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Business Opportunities, Metrics, Challenges, and Algorithms in Recommendation Systems

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ABSTRACT

Recommender systems are commonly used to make recommendations based on a user's preferences. With the ever-increasing amount of information available on the internet, recommender systems have shown to be an effective tool for overcoming information overload. The importance of using recommender systems cannot be emphasised, given its ability to alleviate numerous over-choice issues. There are several different types of recommendation systems, each with its own methodology and concepts. Various applications, such as e-commerce, healthcare, transportation, agriculture, and media, have embraced recommendation systems. This paper examines the present state of recommender system research and suggests future prospects in the field for a variety of applications. This article examines the present state of recommendation systems, including its types, problems, limitations, and business applications. Qualitative evaluation is used to examine the quality of a recommendation system.

Keywords: *Business applications; recommendation systems; machine learning; validation.*

INTRODUCTION

Within the previous few decades, the internet and current web services have grown in popularity, and everyone today has access to a wealth of information [1]. Users may find it difficult to sort through all of this data and extract the most important features. Many online e-commerce companies make product recommendations to their customers and sell millions of things on a single platform. Browsing through all of the options can be overwhelming for a regular user, resulting in information overload. Recommender systems are designed to address the problem of information overload while also personalising the user experience by providing users with accurate, individualised recommendations of items/products based on their preferences [2]. Based on available information, a recommendation system (RS) attempts to forecast whether an item would be valuable to a user [3]. These systems have been rapidly increasing in popularity in recent years, with retailers and e-commerce companies such as eBay and Amazon using them. These businesses amass large amounts of user data and modify RSs to satisfy the demands of both users and businesses [4,5]. In addition to e-commerce and retail, RSs are employed in a variety of other areas, including healthcare, transportation, and agriculture [6–8]. High-quality RSs have a good impact on the users' experience as well as the overall revenue or decision of the business. Many scholars have been interested in RSs in recent years, and many literature studies have been undertaken addressing various RSs' properties, algorithms, and problems [1,9–14]. However, none of these evaluations covered all of RS's characteristics in depth. The authors of [9] concentrated on categorising RSs based on their appearance. [10] provides a survey of RSs who only use social networks, while [11] provides a survey of location-based RSs who only use social networks. RSs are a type of RS. surveyed in [12] from the standpoint of application The algorithms of RSs were the subject of a review in [13], and the properties of RSs were outlined in [14]. We give a detailed guide to RSs in this publication. We examine the challenges associated with contemporary RSs, such as cold start, data sparsity, scalability, and variety, by highlighting several RS categories. We also show how to assess the performance of the RSs using several metrics such as recall, precision, accuracy, the ROC (Receiver operating characteristic) curve, and F-measures. We also discuss the use of RSs in a variety of sectors and domains. The following is the format of this paper: The recommendation categories are presented in Section 2, the main challenges in RSs are highlighted in Section 3, the different evaluation metrics are explained in Section 4, the business adoptions of RSs are introduced in Section 5, and the conclusion and future directions are presented in Section 6.

Recommendation System Categories: Collaborative filtering, content-based, utility-based, demographic-based, knowledge-based, and hybrid-based RSs [15] are the several types of RSs. Content-based and collaborative filtering are the most often used filtering methods. A brief explanation of these categories is provided in this section.

Collabrative Filtering Recommendation Systems: Users' ratings (explicit or implicit) from past data are used to evaluate products in Collaborative Filtering [16]. It operates by creating a database of the user's item preferences. The active user's neighbours with comparable buying preferences will be revealed by mapping them against this database. Item-based filtering and user-based filtering are two types of collaborative filtering approaches [17]. To forecast an item's rating for a specific user, user-based techniques go through two stages. The first stage involves finding users who are similar to the target user. The second stage collects rates from users who are similar to the active user and uses them to generate recommendations. Many collaborative filtering algorithm measures that calculate user similarity have been developed. Mean-squared difference, Pearson correlation, cosine similarity, Spearman correlation, and adjusted cosine similarity are some of the most often used similarity measures in the literature [18,19]. Collaborative filtering is a popular choice for RSs since the embeddings are automatically taught, therefore no domain knowledge is required. The mapping of objects to a sequence of numbers is referred to as embedding in a recommender system. This method of encoding items with learnt vectors is used to train algorithms that detect and extract item relationships and features. Next, collaborative filtering has the benefit of generating models that assist users in discovering new interests. Finally, collaborative filtering is a fantastic place to start for other RSs because it simply needs the rating matrix R to create a factorization model. The rating matrix R is a two-dimensional matrix with n users and m items, with each element rij representing the rating given by user I to item j. Collaborative filtering, while beneficial in many ways, has some drawbacks, such as the cold-start problem, which we will discuss in Section 3.1 of this work.

Content Based Recommended Systems: Content-based techniques seek to create a user profile in order to predict ratings on items that have yet to be seen. Tags and keywords are used in successful content-based techniques. Heuristic functions like the cosine similarity metric are often used to calculate the utility of content-based filtering. In many circumstances, where the values of the characteristics can be easily recovered, content-based filtering can be used. When feature values must be manually entered, content-based filtering is not often used. This operation may be achievable for small datasets, but it is impracticable when hundreds of new products are added everyday. Because the projected recommendations are user-specific, content-based filtering does not require data from other users. As a result, these strategies allow the system to scale up to handle a large number of users. Because this method just analyses the items and user profile for recommendations, content-based filtering is user-independent. Content-based filtering is the polar opposite of collaborative filtering. does not have any problems starting up from a cold start. Before a large number of users offer a rating, new goods or products are suggested. Filtering based on content has a number of disadvantages. To begin with, if there isn't enough information in the material to accurately differentiate products, the recommendation will be inaccurate. These methods necessitate in-depth domain understanding. Second, because they must match the attributes of profiles and items, content-based systems have a limited degree of innovation [18,19].

Demographic-Based Recommendation Systems: Demographic correlation can improve collaborative filtering strategies, as evidenced by a number of quantitative research studies [20]. By categorising individuals based on demographic parameters, demographic RSs can generate suggestions. When the amount of product information is low, demographic RSs are extremely valuable. The goal of demographic RSs is to address and overcome the scalability and cold-start issues.

To obtain suggestions, this system uses user attributes like demographic data (i.e., recommend products based on age, gender, language, and so on) [21]. The main benefit of demographic filtering RSs is that they produce results quickly and easily with only a few observations. These methods also miss out on user ratings, which are crucial in content-based and collaborative filtering algorithms. Filtering approaches based on demographics have a number of drawbacks. For example, given the security and privacy concerns, the complete information collecting for users is unfeasible. Second, demographic filtering is primarily based on user preferences, thus the system is forced to offer the same item to users with similar demographic profiles. Another issue is the difficulty of changing a customer profile as preferences change; this is referred to as the stability vs. plasticity problem.

Utility Based Recommendation Systems: Utility-based RS generates a utility model of each item for the user before making suggestions. This approach constructs multi-attribute users' utility functions and clearly recommends the item with the highest utility based on each item's estimated user-utility [22]. Non-product qualities, like as product availability and vendor reliability, can be factored into utility functions using utility-based RSs. They create utility computations, allowing them to verify both real-time inventory and item features. It allows the user to see the status of the device. Long-term generalisations about users are not held by utility-based systems. Instead, they assess a suggestion based on the user's present needs and accessible options. When the products are not descriptive, the utility-based system has a disadvantage.

Knowledge Based Recommendation Systems: Knowledge-based RS generates recommendations by using explicit knowledge about items and users to develop a knowledge-based criterion [23]. Because its recommendations are independent of the user's ratings, a knowledge-based RS does not require a big amount of data at the start [24]. It makes recommendations based on the user's preferences by assessing products that satisfy the user's requirements. Knowledge-based RSs have been shown to be beneficial for a variety of reasons. They can, for example, avoid the typical ramp-up issue that comes with machine learning techniques to recommendation. In most cases, example systems cannot learn until the user has rated a large number of items. Knowledge-based RSs avoid this problem because their suggestions aren't reliant on user ratings. They also don't need to collect information about a specific user because the recommendations aren't based on the user's preferences. Knowledge-based systems are beneficial as stand-alone systems and as complements to other types of RSs as a result of these factors. The potential knowledge acquisition bottleneck induced by explicitly stating recommended knowledge is one of the key disadvantages of knowledge-based RSs. Knowledge acquisition is the process of gaining knowledge in order to develop the rules and requirements for a knowledge-based system.

Hybrid Based Recommendations: To improve performance, hybrid systems combine two or more strategies. Their main goal is to eliminate the disadvantages of the individuals. Following that, we'll go over a few of the combination tactics. Figurre 1 depicts a variety of hybrid techniques.

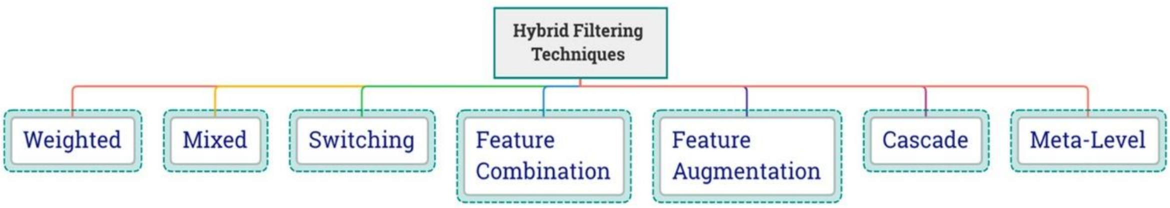

Figure1. *Hybrid Filtering Strategies*

Cascade: The cascade approach is an organised process for forming a strictly hierarchical hybrid, in which a low-priority weak technique cannot cancel, but rather improve, the decisions made by a higher-priority or stronger one. Breaking ties in the score of the stronger and higher priority recommenders is done with the lower priority recommender. On the things that have already been well-differentiated by the first technique, the lower priority technique is not employed. It is also not utilised on the things with low ratings, so they will not be recommended. Because ratings can only be increased, not reversed, the cascade method is resistant to noise in the low priority technique's operation [15–17].

Feature Aumentation: This approach is used to generate an item's rating and then integrate that information into the next recommendation technique's processing. Using the contributing domain's recommendation logic, feature augmentation creates a new feature for each item. When there is a well-developed main recommendation component but a requirement to add additional knowledge features or sources, feature augmentation is used. In contrast to the cascade model, the augmentation hybrid method incorporates the first recommender's output features into the characteristics used by the second [15,23].

Meta-Level: The meta-level hybrid employs an output model that is trained by a recommender and then used as an input by another. This strategy is not the same as feature enhancement. The general characteristics of a learnt model are utilised as input for a second one in a feature augmentation hybrid, whereas the full learned model is used as input in a metalevel hybrid. With raw profile data, the recommender does not work. It's not always easy to create a meta-level hybrid from any given pair of recommenders. Because the contributing recommender must create a model that the actual recommender may utilise as input, not all recommendation approaches can do so. The learnt model indicates a compact representation of the user's preference, which is a benefit of this technique.

Challengesin Recommendation Systems: Because of the organization's changing objectives for using and deploying RSs, measuring their performance is difficult. User happiness is, in general, the most telling indicator. Despite the fact that a heuristic method cannot be used to calculate user happiness, we may still evaluate RSs based on how well they solve common concerns. We present an explanation of the metrics used to test the performance of RSs against major difficulties, such as cold-start, accuracy, data sparsity, scalability, and diversity, in this portion of the review paper.

Cold-Start: Automobiles are the source of the term "cold start." They have trouble starting when the engine is cold, but they have no trouble running once it reaches its optimal temperature. RSs are subject to the same problem. A RS does not operate optimally when there is inadequate information or metadata provided. Cold starts are divided into two categories: product cold starts and user cold starts [25]. When a new product is posted on an e-commerce site for the first time, it goes through a product cold start, which means there are no reviews because there has been no user engagement. If there aren't enough user interactions, the RS won't know when to show the product's relevant ad. When a person establishes an account for the first time and has no product preferences or history on which to base recommendations, this is known as cold-start behaviour. For new or established users, the cold start problem is always present. For example, Tom searches for new televisions on an e-commerce site; he buys one within a week and no longer wants to buy televisions; what happens next? Should the RS now display? New and different items will constantly pique the curiosity of users. When we look at the metrics and approaches for cold-start suggestions, the Bayes classifier comes out on top [26]. In probability and artificial intelligence, Bayesian models are graphical models. Whether content- or collaborative-based, a type of Bayesian reasoning is likely to be used in model-based RSs. The naive Bayes model [25] is the most popular way to use Bayesian models. It has shown to be the most accurate despite its simplicity. Different characteristics are supposed to be mutually independent aspects of the items in the naive Bayes classification [26]. This allows one to estimate the properties of a new object using a set of qualities not available in the training data. To some extent, the cold-start problem is addressed using WALS (weighted alternating least squares) projection and heuristics. If a new item not encountered in training appears in the WALS method, and the system has a few interactions with users, the user's embeddings for this item can be determined quickly without having to retrain the entire model, as shown in Equation 1

$$\min_{u_{i0} \in R^d} \| A_{i0} - u_{i0} V^T \|$$

Equation (1) is equivalent to one iteration in the WALS technique, in which the user's embeddings are kept precise and the system solves for the new item's embedding, and the same process can be repeated for a new user to keep the model up to date. When using heuristics to build embeddings for new objects, the embeddings can be approximated if the system has no interactions. This is achieved by averaging the embeddings of the same category for the object.

DataSparsity: The users' intent to rank a limited number of things leads to data sparsity. Because of a lack of incentives or user knowledge to rate objects, most RSs aggregate the ratings of like users; yet, the reported user–item matrix has empty or unknown ratings (up to 99 percent) [27]. As a result, RSs may make irrational suggestions to those who do not submit feedback or ratings. Assume, for example, that an online bookstore sells two million distinct books to a customer base of X. (active or cold). In that example, each consumer is represented by a 2 million-element integer feature matrix, with the value of each component corresponding to the consumer's rating of a single book. This matrix is known as the consumer-product matrix. As a result, the majority of these matrix entries (up to 99 percent on average) are 0. When comparing any two users for a single item, both entries are quite likely to be 0, resulting in a sparse matrix [29]. Many strategies try to address the problem of data scarcity by predicting users' preferences based on their actions and trusted social relationships. The concept of trust has been employed extensively to improve the resilience of RSs [30]. The belief in the ability of others to deliver accurate ratings is described as trust (explicit and implicit). Many think that the trust chart encoded by Epinions.com can be used to calculate trustworthiness (a website where users can review items). The trust value can be computed by dividing the number of users by the distance between them. This provides a trust-aware RS that uses a web of trust to define how one user can trust another. Every trust declaration is aggregated to form a trust network. Users and trust statements are represented by nodes and directed edges, respectively, in a trust network. The mean error of predicted accuracy has been greatly reduced using these strategies. Many trust-based alternatives have been proposed, with the merging approach [32] receiving special attention. The merge integrates the trusted neighbours of active users in order to improve the overall forecast accuracy of RSs. In particular, the ratings of an active user's trusted neighbour are combined by averaging frequently rated things based on the active user's and trusted neighbor's similarity.

Scalability: Because of the rapid rise of e-commerce companies, scalability issues have become much more prevalent. For large-scale applications, modern RS approaches are necessary to deliver speedy results. RSs can search for a big number of prospective neighbours in real time, but current e-commerce sites require them to look for a higher number. Algorithms also have performance concerns when dealing with users who have a lot of data [32]. For example, if a site contains tens of thousands of data points for one user, finding a suitable neighbour for a specific neighbour might be challenging and time-consuming. Due to the large rise of products or consumers, filtering algorithms that use nearest-neighbor techniques require an increase in computer capacity. For a platform with millions of users, this is impressive. Their major role is to employ a clustering technique to segment users and use each section as a neighbourhood. The neighbourhood of any active user is then determined by peering inside the partition, with the partition serving as the user's neighbourhood. After the neighbourhood selection is complete, traditional filtering methods can be used to generate a prediction [35]. Implementing clustering algorithms has two key advantages. For starters, it reduces the data set's sparsity. Second, it separates the data into smaller segments, which cuts prediction production times dramatically. The scalability issue has also been addressed using singular value decomposition (SVD) [34]. For dimensionality reduction, SVD is used. The SVD algorithm generates a set of uncorrelated eigenvectors. Each customer and product is represented by a different eigenvector. Customers who have rated similar (but not identical) products can be mapped by the same eigenvectors using this method. Predictions can be obtained by calculating the cosine similarity (dot product) between n-pseudo customers and n-pseudo products after the n m rating matrix has been decomposed into SVD component matrices.

Diversity: Depending on the situation, recommendation systems may make suggestions for similar or more different things. Simultaneously, the most accurate results are obtained by recommending items/objects based on the similarity of the user or the objects. This is known as the diversity problem, in which suggestions are made primarily on similarities rather than differences. As a result, the consumer is exposed to a smaller number of things, and highly related niche products may be disregarded. Users can discover objects that they would not have found on their own thanks to the variety of recommendations. One obvious worry is that if an algorithm is solely focused on increasing diversity, accuracy may suffer [36]. Surprisal and personalisation [36] are two criteria that can be used to assess an RS's diversity.The RS's ability to generate unforeseen results is measured using self-information or'surprisal' metrics, which quantify the unexpectedness of an item/object proportional to its global popularity. Inter-user diversity, also known as personalization, is the uniqueness of different users' recommendation lists, and the inter-list distance may simply determine this. To solve diversity issues while retaining item suggestions, the accuracy level must be retained [37]. Overconcentration occurs when the RS is excessively focused on precision. By locating efficient frequent item-sets, the LCM (linear time closed itemset miner) can boost variety [37].

Habituation Effect: Recommendation interfaces are a crucial component of marketing strategy and can be used to distribute marketing content. A variety of factors can be investigated to improve the performance of the interface, including the number of suggestions, images of the recommended item, item descriptions, and layouts [38,39]. When customers are bombarded with a large amount of information, particularly marketing content, the habituation effect sets in, resulting in the phenomena of banner blindness. As a result, even the most perfect algorithmic recommendations may produce false results unless they are displayed to the user in a meaningful way. Marketers typically utilise tactics focused on boosting the visual intensity [40] of presented elements with the use of animations and flashing effects [41] to prevent the banner blindness phenomena. Multi-criteria decision analysis (MCDA) of aspects of graphical interfaces, taking into account visual intensity, attention represented by fixations assessed with eye-tracking, and time required to grab attention after a website is launched, is the best way to lessen the habituation effect.

Evaluation Metrics: Identifying the attributes that create an effective RS and determining how they should be quantified are both necessary steps in evaluating a RS. Recall, precision, accuracy, ROC curves, and F-measure are common measures used to evaluate the performance of a RS.

Recalland Precision: Similar to how RSs select interesting and applicable items from a pool of resources, information retrieval (IR) focuses on collecting relevant documents from a pool. The field of IR is thought to be a good source of tools for RSs, such as measuring metrics. Precision and recall are two important metrics. Precision denotes the proportion of relevant items among all the items that should be recommended to a user, whereas recall denotes the proportion of relevant items among all the items that should be recommended. A user-friendly object is one that appeals to them. A confusion matrix, identical to the one in Table 1, is used to produce precision and recall measures. The confusion matrix depicts the four possible outcomes of any recommendation; if the recommended item is relevant to the user, it will be regarded successful; if it is not, it will be considered unsuccessful.

Table 1. Confusion matrix for a recommender system.

	Successful Recommendation	Not a Successful Recommendation
Recommended	a	b
Not Recommended	c	d

The number of true positive items that are originally recommended and successfully retrieved for recommendations by the RS is represented by "a." The number of things not effectively suggested by the RS, although being designated as recommended, is represented by the variable "b." The number of excluded items recommended by the RS is represented by the variable "c." The genuine negative value "d" refers to the number of items labelled as "not recommended" and retrieved.

A good RS aims to improve both metrics at the same time. For example, it can suggest a wide range of products/items to the consumer, ensuring maximum coverage. The precision would remain the same as the pool's usable product/item ratio.

$$\text{Precision} = \frac{a}{a+b} \tag{2}$$

$$\text{Recall} = \frac{a}{a+c} \tag{3}$$

Accuracy: The decision to choose an RS based on an evaluation metric is complicated and dependent on the demands of the company. Predicted ratings are commonly employed as a system evaluation metric. Because there is no specific way for judging whether a recommendation is accurate or not, determining the correctness of RS is not straightforward [42]. To evaluate an RS's accuracy, split-validation of data for offline comparisons must be used to look for minimal prediction errors. Consider the following scenario Send an RS 80% of a user's buying history data and ask it to predict the rest. In that situation, we can use Equation to calculate the system's accuracy based on genuine recommendations (4).

$$\text{Accuracy} = \frac{\text{Number of success ful recomendations}}{\text{Total number of recommendations}} \tag{4}$$

In many cases, accuracy is utilised to evaluate the metric; for example, the mean square error (RMSE) is used in sAcpoplr.iSncgi. 2a0n20a, l1g0o, xriFtOhmR P, EthERe RroEoVtIEoWf [43]. Alternatives to o9fotfh2e0

The mean average error, normalised mean average error, and mean square error are all referred to as RMSE. RMSE

is the most appropriate because it assesses the inaccuracy of all ratings, regardless of whether theeyy aarree possiittiivvee oorr nneeggaattiivvee. In circumstances where the mistakes cannot be differentiated, the RMSE method is advised. Forecasting a rating difference between 1 and 2 stars, for example, may not be as relevant as predicting a rating difference between 2 and 3 stars.

ROC Curve: Precision/rreeccaallll is replaced by receiver operating characteristic (ROC) analysis. In Figure 22, a precision versus recall curve is illustrated. The better the precision, the lower the lloowerr rreeccaallll vvaalluueess.

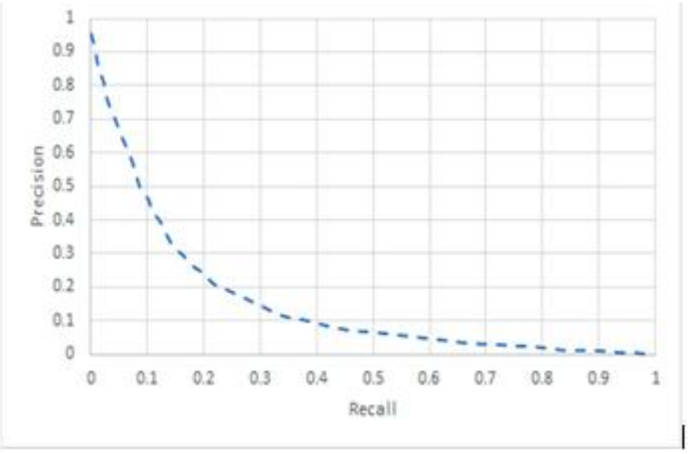

Figure 2. Precision–recall curve.

Figure 3 shows a ROC curve that shows fallout versus recall. The goal of ROC analysis is to extract the relevant items while ignoring the irrelevant ones [44]. This is achieved by maximising the recall (also known as the true positive rate) while minimising the fallout (also known as the false positive rate) (false positive rate). When the threshold is modified, ROC curves are used to visually illustrate the trade-off between recall and precision, which helps us define an item as "to be recommended" or "not to be suggested" [45]. The ROC, accuracy, and recall curves are all optimised in the same way. In Figure 4, the peak of the curves can be pushed towards Precision = 1 and Recall = 1 to optimise the recall and

precision values. An for the remainder of the items ROC curves, like accuracy and recall measurements, presume binary relevance. A successful suggestion or a failed recommendation is assigned to each item.The ROC measure is unaffected by the order of relevant items when this is taken into account. If everything goes well,An optimum ROC curve is obtained when relevant items appear before non-related items [16]. to make use ofWe might examine the area beneath the ROC curve as an assessment of performance [46].ROC curves, like accuracy and recall measurements, presume binary relevance. Items are categorised in one of two ways.whether it'll be a successful or failed recommendation However, by taking this into account,The ROC statistic is unaffected by the sequence of relevant components. If all necessary objects are visible prior to the non-relevant.

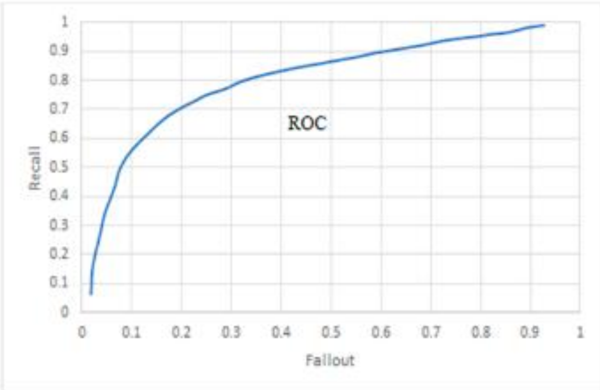

Figure 3. ROC (Receiver operating characteristic) curve for the recall against fallout.

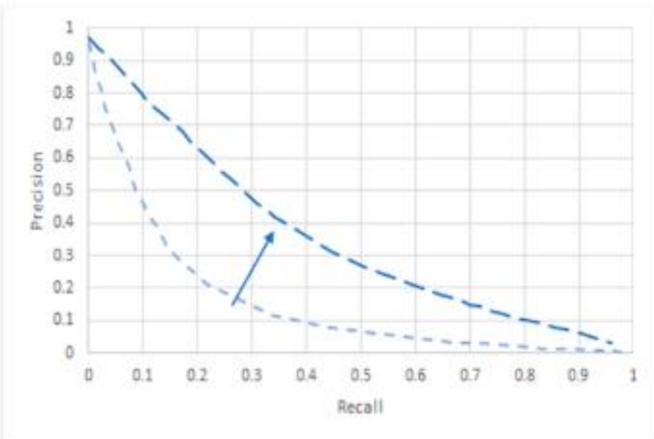

Figure 4. Simultaneous optimization of the precision and recall.

The F-measure, which is generated from precision and recall, demonstrates both recall and precision metrics' behaviour. F-measures may be a more useful statistic than precision and recall, because precision and recall provide different types of information that, when combined, can complete one another. The F-measure will reflect the statistic that outperforms the others. F-measure is the number of tests required to discover the first failure from a probabilistic standpoint [47]. The value of can be changed by altering The consistent mean of precision and recall (F1), where n = 1, is the most popular F-measure. It's worth noting that the highest F-measure value is 1, implying that all predictions are correct recommendations. Understanding ranked retrieval is beneficial. Precision@K denotes the ratio of top-k relevant things, while Recall@K denotes the ratio of top-k relevant items. The assumption behind ranked retrieval is that the user will only look at the top-k results. Because of the upward tendency of the recall value, [48] shows that as the value of k increases, F-measure will likewise increase. Both the F and F1 are calculated in Equations (2) and (3).

$$F_{\beta} = \frac{precision \times recall}{(1-\beta) \times precision + \beta \times recall} \tag{5}$$

$$F_1 = \frac{2 \times precision \times recall}{precision + recall} \tag{6}$$

Business Adoption and Applications: Only a few e-commerce sites used RSs when they first came out. Now, they've evolved into a significant tool that's reshaping the e-commerce landscape. Many of the top e-commerce companies use RSs to help users figure out what they want, reducing the problem of information overload. RSs, on the other hand, aren't just for selling items; they've also been used extensively in the service industry. They can make recommendations in a variety of categories, including location-based information, movies, music, photos, books, and so on. Users can save time and money by using location-based data to locate their way or predict their next position [49]. Furthermore, numerous parties, such as farmers [50], healthcare workers [51], and others, can profit from advice in their decision-making process**.**visitors [52]. Agricultural-items forecasts of RSs developed to offer the best agricultural items (crops) cultivation options to farmers, for example, can aid farmers seeking optimal production plans to prevent loss [50]. RSs play a significant part in the decision-making process in the healthcare industry. Health RSs (HRS) were shown to be used for nutritional, exercise aid, and instructional objectives in research [51]. As a result, in this part, we divide RSs into five categories depending on their commercial adoption: e-commerce, transportation, agricultural, healthcare, and media.

Recommendation Systems ine-Commerce: RSs are used to provide personalised product recommendations to website visitors. They learn from customers and recommend products that are relevant to them. These technologies tailor the experience to the user's preferences. Simply put, a product is recommended in one of three ways: I based on the site's top overall sellers, (ii) based on the customer's demographics, or (iii) based on the customer's previous buy history. A RS personalises a site because it adapts and is unique to each customer. RSs, on the other hand, can help e-commerce businesses sell more in three ways.

• Turning browsers into buyers: People who visit an e-commerce site generally browse the products without purchasing anything, but if the site makes relevant recommendations to them, they are more likely to buy.

• Cross-sell: Recommendation techniques recommend additional products to users in addition to the one they're already purchasing. As a result, the average order size should grow over time.

• Loyalty: In an age when a competitor's website can be accessed with only a few clicks, loyalty is critical. The user-site relationship is strengthened by RSs personalising the site for each user. The greater a

When a consumer utilises a system, the more they train it, the more loyal they become, which improves the quality of their recommendations over time.

Businesses can also utilise RSs as a tool to target customers and provide offers to them. Search engines and advertising businesses, for example, rely on users' behaviour to make effective suggestions. To achieve these goals, several recommendation approaches have been utilised, including statistical methods, raw retrieval, attribute-based methods, user-to-user, and item-to-item correlation techniques. Each step may require multiple sorts of input, such as consumer purchase history or data from user communities, such as item ratings [4]. These techniques frequently result in item predictions, suggestions, or ratings. Amazon.com, Drugstore.com, CDNOW (Compact Discs Now), eBay, Reel.com, and MovieFinder.com are some examples of RSs in e-commerce firms based on [4]. More scholars have taken note of Amazon.com [5].

There are various objections of the collaborative filtering method, such that it is difficult to justify because it simply relies on rating data while ignoring content data [53]. Companies need to choose the best recommendation algorithm as the number of RSs in e-commerce grows; as a result, Geuens et al. [54] provided a methodology for selecting the best collaborative filtering algorithm. They tested the results on two genuine datasets of women's apparel and furnishings, using K-nearest Neighbour (KNN) as a classification approach. A new study [55] uses a deep learning algorithm to create a user interface for an e-commerce website based on user behaviour. approach based on neural networks Their research highlighted the impact of a website's layout on the things that are recommended based on the user's behaviour. Customers' reviews are commonly employed in RSs; a recent survey focuses on sentiment analysis on text reviews in [56]. They've demonstrated that there are three categories of RSs who use text reviews based on terms, subjects, and opinions in general. Despite the fact that RSs have been used in e-commerce for a long time, there are still issues. There's the issue of scalability and data latency, for example. A real-time response is required for an RS on a website with a significant number of users. Also, because not all consumers would rate all of the products, there is a data sparsity issue with rating datasets.

Recommendation Systems in Transportation: With the growing use of GPS-enabled devices, particularly mobile ones, RSs can help in a variety of ways. Because difficulties with information overload are exacerbated while utilising mobile devices. Location-based information systems have benefited from the development of wireless communication services and position detecting technology such as RFID and GPS. In path recommendation, smart transport application of commodities [8,57], tourism industry [58–60], or venue suggestion [61], RSs play a vital role. RS can take users' location data and combine it with public transportation system data to anticipate users' locations and offer the best routes. [49] proposes an algorithm for predicting customers' paths and recommending the optimum bus line. For Android phones, a prototype of their proposed algorithm is also being built.

The data from the users' routes and bus lines are the system's inputs. In smart transportation applications, RSs are used in a variety of ways, including optimization [57] and clustering [8]. For example, in [8], a clustering-based RS is created for commodities transportation. They used principal component analysis (PCA) to minimise data dimensionality and a K-means method to cluster transporters depending on their distance from customers. Based on a user's location and the profile of available transporters, this system offers a suggestion for the best available transporters. Some RSs are designed to assist users, primarily tourists, in locating locations such as the best restaurants. The suggested RS in [59] uses a Bayesian network to construct recommendation score using users' personal information and restaurant features as input.

Because of mobile devices, the advantages of employing an RS in transportation include that it can make recommendations to users regardless of their location or time. Mobile phones have made it possible to obtain useful information about a user's physical location. Despite the fact that mobile devices are rapidly becoming the primary means of accessing information, consumers may have trouble obtaining recommendations on small-screen devices. The more pages a person has to scroll through, the less likely it is that an item will be located. Another issue with using RSs in transportation is data scarcity, as most of these systems rely on user-visited places. Users visit a restricted number of physical sites, resulting in a sparse user–item matrix. Users can also go to places they've never been before. LBSN recommenders differ from typical ones in that they use historical information about the users' location. In addition, social media has made it easier to use LBSN recommenders. They are used to promote a destination, an activity, or a buddy to others. The term "activity" refers to a location's suggestions for fulfilling a user's need for activities such as sports, museums, restaurants, and so on. Some researches looked at users' temporal features for location RSs [63], while others looked at both temporal and geographical attributes [64]. The following are the categories in which RSs are used in transportation:

- Recommendation for a trip
- Recommendation of a path
- Suggesting popular activities in a given area

➢ Recommendation of well-known sites (restaurants)

➢ Recommending transporters is number five (goods transporter, bus lines, drivers).

Recommendation Systems in the e-HealthDomain: For RSs' research, e-health and medical decisions are taken into account, with the goal of assisting medical professionals in making quick and accurate medical decisions. Researchers proposed an RS to recommend medical recommendations to individuals with cardiovascular illness in [6]. They addressed issues with scalability and sparsity in standard collaborative RSs and devised a new strategy using clustering and sub-clustering methods. For clustering, the authors employed k-means, and they assessed their model using precision, recall, and MAE (Mean Absolute Error). In [65], a weighted hybrid recommendation filtering approach was used in conjunction with an autonomic evaluation of patients' requirements to provide tailored mental health therapies. To create user profiles, they used the self-questionnaire method. An order RS for clinics was proposed in [66]. The system makes predictions. The authors attempted to improve order effectiveness by analysing data from five outpatient clinics. In [67], the researchers developed an RS that offers standard treatment strategies for specific symptoms based on medical diverse records and data sources. The authors of [68] looked at the rise in personal data collection and mobile health systems. They created a fuzzy optimization model that incorporates multiple imprecision levels, such as fuzzy, crisp, and interval-valued fuzzy parameters, to improve a mobile wellness recommender. They used accuracy, specificity, and sensitivity to assess their suggested model (i.e., true negative rate). The authors of [69] used deep learning to create an e-health collaborative-based RS. They used the CNN (convolutional neural network) algorithm and used precision, recall, MAE, and RMSE scores to evaluate their recommender. The authors used sentiment analysis to get patient feedback while maintaining the patients' privacy. In [70], the authors created a customised hybrid RS that combined demographic, utility-based, and content-based filtering approaches. They wanted to assist smokers in quitting by providing motivational messages to encourage them to modify their habits. They used the F-measure, MAE, and hit rate to evaluate their model. The authors of [71] proposed a novel strategy for recommending food based on the patients' medical history to address the patients' nutritional demands. Other characteristics included age, weight, gender, calories, protein, and fat. They used a dataset of 30 patients to integrate deep learning and machine learning methods such as naive Bayes, recurrent neural networks, and Long Short Term Memory (LSTM).

that can help them improve their current state of health. The authors of [73] employed a hybrid filtering approach to find a group of uncommon diseases by combining context-based and collaborative filtering strategies. They tested the model on a dataset of Alzheimer's patients.

Recommendation Systems in Agriculture: RSs have a substantial impact on agricultural resource management and use, such as fertilisers, agrochemicals, and irrigation. A fertiliser called RS was created in [7] to nourish the soil and boost its yield. To suggest crops, the authors utilised an ensemble classifier, and their system was assessed using response time and accuracy measurements. Pests in crops were addressed and addressed in [74], where researchers built an RS that identifies pests and offers appropriate remedies. In [75], the authors created a web-based collaborative RS to respond to farmers' questions and keep them up to date on new agricultural trends. They used data from a call centre to create their model. Phone calls are used to respond to the farmers' questions. The authors of [76] built a web-based RS using the Apriori model and hybrid filtering model. They used Apriori to analyse data based on frequently purchased things and to recommend items to users based on both past purchases and the most popular Agri-products. In [50], a collaborative-based RS was developed, in which it recommends the best crop for the farmers depending on their location and weather circumstances. The authors employed cosine similarity, and their dataset included information from 400 farms. In [77], the authors combined K-nearest and Nave Bayes to build a crop RS using an ensemble model with majority voting. The weather conditions were used as an example by the authors in [78]. They devised a hybrid filtering-based recommendation system (RS) that recommends the optimum crop for a given set of weather conditions. For weather prediction, the authors used fuzzy c means, Support Vector Machines (SVM), and Artificial Neural Networks (ANN), and their model was assessed using accuracy measures. The authors of [79] proposed an RS based on ensemble technique that combined different models such as (nave Bayes, random forest, and Linear SVM) to improve agricultural productivity. Based on the input soil dataset, their suggested model suggests crop types. They used the overall average accuracy measure to test their model.

Recommendation Systems in Media and Beyond: Various cultural objects and offers have increased as a result of technical advancements and changes in media, as well as a growth in the number of people visiting cultural sites. As a result, visitors are inundated with information, making it difficult for them to locate their areas of interest. As a result, recommendation systems have emerged as an important tool for providing suggestions that help to alleviate the information overload in this field. To find the relationship between users, [80] uses social information such as artwork attributes (e.g., type, date of creation, artist, and technical material) and user experience in a genuine art event. In the cultural heritage area, it was demonstrated that merging three recommender systems, including content-based, social-based, and context-based, performs effectively. One of the most important sorts of cultural heritage is museums.A survey on intelligent recommender systems for museums that demonstrated how users' geographical information and social interactions were used. In the cultural heritage sphere, mobile apps have also made a significant contribution to the use of RS systems. [82] uses a smart search museum mobile app in conjunction with context-aware and hybrid RSs. They've established a big data architecture that gathers information from social networks about users' tastes, preferences, habits, requirements, and positions in order to provide suggestions. In addition to the cultural heritage domain, RSs are being extended to multimedia content in text, image, video, audio, and other formats to assist users in finding their preferred multimedia content. Users' multimedia data from social media is employed in [83], where metadata, textual comments, user activity logs, and ratings are used to combine users' preferences, views, behaviours, and feedback. A new RS for large data applications was also introduced. Video RSs are common, particularly on Netflix and YouTube. RSs use metadata to deliver tailored movie recommendations; in [84], a machine learning-based RS based on consumers' preferences is introduced. [85] presents another multimedia RS model that makes use of social relationship mining tools and movie metadata. Sentiment analysis, the SVM model, and Word2Vec-based social ties were used to improve the recommendation outcomes. By utilising the data and comments obtained from social relationships and consumer profiles on the network, open social networks (OSN) play a crucial role in offering individualised recommendations to users. The authors of [86] employed lexical analysis of Twitter data to construct ranking scores in order to find individuals who were similar. In [87], a novel music recommendation system is presented that is based on the users' actions and personality factors collected from OSN. To improve recommender accuracy, they combined their findings with a content-based filtering technique. Based on the OSN recommendation system, the authors devised a diffusion interference method in [88]. [89] describes a collaborative and user-centered technique that makes use of They used a portion of the Yahoo Flicker 100 Million multimedia dataset for ranking and similarity calculation. A new trust-based privacy-preserving architecture for decentralised friend recommendation in OSNs (ARMOR) is provided in [90], which uses OSN users' social trust relationships to construct a privacy-preserving buddy suggestion. They used a genuine dataset with Facebook networks for 100 different colleges.

Table2 summarises the commercial adoption of various recommendation systems across the four categories, as well as their references.

Table 2. Business adoption of Recommendation Systems (RSs) in five application areas.

Area	Application	Reference
~~e-commerce~~	Items recommendations to buyers	[4,5]
	Movie or video recommendations	[43]
	Path Recommendation for transporting goodOr passengers	[8,39,49]
Transportation	Recommendations to Tourists	[50–52]
	Venue recommendation	[53–55]
	Medical advice or treatment plan recommendation	[6,46,63,64]
	Recommending Personalized services to patients	[44]
e-health	Appointments recommendation to clinicians	[45]
	Health recommendations in mobile systems	[59]
	Healthy behavioral recommendations	[61]
	Diet recommendation	[62]
	Fertilizer recommendation to farmers	[7]
	Crops issue recommendation	[47]
Agriculture	Assisting farmers inquiries	[48]
	Agricultural products recommendation	[65]
	Crop cultivation suggestion	[40,66–68]
	Event recommendations	[80]
Media	Museum recommendations	[81,82]
	Multimedia recommendations	[83–85]
	Open Social Networks recommendations	[86–90]

CONCLUSIONS AND FUTURE DIRECTIONS

We gave a comprehensive assessment of RSs in this study, including collaborative filtering, content-based, demographic-based, utility-based, knowledge-based, and hybrid-based RSs. Weighted, mixed, switching, feature combination, feature augmentation, cascade, and meta-level techniques for hybrid-based systems are also described and classified. Cold-start, data sparsity, scalability and variety, as well as metrics used to evaluate its performance, are four major problems that affect the performance of a recommendation system. We also explain how recommendation systems have been used in e-commerce and other fields like transportation, e-health, agriculture, and media. To describe many applications in each sector, we rely on a large body of research. We can deduce that: (1) the necessity for more robust recommendation algorithms has led to a larger use of RSs. In the health industry, for example, very precise deep learning approaches have resulted in the application of RSs.

(2) Smartphones and technological improvements have made it easier to use RSs in everyday life. For example, RSs may suggest a route to drivers and passengers, as well as those supporting farmers with their jobs. As a result, the efficiency of RSs has been demonstrated in a variety of settings, and they are becoming increasingly popular. Research in the future Incorporating technological opportunities like blockchain, IoT, and RSs is one of them. With the increasing number of deep learning-based RSs, as well as the number of people and items on online platforms, novel ways that scale effectively with large datasets are a future direction to consider.

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