iJournals: International Journal of Software & Hardware Research in Engineering (IJSHRE)
ISSN-2347-4890
Volume 10 Issue 1 January 2022

A Review of Recommender System Strategies for Enhanced Service Recommendation

Shiraz Ismail[1]; Alhassan Abdul-Barik[2]; Salifu Abdul-Mumin[3]

Department of Computer Science, Tamale TechnicalUniversity, Tamale, Ghana, West Africa[1]; Department of Computer Science, University for Development Studies, Tamale, Ghana, West Africa[2]; Department of Information Systems and Technology, CK Tedam University of Applied Science and Technology, Navrongo, Ghana, West Africa[3].

sismail@tatu.edu.gh[1]; abarik@uds.edu.gh[2]; asalifu@cktutas.edu.gh[3]

DOI: 10.26821/IJSHRE.10.1.2022.100112

ABSTRACT

Recommendation systems have shown to be a powerful tool for filtering and retrieving data regarding user interactions with service items on the internet in particular. These systems have found widespread use in areas such as research, electronic commerce, tourism, social networking, and a variety of other fields. Recommendation systems aid in the filtering of vast amounts of complicated data by allowing users to rate and anticipate their preferences for items that are likely to interest them. As beneficial as recommendation systems are, several design issues exist while creating recommendation systems, such as cold start, sparsity, privacy, robustness, scalability, prediction accuracy novelty, and recommendation diversification, making them less precise and accurate than necessary. A lot of research efforts applying various recommendation methods have been made in time past. Yet, more is still required to meet the information needs of users. This paper provides an extensive study of recommender systems as well as an elaborate assessment of techniques of recommendation that have appeared already in past research endeavours to foster recommendation accuracy, prediction, and sparsity. Also, the authors discuss the benefits and drawbacks of these recommender systems.

Keywords: Recommender systems, service items, collaborative filtering, hybrid filtering

1. INTRODUCTION

Advances in research and technology have had a significant impact on the users' and researchers' habits alike, allowing for the acquisition of knowledge on research papers and items. Many challenges, however still exist in respect of which research articles or items to choose that meet the needs of the user. E-commerce [1], health [2], social networks [3, 4], industry [5], E-study [6], music [7], Internet of Things (IoT) [8,9], food and nutrition information system [10], and marketing [11] all use recommender systems. They use both traditional and current approaches to create personalisation automation in an e-commerce context. [12] as a method of machine learning [13].

Predominantly, RS is designed to predict and identify users' preferences in certain content,relying on their past experiences. The high-level design of a typical RS is depicted in Figure 1. When a user uses a system byliking, clicking, or rating,they give explicit or implicit input about their preferences. It makes sense, for example, to deduce that when a user rates an article about a portable computer, thenthey may be interested in reading about a laptop as well. As a result, the core concept of RS is making inferences on user preferences using such data. RS uses a learning engine to model and anticipates the extent to which user will prefer a new item based on previous feedback from the user.

We present a survey of common recommendation techniques utilised in RS, as well as an overview of standard methodologies including Collaborative Filtering (CF), Content-based RS, Hybrid RS, and Context-aware RS, We also elaborate assessment of past techniques applied to enhance recommendation.

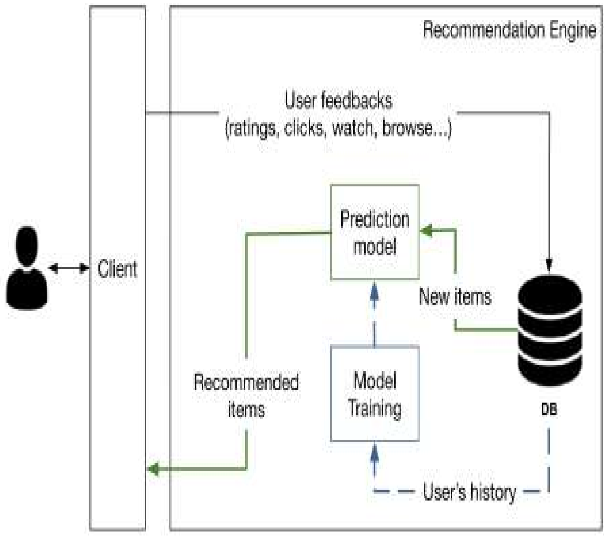

Figure 1: Recommender System architecture [14]

Recommender systems have been fused into popular web portals and commercial systems, some of which are presented in Table 1.

Table 1: Commercial systems that employ recommender system

Category	Recommender Systems
Video	Tudou, YouTube Netflix, Youku, Hulu
News	Google News, Digg
Music	Play Last FM
Social Networking Services	Facebook, Twitter, QQ, LinkedIn
Ebusiness	Amazon, eBay, Kikuu

1.2 Recommendation system challenges

Sparsity problem: It's tough to locate similar consumers for a user who has rated items that haven't had much feedback, therefore making relevant recommendations for that user will be challenging. Despite the lack of availability of ratings, the task is to bridge this gap by calculating appropriate predictions.[15]

Cold start problem: When we add a new product and a new user to the system, neither the person nor the item has a profile.

Novelty and diversity of recommendation:we have in the system new products or item to which user will recommend and make our recommendation has more diversity for the user rather than which products he had seen on the system.

Scalability: The RScapacity to function stably when the size of users and items grows.

Prediction accuracy: Predictionaccuracy must be calculated in relation to the system's training data.

Sparsity: Many system users buy a product but do not rate the products they view or buy.

Privacy: We require certain information on user data to recommend items that match their interests. Users must have access to the information they require to recommend which items they prefer and how they should be used. [16]

Gray shape: When an attacker breaches a recommendation system, they try to create a false impression about an item's ratings to increase or decrease its preference level. [16]

Robustness of Recommender Systems: The vulnerability of RS to cyberattacks is well-known and a huge issue in the development of RS. [16]

1.3 Phases of Recommendation Process

1.3.1 Information gathering phase

This phase necessitates gathering relevant data such as user attributes, behaviours, and resource content from users to develop a user profile or model for prediction. A good user profile is required for a recommendation system to perform effectively. To generate a reasonable recommendation straight away, the system needs to know enough about the user. Recommender systems rely on a variety of inputs, including relevant and high-quality explicit remarks, such as user input evaluating their preference in the item or implicit comments inferred indirectly from user behaviour [17]. It's also possible to get hybrid feedback by combining explicit and implicit feedback

1.3.1.1 Explicit feedback

Typically, an RS will alert the user to give a rating to elements to develop and enhance his model via the system interface. The quality and quantity of ratings a user supplies largely determine the recommendation accuracy.

This technique requires enormous user effort. Additionally, users aren't always ready to provide enough data. Explicit feedback is thought to provide more reliable data since it doesnot work on user preferences from actions. Recommendations from this method are perceived to be transparent, quality and have a high confidence level.[17].From one application to the next, the kind of response changes based on the researcher and the article or item, but it may be divided into three categories: scalar, binary, and unary. Numerical ratings express the researcher's assessments of the item or article on the internet (e.g., 1-5 stars) or ordinal ratings (e.g., strongly agree, agree, neutral, disagree, strongly disagree). Additionally, binary responses have just two potential values, which signify distinct levels of appreciation (for example, likes vs. dislikes or interested vs. not interested).

1.3.1.2 Implicit feedback

To forecast user preferences, the system analyses a variety of user actions, including their historical purchases and navigations, time spent on pages on the web, user links, email content, and button pushes, among others. Thanks to implicit feedback, users are spared the effort of identifying user preferences based on their activity in the system. The method is less accurate, but it does not need the user to exert any effort. Implicit preference statements are also said to be more objective. This is so because users reply in a socially desirable manner devoid of baises[17].

1.3.1.3 Hybrid feedback

Both implicit and explicit feedback features can be employed in a hybrid system to overcome their limitations and give the best-performing system. This can be done by leveraging implicit data to corroborate explicit classification or by allowing users to submit explicit input only when they demonstrate a specific interest. [18]

1.3.2 Learning Phase

The learning phase applies a learning algorithm to filter and use user features based on feedback gathered during the collection phase.

1.3.3 Prediction or Recommendation Phase

At this phase, RS recommends or anticipates the type of items the user might prefer. This can be done either directly based on the data set collected in the information collection stage, which can be memory-based or model based or through user activities previously observed. Figure 2 highlights the recommendation phases

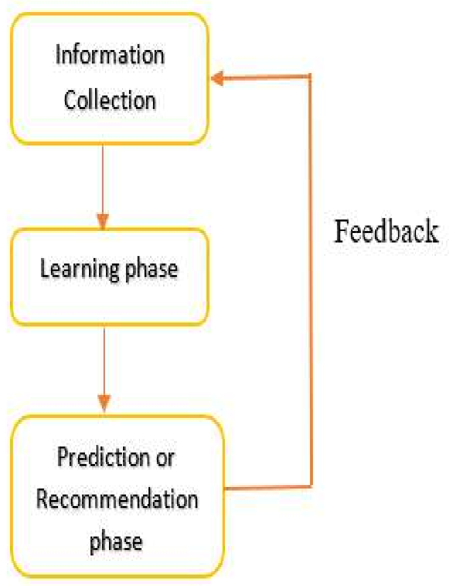

Figure 2: Phases in RecommendationSystem

2. Overview of Recommender Systems Strategies

According to the information sources employed in their recommendations, [19], the current set of recommendation systems may be classified into the following five groups, as illustrated in Figure 3.

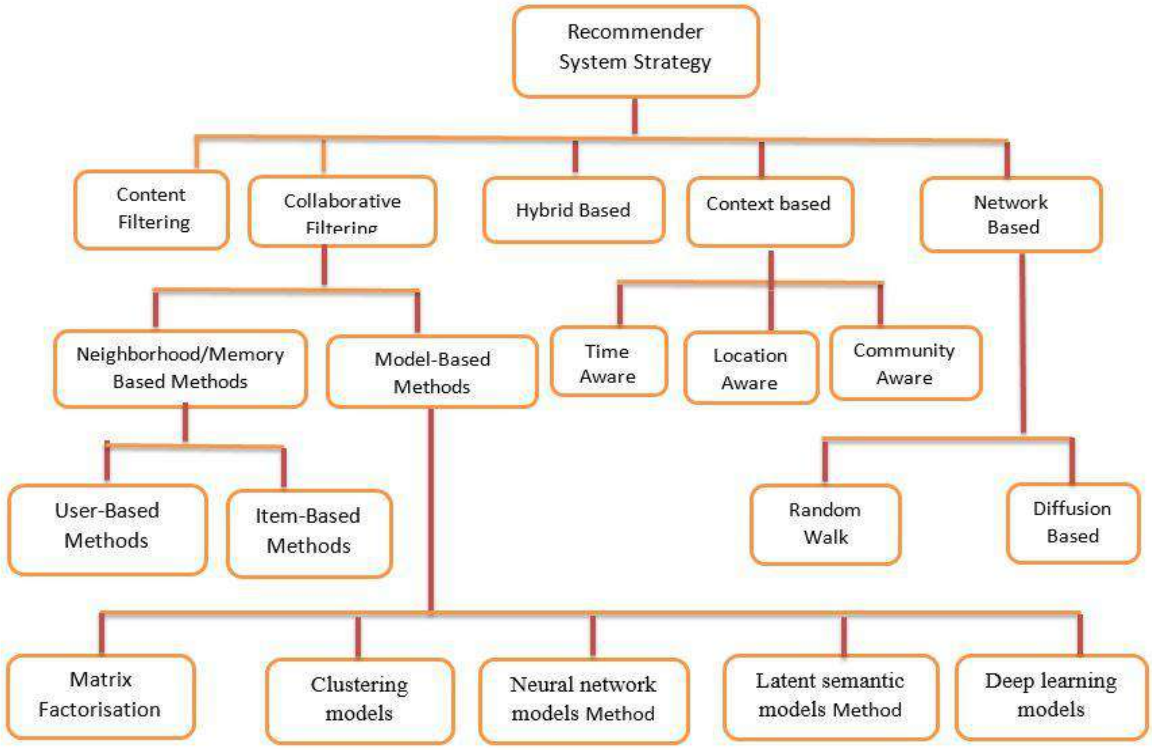

Figure 3: Overview of Recommender Systems Strategies

Data Sparsity (only minor ratios of items are rated), cold-start (difficulty in recommending new articles or new users as a result of insufficient data), diversity (items that are widely known are recommended often), accuracy (suggest important items to the user), and scalability (in an environment with millions of consumers and products, computational power is required to determine recommendations) are just a few of the major challenges [20].

2.1 Collaborative Filtering

Collaborative Filtering (CF) is a popular and widely used recommendation algorithm found in commercial systems like Amazon and Netflix.

The neighbour's actions and behaviours (such as ratings, clicks, watches, or purchasing behaviour) play a vital part in making personal decisions in the CF approach. When you're online, your immediate neighbours share comparable preferences for the present user as indicated in Figure 4. Based on rating data or the behaviour of comparable users, items or articles are recommended for the target user (i.e., nearest neighbours) as shown in Figure 3. Because persons with similar tastes are likely to evaluate the same item with comparable ratings [21]

The primary concept behind this method is that the target user's closest neighbours'opinions may be used to generate a better recommendation [21] since individuals with similar likes are more likely to rate the same item with equal ratings. [21] [22]

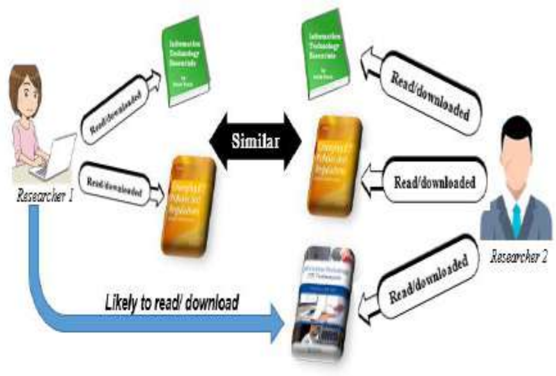

Figure 4: An example of a Collaborative Filtering Based recommendation

The CF-based recommendation has two subcategories; Model-based approaches and memory-based methods [23] [24]. Model-based approaches rely on machine learning techniques to represent the preferences of users using training data and predict unknown ratings using the trained model. The memory-based methods area neighbourhoodbased method that predicts and recommends an intriguing article by an active researcher by using a neighbour researcher with similar interests to an active researcher or a current article with similar features to an article or active article.

2.1.1 Memory/ Neighbor Based CF Technology

Memory or Neighbor-based CF algorithms give suggestions to the target researcher based on data stored in memory. The two forms of memory-based CF are User-based CF and item-based CF [25] [26]

User-based and item-based CF algorithms are demonstrated in Figures 5a, and 5b,respectively.

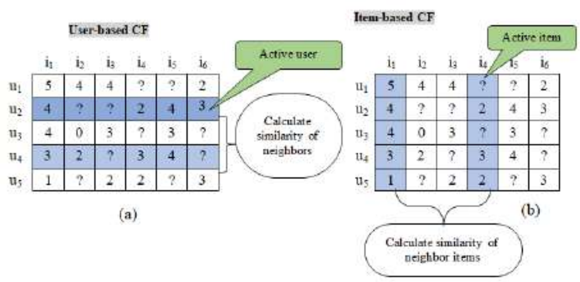

Figure 5a: The logic of User-based CF; Figure 5b: The logic of Item-based CF

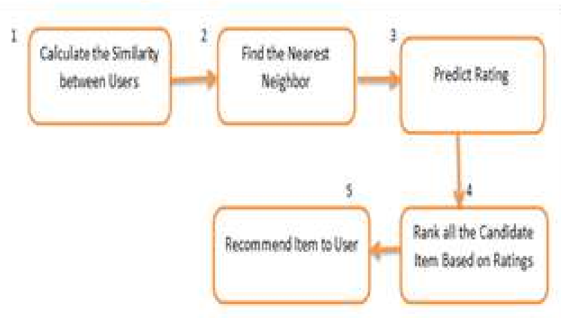

Figure 5c: The logic to recommend item to user.

2.1.1.1 User-Based CF Recommendation Algorithm

The theory behind user-based CF is that users with previous comparable ratings should have similar interests, allowing us to forecast the active user's missing ratings on specific items based on the ratings of similar users on the same items [27].

Calculating the Similarity between Users

Calculating the similarity between a researcher and an article has an impact on the accuracy of recommendation in memory-based CF approaches, thus it's important to do it right. Multiple similarity techniques have been developed for this purpose [28]. Pearson Correlation (PC) and Cosine-based similarity approaches, on the other hand, appear to produce more accurate findings.

The similarity of two users (u, v) using the PC similarity method is defined as:

$$sim(u,v) = \frac{\sum_{x\in I_{u,v}}(r_{u,x}-\bar{r}_u)\cdot(r_{v,x}-\bar{r}_v)}{\sqrt{\sum_{x\in I_{u,v}}(r_{u,x}-\bar{r}_u)^2}\cdot\sqrt{\sum_{x\in I_{u,v}}(r_{v,x}-\bar{r}_v)^2}} \#(1)$$

Where $I_{u,v,}$ the set of articles is rated by both researcher u and researcher v, $\bar{r}_u$ and $\bar{r}_v$ are the mean ratings of researchers' u and v respectively.

Also, the similarity of two articles/items (x, y) using the PC similarity method is defined as:

$$sim(x,y) = \frac{\sum_{u\in U_{x,y}}(r_{u,x}-\bar{r}_x)\cdot(r_{u,y}-\bar{r}_y)}{\sqrt{\sum_{u\in U_{x,y}}(r_{u,x}-\bar{r}_x)^2}\cdot\sqrt{\sum_{u\in U_{x,y}}(r_{u,y}-\bar{r}_y)^2}} \quad (2)$$

Where $U_{x,y}$ is the set of similar articles that the researcher u rates, $\bar{r}_x$ and $\bar{r}_y$ are the mean rating scores of an article x and y respectively.

Equation 3 computes the similarity between researcher (or users) using the cosine-based method.

$$sim(u,v) = cos(\vec{u},\vec{v}) = \frac{\vec{u}\cdot\vec{v}}{\|\vec{u}\|\cdot\|\vec{v}\|} = \frac{\sum_{x\in I_{u,v}} r_{u,x}\cdot r_{v,x}}{\sqrt{\sum_{x\in I_u} r_{u,x}^2}\cdot\sqrt{\sum_{x\in I_v} r_{v,x}^2}} \quad (3)$$

Where I_u and I_v are set of similar articles rated by researcher u and v respectively. Also,

$$sim(x,y) = cos(\vec{x},\vec{y}) = \frac{\vec{x}\cdot\vec{y}}{\|\vec{x}\|\cdot\|\vec{y}\|}$$

$$= \frac{\sum_{u\in U_{x,y}} r_{x,u}\cdot r_{y,u}}{\sqrt{\sum_{u\in U_x} r_{x,u}^2}\cdot\sqrt{\sum_{u\in U_y} r_{y,u}^2}} \qquad (4)$$

Where U_x and U_y are set of similar researchers that rates articles x and y respectively.

Equation (5) for researcher-based similarities and Equation (6) for article-based similarities can be used to predict the ratings that the present researcher u would give a target article x given by $P(u,x)$ after computing the similarities and various weights.

$$P(u,x) = \bar{r}_u + \frac{\sum_{v\in U} sim(u,v)\cdot(r_{v,x}-\bar{r}_v)}{\sum_{v\in U} sim(u,v)} \#(5)$$

$$P(u,x) = \bar{r}_x + \frac{\sum_{y\in I} sim(x,y)\cdot(r_{u,y}-\bar{r}_y)}{\sum_{y\in I} sim(x,y)} \#(6)$$

Memory-based CF has the following advantages: cheaper training costs, ease of deployment, and ease of adding new researcher ratings. When the data gets larger, however, the memory-based technique has a higher computational cost.

Finding the Nearest Neighbors

Finding nearest neighbours is commonly done using one of two methods: k-nearest neighbours or establishing a threshold [29]. The term "nearest neighbours" refers to the users who are closest to you (i.e., greater similarity). If we wish to choose the three best neighbours for Point 1, as illustrated in Figure 6, we set and then choose the top closest points as neighbours:

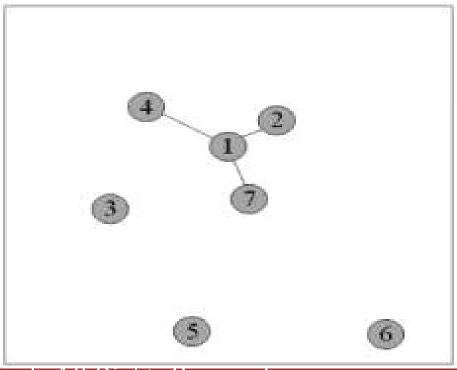

Figure 6: K Nearest Neighbors method.

Given that δ is the threshold value, then if the similarity between user *u* and user *v* is more than δ, then user *v* will be picked as a neighbour. The threshold is the centre of a circle whose radius is the radius of the nearest neighbour. We set the threshold equal to k in Figure 7, therefore points 2, 4, 7, and 3 will be picked [30].

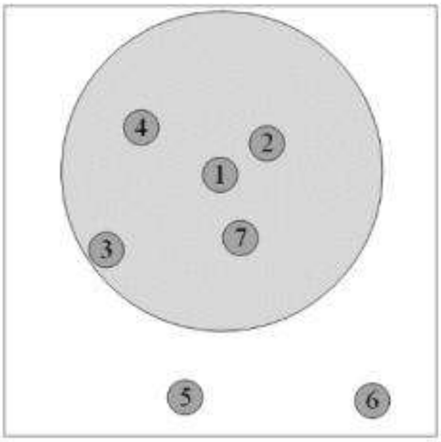

Figure 7: Setting Threshold Neighbor Chosen method.

How to Predict Ratings

Predicting ratings and generating a top-N list of recommendations are the two basic techniques to generate recommendations for the active user. Both must anticipate active user ratings for a new item i based on ratings on item i from users who are the most similar to u. [31] This is how you determine the predicted rating.

$$\hat{r}_{ui} = \bar{r}_u + \frac{\sum_{v\in Nu} sim_{uv}(r_{vi}-\bar{r}_v)}{\sum_{v\in Nu}|sim_{uv}|} \#(7)$$

Where Nu is the similar neighbour set of the user u.

2.1.1.2 Item-Based CF Recommendation Algorithm

In the item-based collaborative filtering method [27], the premise is that users like to buy products that are comparable or relevant to the items they have already purchased. Therefore theuser's rating of items in the nearest neighbour is used to deduce the prediction rating.

Calculate the Similarity between Items.

Between items, the conservative approaches are modified cosine vector and Pearson correlation coefficient.

The Adjusted Cosine Vector

The adjusted cosine vector is computed using Equation 8.

$$sim_{ij} = \frac{\sum_{u\in Uij}(r_{ui}-\bar{r}_u)(r_{uj}-\bar{r}_u)}{\sqrt{\sum_{u\in Ui}(r_{ui}-\bar{r}_u)^2}\sqrt{\sum_{u\in Uj}(r_{uj}-\bar{r}_u)^2}} \#(8)$$

Where Sim_{ij} denotes the similarity between items i and j. U_i and U_j represent the sets of users who rated items i and j, respectively, and U_{ij} denotes the set of users who rated both items i and j.

Pearson Correlation Coefficient

Equation 9 calculates the Pearson correlation coefficient [32].

$$sim_{ij} = \frac{\sum_{u\in Uij}(r_{ui}-\bar{r}_u)(r_{uj}-\bar{r}_u)}{\sqrt{\sum_{u\in Ui}(r_{ui}-\bar{r}_u)^2}\sqrt{\sum_{u\in Uj}(r_{uj}-\bar{r}_u)^2}} \#(9)$$

Where $\bar{r}_i$ and $\bar{r}_j$ represent the average ratings on i and j in U_{ij} respectively.

2.1.2 Model-Based CF Recommendation Technology

Because the CF memory approach has trouble addressing sparse data, researchers have resorted to various CF models to tackle these issues. Statistical and machine learning models are employed in the model-based CF method to learn the rating data and other hidden aspects, and then create recommendations based on the learned data. With the addition of data, the recommendation system should smoothly scale. All previously examined papers were regarded to have an estimated similarity between researchers/articles using standard neighbor-based CF approaches, which are time-consuming and fail to achieve adequate scalability [33].

Following that, approaches based on clustering and classification are introduced to RS to design and develop various model-based recommendation algorithms, such as clusters, to minimisecomputational complexity and enhance recommendation efficiency without sacrificing suggestion accuracy [34][35]. Singular value decomposition- (SVD-) based models [36][33] and probabilistic matrix factorization- (PMF-) based models [37]. The model-based strategy involves first training the model using training data to detect patterns and then making predictions based on the real data[38][39].

Model-based RS was established later to eliminate the primary drawbacks of memory-based CF technology, which requires a preparatory learning process to determine the optimal model parameters before giving a suggestion. Model-based RS can predict user evaluation rapidly when the learning phase is completed. The most competitive and widely used model-based RS is the latent factor model (LFM), which separates the evaluation matrix of the user element into two low-order matrices termed the user feature and item matrices. It can leverage dimensionality reduction techniques to reduce data sparsity and, in most situations, provide better accurate recommendations than memory-based CF while requiring less memory and processing time.

2.1.2.1 Association rule

The association rule emphasises the rule's foundation in user-item data sets, which are utilised to provide suggestions to users. It extracts the rules that forecast item occurrence using other items present in the transaction. [17].

2.1.2.2 Clustering

A cluster is a collection of similar data items belonging to the same group, while those that are dissimilar from one another belong to a separate cluster[17].

2.1.2.3 Decision tree

This approach is based on the analysis of a collection of training instances, which results in three graphs. They're then utilised to categorise samples that haven't been seen yet. This categorisationapproach is easier to understand than others. [17].

2.1.2.4 Regression

The regression approach will be employed when two or more variables are deemed to be systematically associated linearly. It's a strong method for investigating the associative link between dependent and independent variables. [17].

2.1.2.5 Bayesian classifier

This method is based on Bayes' theory and the notion of conditional probability. Every characteristic and class identification is treated as a random variable. The naïve bays classifier is the most frequent Bayesian classifier. [17].

2.1.2.5 Matrix Factorisation

Matrix factorisationis one of the most often used algorithms in RS. One of the most popular variants is singular value decomposition (SVD). [24]. The latent factor model (LFM), nonnegative matrix factorization (NMF), and trust-aware matrix factorization (TMF), [24][40] [41], nonnegative matrix factorization (NMF) [27], and trust-aware matrix factorization (TMF), [42], are all techniques for reducing dimensionality while preserving information content. These techniques help to reduce the computational complexity and hardware requirements for providing recommendations. [36] [40] [36] [40] [36] [40] [In comparison to matrix factorisationmodels and neighborhood-based strategies, the former is seen to be a better option for dealing with the sparsity problem. The recommendation procedure of RS based on MF and an illustration of the Matrix Factorisation model aredepicted in Figures 8 and 9, respectively.

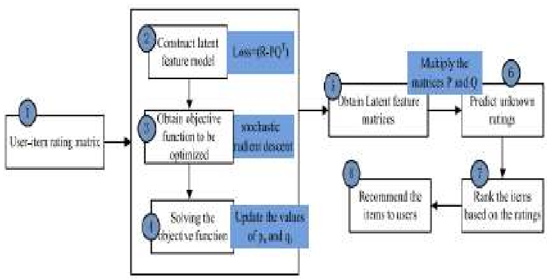

Figure 8: The recommendation procedure of RS based on MF.

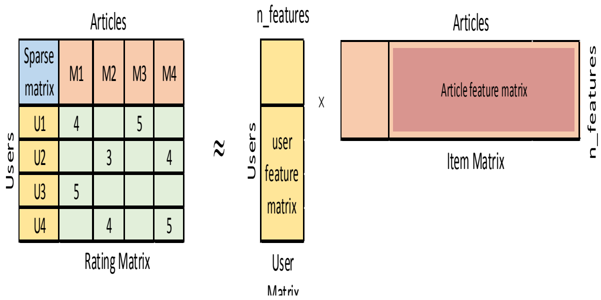

Figure 9: An example of a Matrix Factor is at ion model

The sparsity problem is easily handled by the matrix factorisationmodel, which frequently outperforms neighborhood-based techniques. The MF technique uses a lot of implicit feedback or characteristics gained from analysing the behaviour of the target researcher to identify researcher preference. The authors, study field, region, and other qualities of a publication might be implicit features.If the researcher's hidden feature matrix is U and the article's hidden feature matrix is M the inner product of U and the transpose of M would yield a suitable representation of the rating matrix projected scores, as shown in equation 10.

$$\hat{R}_{u,m} = U_u \cdot {M_m}^T \#(10)$$

To improve prediction accuracy, the MF technique uses an objective function to discover the best hidden features, as stated in Equation 11

$$U^*, M^* = \min_{U,M}\left(\sum_{(u,m)\in R(obs)} (R_{u,m} - {M_m}^T \cdot U_u)^2 + \mu(\|M_m\|^2 + \|U_u\|^2)\right)\#(11)$$

where U_u and M_m are the hidden features of researcher u and an article m, $R_{u,m}$ is the observed rating of researcher u on article m, $\|\cdot\|$ is the matrix's norm, and μ is a regularisation value that prevents the decomposed matrix from overfitting to the original matrix R. To discover the hidden features and minimise the objective function, algorithms like Gradient Descent (GD), Stochastic gradient descent (SGD), or Weighted Alternating Least Squares (WALS) are utilised. Model-based CF algorithms offer a better recommendation, are quicker, and operate well online. However, when fresh information about new users and products is supplied, these models must be updated regularly.

2.2 Content Based Strategies

Content-Based (CB) techniques, also known as cognitive filtering techniques, recommend articles or items to a target user or researcher based on descriptions of the article(s) or item(s) and past users' or researchers' preferences. A content-based recommender system is depicted in Figure 10.

Figure 10: Content-based recommendation

The content-based (or cognitive) approach's main premise is to find the common features of an article or item that has earned a favourable rating from a researcher and then to propose to you additional articles or items that contain similar characteristics. [55], [56], [57]. The method detects common aspects of an article or item that has received good feedback from the researcher and then suggests a new piece that has those traits. In content-based RS, a recommendation is made using rich information about each article's nature in the form of feature vector characteristics. The Term Frequency-Inverse Document Frequency (TFIDF) [56] weights of the most informative keywords for articles in the form of text documents, such as news items [57] or Web documents, are usually included in this vector. [56]. Furthermore, the contents of the article are frequently used to create a preference profile vector for each researcher. The Rocchio algorithm [58] is a method for calculating these profiles that areutilised in numerous content-based recommender systems, including Newsreader [57], [55]. When a researcher reviews an item, this approach updates the researcher's profile by adding the weights of Xi to Xu, in proportion to the appreciation u for i, as indicated in Equation (5).

$$X_u = \sum_{i \in Iu} r_{ui}\, X_i \#(15)$$

The researcher profiles may then be used to offer a new article to a researcher u by recommending the article with the most comparable feature vector Xi to the profile vector Xu

The key benefit of CB approaches is that they solely use the target user's ratings or profile information, allowing them to generate accurate recommendations from other users, even when the target user's ratings are appropriate. However, the fundamental issue of CB approaches is that they are unable to provide excellent suggestions for items that have the needed item attributes for classification.

2.3 Context Aware (CA) Recommendation System Method

There are many recommendation systems based on the CB and CF approaches, and they mostly rely on users and items to generate relevant predictions without taking into account additional information that can increase the recommendation's quality and customisation [60]. However, additional information about the target user's or object's circumstance (also known as the target user's or object's context) is critical in enhancing recommendation accuracy. [60] suggested the Context-Aware (CA) recommendation algorithms as a first step in this direction. Unlike the CF and CB approaches, which employ a two-dimensional (user x item) model to create recommendations, CA methods use a multidimensional model (for example, user x item x location) as their recommendation space. CA recommendation systems offer recommendations based on the user's location, the time of the recommendation, the reason for the recommendation, social ties, and so on. To create suggestions, these systems employ three primary processes. The first is the pre-filtering step, in which a group of relevant items is chosen based on contextual data. The relevant items are then ordered according to their expected ratings in the second phase, often known as the classic recommendation step. Finally, the output of the second phase is filtered and re-ranked in the post-filtering stage. Community-aware, Location-aware, and Time-aware recommendation techniques are the three basic types of CA approaches.

2.3.1 Time-aware (TA) recommendation methods

Time is used as the major contextual element in TA techniques to make recommendations. This type of recommendation work on the assumptionthat over time, user preferences change and that taste evolves with the introduction of new goods

2.3.2Community-aware (CA) recommendation methods

CA recommendation approaches rely on social ties to improve recommendations, based on the premise that users' choices are influenced more by their companions than by those with whom they have no contact. These systems provide item recommendations based on both content and user social behaviour.

2.3.3Location-aware (LA) recommendation methods

These forms of recommendations have been made popular through place recommendations by the tourism industry [61]. When recommending services to a target user, users' location ratings are used to include areas closest to the user and avoid ones farther away. This is done to increase the system's scalability while retaining its quality [62].

2.6 Hybrid Recommendation Strategy

Each of the recommendation systems has shortcomings recommending performance, such as the Collaborative Filtering algorithm's cold start issue and the paucity of a diverse set of resources In a content-based recommendation [63], it is suggested that to improve the performance of the recommendations, the researchers began merging many algorithms. To get their cumulative benefits, several researchers apply a hybrid strategy to overcome pure user cold-start, sparsity of data, and diversity-accuracy challenges in recommendation systems [64]. When compared to using either a collaborative or content strategy, this leads to higher predictive performance but is very expensive. A hybrid-based recommender system is depicted in Figure 11.

Figure 11: An example of a Hybrid recommendation

3. REVIEWING OF RELATED WORKS

Several attempts have already been made to address the numerous design difficulties that occur while developing systems to make recommendations. Lika et al. [43] employed well-known classification methods, which, when paired with similarity approaches and prediction mechanisms, provided the essential means for extracting recommendations.It combines classification methods in a pure CF system, and the addition of demographic data aids in identifying additional users who behave in the same way. Through a series of tests, we demonstrate the performance of the suggested system. Dataset was given by the research group GroupLens. The benefit of the solution is that it produces good numerical results in a variety of settings. However, the system functions better with a big number of users who have previously registered. In such instances, the algorithm achieves lower MAE values, boosting the prediction accuracy of ratings.

Cao, et al [44] use a cooperative filter recommendation approach based on the matrix factorisationmodel to incorporate the similarity between the object image and the category attributes. First, the authors used a matrix factorisationmodel based on user preferences to predict and fill in the missing evaluation items. The article's image features and category attributes were extracted using the neural network VGG16, which were then integrated to determine the similarity between the new article and the historical elements, and the article's neighbours were obtained.They then recommend that the user pick the N subjects with the greatest score based on the predicted new subject's score, which is based on the similarity between the new topic and its neighbours. By combining collaborative filtering with a matrix factorisationmodel, image blending helps alleviate the cold start of new elements.However, the approach fails to successfully solve the cold start problem of new articles and provides useful recommendations for systems with a large number of words and images.

Garcia et al. [45] offer an ad-recommender system based on social semantics and provide a system design with four primary components: Interest Ontology: for utilising a natural language processing (NLP) tool to analyse textual descriptions of advertisements and highlighting characteristics that match the texts. Each ad is represented as a vector, with each dimension corresponding to a different domain ontology ontological concept, and the value of each dimension being determined by the number of appearances of the concept in the ad's description language.The Interest Ontology is used by the User Profile Generator, which generates a vector for each user withas many dimensions as the number of concepts in the domain ontology. Finally, the Ad Recommender collects advertisements in the form of textual descriptions and a set of interconnected users as the input of the system interacting on social media, while the output is the most suitable user-ad recommendation. Precision is used to determine predicted accuracy to, recall, and measure metrics in this study. Precision, often known as a Positive Predictive Value (PPV), is the percentage of recommended things that are actually relevant to consumers. It is calculated using Equation (12)

$$Precision = \frac{Correctly\ recmmended\ ads}{Total\ relevant\ ads} = \frac{tp}{tp+fp} \#(12)$$

where tprepresents the ads correctly recommended to a given user and $tp + fp$comprises all the ads recommended to that user.

Recall is defined as True Positive Rate (TPR) or Sensitivity and it measures the capacity of the system to suggest elements that are relevant to the user and calculated in Equation (13)

$$Recall = \frac{Correctly\ recmmended\ ads}{Total\ recommended\ ads} = \frac{tp}{tp+fn} \#(13)$$

where $tp + fn$are the ads that are of interest to a given user.

F-measure is the harmonic mean of precision and recall, computed as shown in Equation (14).

$$F - measure\ = 2 * \frac{Precision * Recall}{Precision + Recall} \#(14)$$

It was discovered that ad recommender systems can obtain user information and their requirements by looking at their social behaviour. However, a large and diverse number of data presents additional challenges. Semantic technology has shown to be useful in comparable scenarios under these settings, aiding in the handling of data from several sources.

Sivapalan et al. [46] catalogues the difficulties of CF methods, including sparsity, scalability, and synonymy. The work further indicates the use of RS for the high level of customisation. The CF method makes recommendations by comparing the active user to the current applicator's attributes and preferences, as well as applying user ratings, reviews, and data from the whole applicator.Furthermore, the CF technique incorporates several similarity metrics, such as cosine matrix, personal data, and Jaccard similarity. Due to a paucity of data, he determined that sales on major e-commerce sites were diminishing**.** As a result, he advised Recommender System developers to abandon the use of neighborhood algorithms in the implementation of Recommender Systems for large websites. Because it has poorer recommendation accuracy and decreases metric coverage. This technique is frequently used, however, it has limitations such as limited scalability, data sparsity, and the synonymy problem.

A new measure for sparse data is suggested in Patra et al. [47] in a paper titled "A new similarity measure using Bhattacharyya coefficient for collaborative filtering in sparse data."

Wu et al., [48] provide personalised recommendations and examine a mobile e-commerce CF-based recommender system. The study's three key approaches are the input function module, recommendation method module, and output functions module. As a result, they created the CF technique based on Item Classification Forecast to estimate customer ratings for unclassified products by assessing item similarity and then selecting the nearest neighbors using a novel procedural similarity measurement. They also looked at the CF based on item rating prediction to overcome the problem of user data sparsity in mobile electronics commerce. Finally, they raised certain concerns that must be addressed to maintain progress and integrity in future investigations. in upcoming investigations

Lin and Wenzhe[49]used a web mining approach to create and execute a custom-created e-commerce recommendation system. Because data on the web is so complex, using data mining or other methods to offer it as input for e-commerce recommender systems can be difficult**.** To make the proper recommendations, the system examined the core features of each e-commerce project, such as managing users, commodities, and orders. Nonetheless, the proposed method's performance is dependent on computer resources such as CPU power. As a result, further research into the applicability of the RS implementation approach will require performance optimisation and development.

A CF-based recommendation approach incorporating Big Data in proposed by Sun et al. [50]. The approach works on MapReduce and employs the appropriate distributed computing approach. They employ cosine similarity and Pearson correlation in the article CF algorithm. This finding is significant since people do not assess commodities in physical stores. As a result, the article's authors investigated how RS may be utilised for marketing purposes, such as selecting suitable store product combinations and providing product advertisements. It was discovered the system can manage large-scale data amounts, achieve greater scalability, and give a new source of market support for accuracy, in addition to its efficiency for retail products and businesses. Due to the necessity to apply big data technology, this technique is costly and computationally complex.

Using data samples from e-commerce case studies, Aditya et al. [51] examine the performance of memory-based and model-based CF techniques. They used linear and user-based tests to evaluate each method and found that model-based RS outperforms memory-based RS in terms of accuracy, computation time, and relevancy of recommendations. In the recommended goods, they found that the model-based CF outperformed the memory-based CF in terms of computation speed. Other aspects of RS performance, such as diversity, serendipity, coverage, and newness, were not considered in the research.

Hwangbo et al. [52]extended the existing CF approaches to propose mechanisms to advise fashion accessories to customers to integrate the attributes of fashion goods in their recommendation system development for fashion retail e-commerce. Their methodology looked at both offline and online means of acquiring such products. They conclude that the product that a consumer intendsto buy replaces the product that the user has already chosen.

They put it in a genuine retail mall to demonstrate the system's efficiency. The approach proposed beats the collaborative filtering system inthe metric of efficiency.

Jiang et al.[53]created a slope one method based on a mix of user attributes and meaningful. Their technique involves three steps: collecting trustworthy data, calculating user similarity, and using the high slope one algorithm's similarity and weight component. They also used the Amazon dataset to demonstrate that the new technique is more accurate than the traditional slope one methodology.

Gaikwad et al. [54]introduced a model-based CF recommendation system based on the eventual model utilising the created Naive Bayes algorithm in their paper E-commerce Recommendation System Using Improved Probabilistic Model. The Naive Bayes algorithm model was used to calculate query time, search query, and click time. They concluded that their method is more accurate than a simple Naive Bayes model. They discovered that their method was more precise than a simple Naive Bayes model.

Debnath et al. developed feature weighting (FW) for CB recommendation systems to alleviate this restriction. The item's characteristics are assigned a distinct amount of priority in their approach [59], however with repeated computation of similarity values when the attributes are few, the target user gets biassed results. Over-specialization is the term for this issue.

Son and Kim [90] Studies suggest a content-based filtering algorithm based on a multiattribute network analysis that takes into account similarities between items that are not physically related. After testing with "MovieLens," the recommended approach solves data sparsity and over specialisationissues and displays resilience. Furthermore, the suggested solution is unaffected by the cold start problem since it only uses rating data derived from the user's previous knowledge.

Mohammed, et al. [16] address the issue of cold start during recommendations by calculating the average of rated songs using root mean square error. Their trials were conducted on the world's largest online music data sets, which included implicit and explicit user interaction records as well as explicit rating records for things specified by hybrid feedback. Using the cosine vector approach, the authors devised an association rule to track each purchase made for each transaction and compute similarities to produce a recommendation. When data is sparse, precision, recall, and F-metrics evaluations are used to promote novel things to users. The experimental results show that the method is better than collaborative filtering strategies in performance and accuracy metrics. However, the recommendation system was unable to cope with massive data rated objects and users, as well as varied dataset types like movies.

Yadav, et al. [65] developed a hybrid recommendation system to solve the new user cold start. The concept integrated collaborative and social network-based elements with an augmented user profile derived from connected open data. Item similarity is also calculated to aid in the prediction of ratings for products that have yet to be rated. To cope with accuracy and calculation time difficulties in recommendation systems, the researchers employed ontology and collaborative features. The authors' research, on the other hand, did not examine the impact of user preferences on novelty, diversity, or other measures.

In the e-commerce method, Miao [66] introduced excellent mobile recommender systems. To improve suggestion accuracy, the method integrates Content Based Filtering and Collaborative Filtering technologies.In addition, three modules of weighted combination filtering Recommender Systems have been introduced: an input function module that captures and builds user profiles using required data, a core function module that generates recommendations, and an output function module that delivers the content to users. In the meanwhile, the most recent module integrates the findings of two subdivisions: recommendations and predictions. The researcher's work, on the other hand, improves suggestion quality at a large operational expense.

Aprilianti, et al. [67]in Indonesia, designed and deployed. A weighted parallel hybrid technique combining CF and CBF methodologies for e-commerce recommender systems was Furthermore, the suggested approach may solve the shortcomings of these two techniques, such as CBF's lack of variety of items to provide customers and CF's cold-start issue [68], [69]. The approach, on the other hand, has a long reaction time and a high operating cost.

Qiu et al. [70] looked at the complicated e-commerce architecture that can collect a range of data types and use a variety of recommendation algorithms to meet the demands of various recommendation service types. To improve recommendation accuracy and comprehensiveness, they developed a multi-mode recommender system for e-commerce. This technique, on the other hand, gathers a wide variety of user data, combines numerous recommendation approaches that can learn from one another, and then completely blends all of the results into a single conclusion in order to provide asset recommendations to consumers. The system that has been offered is as follows: Solving the problem of data sparsity and cold start provides high accuracy and quick response times, but at a greater operational cost.

To improve the efficacy of RS, Saini et al. [71] suggested a technique to recognise the sequences that occur after clients purchase things. The study proposes the use of sequence pattern mining since the purchase of particular items commonly occurs in stages. However, the technique's flaw is that the author only analyses the customer profile and product description, ignoring customers who have not made any transactions. This method increases suggestion efficiency while also providing a quick response time. Users who had made no purchases, on the other hand, were not taken into account. Table 2 provides a comparison of recommendation system strategies, emphasising performance achievements as well as some noted flaws in the approaches used.

Table 2: Comparison of selected articles on CF, CBF, and Hybrid recommender systems strategies

Author	Method	Achievements	Shortfalls
Yadav, et al. [65]	Ontology Collaborative features	Improve accuracy Reduces computational time	Impact of user features on novelty, diversity and other metrics not considered
Mohammed, et al. [16]	Association rule	better performance Accuracy in prediction	Could not work well with big data items
Gaikwad et al. [54]	Improved Probabilistic Model Naive Bayes algorithm	More precision	Higher computation time
Saini et al. [71]	Sequence pattern mining	Low response time	Users without any purchase were not considered
Aprilianti, et al. [67]	A weighted parallel hybrid method CF and CBF	Minimises cold start problem Increase diversity	Response time is high Operational cost is high
Aditya et al. [51]	Memory Based CF Model Based CF	Improves accuracy	Low accuracy Higher computational time
Lin and Wenzheng [49]	Web Mining	Low response time	Operational cost is high
Miao [66]	Weighted combination filtering	Recommendation quality	Operational cost is high
Sun et al. [50]	Big data	High scalability	Does not consider security issues
Sivapalan et al. [46]	Association rule Collaborative Filtering	Widely used Decreasing dimensionality	Low scalability Data sparsity
Qiu et al [70]	Multi-mode Recommender System	Resolves the data sparsity and cold start problems	Higher operational cost Low response time
Wu et al. in [48]	Improved CF for mobile e-business	Recommendation quality enhanced	Difficulty in acquiring data

4. CONCLUSION

Recommender systems are a hot topic in science right now. These systems recommend items to users based on what they prefer and on their previous ratings of items. Cold start, scalability, privacy, grey sheep, shilling attack, novelty, and sparsity are only a few of the issues that have been cited as limiting the potential of broad adoption of recommender systems. Various techniques have appeared to address these challenges and enhance the quality of recommendation and user experiences when interacting with service items like research articles. This paper also looked at the common recommendation mechanisms used in recommender systems. An assessment of the strength and limitations of these techniques is done also in this detailed review. Based on these assessments we seek future to design an algorithm that will enhance service recommendation and selection in decentralise environment

5. REFERENCES

[1] P. M. Alamdari, N. J. Navimipour, M. Hisseinzadeh, A. A. Safaei and A. A. Darwesh, "A Systematic Study on the Recommender Systems in the E-Commerce," *IEEE Access*, pp. 115694 - 115716, 2 July 2020.

[2] D. Galeano and A. Paccanaro, "A Recommender System Approach for Predicting Drug Side Effects," in *International Joint Conference on Neural Networks (IJCNN)*, Rio de Janeiro, Brazil, 2018.

[3] J. Chen, B. Wang, L. U and Z. Ouyang, "Personal recommender system based on user interest community in social network model," *ScienceDirect*, vol. 526, pp. 1-12, 15 July 2019.

[4] Y. Li, J. Liu and J. Ren, "A Novel Learning Model Based on Trust Diffusion and Global Item for Recommender Systems," *IEEE Access*, vol. 7, pp. 170270-170281, 2019.

[5] L. Yao, Z. Xu and X. Zhou, "Synergies Between Association Rules and Collaborative Filtering in Recommender System: An Application to Auto Industry," *Springer*, pp. 65-80, 2019.

[6] J. K. Tarus, Z. Niu and D. Kalui, "A hybrid recommender system for e-learning based on context awareness and sequential pattern mining," *Springer*, pp. 2449-2461, 2017.

[7] R. Katarya and O. P. Verma, "Efficient music recommender system using context graph and particle swarm; Multimedia Tools Application," *Springer*, vol. 77, pp. 2673-2687,, January 2017.

[8] J. Park, "Resource recommender system based on psychological user type indicator: J. Ambient Intell. Hum. Computing," *Journal Of Ambient Intelligence And Humanised Computing*, vol. 10, pp. 27-39, 2019.

[9] I. Mashal, O. Alsaryrah and T.-Y. Chung, "Testing and evaluating recommendation algorithms in internet of things," *Journal of Ambient Intelligence and Humanized Computing*, pp. 889-900, 2016.

[10] R. Y. Toledo, A. A. Alzaharani and A. L. MArtinez, "A Food Recommender System Considering Nutritional Information and User Preferences," vol. 7, pp. 96695-96711,, 17 July 2019.

[11] S. JothiLakshmi and D. M.Thangaraj, "Design and Development of Recommender System for Target Marketing of Higher Education Institution Using EDM," *International Journal of Applied Engineering Research*, Vols. 3, no. 19,, pp. 14431-14437, 2018.

[12] Y. Li, J. Liu and A. J. Ren, "A Novel Learning Model Based on Trust Diffusion and Global Item for Recommender Systems," pp. 170270-170281, 20 November 2019.

[13] B. M. Shoja and A. N. Tabrizi, "Customer Reviews Analysis With Deep Neural Networks for E-Commerce Recommender Systems," vol. 7, pp. 119121-119130,, 6 September 2019.

[14] M. G. Campana and F. Delmastro, "Recommender Systems for Online and Mobile Social Networks: A Survey," *Elsevier*, pp. 25-97, 2017.

[15] M. K. Najafabadi, A. Mohamed and C. W. Onn, "An impact of time and item influencer in collaborative filtering recommendations using graph-based model," *Elsevier' Information Processing & Management*, vol. 56, no. 3, pp. 526-540, 2019.

[16] M. H. Mohamed, M. H. Khafagy and M. H. Ibrahim, "Recommender Systems Challenges and Solutions Survey," in *2019 International Conference on Innovative Trends in Computer Engineering (ITCE)*, Aswan, Egypt, 2019.

[17] I. F. Olubusola, I. F. Olubusola and O. B. Adefowoke, "Recommendation systems: Principles, methods and evaluation," *Egyptian Informatics Journal*, vol. 16, no. 3, pp. 261-273, November 2015.

[18] J. L. Herlocker, J. A. Konstan, L. G. Terveen and o. T. Riedl, "Evaluating collaborative filtering recommender systems," *ACM Transactions on Information Systems*, vol. 22, no. 1, p. 5–53, 01 January 2004.

[19] W. Li-Cai, M. Xiang-Wu and Z. Yu-Jie, "Context-Aware Recommender Systems," *Journal of Software*, vol. 23, pp. 1-20, 2012.

[20] E. Çano and M. Morisio, "Hybrid recommender systems: A systematic literature review," *Intelligent Data Analysis, vol. 21, no. 6*,, vol. 21, pp. 1487-1524, 2017.

[21] L. Terán, A. O. Mensah and Arianna Estorelli,

"A literature review for recommender systems techniques used in microblogs," *Elsevier*, vol. 103 , pp. 63-73, 1 August 2018.

[22] R. S. Naser and H. N. Nawaf, "Context Aware Web Service Recommender Supported by User-Based Classification," in *2019 International Engineering Conference (IEC)*, Erbil, Iraq, 2019.

[23] F. Ricci, L. Rokach and B. Shapira, "Recommender Systems Handbook," in *Introduction to Recommender Systems Handbook*, New York, USA, Springer, Boston, MA, 2011, pp. 1-35.

[24] L. Lüa, M. Medo, C. H. Yeung, Y.-C. Zhang, Z.-K. Zhang and T. Zhou, "Recoomender System "Physics Reports"," *Elsevier*, pp. 1-49, 2012.

[25] HamidrezaKoohiKouroshKiani, "A new method to find neighbor users that improves the performance of Collaborative Filtering, Expert Systems with Applications," *Elsevier*, vol. 83, pp. 30-39, 15 October 2017 , 15.

[26] H. Liu, X. Kong, X. Bai, W. Wang and T. M. Bekele, "Context-Based Collaborative Filtering for Citation Recommendation," *IEEE*, vol. 3, pp. 1695-1703, 28 September 2015.

[27] J. Li and Q. Zhu, "Semi-Supervised Self-Training Method Based on an Optimum-Path Forest," *IEEE Access* , vol. 7, pp. 36388-36399, 18 March 2019.

[28] L. Haifeng, K. XIiangiie, X. Bai, W. Wang, M. Teshome, Bekele and F. Xia, "Context-Based Collaborative Filtering for Citation Recommendation," *IEEE*, pp. 1695–1703,, 2015.

[29] X. Kong, Y.-S. Chang, Q. Hua, R. Chen, B. Wang and L. Zhang, "A Survey of Collaborative Filtering-Based Recommender Systems: From Traditional Methods to Hybrid Methods Based on Social Networks," *IEEE*, vol. 6, pp. 64301 - 64320, November 2018.

[30] Y. Dou, H. Yang and X. Deng, "A Survey of Collaborative Filtering Algorithms for Social Recommender Systems," in *2016 12th International Conference on Semantics, Knowledge and Grids (SKG)*, Beijing, China, 2016.

[31] S. Ahmadian and P. Moradi, "A reliability-based recommendation method to improve trust-aware recommender systems," *ScieceDirect*, pp. 7386-7398, 2015.

[32] J. Salter and N. Antonopoulos, "CinemaScreen recommender agent: combining collaborative and content-based filtering," *IEEE*, vol. 21, pp. 35 - 41, February 2006.

[33] M. Jamali and M. Ester, "A matrix factorisation technique with trust propagation for recommendation in social networks," *ACM Digital Library*, pp. 135-142, 2010.

[34] C. B. D. R. G. Aurilio, "Trust-Aware Clustering Collaborative Filtering: Identification of Relevant Items," in *FIP International Federation for Information Processing 2012*, Berlin, Heidelberg, 2012.

[35] J. Li and Q. Zhu, "Semi-Supervised Self-Training Method Based on an Optimum-Path Forest," *IEEE*, Vols. Neurocomputing, vol. 275, pp. 180–191,, 2018..

[36] M. Nilashi, O. Ibrahim and K. Bagherifard, "A recommender system based on collaborative filtering using ontology and dimensionality reduction techniques," *ScienceDirect*, vol. 92, pp. 507-520, 2018.

[37] R. Salakhutdinov and A. Mnih, "Probabilistic matrix factorisation," in *Proceedings of the 21st Annual Conference on Neural Information Processing Systems*, Vancouver, Canada, 2007.

[38] Z. Shajarian, S. A. Seyedi and P. Moradi, "A clustering-based matrix factorisation method to improve the accuracy of recommendation systems," in *2017 Iranian Conference on Electrical Engineering (ICEE)*, Tehran, Iran, 2017.

[39] J. McAuley and J. Leskovec, "Hidden factors and hidden topics: understanding rating dimensions with review text," in *Proceedings of the 7th ACM Conference on Recommender Systems, RecSys 2013*,, China, 2018.

[40] J. J. McAuley and J. Leskovec, "Hidden factors and hidden topics: understanding rating dimensions with review text," in *13: Proceedings of the 7th ACM conference on Recommender systems*, China, 2013.

[41] X. Luo, M. Shang and S. Li, "Efficient Extraction of Non-negative Latent Factors

from High-Dimensional and Sparse Matrices in Industrial Applications," in *2016 IEEE 16th International Conference on Data Mining (ICDM),*, Barcelona, Spain, 2016.

[42] S. Sun, C. Zhao and Z. Zhang, "A matrix factorisation based trust factors model," in *2015 IEEE International Conference on Information and Automation*, Lijiang, China, 2015.

[43] B. Lika, K. Kolomvatsos and S. Hadjiefthymiades, "Facing the cold start problem in recommender systems," *Elsevier, Expert Systems with Applications,* vol. 41, no. 4, pp. 2065-2073, March 2014.

[44] Y. Cao, W. Li and D. Zheng, "A hybrid recommendation approach using LDA and probabilistic matrix factorisation," *Springer Limk,* p. pages8811–8821, 2019.

[45] F. García-Sánchez, R. Colomo-Palacios and R. Valencia-García, "A social-semantic recommender system for advertisements, Information Processing & Management," *ScienceDirect,* Vols. 57, 2, March 2020,, pp. 1-16, 2020.

[46] S. Sivapalan, A. Sadeghian, H. Rahnama and A. M. Madni, "Recommender systems in e-commerce," in *2014 World Automation Congress (WAC)*, Waikoloa, HI, USA, 2014.

[47] B. Kr.Patra, R. Launonen, V. Ollikainena and S. Nandib, "A new similarity measure using Bhattacharyya coefficient for collaborative filtering in sparse data," *Elsevier, Knowledge-Based System,* vol. 82, pp. 163-177, July 2015.

[48] J. Wu, L. Ping, H. Wang, Z. Lin and Q. Zhang, "Research on Improved Collaborative Filtering-Based Mobile E-Commerce Personalized Recommender System," in *2008 International Conference on MultiMedia and Information Technology*, Three Gorges, China, 2008.

[49] S. Lin and X. Wenzheng, "E-Commerce Personalized Recommendation System Based on Web Mining Technology Design and Implementation," in *2015 International Conference on Intelligent Transportation, Big Data and Smart City*, Halong Bay, Vietnam, 2015.

[50] C. Sun, R. Gao and H. Xi, "Big data based retail recommender system of non E-commerce," in *Fifth International Conference on Computing, Communications and Networking Technologies (ICCCNT)*, Hefei, China, 2014.

[51] P. H. Aditya, I. Budi and Q. Munajat, "A comparative analysis of memory-based and model-based collaborative filtering on the implementation of recommender system for E-commerce in Indonesia: A case study PT X," in *2016 International Conference on Advanced Computer Science and Information Systems (ICACSIS)*, Malang, Indonesia, 2016.

[52] Hyunwoo, Hwangbo, Y. SokKim and K. J. Cha, "Recommendation system development for fashion retail e-commerce," *ScienceDirect, Electronic Commerce Research and Applications,* vol. 28, pp. 94-101, 2018.

[53] L. Jiang, Y. Cheng, J. L. Li Yang, H. Yan and X. Wang, "A trust-based collaborative filtering algorithm for E-commerce recommendation system," *Journal of Ambient Intelligence and Humanized Computing,* p. 3023–3034, 29 June 2018.

[54] R. S. Gaikwad, S. S. Udmale and V. K. Sambhe, "E-commerce Recommendation System Using Improved Probabilistic Model," in *Information and Communication Technology for Sustainable Development, 2018*, Singapore., 2017.

[55] M. Balabanović and Y. Shoham, "Fab: content-based, collaborative recommendation," *ACM Digital Library,* pp. 66-72, 1997.

[56] D. Billsus and M. J. Pazzani, "User Modeling for Adaptive News Access," *ACM Digital Library,* p. 147–180, 2000.

[57] K. Lang, "News Weeder: Learning to filter netnews.," in *Proc. of the 12th Int. Conf. on Machine*, San Mateo, CA, USA , 1995.

[58] C. Buckley and G. Salton, "Optimisation of relevance feedback weights," in *SIGIR '95: Proceedings of the 18th annual international ACM SIGIR conference on Research and development in information retrieva*, New York, NY, USA, 1995.

[59] L. Tao, J. Cao and F. Liu, "Dynamic feature weighting based on user preference sensitivity

for recommender systems," *ScienceDirect*, , vol. 149, pp. 61-75, 01 June 2018.

[60] A. Pashazadeh and N. J. Navimipour, "Big data handling mechanisms in the healthcare applications: A comprehensive and systematic literature review," *ELsevier*, pp. 47-62, June 2018.

[61] Chia-ChenChen and Jia-LunTsai, "Determinants of behavioral intention to use the Personalised Location-based Mobile Tourism Application: An empirical study by integrating TAM with ISSM," *Future Generation Computer Systems*, vol. 96, pp. 628-638, 26 July 2019.

[62] J. Levandoski, M. Sarwat, A. Eldawy and M. F. Mokbel, "LARS: A Location-Aware Recommender System," in *2012 IEEE 28th International Conference on Data Engineering*, Arlington, VA, USA, 2012.

[63] Z. Yang, B. Wu, K. Zheng, X. Wang and L. Lei, "A Survey of Collaborative Filtering-Based Recommender Systems for Mobile Internet Applications," *IEEE Access*, vol. 4, pp. 3273 - 3287, 2016.

[64] A. Menu, L. Shi, L. Liu, M. Ahmed and J. Panneerselvan, "Hybrid recommendation–based quality of service prediction for sensor services," *International Journal of Distributed Sensor Networks*, 21 May 2018.

[65] U. Yadav, N. Duhan and K. K. Bhatia, "Dealing with Pure New User Cold-Start Problem in Recommendation System Based on Linked Open Data and Social Network Features; Mobile Information Systems,," *Hindawi*, vol. 2020, pp. 1-20, 23 June 2020.

[66] J. F. Miao, "Design and implementation of personalisation recommendation system in mobile e-commerce," *Trans Tech Publications, Ltd.*, pp. 4506-4509, July 2014.

[67] M. Aprilianti, R. Mahendra and I. Budi, "Implementation of weighted parallel hybrid recommender systems for e-commerce in Indonesia," in *International Conference on Advanced Computer Science and Information Systems (ICACSIS)*, Malang, Indonesia, 2016.

[68] (. M. I. Anupriya Gogna and (. I. Angshul Majumdar, "A Comprehensive Recommender System Model: Improving Accuracy for Both Warm and Cold Start Users," vol. 3, pp. 2803-2813, 2015.

[69] M. Mansoury and M. Shajari, "Improving recommender systems' performance on cold-start users and controversial items by a new similarity model," *International Journal of Web Information Systems*, vol. 12, pp. 126-149, June 2016.

[70] Z. Qiu, M. Chen and J. Huang, "Design of Multi-mode E-commerce Recommendation System," in *Third International Symposium on Intelligent Information Technology and Security Informatics, 2010*,, Jian, China, 2010.

[71] S. Sain, S. Saumya and J. P. Singh, "Sequential Purchase Recommendation System for E-Commerce Sites," in *IFIP International Conference on Computer Information Systems and Industrial Management (CISIM), Lecture Notes in Computer Science*, Bialystok, Poland, 2017.