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SURVEY

Time-Aware Recommender Systems: A Comprehensive Survey and Quantitative Assessment of Literature

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ABSTRACT Recommender systems (RS) are among the most widely used applications in data mining and machine-learning technologies. These technologies recommend relevant products to customers, such as movies to watch, items to buy, and books to read. The difference in user preferences over time is one of the most significant issues faced by recommender systems. Researchers have focused on time-sensitive recommender systems, and numerous studies have been conducted in this field. These studies aim to consider the time factor while offering recommendations to users by incorporating and utilizing temporal data in recommendations. In this work, we review existing works in this field and present the most prominent techniques and algorithms that have the ability to capture changes in user preferences over time, and the most important application areas for these recommendations. In addition, we present a quantitative assessment of comprehensive literature that investigates publications in terms of publication time, publication type, and datasets used. Finally, we highlight a range of findings and conclusions and provide the reader with insights based on a general analysis of time-sensitive recommender systems.

INDEX TERMS Recommender systems (RSs), time sensitive recommender system, context-aware recommender systems, time aware, artificial intelligence (AI), machine learning, deep learning.

I. INTRODUCTION

Nowadays, owing to the huge increase in information on the Internet, the demand for recommender systems is increasing in all sectors, including education, tourism, and business. Recommender systems help users to make better, more appropriate choices, and assist them to discover new products like movies, music. In addition, recommender systems can be extended to discover new places, such as restaurants and hotels, based on the characteristics of the users or recommended items. Recommender systems have become important in helping users to quickly make decisions when they are in a difficult situation for the reason that faced many options '' over choice'' [1].

Generally, recommender systems can be categorized into four types: collaborative filtering, content-based filtering, knowledge-based filtering, and hybrid-based filtering. Items are chosen based on the correlation between the present (active) user and other users of the system in collaborative filtering, which is also known as social filtering. The association between items and user preferences was used to recommend content-based filtering items. To deliver recommendations to the user, the interests of the user are first examined, and the results of the user profile analysis were compared with the products available on the system. In a knowledge-based recommender system, providing a recommendation infers a user's needs and preferences. This type of recommender system can explain the relationship between a specific item and a possible recommendation by understanding how it meets certain user demands. Finally, a hybrid recommendation was created by combining more than one recommender system type. This might be a great way to overcome the constraints that are faced when we use only one recommendation method. Collaborative filtering

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and content-based methods are the two most commonly used types of recommender systems. Fig. 1 and 2 present the two techniques [2], [3], [4].

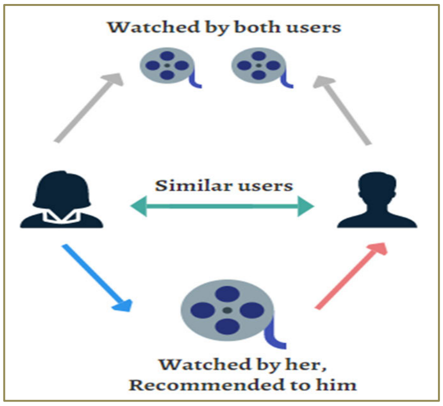

FIGURE 1. Collaborative filtering.

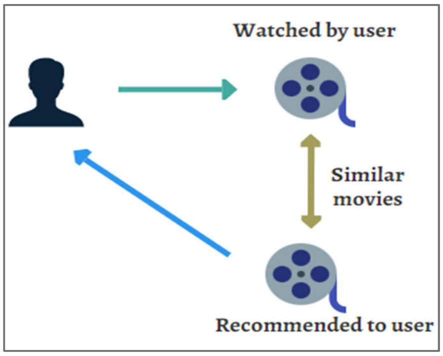

FIGURE 2. Content-based recommendation.

Currently, trends in recommender systems are evolving to follow changing user preferences based on the passage of time, changing user interests, advancing age, and recent trends in technology. Its development is one of the motives that shed light on the latest findings of studies on the development of time-sensitive recommender systems.

However, one of the RS's drawbacks is that it fails to capture user preference patterns that may vary over time, resulting in a decreased recommendation accuracy [5]. For example, when a user is younger, he or she may appreciate animation films, but as he or she gets older, his or her preference may shift to action or drama films. As a result, understanding the dynamics of user choice is critical for better anticipation of future user behavior, which is difficult. To address this weakness, time-sensitive recommender systems should be used. A time-sensitive RSs are the techniques that help in predicting the user's preferred activity at a particular time, how to recommend the most desirable item at the appropriate time, and how to predict when a user will return to a service or product [6].

Additional data were incorporated into the models to accurately capture user preferences. Many studies have been conducted to investigate temporal dynamics and how user preferences change over time. To track changes in global user and item behaviors, drift and decay factors were utilized [7]. Furthermore, because the sparsity problem would be exacerbated, the necessity of simulating the temporal dynamics of user preferences poses certain challenges. In addition, some studies have explored merging multimodal information with scores to reduce data sparsity.

To address these research gaps, this paper presents a survey of time-sensitive RSs to review the literature in the field also their evolution and findings over time and discuss the effect of time on inter-temporal recommender systems to capture changing user interests. The fundamental purpose of this paper is to serve time-sensitive recommender systems by reviewing previous studies and determining what is new in this field. The specific contributions of our work are as follows:

- Support studies in the field of artificial intelligence, particularly in time-sensitive recommender systems.
- Find the modern approaches and algorithms in time-sensitive recommender systems.
- Present the latest results in general in time-sensitive recommender system studies.
- Contribute to finding the most popular datasets used in time-sensitive recommender systems.
- Determine the most important challenges facing researchers in this field.
- This study analyzed the advantages and disadvantages of the current temporal models.
- We present a summary of the quantitative assessment of comprehensive literature in this field to assist researchers.
- This study includes recommendations for new lines of research.

The remainder of this paper is organized as follows. Section II provides the necessary background information regarding time-sensitive recommender systems and some techniques and preliminaries. Section III provides a discussion of related work. The techniques, advantages, challenges, evaluation metrics, and applications of the time sensitivity of RSs are presented in Section IV. Section V presents a quantitative assessment of the comprehensive literature that analyzes these publications. Section VI presents insights, with a discussion and conclusion in Section VII.

II. BACKGROUND

Data mining is a technique for extracting meaningful information from enormous datasets by detecting correlations and patterns among the data. Such recommendations are built using a variety of data-mining analysis approaches. This section covers the key techniques utilized in recommender systems.

- Text Mining

  Text mining is a technique used to extract text-related information from data to identify important text information. They can be used to capture context information as well as user preferences (user profiling). Text mining can be used for this purpose on user reviews, text descriptions associated with products, and other texts written by users (e.g., posts in social networks) [8].

- KNN (K-Nearest Neighbor)
  K-Nearest Neighbor (KNN) is a classification technique that classifies a dataset by classifying the K-nearest neighbors of the test and train tuples. KNN help to find clusters of similar users based on common item ratings and then uses the top k nearest neighbors' average rating in the matrix to make predictions [9].
- Clustering
  Clustering is used to describe data by identifying bounded categories or clusters. It is commonly used in recommender systems because of its low redundancy and ambiguity. The most common clustering method in recommender systems is k-means clustering. The idea of a clustering algorithm is to arrange a collection of items in such a way that they are more similar to each other than to those in other clusters. Users can be grouped into many clusters using clustering techniques. In recommender systems, clustering techniques are used to find user groups that have similar tastes. Due to its resistance to sparsity problems, this method significantly enhances performance [10].
- Matrix Factorization
  Matrix Factorization is a technique for describing items and user data by inferring items from user evaluation data and storing them as vectors. By storing the user's assessment data in a rating matrix, the major goal of this technique is to determine the dimension of the latent factor that conveys the user's information and desire. Matrix factorization enables the incorporation of more information. When there is no explicit feedback, recommender systems can infer user preferences by employing implicit feedback, which infers preferences by analyzing user behavior, such as past purchases, browsing patterns, search behavior, or even mouse clicks. Implicit feedback is frequently represented by a densely populated matrix because it typically indicates the existence or absence of an event. In comparison to traditional nearest-neighbor methods, matrix factorization models are more effective at producing product recommendations. A recommender is generated by factors that have high correspondence between the product and the user [11].
- Neural Network
  The application of neural networks has grown in recent years in various sectors, including speech recognition, picture recognition, photo search, and language translation. On the other hand, despite the fact that neural networks have just recently been introduced and used in the recommender system field compared to other sectors, many studies are being undertaken as one of the key areas of interest in recommendation-system-related research. In recommender systems, neural networks are used for classifying and prediction purposes. Additionally, for a personalized rating of items, multi-layer neural networks can be used to non-linearly represent interactions between users and items based on implicit input. By combining these representations with latent factors of user preferences, neural networks enable the representation of temporal and contextual aspects of user activity to make more accurate recommendations [12].

A. RECOMMENDER SYSTEMS GENERATION

Currently, there are three generations of recommender systems. Each generation addresses the problems of the previous generation and seeks to solve them in different ways. In this section, we will go over generations and discuss the most important issues they have faced [13], [14]:

1) 1ST GENERATION (WEB1.0 RECOMMENDATION)

First-generation or Web 1.0 recommender systems deal with e-commerce, since the development of Web 1.0 recommender systems, object recommendations have become a major field of concern for researchers who have investigated several recommendation approaches. Web 1.0 Recommender systems contain two key elements.

Users and items: There is a binary relationship between them. Users give ratings to items based on their preferences, which can be binary (like or dislike) or on a scale of one to five. Many problems occur in Web 1.0, such as the cold start problem, sparsity, and overspecialization. In addition, Web1.0 focused on the four main types of recommender systems: knowledge-based, content-based, collaborative filtering, and hybrid recommendation. Also, "Tapestry" the first collaborative RS that filters a user's queries on the mailing list.

2) 2ND GENERATION (WEB 2.0 RECOMMENDATION)

The second generation or Web 2.0 typically uses social networks and social contextual information, such as follows, followed, tweets, and posts, to acquire accurate and diversified recommendations. Since the rise of social tagging services, tag recommendations have become a popular topic of discussion. Researchers have begun to focus on several new techniques and aspects, such as matrix factorization, personality-based, and web usage mining. Scalability and privacy are two of the most important concerns and issues facing this generation.

3) 3RD GENERATION (WEB 3.0 RECOMMENDATION)

With the widespread usage of mobile devices, there is a growing trend toward location-based or Internet of Things information (e.g., GPS locations, RFID, and real-time health signals) being used to generate recommendations. Web 3.0, a higher quality recommendation, is also a more complex and expensive implementation.

B. TIME SENSITIVE RECOMMENDER TECHNIQUE

Because user preferences change over time, many recommender system techniques have been established and developed to access and capture user preferences that change. In this section, we briefly review the most recent and important techniques used in time-sensitive recommendations field [10], [11], [17]:

- k-nearest-neighborhood
- Time-dependent Matrix Factorization (TMF
- Time-SVD + +

We explain these techniques for time-sensitive recommender systems in more detail in section IV.

C. RELATION BETWEEN CONTEXT-AWARE AND TIME-AWAR

Context awareness refers to a system or component's ability to gather information about its environment at any given time and adjust its behavior in response. Any information relevant to a specific entity, such as person, device, or application, is included in the context. Consequently, contextual data can be categorized by time, location, device, identity, user, role, privilege level, activity, task, process, and neighboring devices/users [18].

Our study focuses on a time-aware recommender system (TARS), which is a type of context-aware recommender system that considers time while estimating the target item's rating. These systems give a high priority to data that is close in time to the current time or close in time to the target user data, but TARS systems do not evaluate the target user's preference change or concept-driven data [19].

III. RESEARCH METHOD AND SELECTION CRITERIA

While there are already many literature reviews, focusing on the Recommender systems, there are not many recent studies regarding time-sensitive recommender systems surveys. Therefore, this study focuses on covering all the contributions in time aware RSs topic and the directions of researchers in the future. The research method adopted for this study is a comprehensive survey study which considers the techniques specified in the time aware RSs to gain an overview of time sensitive RSs contributions and quantitative assessment of literature.

The search strategy is to review relevant studies related to the time-aware RS topics published in the area of computer science and covering the period 2005-2021 in the following databases: IEEE, ACM and Springer. Also, we used Google Scholar search engine. The search started by searching in general; the plan is aimed to filter the results to get the most related. Therefore, the first result of filtering is the year of publication. Secondly, filtering using range results to the articles related to our search keywords in the title, abstract, and keywords.

Therefore, this survey focuses on specific keywords written in the following strings:

•(''Time Aware Recommender System'' OR ''Time Aware Recommendation'').

•(''Time Sensitive Recommender System'' OR ''Time Sensitive Recommendation'').

Some papers are not available as a full text, only the abstract, title, author, and keywords, so this information was used to review the study. The year range, keywords, included, and excluded elements have been unified in all of the other selected databases. Finally, we remove the duplicated papers and the studies related to Recommender Systems but not related to the selected criteria (Time-Aware).

IV. LITERATURE REVIEW

Researchers have created many recommendation algorithms in response to a variety of practical applications.

Bansal et al. [20] suggested a content-based recommendation engine, while Suganeshwari and Ibrahim [21] showed collaborative filtering (CF). Wang et al. [22] explained hybrid approaches in a user-personalized review rating prediction method, which are the three types of methodologies available. The relationship between users and items is utilized to anticipate user preferences, usually in the form of item ratings, using a prominent technique in RS to predict ratings. Koren [7] introduced matrix factorization (MF), a well-known CF method that has been demonstrated to operate in real-world circumstances. In addition, Suganeshwari and Ibrahim [21] explained that matrix factorization (MF) predicts ratings using latent features acquired from historical ratings data to characterize users and goods.

Traditional RS methods primarily focus on the development of individualized suggestions for users whose preferences are thought to be static and thus do not consider changes in user preferences over time. To describe consumers' dynamically changing preferences and handle the temporal dynamics problem,time information has been included into the CF approach according to [5], [23], and [24]. To address this issue, time-aware RSs have been actively studied recently, considering the possibility that user preferences may change over time. The task of recommendation, that is, the methods of rating prediction and suggestion, can be used to categorize these works. Koren [7] was the first to investigate models based on probabilistic MF for TimeSVD++ methods.

In the neighborhood model, they added user bias, item bias, and implicit feedback as well as a latent factor and time change. Furthermore, the dynamic time drift model (DTDM), according to Sun and Dong [25], uses clustering and a time factor matrix to determine how far users' interests moved within a class. Chua et al. [26] applied dynamic matrix factorization (DMF) techniques to create distinct temporal factorization models that accommodate different latent states at different time steps. Non-negative matrix factorization is employed to track the evolution of user actions over time.

Furthermore, session-based temporal graph (STG) techniques Xiang et al. [27] used session-based temporal graphs in multiple time bins and defined each time bin. Another model by Li et al. [28] used similarity and forgetting functions to create a combined RS method. To date, few studies have used time weights in the latent transition model. In addition, tensor factorization, such as the Bayesian probabilistic tensor factorization (BPTF) model proposed by Xiong et al. [16] represents the proposed ratings with a three-dimensional tensor (user, item, and time). The inner product of the latent factor vector is utilized to allow the model to learn the global evolution of latent features and ratings, but the model's sensitivity is insufficient for capturing local changes in preferences. Rafailidis and Nanopoulos [29] suggested a novel measure of preference dynamics to capture the pace at which each user's preferences fluctuate using tensor matrix factorization as a dimension to construct continuous user–item interactions throughout time. The rating matrix tends to rate only a small number of items, owing to sparsity concerns, resulting in a high percentage of missing scores. Several temporal dynamic models have recently addressed this issue. Using an updated nonnegative matrix factorization (NMF) approach that jointly learns topic evolution by mapping a matrix to capture shifts in interest across two periods, Vaca et al. [30] presented a collective MF to represent the online topic discovery challenge. However, this technique is limited to news subject discovery, and cannot be used in regular recommender systems.

To predict changes in user preferences over time, Zhang and Wang [31] introduced temporal matrix factorization (TMF) and Bayesian TMF (BTMF) models. The central idea is to represent evolution using a latent transition matrix that reflects the time-invariant features of users' temporal dynamics. In addition, Rafailidis et al. [32] addresses data sparsity by including both temporal dynamic and multimodal information; however, it only employs implicit feedback from user comments and ignores the hidden meanings of additional data. TMRevCo techniques by Wu et al. [33] also considered temporal dynamics and side information. They increased performance by utilizing a CoFactor item correlation measure and connecting CoFactor item factors with MF item factors; however, they only looked at item correlation features, which is not the case with our method.

Aggarwal [15] introduced a time- and location-sensitive recommender system. He then lists two different ways to use time-sensitive recommender systems: explicit rating (in this scenario, dates are associated with explicit ratings) and implicit feedback (in this scenario, the historical sequence of user actions, such as purchases and webpage clicks, are used to develop predictions about future behaviors). In addition, he explained ways to use temporal information that can improve the effectiveness of prediction: encencency-based models, periodic context-based models, and models that explicitly use time as an independent variable. A recent approach, and one of the most common methods of the last type, is the time-SVD++ model. Finally, Aggarwal [15] reviewed some practical issues in this field and considered time sensitivity as one of the most difficult types of recommender systems.

Existing time-related algorithms typically include a time factor in the training phase, which makes the process more difficult. To address this problem, Sun et al. [17] proposed a time-sensitive collaborative filtering model. It maintains the original training phase and makes some changes in the prediction phase. During the recommendation process, the proposed model arranges items by time for each user in a sequence. This sequence is called the temporal behavior sequence. It begins by locating the most recent item in the current user's tim–behavior sequence, which indicates the current user's most recent choice. Second, it stores the item's timestamp after locating it in the time behavior sequence of its closest neighbors. Finally, it recommends items with timestamps greater than the preserved timestamp based on the time-behavior sequence of the closest neighbors. In an experiment, he compared the traditional user-based collaborative filtering recommendation algorithm with the proposed model. Sun et al. [17] used the MovieLens data set. In the evaluation phase, they used two metrics: the hit rate and recall. The results indicate that the proposed model is better, more accurate, and efficient than the traditional user-based collaborative filtering algorithm model. This helps maximize the rate of conversion by users. Therefore, they can be used on e-commerce websites.

Most recommendation algorithms do not explicitly consider the temporal behavior and repetitive activities of the users. To learn how to recommend the most preferred item in time, and how to anticipate the user's next return time to the service, Du et al. [6] proposed a new framework for capturing recurrent temporal patterns in a large collection of user-item consumption pairs that combines self-exciting point processes with low-rank models. They used the last.fm dataset, which consists of music streaming logs of between 1,000 users and 3,000 artists. Then, the dataset was split into a pair of training/testing subsequences. Du et al. [6] evaluated the predictive accuracy for each testing event for two tasks: item recommendation and returning time prediction. The results showed that the scalability and predictive performance of the proposed algorithm were better than scalability and predictive of competitors' algorithms. Furthermore, their optimization approach can be utilized to solve general non-negative matrix rank minimization problems with various convex losses, which could be of independent interest.

To solve the problems of user interest drift, low precision, and long tail, Pang et al. [34] proposed a new algorithm called FSTS, which adopts stability variables and time-sensitive factors. In their experiment, they used the MovieLens dataset and four evaluation criteria: precision, recall, popularity, and coverage to evaluate the FSTS algorithm. The feature vector and time-sensitive factor are used in the prediction process to extract item features and address user interest drift. Consequently, with minimal temporal complexity, the FSTS algorithm enhances both the prediction and performance algorithms. However, the dynamic transformation of the time-sensitive factor was weak.

One of the primary issues of recommender systems in providing personalization to users is the identification of specific temporal preferences. To solve this problem, Cami et al. [35] proposed a content-based movie recommender system that utilizes user modeling to record temporal user preferences and predict the preferred films. The proposed method creates a user-centred framework by incorporating the content attributes of rated movies (for each user) into a Dirichlet process mixture model to infer user preferences and generate a good recommendation list. Cami et al. [35] divided the proposed method into two main stages: modeling the temporal preferences of the user and a content-based movie recommender system. The authors used the MovieLens dataset in the experiment. Precision@N, recall @N, and F1-measure@N were utilized to evaluate the results of the proposed method. Subsequently, they compared the proposed method with the time-SVD++ algorithm. The results of this study reveal that the proposed recommendation method outperforms existing movie recommender systems in terms of performance.

One key finding on online social platforms is that users' interests and topic popularity vary rapidly, posing significant problems to existing recommender systems in providing the right topics at the right time. Chen et al. [36] proposed a temporal recommender system called TeRec based on an online ranking technique. This enables users to obtain recommendations of topics according to their interests or preferences in real time, and they can also create quick feedback according to the recommendations. They used the Weibo dataset, which consists of 87287 users, 29334 tags, and nearly 20 million tweets. In their evaluation, Chen et al. [36] used the Top-N recall metric. That is, whenever they recommend a Top-N list to a user, they check whether the item actually utilized is on the Top-N list. Their algorithm outperformed the others in terms of real-time hashtag recommendations for Twitter streams, as evidenced by the results.

To improve job recommendations, Liu et al. [37] combined temporal learning with sequence modeling to capture complicated user-item activity patterns. Their solution consists of three main sections. First, they offered a time-based ranking model for historical observations as well as a hybrid matrix factorization across time-reweighted interactions. Second, they developed an RNN-based recommendation model based on sequence features in user-item actions. Finally, using RNNs for sequence modeling, Liu et al. [37] modeled the entire collection of user-item interactions from the same user as a sequence ordered by time rather than considering user-item interactions as independent pairs. To evaluate their work, they used P@N to denote the precision at N and the recall. The results of the empirical study confirmed the effectiveness of using historical data to predict user preferences as well as temporal learning and sequence modeling to improve recommendations. The proposed RNN-based model outperformed the most widely used matrix factorization models.

Lv et al. [38] proposed a novel model called time-sensitive collaborative interest-awareness (TSCIA). It explicitly collects similar interests from neighboring sessions to simulate the overall collaborative interest while also considering users' interest drifts. Two datasets were used: Diginetica obtained from CIKM Cup 2016 and Retailrocket. Retailrocket, which contains six months of user-browsing actions, comes from an e-commerce company. Two evaluation metrics were used in the evaluation model: hit rate (HR@K) and mean reciprocal rank (MRR@K). Their model was compared to a set of baselines, including traditional approaches and cutting-edge neural session-based recommendation algorithms such as Pop, Session-Pop, Item-KNN, Session-KNN, GRU4Rec, NARM, STAMP, and CSRM. The efficacy and rationality of the proposed model are compared to the aforementioned models through extensive experimental findings and qualitative experimental assessments.

In the prediction process, clustering algorithms can assist recommender systems in grouping users into relevant clusters, which are referred to as neighborhoods. Although user preferences change over time, typical clustering methods ignore this critical feature. To address this issue, Ahmadian et al. [39] proposed a social recommender system based on temporal-clustering SRTC. The suggested method considers the temporal information of user ratings of items, as well as social information among users. 1) Network construction, 2) temporal user clustering, and 3) recommendations are the three essential steps in the proposed method. In their experiments, they used the Epinions dataset, which contains 49,290 users and 139,738 items. Users' opinions on existing items were expressed as numerical ratings ranging from 1 (minimum) to 5 (maximum). In this study, three evaluation metrics were used to compare the performance of the proposed method with other methods in terms of accuracy and coverage metrics: mean absolute error (MAE), root mean squared error (RMSE), and catalog coverage (CC). The results of the comparison indicate that the proposed method (SRTC) is outperforms several existing methods in terms of accuracy and coverage metrics. The proposed method was compared with six existing algorithms in the same field, including clustering-based recommender methods: K-means collaborative filtering (KMCF), trust-aware clustering collaborative filtering (TRACCF), and multi-view K-medoids (MV). In addition, time-based recommender methods include collaborative filtering with temporal contextual information (CFTCI), adaptive time-based collaborative filtering (ATCF), and time-based singular value decomposition (timeSVD++).

Because collaborative filtering (CF) is one of the most commonly used methods for recommendations, traditional CF methods usually cannot track temporary dynamic user preferences and subject changes to provide appropriate recommendations in relation to changing user interests over time. For this, Wangwatcharakul and Wongthanavasu [40] proposed a novel temporal recommender system based on multiple transitions in user preference drift, called MTUPD, which employs a multitransition factor and an adaptive time weight using the forgetting curve function to compute user preference correlations at different time periods. In addition, Wangwatcharakul and Wongthanavasu [40] applied a topic model that automatically classified hidden topic factors in each time period and incorporated the transition method for both user preferences and relevant review topics to address the sparsity problem. User reviews have been exploited as an auxiliary information source to discover hidden topic evolutions that can describe why the user gives a certain rating by using topic modeling techniques at different time steps. They used eight datasets in their experiment to prove the accuracy of the proposed model: automotive, baby, fine food, video games, toys and games, movies and TV, software, and health. The MTUPD model can be used as a splitting temporal dynamics tool for monitoring the evolution of user preferences over time. While other algorithms (TimeSVD++, BPTF, TimeTrustSVD, BTMF, TCMF, TMRevCo, DCF) can examine the evolution of user preferences by capturing user interest drifts in a single transition step, the MTUPD model can do so by capturing user interest drifts in several transition stages. Other models, on the other hand, track the evolution of user preferences at each time step but ignore the user preference transition factor. Additionally, they ignore the rating sparsity issue in order to deal with the temporal problem. In terms of the RMSE and top-n recommendation, the suggested MTUPD performs the best on the eight datasets.The experimental results showed that the model significantly outperformed the modern dynamic collaborative filtering models.

Recommending movies of interest to audiences is a challenge because the recommendation scenario is quite different from all the current recommendation apps. Xue et al. [41] proposed a novel spatiotemporal approach called Pegasus to recommend movies to on-demand cinemas based on the idea of collaborative filtering. The model exploits POI (Point) information about cinemas and descriptions of film content, independent of cinemas' historical film consumption records. It also explores the temporal dynamics and spatial influences rooted in audience behaviors and captures similarities between cinemas, changes in audience crowds, time-changing features, and regional disparities in film popularity. Extensive experiments and empirical tests were conducted using real-world data from iQIYI between July 1, 2016, and September 1, 2018. There were 743,558 consumption records of 5,879 movies in these 207 cinemas. Experimental results and post-publication feedback showed that Pegasus was good.

Traditional collaborative filtering systems do not use temporal information. Ullah et al [42] introduced a hybrid recommender system that accounts for item attribute similarity, user rating similarity, user demographic similarity, and temporal information to recommend users at the current time. Ullah et al [42] could not find a dataset that contains time information with rating information for movies. However, they used a dataset from Movie Lens and added time ranges, considering 24 time ranges, 200 users, and 1000 movies with four features in each time range. The results of the algorithm show the degree of comparative advantage at a specific time to quickly and accurately provide the final recommendation, which is highly desirable.

Importance of the time factor and its role in improving the accuracy of trust in social recommender systems. Frikha et al. [43] suggested incorporating a temporal factor into measuring trust among social network friends by identifying and evaluating all possible relationships that might exist between these users. They developed the Facebook 'Trusted Friends' application to show the importance of time in user interactions to identify socially trusted friends. Frikha et al. [43] also developed a Tunisian medical tourism ontology to represent all medical tourism information, considering the time factor in calculating trust between users. This dataset was obtained from Facebook. The results showed that trust is sensitive to the temporal factors of interactions between users.

In recent years, has explored the idea of adopting collaborative ranking (CR) for recommendation, there have been few attempts to incorporate temporal information for POI recommendation using CR. Therefore, Aliannejadi et al. [44] presented a thorough data analysis of two POI recommendation datasets looking at several variables related to sparsity, time-sensitivity, and numerous check-ins. Based on the data analysis, the authors suggested a joint two-phase time-sensitive regularized collaborative ranking model for point of interest recommendation employing a two-phase CR model, known as JTCR. Additionally, the authors demonstrated how to incorporate geographic influence into the goal functions and suggested a time-sensitive regularizer to capture long-term user behavior and POI popularity patterns. The experimental outcomes on the two benchmark datasets showed that the suggested model performs better than other cutting-edge approaches. The authors compared JTCR performance with and without the use of a time-sensitive regularizer, and they analyzed its effects (JTCR-NoVar). All assessment measures for Foursquare show a statistically significant improvement for JTCR versus JTCR-NoVar, indicating that adding the time-sensitive regularizer helps JTCR to rank more relevant venues higher. With regard to Gowalla, there have been sizable gains that show how the proposed time-sensitive regularizer enhances JTCR performance by penalizing users and POIs who show less consistency in their check-in and popularity, respectively. This finding supports the notion that a POI's popularity and its popularity variance have a negative relationship. The results showed that the model can handle the data sparsity issue by accounting for both visited and unvisited POIs in the training phase as well as their individual geographic distances. Additionally demonstrated how the second phase can place more pertinent POIs higher in the ranking, demonstrating why the two-phase model is preferable than both the baselines and the first stage of the algorithm. This implies that while individual check-ins offer insightful data on users' preferences, many check-ins paint a more complete picture of their behavior and routines.

Ding and Li [23] provided a novel approach for computing time weights for various objects in a way that gives outdated data a lower weight. Consumers' purchasing patterns differ. Even the same user can perform varied reactions to different objects. Clustering was used in the suggested technique to distinguish between different types of objects. Ding and Li [23] tracked changes in each user's purchase interest for each item cluster and applied a tailored decay factor based on the user's purchasing history. The results show that the proposed approach significantly enhances the precision of item-based collaborative filtering without introducing higher-order computational complexity.

To improve the performance of collaborative filtering recommendations, Min and Han [24] proposed a mechanism for recognizing a user's time-varying pattern. Profiling, identifying changes, and making recommendations are the three phases of this technique. The proposed methodology uses customer data from various periods of time to detect changes in customer behavior and then uses that information to improve the performance of suggestions.

Sun et al. [45] offered an item popularity model based on user interest feature in order to address the issue of goods popularity bias by introducing the prevalence of items into the user interest model. Traditional models typically do not take consumers' interests into account, which might make it challenging to pique their interest. The two types of similarity models are combined into a novel method called item popularity similarity with time sensitivity (IPSTS), and their respective weight factors are given in order to balance their effects. The algorithm doesn't need any other data, such as trajectory information, other than the user rating ratings. In contrast to non-negative matrix factorization (NMF) and latent Dirichlet allocation, it defines user similarity as the linear combination of item popularity and temporal sensitivity (LDA). The findings indicate that the IPSTS Model's MAE is lower than that of the Pearson Model and the Euclidean Model. The final testing findings show that IPSTS can successfully lower Mean Absolute Error (MAE) and Root Mean Square Error values (RMSE).

Users' interests may change over time, and it can be difficult to create effective personalized recommender systems without accurately predicting users' changing preferences. In real systems, the users-items interaction network is frequently very sparse, which prevents many recommenders from making reliable predictions. The fact that there are frequently only a few ratings for each user, creating an extremely sparse bipartite users-items network, is another important issue for recommender algorithms. Rezaeimehr et al. [46] proposed a novel time-aware recommender system called TCARS to address these issues. This technique is based on finding overlapping user community structures. Some steps that make up the structure of the suggested recommender algorithm are a time-aware method based on a time-weighted similarity matrix between users to detect overlapping communities, then a time-weighted mining algorithm based on association rules and temporal overlapping communities to model drift of users' interests over time, and a new recommendation model based on users' dynamic temporal interests and multi-memberships in their overlapping communities. Two real-world datasets were used as the basis for the experiments. To complete the recommended lists for users, this technique effectively utilized the time of ratings and an enhanced overlapping community identification mechanism. The results showed that the suggested algorithm has higher recommendation precision than some other techniques. TCARS achieved accurate findings when compared to a number of other techniques.

In a different approach, Margaris and Vassilakis [47] proposed a model with an offline component and an online component to capture the influences over the long and short terms. With the online component, the short-term influence is constantly being updated with fresh data, making it more susceptible to unstable or transient preferences. The data now saved in the online component is used to update the long-term impact, which contains preferences that are more stable, much less frequently.

The dynamic attention-integrated neural network (DAINN) for the personalized recommendation task was proposed by Zhang et al [48]. In particular, by combining users' long-term interests, user behavior sequence patterns, users' main goal in the present session, as well as public behavior mining into a cohesive framework, DAINN models the users' dynamic interests over time. The authors used dynamic topic modeling and the convolutional neural network (CNN) phrase model to successfully learn the item semantic embedding and increase recommendation accuracy. It is very crucial to manage the wide range of user clicking behavior. Also used three real-world datasets to apply their model. The method put forward by DAINN can handle the wide range of clicker variation and identify the primary goal of the user for the current session. DAINN is able to provide personalized recommendations and learning users' preferences in real-time.

Ahmadian et al. [49] used temporal reliability and confidence measures to offer a novel time-aware recommender technique called RSTRC. The primary goal is to take into account how user preferences have changed over time when computing the metrics. The suggested approach, in contrast to other previously produced studies, adds the time factor into the reliability and confidence metrics, taking into consideration how user behavior evolves over time. The suggested method is an initial attempt to integrate confidence measures and temporal reliability into the recommendation process. To assess the potency of the user rating profiles, an effective probabilistic approach is presented.

This model determines the bare minimum of ratings that must be provided for the recommender system to generate trustworthy recommendations. Additionally, a novel approach is used to add certain implicit ratings to the users' rating profiles that have insufficient ratings. It should be mentioned that the implicit ratings that are added to the rating profiles are chosen based on their dependability values. It has been demonstrated that this improves the performance of the suggested method in terms of delivering recommendations that are more precise. The suggested technique also addresses the issue of data sparsity by creating a user-item rating matrix that is denser. For the purpose of assessing the accuracy of forecasts, a temporal reliability measure was developed. Additionally, those anticipated ratings with low reliability are recalculated using a powerful method. The majority of the neighbors in the target user's neighborhood set are used in the prediction process in the literature's existing studies, however some neighbors may have an adverse effect on the predicted ratings' accuracy. By identifying and eliminating these unproductive users from the neighborhood set, the authors were able to remedy this issue. Using a temporal confidence measure, the ineffectual users were found for this purpose. Extensive testing on three benchmark datasets demonstrates the proposed method's superiority over contemporary recommender systems.

Harshvardhan et al. [50] developed an unsupervised Boltzmann machine-based time-aware recommender system (UBMTR) that analyzes user-movie ratings data to identify underlying hidden features in relation to the time at which each review was given (temporal information). The model uses a dual-input of ratings and time to produce binary values by sampling from a Monte Carlo Markov Chain using the contrastive divergence procedure. To improve feature extraction and give individualized content recommendations, the authors used user temporal data. This approach specifically aims to take advantage of the correlation that exists between the temporal conditions and the content sought. Boltzmann machine-based recommender systems that incorporate temporal information are hardly ever used in practice, which makes further study in this area necessary. RBMs are skilled at filling in the gaps left by missing values and can handle unstructured data and imbalanced datasets by encoding the raw data into latent variables. The UBMTR beats several prior attempts at recommender systems that used CF, deep learning, or their hybridized models by using RBM.

Cross Domain Collaborate Filtering (CDCF), a novel technique, has recently been developed to address the sparsity issue in recommender systems. By transferring rating information from auxiliary areas, CDCF overcomes the sparsity issue. The majority of earlier research relies mostly on one-side (user- or item-side) auxiliary domain data to support the recommendation in the target domain.

A two-side Cross Domain Collaborate Filtering model (CDCF) was proposed by Yu et al. [51]. The user-side domain and the item-side domain are two auxiliary domains that the authors supposed to exist. The feature vector was created by the authors using the inferred user and item features, and the associated rating served as the class label. As a result, the exchanges between users and items can be thought of as training samples. Yu et al. [51] final stage involved using an SVMs model to address the converted classification issue.

The ability of the current model (CDCF) to utilize both user-side and item-side shared information is one of its main advantages. The domain independent user and item features can also be inferred. As a result, it can more efficiently transfer information from auxiliary domains.

Most of recommender systems utilize user- or item-side supplemental domain data. Yu et al. [52] proposed a cross-domain collaborative filtering algorithm with expanding user and item features via the latent factor space of auxiliary domains in order to get around this problem. Extra user and item features were extracted from user- and item-side auxiliary domains using the Funk-SVD decomposition method. In order to predict missing ratings, a classifier was lastly trained using the C4.5 decision tree algorithm. The proposed algorithm can transfer more useful information to the target domain when compared to earlier one-side CDCF algorithms.

The key advantage of this model is that it can easily handle the scenario of multiple auxiliary domains, assess the importance of auxiliary domains, and effectively transfer knowledge from auxiliary domains. Additionally, it can effectively reduce the sparsity issue and resolve the cold-start issue.

Yu et al. [53] presented a Two-Sided CDCF model that takes into account both accuracy and efficiency based on selective ensemble learning. (TSSEAE). CDCF issues are transformed into ensemble learning problems in TSSEAE, with each combination representing a classifier. By doing this, it is possible to transform the issue of choosing combinations into the selective ensemble learning problem of choosing classifiers. To find Pareto-optimal solutions for the selective ensemble learning issue, a bi-objective optimization problem is finally solved.

The main advantage is demonstrating that, in various experimental settings, TSSEAE significantly outperforms all other state-of-the-art algorithms. TSSEAE can match the recommendation accuracy of TSSEA, which only takes into account recommendation accuracy, while operating more efficiently.

V. TIME SENSITIVE RECOMMENDER SYSTEMS

Generally, prediction techniques do not focus on how popular items and consumer preferences change over time. Time-sensitive recommender systems are intended to recommend items to users at the most appropriate time. Time is an important aspect in making a final selection and is employed in various ways to obtain accurate predictions. As a result, by recording users' interests over time, the temporalis is a viable avenue for improving RS quality. The time-weighted collaborative filtering approach is one of the numerous time-sensitive approaches available. We list the most common techniques for time-sensitive recommendations as follows [5]:

- k-nearest-neighborhood (KNN)
  To avoid data sparsity, the k-nearest neighbor (KNN) technique is most widely used. The drawback of the KNN technique is that it has poor coverage for users who exchange goods with the current user and even fewer ratings for the active user's neighbors. When the rating matrix is sparse, the neighbors produce a mediocre prediction. Neighbors, on the other hand, can be used with other variables (e.g., baseline, latent, and time) to predict sparse rating scores.
- Matrix Factorization (MF)
  Because it is one of the successful ways of addressing data sparsity and cold-start difficulties, MF has recently become a prominent approach for collaborative filtering. Three techniques were combined in matrix factorization: SVD, baseline, and latent factors. MF is commonly used to find latent semantic components and performs well in dealing with the scalability issue. A sequence of stages involving SVD, baseline, and latent factors was used to process the MF. By describing the attributes of both users and objects, MF extracts latent factors from a matrix of rating scores, thereby simplifying the rating scores. SVD is a straightforward MF method for extracting the latent feedback between users and products. Moreover, the KNN technique can be combined with matrix factorization.
- Time-SVD + +
  The most well-known and broad technique in time-sensitive recommendations is timeSVD++, which simulates user preferences and item attributes by introducing multiple time bins and unexpected drifts, as illustrated by the Netflix Prize competition. In timeSVD++, additional implicit feedback and temporal effects are considered.
- T-UCF (Time weight User-based Collaborative Filtering)
  This utilizes an exponential decay formula to show how old data decays over time.
- CE (Collaborative Evolution)
  A time-aware matrix factorization approach uses temporal regression to deal with the dynamic evolution of user latent vectors over time.
- CTR (Collaborative Topic Regression)
  LDA is uses LDA to combine the content of items, and assumes that the item latent vector and item topic distribution have a linear connection.
- CDL (Collaborative Deep Learning)
  A hierarchical Bayesian model that combines deep representation learning for content and collaborative filtering for a rating (feedback) matrix.
- GRU (GRU-based RNN)
  GRUs are used to collect long-term data, and the global dynamic evolution of item ratings can be interpreted.

In addition, there are many innovative algorithms and models that serve the field of time-sensitive recommender systems, for example [16], [36], [38], [41], [54]:

- Bayesian Probabilistic Tensor Factorization (BPTF)
- The novel temporal approach called (Pegasus)
- Temporal recommender system called (TeRec)
- Neural Ordinary Differential Equation (NODE)
- Time-Sensitive Collaborative Interest Aware (TSCIA

Furthermore, we have several approaches to time sensitivity that have improved the quality of RS. Short/Long-term preference modeling: Another method for dealing with sequentially ordered data is called SLPM, which focuses on how to separately model users' short- and long-term behavior. According to the SLPM, each user may have two models: one for short-term preferences and another for long-term preferences [55].

A. LONG-TERM PREFERENCES

Long-term preferences have a global temporal effect on all the attributes of users and items, whereas short-term preferences have a local temporal effect.

B. SHORT-TERM PREFERENCES

The traditional collaborative filtering approach does not use temporal features to provide suggestions. Indeed, in web mining research, sessions have been widely used and identified, for example, in the analysis of movie tastes over time. Short-session data were gathered by analyzing the neighborhood's relationships with other users. The flaw in this technique is that it ignores other latent aspects such as the user mood component. To this end, [56]stressed the importance of using a short-term preference model to re-rank the recommendation lists because it has been shown to significantly improve accuracy.

1) TIME SENSITIVE RECOMMENDATION ADVANTAGES

A time-sensitive recommender system helps to understand the content of unstructured information shared by users over time. Information shared over time can be aggregated differently to understand the attractiveness and periodicity of topics occurring in different time periods. This includes decision support for social media marketing [57].

Increase in the value of average order. When a recommendation engine is used to show personalized choices, the average order value increases. Advanced measurements and reporting can demonstrate a project's efficiency with certainty. This is because the time-sensitive recommender system considers user preferences over time [58].

Offer recommendations and directions with better quality and higher accuracy because they address user preferences over time.

Customer satisfaction frequently refers to customers' previous browsing product recommendations. Specifically, they believed that they would be able to locate better opportunities for good items. It would be helpful if their surfing data from the previous session were available when they left the site and returned later. Client retention results from this form of customer pleasure [59].

Discovery is a time-sensitive recommender system that can detect and discover user preferences over time. For example, any website's "Frequently Bought Together" section provides unexpected recommendations that are comparable to what we already like. People like to recommend things they would like, and when they use a site that completely matches their preferences, they are likely to return to that site.

2) TIME SENSITIVE RECOMMENDATION LIMITATIONS

Numerous problems are encountered based on the type of recommendation. General and personal recommendations were the two most common types of recommendations. Several researchers have focused on general recommendations based on rating scores and have utilized a variety of methods to address common problems with general recommendations, such as missing rating scores in the rating matrix, data sparsity, and cold start. Missing rating scores in the general rating matrix are solved using a well-known prediction method, such as matrix factorization or k-nearest neighbors.

Additionally, in a time-sensitive recommender system, decay and drift are major gaps or limitations which we will be described [5]:

- Time decay: Time has a significant influence on the anticipated values, and the time decay vector is used to track item popularity. An exponential decay rate was used to obtain the decay vector, which was used to measure the weight of each recorded rating score.
- Interest drifting: Rating scores are useful elements for determining a user's mood, but ratings on items tend to wander over time for a variety of reasons that cause the user's mood to shift over time, such as new movies or product announcements.

According to [44] the benefits of the collaborative ranking model, which prioritizes ranking visited locations higher than unvisited ones, address data sparsity by taking into consideration unvisited locations during the training phase. Although the training strategy's drawbacks call for negative training examples, the authors treated all unseen POIs as negative samples, which makes the model more complex.

According to [15] Time-SVD++ is used to decompose a matrix (typically a set of observations) in order to find the directions in which the observations have the largest variance; in other words, finding the directions in which data are distributed, which is useful for dimensionality reduction; however, it is impossible to discuss its speed and cannot be rated as fast or slow. Also, it is dealing with lacking data requires attention.

In the paper [40] the proposed model MTUPD used as a splitting temporal dynamics tool for monitoring the evolution of user preferences over time. Although MTUPD has benefits, it contains certain limitations, presenting some intriguing research directions. It is common practice to monitor changes in user preferences and analyze user reviews, but this might be challenging for new users. Other information, such as a user profile, is just waiting to be uncovered in order to address the cold start issue. In addition, there are fewer latent components in ratings than there are hidden issues in reviews. As a result, the model's equivalence assumption might not always be appropriate.

According to [47] the proposed rating elimination method has the advantage that it may be used as a pretreatment step in any CF-based algorithm. Dropping invalidated ratings encourages database consistency, which in turn improves prediction accuracy.

3) APPLICATION DOMAINS

The recommender system has been expanded and used in various service areas. In this study, we analyzed time-sensitive areas of recommendation. In this section, we discuss the most prominent areas and services in time-sensitive recommender systems.

- Cinema
  On-demand cinema is a relatively new type of offline entertainment facility that has seen remarkable growth in recent years. Recommending films of interest to potential audiences in on-demand cinemas is exciting but difficult because the recommendation scenario differs significantly from all other existing recommendation applications, such as online video recommendation, offline item recommendation, and group recommendation, according to Xue et al. [41] introduced a novel movie selection system for on-demand cinemas called Pegasus, which can simultaneously model the temporal dynamics and spatial impacts of audience behaviors. Owing to the unique qualities of on-demand cinema recommendations, it makes use of point of interest (POI) information surrounding cinemas as well as movie content descriptors, in addition to previous movie consumption records. Pegasus investigated the temporal and spatial aspects that shape audience behavior, capturing commonalities between theatres, crowd changes, time-varying features, and regional variations in movie popularity. This provides a simple and effective method for recommending movies to on-demand theatres.
- Social media marketing
  Online social network services (SNS) such as Facebook, Instagram, Twitter, and LinkedIn are massive digital-based social exchanges that allow users to not only lifelog their everyday lives, hobbies, and interests but also communicate with other users according to [60]. The massive expansion in the use of social media sites has been accompanied by a massive increase in user data. It is feasible to gather content information from people who register with posts on social media. User evaluation data, in addition to rating data, can be collected, as well as various types of feedback data such as likes and comments. The information gathered is not just used for SNS suggestions, but it can also be used in recommender systems for other enterprises, according to [61]. Most businesses use social media for marketing and play an increasingly important role in purchasing decisions. Time awareness is essential for more

accurately estimating users' future interests in order to better address social media marketing efforts aimed at increasing traction, such as posting the correct message at the right time. On Twitter, De Maio et al. [57] examined users' interests over time. It employs text analysis services to semantically tag tweets and monitor concepts over time by looking at post frequencies. By sampling the user's interest using three different techniques, vectorial representation, symbolic aggregation approximation, and median, a model-based approach implementing K-nearest neighbors is utilized to estimate the user's similarity representing their profile.

- Education Servic
  Smart education has gradually begun to be used in education, because of the widespread availability of various smart devices and the growth of wireless networks. Without time or space limitations, smart education can access huge digital resources and provide personalized learning tailored to the requirements, goals, talents, and interests of learners. Furthermore, the instructional format was enhanced by matching the digital age's learning trend [62]. As a result, the area of education services employs a recommender system to deliver learning resources that considers learners' learning styles and knowledge levels, resulting in a more effective and efficient learning experience. In other words, learners receive tailored learning content.
  The content-based filtering recommendation model was mostly employed after evaluating the learners' profile information and learning object information in the study of proposing learning content suited for learners with an emphasis on the similarity between learners and learning objects [63]. Shu et al. [64] used a content-based filtering recommendation algorithm that learns learning resource text data using neural network technology, and then presents learners with appropriate learning resources by combining them with their preferences. In addition to following up on the learner's age over time, changing his interests and level of education, and following up on the materials that have been recorded, whether they contain parts. Therefore, time-sensitive recommender systems are important in education.
- Jobs
  Various sites in the recruiting sector provide job posts for various job roles and employment positions. As a result, gathering information and determining the most relevant user-job relationship mapping based on a user's abilities and interests is a difficult and time-consuming task. Bansal et al. [20] proposed a content-based recommendation engine that matches user interests and capabilities with the features of a job ad to automatically deliver the best options. The proposed engine uses multiple text filters and feature similarity evaluations to generate an intended recommendation. In addition to following up with the applicant over time and changing his job interests, level of education, and experience, in addition to suggesting suitable jobs for him over the progression of time, hence the importance of time-sensitive recommender systems in jobs.
- Healthcare Service
  As the public's interest in health increases, the number of people who use smart wearable devices has begun to rise, as technology has grown more compatible with smartphones, and their usability has improved. In addition, wearable devices that enable self-diagnostics collect a large amount of biometric data from users to aid in disease-related research or proper diagnosis based on individual body scenarios, and they have been useful in research that advises treatment [61].

4) EVALUATION METRICS

It is necessary to determine the efficiency of the recommender system; therefore, it is necessary to evaluate the performance of the recommender system model. In this section, we review some evaluation metrics used to evaluate time-sensitive recommender systems.

The metrics used to evaluate the standard deviation of the residuals (prediction errors) of the recommender system were the root mean squared error (RMSE). The mean squared error (MSE), which is computed by dividing the sum of the squares of the difference between the actual and anticipated grades by the total number of grades predicted according to [65], is a metric often used to measure the prediction accuracy. In addition, there are several other metrics besides RMSE, such as Mean-Absolute-Error (MAE) [66] is the degree of measurement error. That which difference the measured value from the "actual" value is the difference. R^2 or Coefficient of Determination [67] is a value between 0 and 1 indicating how accurately a statistical model predicts a result. Adjusted R^2 [67] is a corrected model accuracy (goodness-of-fit) metric for linear models. The mean absolute percentage error (MAPE) [67] is the average or mean of forecasts' absolute percentage mistakes.

Common evaluation metrics for recommender systems include precision [68] is the level of quality with which an action is taken or a measurement made; suitable for exceedingly precise measurement or action; it kept to low tolerance in manufacture; and characterized by accuracy of execution. Recall [68] refers to statistics that has been retrieved from a collection, corpus, or sample space and is a performance metric. Thus, relevance serves as the foundation for both precision and recall. Accuracy [69] is statistical bias of a particular measure of central tendency is described as a measure of solely systematic mistakes; poor accuracy results in a discrepancy between the outcome and the true value. F-measure [68], often known as the F-score, is a measurement of a test's accuracy used in statistical analyses of binary categorization. It is calculated using the test's precision and recall. Receiver operating characteristic curve (ROC) curve [65] is a graphical plot that demonstrates how a binary classifier system can diagnose problems as its discrimination threshold is changed. Area under the curve (AUC) [70] is used to summarize the ROC curve and is a measure of a classifier's ability to discriminate between classes. The model performs better at differentiating between the positive and negative classes the higher the AUC. The value of the qualitative assessment index for this recommendation model was calculated using a confusion matrix. This matrix allows for a quantitative evaluation by determining whether the user's favorite item is one that the recommender system recommends. Each column indicates whether the recommendation model has recommended the relevant item and each row represents an item that reflects the user's desire.

The performance of the recommendation model was assessed using accuracy as a metric. The ratio of successful suggestions to all recommended items is referred to as the accuracy. Accuracy can be used to intuitively assess model performance. Precision is calculated by determining the proportion of items that match a user's taste, based on the model's item recommendation. Calculating the ratio of items to be recommended to the user using the recommendation model based on the item selected by the actual user yields the recall. The precision and recall were mutually exclusive.

As a result, the F-measure value is occasionally calculated while checking the result of two-indicator integration [71]. The estimated harmonic average of precision and recall is the F-measure. Precision, recall, and F-measure have values ranging from 0 to 1; the greater the value, the better is the performance of the recommendation model. The ROC curve is a graph depicting the relationship between FPR and TPR. This method is primarily used to visually explain the ratio of precision and recall performance outcomes. It is difficult to place a numerical number on the ROC curve because it is a graph. The AUC index is mostly used to adjust for this problem. The area under the ROC curve is known as the AUC and can be used to determine the accuracy of a recommendation model. The model's performance can be judged to be outstanding because the AUC value was closer to 1.

According to [65] the comparison of accuracy and root mean squared error (RMSE), As a result, RMSE and accuracy have no relationship other than the fact that they are performance metrics. They do serve as a performance indicator for two distinct supervised issue subtypes. While accuracy is used to assess classification algorithms, RMSE is used to assess regression techniques.

VI. QUANTITATIVE ASSESSMENT

In this section, we present a quantitative assessment of the comprehensive literature that investigates publications in terms of publication time, publication type, and the datasets used. Table 1 summarizes the quantitative assessment section.

We noticed a growth in studies in the time-sensitive recommender systems field, and researchers have paid more attention to it, especially after advanced techniques have been used to build recommender systems. There is also an increasing need to understand how users' preferences change over time to optimize their experience. Fig.3. shows the distribution and temporal change in publication years.

Additionally, we divided the studies into different categories based on how they were published. Conference papers and journal papers are the two major forms of publications that we obtained. Fig. 4. shows the general distribution of publication types. Although conferences publish many of these studies, journal papers are the most common type of publication for research papers. Also, evident from the trend during recent years, journal papers are increasing.

Finally, the distribution of the dataset was used in previous studies. Fig.5. shows the distributions of the datasets. Although some researchers employed custom and private datasets, the majority of trials used public and common databases. With this crucial information in mind, it's clear that the MovieLens dataset is the most popular in the tests, accounting for 34% of the study, and the "other" dataset accounts for 15%. Netflix, EachMovie, employment, last.fm, and Amazon databases were used in 9% of the cases. Douban has a 8% share and Yelp has a 4% share. We also note the most common domains of time-sensitive recommender system studies in movies (61%). Restaurants made up 25%, music 7%, and 7% in the domain of the job. Fig.6. shows the distribution of domains.

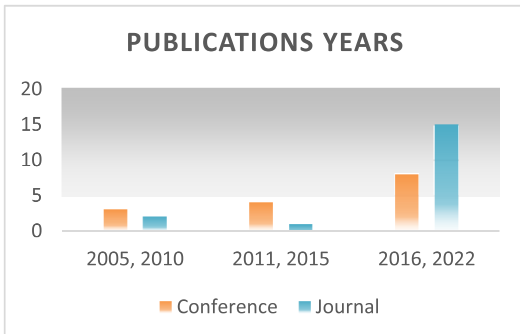

FIGURE 3. Distribution and temporal change of publications years.

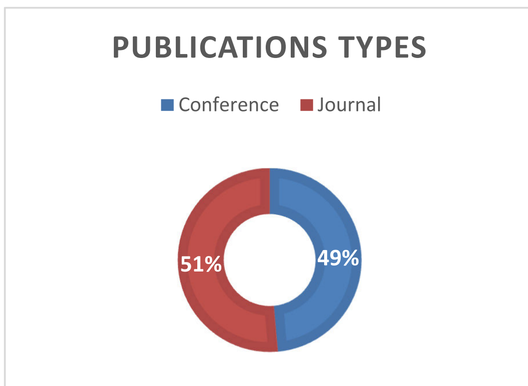

FIGURE 4. Distribution of publication types.

VII. INSIGHTS AND DISCUSSIONS

As we discussed in detail how prediction techniques in the field of time-sensitive recommender systems are affected,

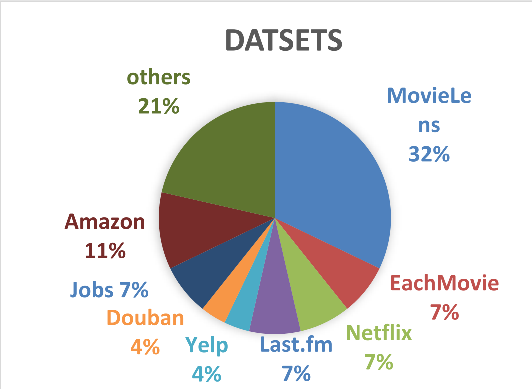

FIGURE 5. Distribution of datasets.

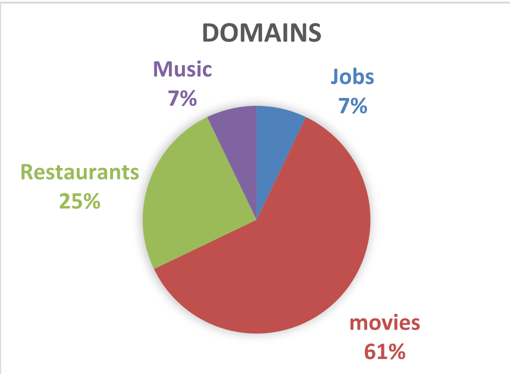

FIGURE 6. Distribution of domains.

these techniques also exhibit effective performance and clear efforts in the field of time-sensitive recommender systems. Time is an important aspect in the final choice of the user, and it is employed in different techniques to obtain accurate predictions.

In this section, we discuss a range of findings and conclusions, and provide the reader with insights based on a general analysis of time-sensitive recommender systems. Also, we presented a comparison in table 2 to clarify the advantages and disadvantages of some techniques.

- Time-sensitive RS is intended to recommend products to consumers at an appropriate time. Time is an important aspect in making a final selection and is employed in many ways to obtain accurate predictions.
- Context-aware recommender systems encompass several types of time-sensitive systems. The concept of time can significantly improve the efficacy of recommender systems. In addition, the temporal diversity of recommendations is a significant component that influences the quality of RS and provides feedback on the changing tastes of users over time.
- TimeSVD++ is the most representative method for incorporating temporal dynamics into recommender systems and can lead to large gains. Within the modelling process, time-SVD ++ uses time as an independent variable. To manage local temporal fluctuations, such an approach leverages more refined user- and item-specific trends, and it can also account for intermittent temporal noise in the ratings.
- Matrix factorization is a well-known recommender system mode; however, it has the drawback of treating all prior actions as static and failing to capture the dynamics of user preferences and item attributes. This approach, on the other hand, excels in terms of accuracy and scalability, and it's quite easy to incorporate more data sources for the recommender.
- K-Nearest Neighbor (KNN) must choose an acceptable value for K, which controls the model's performanc; there are inefficiencies that necessitate repeated experiments, as well as the issue of K bias. Furthermore, while evaluating data with a large input size, KNN's performance of the KNN suffers. Consequently, when the input data are large, dimensionality reduction should be utilized to transform the data into a comprehensible expression.
- The clustering technique is primarily utilized to identify user groups that are similar to each other. Clustering is mostly utilized in the recommender system industry when clustering and assessing the similarity of data for content-based filtering and hybrid recommendation models.
- Neural networks are commonly used to increase accuracy by combining current user history with their preferences and considering users' shifting tastes over time for session-based recommendations. Text, audio, and image inputs have also been employed in feature engineering. The features of many items that the researcher had not considered before can be analyzed using a neural network.
- Techniques use assessment metrics that are commonly employed in recommender systems to measure the statistical accuracy. For prediction accuracy, mean squared error (MSE), mean absolute error (MAE), and root mean squared error (RMSE) are common measurements. For classification accuracy, precision, recall, F1-measure, and receiver operating characteristic (ROC) curves are common measures.
- Several techniques, such as functional factorization, content-based hybrid, and probabilistic factorization, have been used to address the cold-start problem.
- Scalability is a result of user and item information overload, which increases the calculation complexity. Several technologies such as clustering have been used to improve scalability.
- By training a set of weights, machine learning can extract the drift factor, which aids in extracting the user's behavior and interests at the appropriate time.

In addition, we would like to direct researchers to discuss research topics and future directions in the time-sensitive field of recommender systems. We have included the obstacles and difficulties that we observed that may benefit researchers in directing solutions and studies.

TABLE 1. Summarizes of the quantitative assessment.

Authors	Publication year	Publication type	Datasets
Bansal et al. [20]	2017	Conference	Jobs dataset
Wang et al.[22]	2018	Journal	Yelp2013, Yelp2014 (Restaurants) Douban (movie)
Koren [7]	2009	Journal	Netflix
Ding and Li [23]	2005	Conference	EachMovie, GroupLens (movies)
Min and Han [24]	2005	Journal	EachMovie
Sun and Dong [25]	2017	Journal	MovieLens
Chua et al. [26]	2013	Conference	Publications from DBLP and ACM Digital Library (ACMDL)
Xiang et al. [27]	2010	Conference	CiteULike and Delicious
Li et al. [28]	2019	Journal	MovieLens
Xiong et al. [16]	2010	Conference	Netflix and MovieLens
Rafailidis and Nanopoulos [29]	2014	Conference	Last.fm (music)
Vaca et al. [30]	2014	Conference	Yahoo News, Semi-synthetic dataset (news)
Zhang and Wang [31]	2016	Conference	Amazon and Beeradvocate
Rafailidis et al. [32]	2017	Journal	Fine Food, Movies
Wu et al. [33]	2018	Journal	Amazon
Sun et al. [17]	2016	Conference	MovieLens
Du et al. [6]	2015	Conference	last.fm
Pang et al. [34]	2020	Journal	MovieLens
Cami et al. [35]	2017	Conference	MovieLens
Chen et al. [36]	2013	Journal	Weibo (hashtag from Twitter)
Liu et al. [37]	2016	Conference	Jobs
Lv et al. [38]	2020	Conference	Diginetica and Retailrocket (e-commerce)
Ahmadian et al. [39]	2018	Conference	Epinions (Users' opinions, social media)
Wangwatcharakul and Wongthanavasu [40]	2021	Journal	Automotive, baby, fine food, video games, toys&games, movies and TV, software, health.
Xue et al. [41]	2019	Conference	iQIYI (movies)
Ullah et al. [42]	2012	Conference	Movie Lens
Frikha et al. [43]	2016	Conference	Facebook
Aliannejadi et al. [44]	2020	Journal	Foursquare and Gowalla
Sun et al. [45]	2021	Journal	MovieLens
Rezaeimehr et al. [46]	2018	Journal	MovieLens
Margaris and Vassilakis [47]	2018	Journal	Amazon
Zhang et al. [48]	2019	Journal	Real word datset
Ahmadian et al. [49]	2022	Journal	Real word datset

TABLE 1. *(Continued.)* **Summarizes of the quantitative assessment.**

Harshvardhan et al. [50]	2022	Journal	Real word datset
Yu et al. [51]	2018	Journal	Amazon dataset
Yu et al. [52]	2019	Journal	Amazon dataset
Yu et al. [53]	2021	Journal	Amazon dataset

TABLE 2. **Comparison between some techniques.**

Model	Advantages	Disadvantages
TimeSVD++	Recommending a time-variant bias in each timeframe to account for users' shifting preferences.	Does not address the sparsity problem.
The bayesian probabilistic tensor factorization (BPTF)	Adds latent vectors in the time dimension to the Bayesian matrix factorization to offer temporal data. To forecast ratings, it is set up as a three-dimensional tensor (user, item, and time). To account for the population-level preference for latent traits, the model updates its collection of latent features every time period.	N\A
TimeTrustSVD	Examines how users and objects are affected by time and trust relationships, as well as how scores are affected by time drift.	In this approach, user feature vectors are not configured using temporal data.
Bayesian temporal matrix factorization (BTMF)	By adding priors to the TMF hyperparameters, learns a transformation matrix for each user's latent function to capture the temporal dynamics.	Grid search tuning a model with multiple regularization parameters is still very computationally expensive.
Temporal collective matrix factorization(TCMF)	The ratings and multimodal data between the subsequent time points in this model are used to create the user temporal patterns, and a joint decomposition model is used to describe the preference dynamics.	N\A
DCF	The approach is based on collaborative filtering and uses transition patterns between successive time periods for each user to capture the dynamics of user choice.	For the purpose of identifying transition patterns, the model simply takes into account one stage time period.
short-term preference model	Re-rank the lists of recommendations that have been shown to be much more accurate.	It can be erroneous to predict the yield curve of a bond since it occasionally overestimates potential short-term rates.
neural network	Highlighting users' primary goals or combining users' past interests. Can accommodate the wide range of users.	N\A
MTUPD (multiple transitions in user preference drift)	By collecting user interest drifts in numerous transition steps, the MTUPD model is able to analyze the evolution of user preferences.	The cold start problem.
RSTRC	Adds the time factor into the reliability and confidence metrics, taking into consideration how user behavior evolves over time. Using a temporal confidence measure, the ineffectual users were found.	N\A
UBMTR	RBMs are skilled at filling in the gaps left by missing values and can handle unstructured data and imbalanced datasets by encoding the raw data into latent variables. The UBMTR beats several prior attempts at recommender systems that used CF, deep learning, or their hybridized models by using RBM.	Intelligibility suffers as a result of the workflow path of the predictions losing information due to stochastic data transfer across the undirected layers of the RBM.
Cross-Domain Collaborative Filtering (CDCF)	Solve the sparsity problem. Extract user and item information.	The use of all the auxiliary domains may not be optimal and would result in low efficiency.
(TSSEAE)	Ensure that recommendations are accurate and efficient.	N\A

- A few temporal-based factorization algorithms have handled the data sparsity problem as well as additional subproblems, such as user interest drift or item popularity decay over time.
- Because the neighbors' feedback is modest due to a high percentage of missing data in the rating matrix, short-term preferences based on neighbors have a low prediction efficiency.

- Short-term preferences by both latent and baseline values are low because of the significant share of sparsity in the rating matrix. This is because a sparse matrix limits the capacity to use the quality input of nearby users when predicting a suitable rating for an active user.
- We direct researchers to investigating how to consider multimodal information such as POI category, user reviews, and opening hours with the recent advances in applying deep neural models for POI recommendation and their power to capture complex structures of user-POI interactions [44].
- Try to combine joint learning approach with the existing deep recurrent neural models to explore its potential benefits to a deep neural recommender model.
- Plan to explore various strategies for negative sampling and evaluate their effect on Collaborative Ranking algorithm.
- According to [40], we direct researchers to expand the model to handle the issue of cold-start customers who lack ratings or connections based on streaming data in either previous or present time periods. One potential solution to this issue is the introduction of additional side information, such as user profiles and social information.
- Users will confront challenges like personal information security and privacy protection as more and more algorithms for recommendations emerge. The researchers can employ blockchain technology to preserve privacy, or you can integrate user privacy protection measures into current recommendation technologies.
- According to [47], we direct the researchers to look into additional rating abstention interval values and set various rating abstention intervals for various consumers.
- Additionally, compare this method [47] to other rating prediction methods like matrix factorization.
- According to [48] inspire researchers to look into customized session-based models in other industries, like internet marketing and e-commerce.
- The results of time-sensitive RS-based MF are unsatisfactory, particularly in terms of the personal interplay between long- and short-term preferences, which reflect changes in the attributes of users' and items' over time.
- Owing to the relatively sparse matrix, the rapid expansion of information on RS has created numerous issues related to information overload. Consequently, by focusing on the important elements connected to temporal preferences, such as mood drifting and time decay, a suitable recommendation based on CF may be offered. Factorization approaches can be used to combine short- and long-term desires.
- According to [50] the category—which, as a result of the dearth of study in this area, generally exists in isolation—includes the suggested model. An developing field is recommendations by temporal modeling, however it is limited to models produced by discriminative models like CNNs and machine learning classifiers like Naive Bayes, random forests, etc. Future directions for this research include using generative models like RBMs, DBNs, DBMs, VAEs, and GANs to realize temporal modeling of data for understandable recommendation.
- In order to demonstrate that the suggested model (CDCF) in [51] leads many advanced single domain and cross domain CF methods, we suggest researchers to conduct extensive experiments.
- According to [53]direct researchers to adopt other evaluation indicators, such as diversity and serendipity, to fully test and improve recommendation performance by incorporating user reviews.

The fundamental goal of modern RS is to create applications that fulfill the changing needs of dynamic consumers.

VIII. CONCLUSION

The number of accessible web and application services has increased in parallel with the adoption of the internet, smart devices, and social media. Because of the rise of these services, a variety of recommender systems must be developed to aid consumers in quickly receiving item information and making decisions within the rapidly increasing volume of item information. One of the most important aspects of recommender systems is time-sensitive suggestions, which improve the efficiency of recommendation by recommending items to the user based on the time factor and changes in the user's interests and preferences over time. The main goal of this study is to examine the existing literature on time-sensitive recommender systems to assist new researchers in gaining a thorough understanding of the field. In addition to reviewing the most significant issues and weaknesses that researchers are still working to resolve by developing various algorithms and models that serve time-sensitive recommender systems, this paper also discusses the most important difficulties that researchers are still working to. We also performed a quantitative assessment of the existing research on the topic and found that researchers have recently become increasingly interested in this area. In future work, we aim to enhance and build a time-sensitive recommender system based on modern algorithms, investigate the impact of the time factor on the recommender system's performance and efficiency, and examine the most relevant advantages and disadvantages of these algorithms.

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