A hybrid recommender model is an essential step in the development of recommender systems.

It helps to overcome several challenges related with the limits and drawbacks of other filtering models. In general, the hybrid recommender model is an important step.

3. RECOMMENDER SYSTEMS ISSUES

Despite the fact that recommender systems (RS) have achieved a great deal of success and broad acceptance, they are confronted with a great deal of difficulty that has to be addressed in order to enhance their functionality and usefulness.

When it comes to RSs, the three most significant issues they encounter are dependability, data bias, and fairness.

The capacity of an RS to survive assaults from malicious actors and to continue to function effectively even in the face of such circumstances is what constitutes its dependability [37].

It is possible for attacks to take many forms, such as the modification of data, model parameters, or even the recommendations that are generated. Consequently, establishing the robustness of an RS is the most important factor in determining its dependability and security.

The term “data bias” refers to the possibility that the training data may provide an erroneous representation of the preferences of the users, which might result in suggestions that are not accurate [38].

This kind of prejudice involves a variety of different types of bias, such as exposure bias, selection bias, and popularity bias. It is essential to take into consideration these issues and devise strategies to address them in order to make improvements to MS.

The term "fairness" refers to the fact that the results of the RS guidelines have to be founded on the principles of impartiality and fairness.

One of the requirements for user-based fairness is that suggestions must not be relied on sensitive user characteristics that may potentially lead to discrimination [39].

The term "object-based fairness" refers to the expectation that the RS will make every effort to ensure that identical products that fall under the same category are suggested in an equitable manner.

3.1. Robustness issue

In recent years, attacks against recommender systems have emerged as a common way for evaluating the dependability and security of these systems. These assaults are now being extensively studied by researchers, who are also working to create strategies to identify and guard against them [40].

The term "data perturbation" refers to the method by which attackers may alter the values of individual pixels in pictures or text in natural language processing systems. Natural language processing allows for the representation of items or people as embeddings, which provides attackers with an increased number of options to launch attacks [41].

There are two types of assaults: black box attacks and white box attacks. White box attacks are based on the assumption that the attacker is aware of the structure and parameters of the model and use gradient techniques to locate perturbations. Black box attacks are types of attacks in which the attacker does not have access to model knowledge and instead use alternative means to launch an attack, such as DeepFool or model replacement [42].

On the other hand, data poisoning attacks are attacks in which an attacker injects bogus users and ratings into a recommender system in order to change the suggestions that are generated. The purpose of these assaults is to alter the data that is stored in the system in order to exert influence on the recommendations.

When it comes to attacks, there are two categories: targeted and non-targeted. The purpose of targeted attacks is to trick the system into believing that it belongs to a certain phony class. These attacks have a defined target class. The objective of non-targeted assaults is to alter the class of a recommender system without having a particular targeted objective in mind [43].

The protection of recommender systems is accomplished by the use of a variety of techniques, such as competitive learning and model distillation. A game is played between an opponent and a model in adversarial learning. In this game, the adversary is attempting to locate a disturbance, while the model is attempting to protect itself from it. The objective function is as follows:

$$\arg\min_{\theta}\max_{\sigma,\|\sigma\|\leq\epsilon} L(\theta+\sigma), \quad (1)$$

where ϵ denotes the upper bound of perturbation; σ refers to proper perturbation, while θ represents model parameters.

In order to make the student model more resistant to assaults, the process of distillation entails transferring information from the instructor model to the student model [44].

The security and dependability of recommender systems should be taken into consideration, and proper security measures should be developed in order to identify and prevent assaults. This is because of all the aforementioned characteristics.

3.2. Data bias issue

Obtaining data on user behavior for recommender systems by observation rather than controlled studies results in variances that cannot be avoided due to the presence of a number of different variables. Ignoring these variances in the design of recommender systems might result in a loss in the efficacy of the models, which will have an impact on the level of happiness and confidence that users have in the system. It is for this reason that the elimination of bias and the enhancement of the dependability of recommender systems have become important study topics in this field [45].

A number of factors, including as popularity bias, selection bias, exposure bias, and position bias, may all contribute to the phenomenon of bias associated with the recommender system. Each of these categories of biases has the potential to severely impact both the performance of the system and the accuracy of the suggestions. The phenomenon known as popularity bias takes place when some products are more influential and engage with people more often than others. Because of this, the recommendation system may give preference to certain popular things, which may result in a

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decrease in the amount of customization and impartiality with which suggestions are made [46].

Selection bias is a phenomenon that arises from the fact that people tend to give either highly positive or very negative ratings to products, while the majority of items get ratings that fall somewhere in the middle. The reliability of ratings and recommendations may be impacted as a result of this.

Due to the limited amount of time that users have and the fact that they are only able to see a portion of the products that are available in the system, exposure bias occurs. Users are unable to see other things, which might result in evaluations and recommendations that are completely different from one another.

The phenomenon known as location bias describes the tendency of users to pick products that are positioned in prominent and visible places, even if these objects do not always satisfy their requirements. Because of this, the ranking of suggestions may be impacted, which may result in discrepancies [47].

The researchers use a variety of methods, including smoothing techniques, calibration of scores, and propensity scores, in order to bring these variances down to a more manageable level. These strategies are designed to enhance the accuracy and fairness of recommender systems, as well as to limit the number of results that are discriminatory. For this reason, it is essential to take into consideration and address these various types of bias in order to guarantee that the suggestions provided to consumers are credible and fair.

3.3. Fairness issue

The concept of fairness in recommender systems is an essential component, particularly with regard to customized suggestions. Both user-based fairness and object-based fairness are significant parts of this topic that may be separated into their own categories [48].

User-based fairness: The primary objective of user-based fairness is to eliminate the possibility of users being discriminated against on the basis of their personal traits or sensitive qualities. Taking this step is essential in order to guarantee that the recommender system does not discriminate against certain user groups. A variety of learning strategies, including meta-learning, confrontational learning, federated learning, reinforcement learning, and others, are used by scholars in order to overcome this problem. In the case of suggestions, for instance, meta-learning algorithms may be of assistance in taking into consideration the personal qualities of users and preventing discrimination based on such features. Additionally, models that are being built that take into consideration contextual aspects in an adaptable manner are being developed in order to increase the accuracy of suggestions, which adds to user-based fairness [49].

The object-based fairness principle is an essential component of fairness that must be implemented in order to guarantee that every item has an equal opportunity of being suggested to users. Object-based fairness is often used to situations like cold start and lengthy tails, which are examples of problems. The resolution of these problems is accomplished by the use of strategies such as adversarial learning, meta-learning approaches, and reinforcement learning. It is possible to prevent bias for popular items and guarantee that all objects are treated on an equal playing field via the use of adversarial learning. Increasing the fairness of suggestions may be accomplished via the use of meta-learning techniques, which can take into consideration the qualities of objects [50].

In general, the problem of fairness in recommender systems is a significant one, and academics are actively working on creating approaches to offer users with suggestions that are fair and objective. A separate strategy is required for each facet of fairness, and it is taken into consideration from a variety of angles in order to reach the greatest possible outcomes.

CONCLUSIONS

There has been an increase in the number of online services and apps as a result of the growth and dissemination of the Internet, smart devices, and social networking services. Therefore, there is a need to build a range of recommender systems that can assist users in quickly obtaining product information and making judgments in light of the fast rise in product information that has occurred as a result of the development of these services. Therefore, recommender systems for a variety of application domains that make use of real-time data from wearable devices and the flow of clicks give superior outcomes in many instances.

A healthcare recommender system, for instance, may make recommendations for outcomes such as diagnosis and treatment; however, these outcomes have a lower degree of affinity than those that are based on clinical data. On the other hand, they are of substantial use as auxiliary information that may give prompt advise for counseling services and quick action. This is because real-time data delivers a more relevant result that reflects the present status of patients.

There has been a substantial amount of advancement in this field over the course of the previous several years, as seen by the many novel techniques and algorithms that have been examined in this study. The expanding quantity of data and processing power, in conjunction with the wide variety of recommender systems and the applications they may be used for, has resulted in the creation of a research environment that is both rich and dynamic. Two of the most significant areas of algorithmic application are the analysis of sentiment and recommender systems.

Over the course of the last twenty years, the research community has changed its attention from recommender systems to sentiment analysis in the field of soft computing. The use of fuzzy logic for aspect-based sentiment analysis or reasoning based on a sentiment knowledge base are examples of the types of research that are anticipated to be conducted in this field.

Overall, the purpose of this research was to present a review of recommender systems that was both complete and up to date in order to have a better understanding of the current situation in such a subject. Because of the wide variety of applications that recommender systems may be used for, as well as the increasing quantity of data and computer resources that are accessible, a research environment that is both rich and dynamic has been established for these systems. The future of recommender systems has a tremendous deal of promise and has the potential to bring about significant advantages for mankind, despite the fact that the area is still confronted with obstacles such as concerns of justice, data bias, and dependability.

Researchers are now examining the potential of ChatGPT, which is based on generative pre-training (GPT) technology, to enhance relevant domains such as recommender systems (RS). This is due to the fact that ChatGPT is currently widely used. It is becoming more common in the area of recommendation systems (RS) to make use of conversational recommender systems, which are able to create user-generated suggestions via dialogue.

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Рев'ю

Рекомендаційні системи: моделі, виклики та можливості

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АНОТАЦІЯ

Метою даного дослідження є надання повного огляду останніх розробок у сфері рекомендаційних систем. Для того, щоб представити огляд поточного стану справ у цьому секторі та висвітлити останні події в розробці рекомендаційних систем, були проаналізовані наукові роботи, які були доступні в цій галузі. **Було визначено місце** рекомендаційних систем в сучасному світі, висвітлена їх актуальність та роль у повсякденному житті людей в сучасному інформаційному середовищі. Розглянуті переваги рекомендаційних систем та їх основні властивості. **З метою формального** визначення поняття рекомендаційних систем було надано загальну схему роботи рекомендаційних систем та здійснено формальну постановку завдання. **Проведений огляд** різних видів рекомендаційних систем. Було визначено, що персоналізовані рекомендаційні системи можна розділити на системи, засновані на фільтрації вмісту, системи, засновані на колаборативній фільтрації та гібридні рекомендаційні системи. Для кожного типу систем було надано їх визначення та розглянуті останні актуальні наукові роботи, присвячені тому чи іншому типу рекомендаційних систем. **Окремо розглянуті виклики**, з якими стикаються сучасні рекомендаційні системи. Визначено, що до таких викликів відноситься питання робастносі рекомендаційних систем (здатності системи протистояти різним атакам), питання зміщення даних (сукупність різних факторів даних, які призводять до зниження ефективності рекомендаційної системи), а також питання справедливості, яке пов'язано з дискримінацією користувачів рекомендаційних систем. **Загалом, це дослідження** не тільки дає вичерпне пояснення рекомендаційних систем, але й надає інформацію значній кількості науковців, які цікавляться рекомендаційними системами. **Ця мета досягнута** шляхом проведення аналізу широкого спектру технологій і тенденцій у сфері послуг, які є сферами, де використовуються рекомендаційні системи.

Ключові слова: Рекомендаційна система; машинне навчання; нейронні мережі; глибоке навчання; класифікація; система фільтрації інформації; інформаційна система

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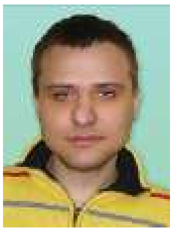

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