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RESEARCH ARTICLE

User Cold Start Problem in Recommendation Systems: A Systematic Review

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ABSTRACT The recommendation system makes recommendations based on the preferences of the users. These user preferences usually come from the user's basic information, item rating, historical data, and so on. The ''user cold start problem'' happens when a new user cannot be appropriately suggested due to a lack of more detailed preference information. In many instances, the user cold start problem hinders the use of the recommendation system. Many researchers are currently trying to discover a solution to the user cold start problem. Unfortunately, there are two drawbacks in the current systematic reviews of how to deal with the user cold start problem. First, systematic reviews on how to deal with the user cold start problem are scarce or outdated. Second, existing reviews lack the distinction between the user cold start problem and the item cold start problem. Nevertheless, the solutions to the two problems differ. To address these problems, our study thorough review of all literature published by researchers from January 2016 to April 2023 about 8 years. Firstly, this study analyzes the literatures on approaches that addressed the user cold start problem during the past eight years and divides them into two categories: data-driven technology and approach-driven technology, and then describes and classifies each type of technology in detail. Secondly, this study also analyzes the main evaluation criteria currently used in these methods to provide a reference for researchers in related fields. Finally, this paper also points out the future research direction of this field.

INDEX TERMS Recommendation systems, user cold start, systematic review.

I. INTRODUCTION

With the continuous development of the Internet, mobile Internet, big data, and other technologies, people's lives are being saturated by an increasing amount of information. Thus, users face the problem of information overload. How to enable users to efficiently and quickly find the requested items from a large amount of information has become the current research hotspots and difficulties.

The recommender system can provide items that may be of interest to users based on their previous interaction data in the system. It also uses user feedback to optimize the system's recommendation capabilities [1]. Compared with categorized queries and search engines, the emergence of a recommendation system can help users find information that meets their needs quickly and accurately [2]. This improves user satisfaction and user experience [3]. Today, recommendation systems are widely used in e-commerce [4], [5], social networks [6], [7], news [8], [9], video [10], [11], music [3], [12], education [13], [14], [15], and other fields. It provides more intelligent and personalized services for users. Recommender systems play an important role in the current society.

However, the cold start problem of recommender systems is a common problem in recommender systems [16], [17], [18], [19]. It is mainly divided into user cold start [20] and item cold start [21], [22]. To make the cold-start problem easier to understand, a simple example of recommendation using user ratings is exemplified in Table 1. In Table 1 rows represent users. The columns represent n items. The rating

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matrix represents the user ratings of the items in the range { 1, 2, 3, 4, 5 }, and the ratings can only be integers. The score represents the user's rating for the item, and if the user has not rated the item, it is denoted by "−".

TABLE 1. The cold start example.

Item 1	Item 2	Item 3	Item 4	...	Item n
Alice	3	4	2	...	-
Bob	2	1	5	...	-
Tom	-	4	-	...	-
Adam	2	2	3	...	-
Cary	-	-	-	...	-

A. ITEM COLD START

For new items, the lack of historical data makes it difficult to understand the characteristics of items and user preferences, which leads to inaccurate recommendation results. As in Table 1, Item n is new and has no user ratings. Therefore, it is not possible to recommend this item based on user ratings.

B. USER COLD START

For new users, it is difficult to accurately predict users' interests and behaviors due to the lack of historical data, which leads to inaccurate recommendation results or even useless recommendation results. As show in Table 1, the new user Cary has not used the items in the recommender system and has not evaluated the items after using them. If the user's evaluation information is used to recommend items to the user, it is difficult to accurately recommend the desired items to Gary.

This affects the performance and accuracy of the recommendation system and is more obvious when the number of new users and new items is large. There are currently many different approaches to solving cold starts to improve the accuracy and performance of recommender systems [23]. The methods used to solve different cold starts are different, and this paper focuses on user cold start issues.This paper refers to the user cold start issue as the new user issue in later the paper.

The mitigation of the user cold start problem is essential for the large-scale utility of recommender systems. It can no longer solely point out the accuracy of recommendation, however additionally enhances the user experience. How to resolve the user cold start issues? This problem has been a hot spot in the research of a variety of recommender systems in recent years.

Several systematic literature reviews exist for cold start problems in recommender systems [24], [25], [26]. However, in general, it is known that different approaches are used to solve different cold start problems. Currently, there are few systematic reviews of the literature that address the new user problems. Son [27] provides a detailed discussion of the new user problem in three categories. However, this research was published earlier and does not cover the recent years of research on solving user cold start problems.

The following sections of the paper are organized as follows. Section II presents previous work related to the user cold start issues. Section III specifically describes the process followed in this paper to write the systematic literature review. Section IV describes the literature statistics. Section V presents the results of this thesis and the analysis of the results. Section VI presents a discussion of the user cold start issue in recommender systems and the main research directions. Finally, Section VII is the conclusion.

II. RELATED WORK

The research on cold start questions for new users is summarized in the paragraphs that follow.

Panda and Ray [26] conducted a study and review of 91 articles on cold-start mitigation. The study was the first to categorize the various approaches into data-driven and method-driven strategies. It also categorized method-driven strategies into five main approaches based on the methods used by the researchers. The study also analyzed the benchmark algorithms used for comparison and the evaluation metrics used to assess the cold start problem. However, the study did not separate user cold starts from project cold starts. In solving the cold start problem, these two problems are solved differently.

Camacho and Alves-Souza [25] investigated the research on the application of data from social networks between 2011 and 2017 to alleviate the cold start issue. In recommendations without purchase history or preference selection, the analysis discovered. Information from social networks can be effectively utilized to make up for users' data shortages. delivering more persuasive suggestions. However, this paper only study on using social networks to address the issues facing new users. However, other good solutions like the application of deep learning, machine learning, etc. are no longer being taken into consideration.

Son [27] also a comprehensive study of the issue of cold starts for new users. The researchers provide a comparative analysis of three approaches for the new user cold-start problem, including (i) using other sources of information, (ii) choosing the most significant similar user categories, and (iii) improving predictions with a hybrid technique. Several important algorithms, including MIPFGWC-CS, NHSM, FARAMS, and HU-FCF, are also compared and examined in the study. However, this systematic review was finished in 2014, and there are a lot of new techniques that this paper hasn't considered lately.

Abdullah et al. [28] provides a detailed classification and introduction of methods to address the new user problem through assisted information. It also includes a thorough explanation of how to acquire and extract auxiliary data. This systematic review focuses on data-driven strategies for solving the new user cold start issue. Less consideration is given to the method-driven strategy.

In conclusion, there are several issues with the existing study of the literature on how to solve the user cold start problem. (i) The user cold start problem is addressed in outdated evaluations of the literature. The most recent relevant literature is not taken into consideration. (ii) The analysis for resolving the user cold-start problem solely concentrates on one specific kind of approach. They do not take into account other method categories like machine learning, deep learning, etc (iii) The review is based on all cold-start problems, with no differentiation made between user and project-specific problems. The resolutions to these two problems, however, differ from one another.

The user cold start issue has a significant impact on how recommender systems are used. Unlike other reviews of the cold start problem, this review only looks at the user cold start problem literature from the last eight years. The approaches employed are categorized and thoroughly examined in this study to be as comprehensive as possible. The study also offers an in-depth review of the evaluation criteria and open problems currently applied to these methods.

III. SYSTEMATIC LITERATURE REVIEW METHODOLOGY

A thorough evaluation of the literature is crucial for raising the standard of knowledge-based research. To conduct a more impartial literature review, a systematic literature review entails choosing, analyzing, and synthesizing important scientific papers. The systematic literature review's strategy is presented in this section. The methodology is primarily based on the guidelines used by [29] and [30].

A. RESEARCH QUESTIONS

As noted above, with the growing research on user cold start recommender systems. However, there are few overview researches in this area. All existing studies are based only on classical surveys and reviews of the current state of research. Therefore, a systematic literature review is needed. This is regarded as the best method to offer a thorough and objective analysis of the published findings. Several of the research questions (Qs) are asked by this literature review, as defined in Table 2.

TABLE 2. Research issues for organized literature review.

Questions Number	Questions Description
$Q1$	What research topics are being addressed user cold start in the recommendation system?
$Q2$	What are the metrics for evaluating the overall performance of fixing user cold start problems?
$Q3$	What are the open questions and future research directions when solving user cold start problems?

To begin the systematic literature review study. It is first defined that the questions shown in Table 2 originate from the following keywords: (1) recommendation system or recommender system, (2) user cold start or cold start user, and (3) cold start. Examples of such strings are given in Table 3.

B. SYSTEMATIC LITERATURE REVIEW FLOW

The process of completing this systematic literature review includes seven steps, as shown in Fig. 1.

- *Step1: Definition researching questions and keywords. The study question (see Table 2) and the search keywords for this paper are finally both identified.*

TABLE 3. Search strings for systematic reviews of the literature.

Libraries	Search strings	Web links
IEEE Xplore	("Recommender System" OR "Recommendation system") AND ("User cold start" OR "Cold start user" OR "Cold start")	https://ieeexplore.ieee.org/Xplore/home.jsp
ACM	"Recommender System" / "Recommendation system" &&"User cold start" / "Cold start user"/"Cold start"	https://dl.acm.org/
Web of Science	("Recommender System" OR "Recommendation system") AND ("User cold start" OR "Cold start user" OR "Cold start")"	https://webofscience.com

- *Step 2: Choose search keywords and browse the literature database in step two. In this stage, the search string is specified by the format of the selected search database (as shown in Table 3). The databases used for this study include IEEE, ACM, and Web of Science. These three datasets pretty much cover everything a cold-start recommender system user could need to know.*
- *Step 3: Define both exclusion and inclusion standards. A series of criteria were used to choose which articles to read in-depth. These specifications are shown in the Table 4.*
- *Step 4: Search for papers. In this phase, we search for articles utilizing the search keywords that were developed using the research's study questions and keywords (Table 3).*
- *Step 5: Article pre-selection. The abstracts and titles of all the publications that were retrieved in the previous phase are the only things that are read in this step. These publications were either selected for a careful reading or excluded based on the standards for inclusion and exclusion.*
- *Step 6: Thoroughly read the selected paper. This stage aims to consolidate and analyze the literature. Literature that met the criteria was screened by reviewing and searching relevant literature using quality evaluation criteria (shown in Table 5). Each piece of literature was examined and thoroughly evaluated to verify that it answered the formulated questions posed.*

TABLE 4. Criteria for systematic literature review inclusion and exclusion.

Criteria for inclusion	Criteria for exclusion
CI1 - Paper was released between January 1, 2016, and April 1, 2023,	CE1 - Papers were not written in English.
CI2 - Paper to alleviate the new user problem in recommendations	CE2 -The literatures were published before January 2016
CI3 - Paper for mitigating the cold-start problem (include user cold start)	CE3 - Paper for literature review
CI4 - Publication from conference and journal only	CE4 - books, theses, notes, tutorials, or studies.
	CE5 -Paper on Item cold start

- *Step 7: Classification. These papers are then assessed. Additionally, they are rated as being entirely irrelevant, hardly relevant, or extremely relevant to the study issue.*

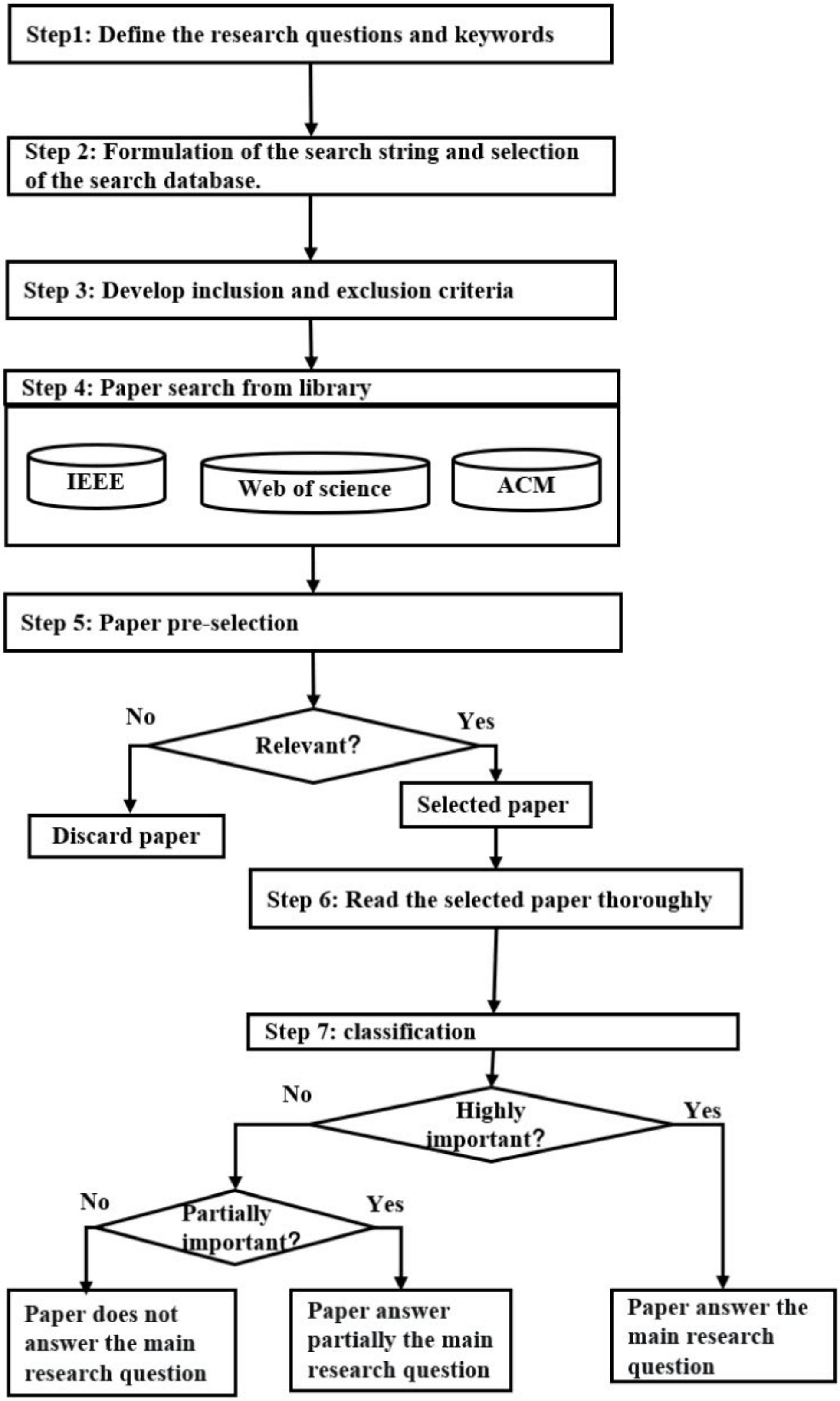

FIGURE 1. The systematic literature review flow diagram.

TABLE 5. Quality assessment and selection.

Evaluation questions to use while sorting papers at step 7 in Fig. 1	Grade
Q1 - Does this literature address the new user issue?	yes - 2 partially - 1 no - 0
Q2 - Does this literature provide a workable answer to the issue facing the new user?	
Q3 - Does this literature address evaluation metrics for solving the user cold start problem?	
Q4 - Is this literature about methods and approaches to solving users' cold start problems?	
Q5 - Does this literature cover open questions or future research directions for the user cold start problem?	

C. PAPER SEARCH

After identifying the literature database. Searched online databases based on search strings. 1480 relevant literatures were searched. The number of literature returned varied as each literature database used a different strategy in its search engine.

The most relevant literature was selected. Firstly, by reading the title, abstract, and conclusion irrelevant studies were removed. In the end, 117 documents were obtained. Then, 117 documents were screened by applying inclusion/exclusion criteria. Ultimately, 74 literatures were retained. As shown in Fig. 2.

IV. DESCRIPTIVE STATISTICS OF THE LITERATURE

Table 6 shows the results of paper retrieval and selection for systematic literature review. The total quantity of publications discovered in every database can be seen in this table.

TABLE 6. The quantity of articles found in Fig.1's phases 4 through 7.

Databases	Literatures discovered in step 4	Literatures preselected in step 5	Completely reading in step 6	Highly relevant in step 7
IEEE	283	34	30	17
ACM	221	52	23	15
Web of Science	154	31	21	13
Total	658	117	74	45

Fig. 3 shows the distribution of completed reading and evaluation of 45 selected papers in each publication year (2016-2023), respectively at step 6 and step 7 (in Fig. 1). The quantity of relevant literature reached the maximum in 2020, with 11 papers, and there may be an even sharper rise from 2023. This shows that there is an increase in interest in finding solutions to the cold start issues related to recommendations. Because the year has barely begun, the results of 2023 cannot be considered final.

In this study, 45 research papers from 35 various meetings and journals with peer review were selected (see Table 7). These publications mostly focus on the field of computer science, systems for information and related topics. The two with the highest counts, both with a value of 4, are "IEEE Access" and "ACM Transactions on Information Systems". "ACM SIGKDD International Conference on Knowledge Discovery and Data Mining" and "43rd International ACM SIGIR Conference on Research and Development in Information Retrieval" are the next, with 3 total.

V. QUALITATIVE SYNTHESIS OF THE LITERATURE

A. WHAT RESEARCH TOPICS ARE BEING ADDRESSED USER COLD START IN RECOMMENDATION SYSTEM?

This paper provides an in-depth study of 45 selected papers. An overview of approaches to address the new user issue is presented. In this research, we primarily categorize these techniques into two primary groups: data-driven techniques and method-driven techniques. As shown in Table 8.

- *Data-driven techniques*

These articles offer ideas for approaches inspired by efficient data utilization and the connection between user and project attributes. The new ways to resolve the issues of cold start are proposed by using person region data, person social community data, person belief information, and individual cross-domain data.

- *Approach-driven techniques*

This category of approaches mitigates the cold start problem by proposing new algorithms or improving old ones. The study further classified them into five categories. Deep learning-based approach, Matrix factorization-based approach, hybrid approach, the improvement over collaborative filtering-based approach, the improvement over content-based approach.

1) DATA-DRIVEN TECHNIQUES

- *Cross-domain data*

Table 9 presents a line-by-line comparison of the main ideas, Datasets, evaluation indicators, strengths, and weaknesses of the selected literatures.

Utilizing user preferences from several domains enables the creation of more thorough user models and improved suggestions. For instance, using cross-domain recommendations to address the target domain's cold start issue. Cross-domain recommendation mechanisms make or enhance recommendations for the target domain using information garnered from the source domain [43], [44]. Numerous scenarios and tasks can be employed for cross-domain recommendation. Cross-domain recommendation systems are therefore more organized and complex than one-domain recommendations.

Cremonesi et al. [43] first proposed the classification of scenarios for cross-domain recommendation, and later studies largely agreed with this categorization. As illustrated in Fig. 4, they identified four distinct recommendation scenarios: no overlap, user overlap, item overlap, and complete overlap. The most common methods for solving problems involve user and item overlap and user overlap.

Many methods for task classification in cross-domain recommender systems. It can be combined according to the cross-domain information. It is divided into two types: Aggregating knowledge and Linking/transferring knowledge.

The Aggregate Knowledge task first aggregates knowledge from different source domains into the target domain. Then

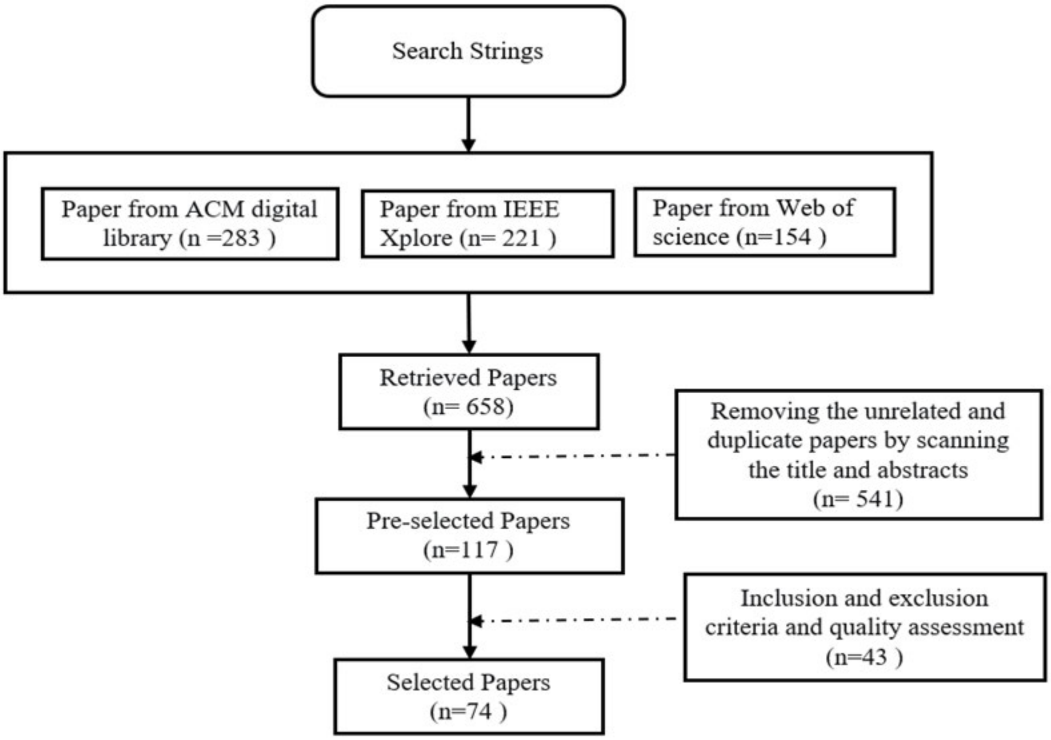

FIGURE 2. The paper selection process.

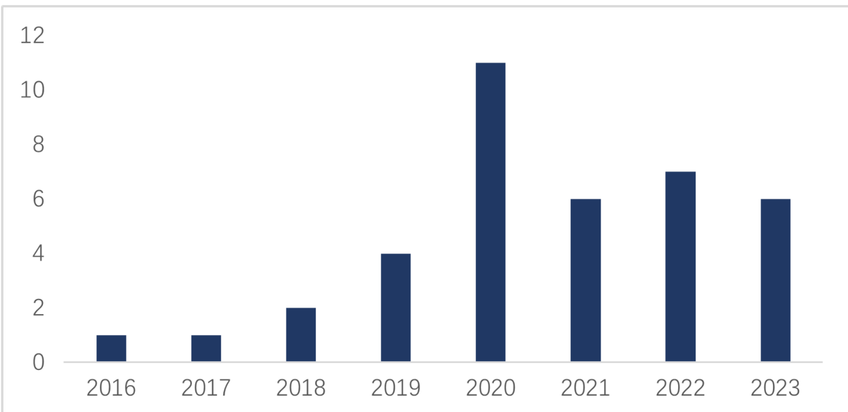

FIGURE 3. The number of papers per year.

recommendations are made. As shown in Fig. 5. For example, fusing user preferences from different source domains not only allows cross-system research but also solves the user cold-start problem.

The establishment or transference of information among domains in support of recommendations is referred to as linking and transferring knowledge (shown in Fig. 6). Because they both fall under categories that can be semantically mapped, such as comedies and humor, we can correlate a certain comedy movie with a humor book, for instance.

The literature is displayed in Table 10 according to the categories of Gathering information and Transferring information.

Jin et al. [45] proposed a cross-domain recommendation algorithm, called RACRec. RACRec solves the problem of predicting full new users in recommendation. RACRec is a cross-domain recommendation algorithm that uses a review selection strategy to dynamically choose appropriate cross-domain methods for each user.

Wang et al. [46] employ auxiliary data from the advertising sector to address the issue of user cold start in online shopping. The procedure examines the user's web browsing history on the advertising platform and generates recommendations from it.

Zhao et al. [47] proposed a method called CATN, a recommendation method to address user cold start problems. The

TABLE 7. Distribution of selected papers for journals and conferences.

Category	Publication channel	Count of papers
Journals	(1) IEEE Access	4
	(2) ACM Transactions on Information Systems	4
	(3) IEEE Transactions on Knowledge and Data Engineering	2
	(4) ACM Transactions on Knowledge Discovery from Data	1
	(5) ACM Transactions on Intelligent Systems and Technology	1
	(6) IEEE Open Journal of the Industrial Electronics Society	1
	(7) IEEE Transactions on Computational Social Systems	1
	(8) ACM Transactions on the Web	1
	(9) Mobile Information Systems	1
	(10) User Modeling and User-Adapted Interaction	1
	(11) Electronics (Switzerland)	1
	(12) International Arab Journal of Information Technology	1
	(13) International Journal of Applied Management Science	1
	(14) Applied Intelligence	1
Conferences	(1) ACM SIGKDD International Conference on Knowledge Discovery and Data Mining	3
	(2) 43rd International ACM SIGIR Conference on Research and Development in Information Retrieval	3
	(3) IEEE International Conference on Data Mining	2
	(4) The International Joint Conference on Neural Networks	1
	(5) 2019 2nd Scientific Conference of Computer Sciences	1
	(6) 2022 5th International Conference on Data Science and Information Technology	1
	(7) 2022 IEEE Region 10 Symposium	1
	(8)IEEE International Conference on Multimedia and Expo	1
	(9) 2022 International Conference on Computer Technologies	1
	(10) 31st AAAI Conference on Artificial Intelligence	1
	(11) 45th International ACM SIGIR Conference on Research and Development in Information Retrieval	1
	(12) 2018 IEEE International Symposium on Multimedia	1
	(13) ACM International Conference Proceeding Series	1
	(14) 2016 International Conference on Recent Trends in Information Technology	1
	(15) International Conference on Networking and Network Applications	1
	(16) 17th Conference on Computer Science and Intelligence System	1
	(17) 44th International ACM SIGIR Conference on Research and Development in Information Retrieval	1
	(18) The World Wide Web Conference	1
	(19) 12th ACM Conference on Recommender Systems	1
Total		**45**

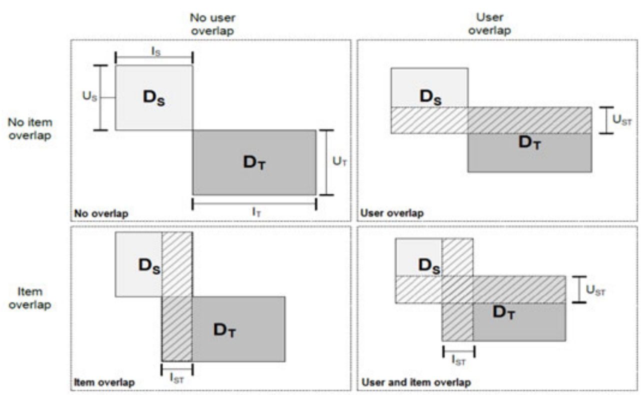

FIGURE 4. The scenarios where user set and item set data overlap.

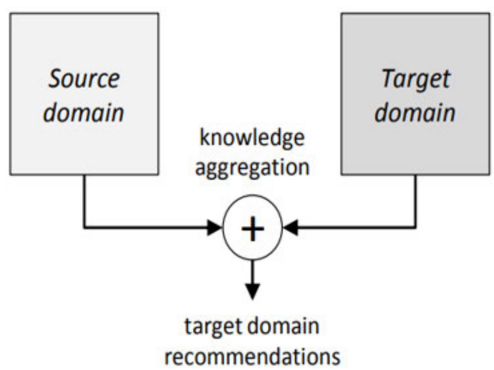

FIGURE 5. Aggregating knowledge.

CATN extracts features from review documents. It enhances the user representation by using auxiliary comments from similar users.

A cross-domain recommendation model entirely based on the partial least squares regression technique was proposed by Li et al. [48]. The latent properties of users in the source domain and users in the target domain can be accurately correlated using these models by researching a matrix of regression coefficients. Even target domain users' cold start issues can be solved by the model.

- *Social network data*

In Table 11, a line-by-line comparison of the main ideas, Datasets, evaluation indicators, strengths, and weaknesses of the selected literatures is presented.

The unprecedented growth of various social networking platforms has greatly enriched the daily lives of users. Social networks are a source of information. In addition to determining the impact of a user on other users. It also provides valuable data to determine user preferences for items. All of this knowledge can be very helpful in making more accurate and objective product recommendations to users, which will significantly help to solve the user cold start issue. Utilizing information from social networks, there are

TABLE 8. Classification of approaches for alleviating the user cold start problem in recommender systems.

Strategy	Classification	Number	Literatures	Features	Challenges
Data-driven approaches	(1) Cross-domain data	5	[45]–[49]	It can be a good solution to the problem of cold start for new user users	(1) Poor robustness (2) Complex model structure (3) Poor model interpretability
	(2) Social network data	5	[31], [50]–[53]	It can be a good solution to the problem of cold start for new users. Even if new users don't have personal history data, they can still benefit from relationships with friends and followers.	(1) Data sparsity (2) Social noise: e.g., disinformation, advertisements, and spam. (3) Privacy issues
Method-driven approaches	(1) Meta-learning	14	[54]– [67]	Solve the user cold start problem. It can learn quickly with little data or lack of historical behavioral data.	(1) Models are often complex (2) Overfitting risk (3) Poor interpretability
	(2) Deep learning	8	[32]– [39]	Deep learning has the potential to solve the user cold-start problem, especially when dealing with large-scale and multimodal data.	(1) Massive data requirements (2) High computational resource requirements (3) Interpretive problems (4) Overfitting
	(3) Matrix factorization	4	[68]– [71]	Potential feature vectors can be used to generate recommendations to solve the user cold-start problem.	(1) Requires large amounts of data (2) Not applicable to multimodal data (3) Not applicable to personalized recommendations (4) Pure cold start problems
	(4) Improved New Approach Based on Collaborative Filtering	6	[73]– [78]	The method is built based on collaborative filtering to solve the user cold-start problem by exploiting the potential interests and associations mined from the user's historical behavior.	(1) Over-reliance on historical behavior (2) Difficulty in dealing with data sparsity (3) Pure cold start problems
	(5) New improved content-based approach	3	[40]–[42]	It does not require users' historical behavioral data, so it has an advantage for new users or data-scarce situations and can solve the problem of user cold start.	(1) Difficulty in acquiring content features (2) Problem of recommending new items

TABLE 9. Reviewing and comparing Cross-domain data approach.

Article	Main ideas	Datasets	Evaluation indicators	Advantage(s)	Disadvantage(s)
Jin et al. (2020) [45]	Solving the fully user cold-start problem with RACRec, a review-aware cross-domain based recommendation algorithm	Amazon Dataset	AUC, RMSE	Good solution for full-user cold starts	Solving non-cold-start problems doesn't work well.
Hanxin Wang et al. (2020) [46]	A user information sharing model based on online shopping and advertising platforms to solve the user cold start problem.	Advertising datasets, online shopping datasets	HR@K, NDCG@K	Best performer onHR@K, NDCG@K	No consideration in real-time.
Zhao et al.(2020) [47]	A cross-domain model is proposed to transfer user preferences from the source domain to the target domain to solve the user cold-start problem.	Amazon dataset	MSE	The model has robustness, short convergence time, and excellent timeliness.	No consideration in real time
C. Te Li et al. (2018) [48]	Partial Least Squares is utilized to use the user's ratings as eigenvalues and map the variables to the same space to achieve cross-domain recommendations.	Epinions dataset	MAE, RMSE	Advanced missing data input methods for new user latent factors and short model training time	Artificially entering default values for the rating matrix may result in inaccurate data attributes. Unable to handle non-linear user comments.
Zhu et al. [49]	Propose a cross-domain migration-meta-framework (TMCDR) to mitigate the generalization problem of cross-domain recommendations and solve the user cold-start problem.	Amazon dataset, Douban dataset	AUC, NDCG@K	Efficient and better compatibility	No consideration in real-time

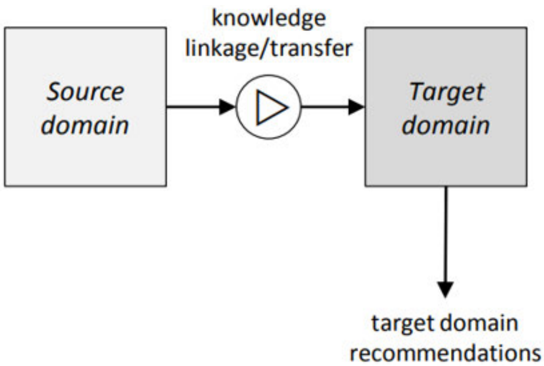

FIGURE 6. The linking and transferring knowledge.

TABLE 10. Classification of literatures on cross domain.

Task classification	Literatures
Aggregating knowledge	[45]–[47]
Linking/transferring knowledge	[48], [49]

two groups of strategies for reducing the user cold start issue. The first group includes feature mapping models [53] and the second, similarity-based models [50], [51], [52].

It's easy to use the similarity-based model. Their equation can be written as

$$Y_s = WY_t. \quad (1)$$

where W is the similarity matrix. In general, W is the similarity between the relation source domain Y_s and the target domain Y_t.

A cold-start recommender system based on linked open data and social network elements has been proposed for new users [50]. This technique uses the user profile generator module to automatically create a user's profile when they first log in using their Facebook ID and, if applicable, their DBpedia ID. After that, "user clusters" are created using the user's profile information and class labels to train a classifier. A classifier is then fed the data from the new user to make a prediction about which category the new user belongs to. The system will only review the user ratings given to each "program" by members of the "group" to which the new user belongs once that group has been identified. Finally, the average weight of the ratings given by the users in the predicted cluster to each Item cluster was calculated, and the Item cluster with the highest rating was recommended to the new user.

Reshma et al. [51] alleviate the cold start problem by using user social behavior. The customer rating matrix is used in the suggested method to determine the nearest neighbors first. The properties of social network data are analyzed in the subsequent stage to determine the attribute comparability between every other user and those who are active. In the third stage, a group of neighbors are selected from the network of friends, and the social similarity is determined as a weighted sum of these values. The final planned rating of the item is then calculated by adding the weighted total of the forecasted ratings for each set of neighbors obtained in the first two steps, which are computed independently for each group of neighbors.

Li et al. [52] gathered user information for the new user issue by examining their social network information. Learning from side data (such as consumer social interactions, human traits, etc.). Once it is done, teach new users the information. This method helps to mitigate the issue with cold starts.

A latent feature representation and social network data frequently show up as attribute mapping in attribute mapping methods.

Predict whether cold-start users will become important users on the growing online social network (Medium) by using user data from the most popular online social network (Twitter) [53]. To transfer descriptive information and knowledge of dynamic actions to the most influential online social networks, they used a supervised-based machine learning approach.

A unique model of LoCo is put out by Sedhain et al. [31]. Through stochastic SVD, it directly and effectively learns a low-rank linear model. In comparison to state-of-the-art user cold start advice, the results validated in this study on four real datasets demonstrate considerable improvements in LoCo.

2) APPROACH-DRIVEN TECHNIQUES

- *Meta-learning*

In Table 12, a line-by-line comparison of the main ideas, Datasets, evaluation indicators, strengths, and weaknesses of the selected literatures is presented.

A current trend in machine learning is called meta-learning. It enables quick adaptation to new tasks using a limited set of examples. One might consider of the new user suggestion challenge as a learning problem from a limited number of samples. Because of this, the user cold start problem can be solved extremely well using the meta-learning approach. Plenty of researchers are currently employing meta-learning to solve the new user issue. [54]

Three categories of meta-learning exist: metrics-based, model-based, and optimisation-based. [55] The following Table. 13 categorizes the meta-learning techniques addressed to the new user issue.

The goal of metrics-based meta-learning is to identify patterns among samples within a task. Jiang et al. [56] suggest using user clustering to group individuals with similar interests based on their shared knowledge. The transformation network is built using the user's clustering data, and it transforms the global initialization parameters gained by meta-learning into the cluster's ideal starting parameters. It can lessen the detrimental impacts of users with various tastes and enhance the meta-learning model's functioning.

Model-based meta-learning updates parameters quickly through several training steps. Using memory enhanced meta optimization (MAMO), Dong et al. [58] suggested a cold beginning strategy. A feature-specific memory is meant to

TABLE 11. Reviewing and comparing Social network data approach.

Article	Main ideas	Datasets	Evaluation indicators	Advantage(s)	Disadvantage(s)
L. Briand et al. [31]	Leveraging social metadata (e.g., users' friend groups and page likes) to address user cold starts.	MovieLens dataset, Yahoo! Webscope R4 dataset	precision@k, recall@k, mAP@k	Best performer on Precision and Recall scores	No consideration non-linear variants and in real-time
U. Yadav et al. [50]	The pure new user cold-start problem is addressed by constructing user profiles based on linked open data, collaborative features, and social network-based features.	MovieLens dataset, Yahoo! Webscope R4 dataset	time throughput, MAE, precision, recall, F-measure	High throughput and accuracy.	Without considering user feature downscaling and in real-time
Reshma et al. (2016) [51]	Combining Social Network Graph (SNG) features and User Rating Matrix (URM) to solve the user cold start problem.	Movie Lens dataset, synthetic social network datasets	MAE, Coverage	Low MAE	The trustworthiness of the data and the modeling time were not taken into account.
JJ. Li et al. (2021) [52]	Learning from side information (e.g., user attributes, social relationships, etc.), transferring learning knowledge to new users, and mitigating the user cold-start problem and the long-tail problem.	Flickr, Blog-Catalog, YouTube, Hetrec11-LastFM	precision@k, recall@k, mAP@k	High accuracy, fast speed.	Not considering multi-source side information. No consideration in real-time.
Q. Gong et al. [53]	Ease user cold starts by utilizing user information on online social networks such as Twitter and Medium.	Medium, Twitter dataset	AUC	High AUC, Models are easy to generalize	Only the Medium and Twitter domains were used for the data. No consideration in real-time.

provide individual deviation items while configuring the model's parameters. Comprehensive tests on two regularly used data sets show that MAMO outperforms cutting-edge solutions.

Optimization-based meta-learning aims to adjust the optimization algorithm so that the model can learn well from a small number of examples. The novel user sequence recommender framework known as metaCSR based on meta-learning was proposed by Huang et al. [55]. When learning effective initialization for new users, the framework employs Model-Agnostic Meta-Learning (MAML) to extract and spread transferable information from previous users. MetaCSR has demonstrated high performance in learning typical patterns from regular users through experiments. Shen et al. [61] proposed the RESUS to resolve the cold user CTR prediction problem through meta-learning. The method may quickly learn from a narrow range of user-specific interactions, and the learning can be applied to deduce individual preferences. The method is experimentally confirmed to improve the predictability of click-through rates for chilly users.

- *Deep Learning*

Table 14 presents a line-by-line comparison of the main ideas, Datasets, evaluation indicators, strengths, and weaknesses of the selected literatures.

The deep learning algorithm is a particular kind of neural network-based machine learning algorithm. It learns and classifies input data using a multi-layer neural network. Deep learning techniques including Autoencoder, Graph Neural Networks, Generative Adversarial Networks, and others have been used in recommendation algorithms.

Briand et al. [32] use deep neural network architecture and user clustering from heterogeneous information sources to solve the new user issue. A brand-new service recommendation technique for multiplex interaction, known as MISR, was proposed by Ma et al. [16]. This strategy functions by incorporating three different kinds of service and mashup interactions within DNN. A deep neural network-based DeCS framework is suggested by Mondal et al. [33]. The collaborative filtering recommendation's new user issue is solved using this technique. The suggested framework, DeCS, may be applied to various data sets and aids in system performance improvement. Kumar et al. [34] provide a video recommendation system that overcomes the cold start problem and makes use of intrinsic information to suggest films. The deep neural network of the architecture is fed with the output of the C3D model, mainly video-level characteristics.

Chen et al. [35] proposes an end-to-end recommendation system ColdGAN based on the Generative Adversarial Network, which can generate accurate data under imprecise data. ColdGAN is simple and effective in restoring lost functions of related items and effectively solves the problem of new users.

Hao et al. [36] proposed a multi-policy approach for new user recommendation (MPT). The model uses user and item dependencies obtained by a GNN encoder and introduces a Transformer encoder to obtain long-term dependencies. A brand-new inductive heterogeneous graph neural network (IHGNN) model is put out by Cai et al. [37]. To address the sparsity of user features issue, the model makes use of relational information from the new user recommendation system. Hao et al. [38] presented a recommendation

TABLE 12. Reviewing and comparing Meta-learning approach.

Article	Main ideas	Datasets	Evaluation indicators	Advantage(s)	Disadvantage(s)
Y. Lu et al. [54]	A hypernetwork-based meta-learning recommender system is proposed to solve the user cold-start problem.	Movielens, BookCrossing	NDCG@N, Recall@N, Hits@N	Faster user interest capture and better recommendation performance	Explosive parameters not considered.
Huang. et al. [55]	A meta-learning-based framework for the cold-start sequential recommendation.	MovieLens-1M, Last.fm, Amazon-Video	AUC, MAP, Hit@N, NDCG@N	Better performance in both user cold start situations and non-cold start situations, good generalization to new tasks	No consideration in real-time.
Jiang, F.et al. [56]	A meta-learning-based user-adaptive learning recommendation model, which can share information in a more fine-grained way, improves the performance of meta-learning models in cold-start scenarios.	MovieLens, Yelp	MAE, RMSE nDCG@N	smaller MAE or RMSE value, and larger nDCG@5 value	No consideration in real time.
G. Wang et al. [57]	The model is based on a meta-transition learning framework. Co-neighborhood correlation is utilized to enhance the learning process of dynamic patterns in user preferences.	Electronics, Movielens-25M, VOD	MRR, Hit@N, NDCG@N	high accuracy	Robustness needs to be improved
M. Dong et al. [58]	The authors designed a specially characterized memory to store user profiles and previous training sets to solve the user cold-start problem.	MovieLens-1M, Book-crossing	MAE, NDCG@N, DCG@N	Good results in solving users' cold start problems, fast testing speeds	No consideration when additional information is not available, Slow training speed
S. Liu et al. [59]	Recommendation models combining attention mechanisms and meta-learning	MovieLens-1M, Book-Crossing	MAE, RMSE	It can be a good way to alleviate the user cold start problem during the recommendation process with smaller data. Contains application examples.	No discussion of inputs that do prefer information, generalization is poor.
J. Misztal-Radecka et al. [60]	An unsupervised Meta-User2Vec approach is used to construct user representations. A metadata neural embedding approach is used to generate a list of new users and new item corrections.	MovieLens, Deskdrop, Onet	NDCG@N	Potential features are considered and are easy to implement.	No consideration of multiple data fusion
Y. Shen et al. [61]	A nearest-neighbor and ridge regression-based predictor for fast learning from a small number of user-specific interactions to infer remaining user preferences and alleviate the user cold-start problem.	Movielens, Frappe, Taobao	Logloss, AUC, RelaImpr	High accuracy of click-through rate prediction. more robust, Short learning time.	No consideration of multiple data fusion
H. Lee et al. [62]	A meta-learning-based recommendation model is proposed to alleviate the user cold-start problem due to low user interaction and preference information.	MovieLens, Bookcrossing	MAE, NDCG	More accurately discriminated user preferences, Need smaller data	No consideration of multiple data fusion, Poor performance without user data
X. Lin et al. [63]	A new task-adaptive mechanism for meta-learning recommenders that computes user preferences to alleviate the cold-start problem.	MovieLens, Last.FM3, Gowalla	Precision@N, NDCG@N, MAP@N	High Precision, good performance with smaller data.	No consideration of multiple data fusion, Poor performance without user data
T. Wei et al. [64]	MetaCF is a new meta-learning paradigm, MetaCF uses dynamic subgraph sampling to construct representative training tasks.	Amazon-Electronics, Amazon-Kindle, m LastFM (author)	HR@10, NDCG@10	A small number of interactions can quickly and efficiently adapt to new user recommendations	No consideration of multiple data fusion, Poor interpretability
K. P. Neupane et al. [65]	A novel recommendation model integrating meta-learning and evidence learning is proposed. Addressing uncertainty-aware cold-start recommendations.	MovieLens-1M, Book Crossing, Netflix, Last.fm	RMSE, NDCG	Recommendations work well for users who rarely interact.	No consideration of multiple data fusion, Poor interpretability
H. Bharadhwaj [66]	Using meta-learning, learn user IDs, item IDs, and user ratings to solve user cold-start problems.	Movielens 100k, Netflix Prize, My-FitnessPal	Precision@k, AUROC, Mean Reciprocal Rank (MRR)	Robust, fast training, good generalization, high accuracy	Poor interpretability, No consideration in real-time. No consideration of multiple data fusion.
H. Wang et al.[67]	Integrating meta-learning and Reptile into the ML2E algorithm to solve the cold-start recommendation problem.	MovieLens-1M, Book-Crossing	Logloss, AUC	Low Logloss, and High AUC in Solving Cold Start Problems generalization is poor	Poor interpretability.

TABLE 13. The meta-learning methods used to solve the user-cold start problem.

Meta-learning category	Literatures
Metrics-based method	[56], [57]
Model-based method	[54], [58]–[60]
Optimization-based method	[55], [61]–[67]

method based on the GNN model. The model enhances the aggregation capability of graph convolution based on a self-focused meta-aggregator. The method can after better mitigate the new user problem. A new framed attribute graph neural network (AGNN) is developed using attribute graphs. Qian et al. [39] AGNN can generate strictly cold user/item preference embeddings by learning attribute distributions with an extended variational self-encoder (eVAE) structure.

- *Matrix Factorization*

Table 15 presents a line-by-line comparison of the main ideas, Datasets, evaluation indicators, strengths, and weaknesses of the selected literatures.

Zhou et al. [68] proposed a matrix decomposition recommender system method based only on homomorphic encryption and social networks. The method introduces the preference information of users similar to new users as features in the recommender system. The new user problem is solved with this method. Natarajan et al. A Matrix Factorization Model (CD-SemMF) based on cross-domain semantic association is presented to solve the new user issue in collaborative filtering recommendations employing Linked Open Data (LOD). Lin et al. [70] A MetaMatrix Factorization (MetaMF) model is proposed that is capable of generating private item embedding and rating prediction models using meta-networks. Chen et al. [71] find that combining regularization differentiating functions with a matrix factorization-based approach can better predict users' preferences for items to address the new user issue.

- *Improved New Approach Based on Collaborative Filtering*

Table 16 presents a line-by-line comparison of the main ideas, Datasets, evaluation indicators, strengths, and weaknesses of the selected literatures.

When used directly, collaborative filtering algorithms cannot effectively address the user cold start issue. Many researchers are working to develop a collaborative filtering algorithm to address the user's cold start issue Collaborative filtering algorithms cannot effectively solve the new user issue when used directly. Many researchers are working to develop collaborative filtering algorithms to solve the new user issue [72]. To deal with the limited data of user characteristics, Z. Zhang et al. [73] propose a novel inductive heterogeneous graph neural network (IHGNN) architecture that utilizes the relational data from the new user recommendation system.

A new CF framework called Augmented Reality CF was proposed by Chae et al. [74]. It effectively addresses the new issue and raises the overall effectiveness of the recommendation. The fundamental goal is to create fictitious yet believable people and things. The rating matrix is then expanded using them as extra rows (users) and columns (things).

Duricic et al. [75] explore the use of Katz similarity (KS) in a collaborative filtering (CF) algorithm for cold start users. This is the rule-equivalent similarity measure in the network for selecting the k nearest neighbors.

Chao et al. [76] proposes an innovative way to solve challenges faced by new users by using leader recommendations. The Collaborative Filtering technique chooses potential leaders based on previous user ratings. These potential leaders have multiple ratings and have excellent historical data fit. As a result, they may be relied upon to suggest products to new consumers.

Al-Bakri Hassan [77] proposed a collaborative filtering model for user authenticity information based on fuzzy c-mean clustering. The method makes use of a new measure formula. The formula uses combination coefficients to combine user evaluation with fuzzy authenticity information.

Zahid et al. [78] presented standardization techniques combined with systematic filtering methods and Matrix factorization methods to solve the new user issue in recommendation, considering variables that are not directly related to user profiles but are meaningful enough to ultimately recommend to users.

- *New Improved Content-based Approach*

Table 17 presents a line-by-line comparison of the main ideas, Datasets, evaluation indicators, strengths, and weaknesses of the selected literatures.

Content-based recommendation algorithm is an algorithm that recommends similar items according to users' historical behavior and item attributes. The core idea of this algorithm is to use the characteristics of the object itself to recommend, rather than relying on the user's behavior. The benefit of a content-based recommendation algorithm is that it can deal with different types and fields of items, and does not need the user's personal information and behavioral data. The drawback is that it is unable to account for users' shifting interests and preferences, so the recommendation may be inaccurate in some cases. Content-based recommendation algorithms suffer from user cold-start problems, and currently, many scholars have improved content-based recommendation algorithms to alleviate new user problems.

A frequently occurring pattern mining framework (FPRS) for recommender systems is presented by Kannout et al. [40]. To alleviate the cold-start issue for new users and new items, FPRS combines the created frequent item sets with a content-based strategy. The method's efficacy is confirmed by empirical study. The term frequency-inverse document frequency (TF-IDF) text mining technique was used by Chia et al. [41] for data filtering and information retrieval.

TABLE 14. Reviewing and comparing Deep Learning approach.

Article	Main ideas	Datasets	Evaluation indicators	Advantage(s)	Disadvantage(s)
L. Briand et al. [32]	Solving the cold start problem based on deep neural network architecture and user clustering from heterogeneous information sources.	Deezer data	Precision@K, Recall@K, NDCG@K	High recommendation accuracy, realizes online and offline testing and can be applied in real-time.	poor interpretability
R. Mondal et al. [33]	Deep neural network-based modeling to solve the cold-start problem in collaborative filtering recommender systems.	MoviLens, Amazon, Douban dataset	MSE, RMS, MAE	higher accuracy	Poor interpretability
Y. Kumar et al. [34]	Modeled using deep learning algorithms to provide content-based recommendations to users. Mitigating the cold start problem.	TV shows, Movies	Recall@K, Hit@k	Highly accurate and more robust.	Poor interpretability
C. C. Chen et al. [35]	ColdGAN, an end-to-end gan recommender system that does not use side information, is proposed to solve the new user cold start recommendation problem.	MovieLens-1M, Amazon Gift Cards, Goodreads Book Reviews	precision @ k, recall @ k, F1@ k, nDCG@ k	Highly accurate	Poor interpretability
B. Hao et al. [36]	Resolving short-range and remote dependencies of users and items with GNN and Transformer encoders to solve the user cold-start problem.	MovieLens-1M, MOOCs, Gowalla	Recall@K, NDCG@K	Highly accurate and more robust.	Poor interpretability
D. Cai et al. [37]	An inductive heterogeneous graph neural network model is employed to mitigate the sparsity of user attributes in user cold-start.	Tiktok dataset, Kwai dataset, MovieLens (MLs) dataset	NDCG@k, Recall@k, Precision @k, and AUC	High-quality user representation. Handles multi-modal data with high accuracy.	Poor interpretability and long training time
B. Hao et al. [38]	GNN-based to learn a representation of cold-start users.	MovieLens, MOOCs, Last.fm	Recall, NDCG	Good generalization, high accuracy.	Poor interpretability
T. Qian et al. [39]	Solving the strict cold-start problem in recommender systems using attribute maps and neural mapping.	MovieLens, Yelp	RMSE, MAE	Models are stable and easy to train, with high accuracy for strict cold and warm starts	poor interpretability.

To solve these issues, a system called Cold-Transformer is proposed by Li et al. [42]. Context-based adaptive embedding is created by Cold-Transformer to account for variations in feature distribution. To convey the related user preferences, it changes the embed of a new user into a hot state that is more similar to an existing user.

B. WHAT METRICS ARE EMPLOYED TO ASSESS THE EFFECTIVENESS OF USER COLD START?

An overly performant recommender system is the ultimate goal of recommender system design. How should the effectiveness of a particular recommender system be assessed to address the user cold-start issue? Three commonly utilized metrics - ranking measures, classification accuracy metrics, and rating prediction metrics - are categorized. Table 18 displays the distribution of the studied studies regarding the prediction metrics.

Mean Square Error (MSE), Root Mean Square Error (RMSE), and Mean Absolute Error (MAE) are the three main rating prediction metrics. As the value of the measure falls, the precision rises. Area under the curve (AUC) and recall, precision, f1 score, and recall are often used evaluation measures for the classification accuracy metric.

Ranking Metrics is the value obtained in the recommendation for a given user U and a test set S, after calculating the ranking of all possible recommendation results for S by that user U. If a recommendation system has a higher Top-K accuracy, it means that it can better predict and rank the items of interest to the user. top-K accuracy is mainly ndcg@K, Hit@K, etc.

Multiple types of evaluation metrics are used in most of the literature to evaluate models. Rating prediction metrics (MSE and RMSE) and Ranking Metrics (ndcg@K) were used in the paper [56]. The literature [49] used AUC and NDCG@K. Huang et al. [55] used AUC, MAP, Hit@K and NDCG@N. MAE, NDCG@K and DCG@K were used in the literature [58] and [62]. NDCG@k, Recall@k, Prision@k, and AUC were used in the literature [37].

Some literature uses only one type of evaluation metric in the performance evaluation process. As in the literature [42] and [53] the AUC was used to evaluate the model. In the literature [59] used NDCG@N for evaluation model. In the literature [76] used RMSE for evaluation. Most of this literature uses Ranking Metrics for model evaluation [39], [59], [69], [71]. As in the literature [36] and [38], only Recall@K and NDCG@K were used.

TABLE 15. Reviewing and comparing Matrix Factorization approach.

Article	Main ideas	Datasets	Evaluation indicators	Advantage(s)	Disadvantage(s)
T. Zhou et al. [68]	Homomorphic encryption-based multi-party secure computational recommender system combines multi-party information for user recommendation.	Epinion, Hetrec11, FilmTrust	RMSE	User privacy protection. Good generalization	Not applicable to multi-modal data, Pure cold start hard.
S. Natarajan et al. [69]	A matrix decomposition model based on cross-domain semantic associations is used to solve the user cold-start problem in collaborative filtering recommender systems using Linked Open Data (LOD).	Facebook dataset	MAP, MAE, RMSE	Highly accurate.	Not applicable to multi-modal data, Pure cold start hard.
Lin, Y. et al. [70]	Introducing a federated matrix factorization (MF) framework to solve the user cold-start problem.	Douban, Hetrec-movielens, Movie-lens1M, and Ciao	MAE, MSE	higher rating prediction.	Pure cold start hard.
H. H. Chen et al. [71]	Assigning a regularization weight Ap to the specification of the latent factors for all users and another regularization weight Aq to the specification of the latent factors for all items solves the user cold start problem.	FilmTrust rating dataset, the Yahoo! Movies rating dataset, and the Amazon Musical Instruments (AMI) rating dataset	RMSE, MAE	It can solve the long-tail problem of commodities and the sparsity of user data with higher accuracy	Not applicable to multi-modal data, Pure cold start hard.

TABLE 16. Reviewing and comparing improved new approach based on collaborative filtering.

Article	Main ideas	Datasets	Evaluation indicators	Advantage(s)	Disadvantage(s)
Z. Zhang et al. [73]	A recommendation method utilizing bipartite networks to solve the new user cold-start problem.	MovieLens10M, Netflix	precision, recall	High Accuracy and Recommendation Diversity	Easy to fall into local optimality
D. K. Chae et al. [74]	The model generates virtual, but plausible, representations of users and items, which are then used as additional rows to augment the rating matrix (i.e., users) and columns (i.e., items) to solve the user cold-start problem.	Movielens 100K, Movielens 1M, Watcha, and CiaoDVD	nDCG and MRR	High Accuracy, Fast model training.	Over-reliance on historical behavior, hard for pure cold start problems
T. Duricic et al. [75]	A trust network is used to generate a similarity matrix which is used to select k nearest neighbors to recommend items.	Epinions	nDCG, Precision and Recall	High Accuracy	Over-reliance on historical behavior, hard for pure cold start problems.
X. Chao et al. [76]	The CF model is used to select candidate leaders from historical user rating data. These candidate leaders recommend goods to new users.	MovieLens	RMSE	Lower RMSE	No multi-data fusion, no consideration of time series
N. F. Al-Bakri et al. [77]	Solving the user cold-start problem by combining user reviews with fuzzy truthfulness information using a fuzzy similarity metric formula.	MovieLens	similarity matrices	High Accuracy	Over-reliance on historical behavior, hard for pure cold start problems
A. Zahid et al. [78]	Normalization techniques combined with CF and MF methods are used to solve the cold-start problem in recommender systems.	MovieLens, Group Lens	MAE, RMSE, NMAE, Rank Accuracy	High Accuracy, good performance for pure cold start problems	Over-reliance on historicalbehavior

VI. DISCUSSION AND DIRECTIONS FOR FUTURE RESEARCH

A. DISCUSSION

The cold start issue is one key issue that affects the accuracy and precision of recommendations. With the cold start issues, there are new user issues and new item issues. The problem with new users is that when they start to show up throughout the recommendation process, better recommendations cannot be produced due to a lack of user-specific data.

This literature review divides the approaches to solving user cold starts into two groups. Data-driven and method-driven. Show as Fig. 7.

TABLE 17. Reviewing and comparing new improved content-based approach.

Article	Main ideas	Datasets	Evaluation indicators	Advantage(s)	Disadvantage(s)
E. Kannout et al. [40]	The generated frequent item sets are combined with a content-based approach to mitigate the cold-start problem for new users and new items.	MovieLens 100K, MovieLens 1M	F1, Precision, Recall, Recall	High accuracy No multi-data fusion	No consideration of time series
E. J. Chia et al. [41]	Retrieve frequent movie types using Term Frequency-Inverse Document Frequency (TF-IDF) and generate a matrix. The matrix is used to generate recommendation models applying different similarity techniques such as cosine similarity, Pearson correlation coefficient, and Euclidean distance.	Movie	Average similarity	High similarity	Hard for pure cold start problems
P. Li, R et al. [42]	The model adapts to user embedding by aggregating the corresponding contextual information through Transformer. A two-tower architecture is used to decouple the user and the target item to solve the user cold-start problem.	MovieLens-1M, Taobao Display AD, Industrial Dataset	AUC, RelaImpr	High Accuracy	Hard for pure cold start problems

TABLE 18. Distribution of studies related to evaluation metrics for user cold start problems.

Rating prediction metrics	Evaluation Metrics	Literatures
Rating prediction metrics	MSE, RMSE, MAE	[33], [39], [45], [47], [48], [51], [56], [58], [59], [61], [62], [65], [68]–[71], [76], [78], [79]
Classification accuracy metric	Recall, Precision, F1-Score, AUC	[37], [38], [40], [42], [45], [49], [50], [53], [55], [61], [67], [73], [75]
Top-K accuracy metric	ndcg@K, Hit@K, recall@K, precision@K, AP@K	[31], [32], [34]–[38], [46], [49], [52], [54], [55], [57], [58], [60], [63]–[66], [74]

Data-driven mainly utilizes different user information to solve the new user issue. Such as user social network data, user demographic data, etc. The advantage of these methods can better solve the problems that new users have no historical behavior data by using user-related data (such as social network data). It can better alleviate the user cold start problem. However, these methods have some problems such as the difficulty of multi-domain user feature fusion, user data privacy and user data acquisition.

Method-driven solves the problem by applying different algorithms or models. In this paper, method-driven is subdivided into five categories. They are meta-learning methods, deep learning methods, matrix factorization methods, new methods based on collaborative filtering, and new methods for content-based recommender systems. The advantage of these methods is that some rules are used to solve the user cold start problem. For example, machine learning related methods can be recommended to new users through rapid learning, and multi-feature fusion can be better solved. However, such methods have the defects of complex models and poor results for pure cold start problems.

This study's primary finding is very beneficial to cross-domain and social network data to address user cold start difficulties. As part of the selection or filtering process, researchers frequently analyze data or inferences using pre-established standards. This is because it's possible that the additional data, which mainly consists of assumptions and information from questionable sources, isn't accurate and trustworthy. Researchers have chosen and sorted these facts in this order based on their dependability. The study found that machine learning and deep learning techniques are being used more often in a range of academic fields. DNN, GNN, and other techniques are being used by more researchers to alleviate the problem of new users, as can be observed in Fig. 8.

In recommender systems, the use of deep learning or machine learning techniques can successfully capture non-linear correlations between users and items. Deep learning can handle intricate and sophisticated interactions in knowledge gathered from a variety of sources (like text embeddings, context embeddings, and visual embeddings), as well as the encoding of complex conceptions as higher-level information presentations. To solve user cold start difficulties, additional research using deep learning or machine learning methods is required. The new user issue is being addressed in research on deep learning algorithms. Graph neural networks or the Attention mechanism are being used by more and more researchers. View as in Fig. 9.

The research in this paper found that recommendations for films, music, and books are the most researched areas. This is because there are more publicly available datasets in these domains. Recommendation methods for shopping and e-commerce are next in research. This is because shopping and product review datasets are more readily available. However, recommendation methods in the field of education are less researched yet extremely important. This suggests new research directions for recommender systems scholars.

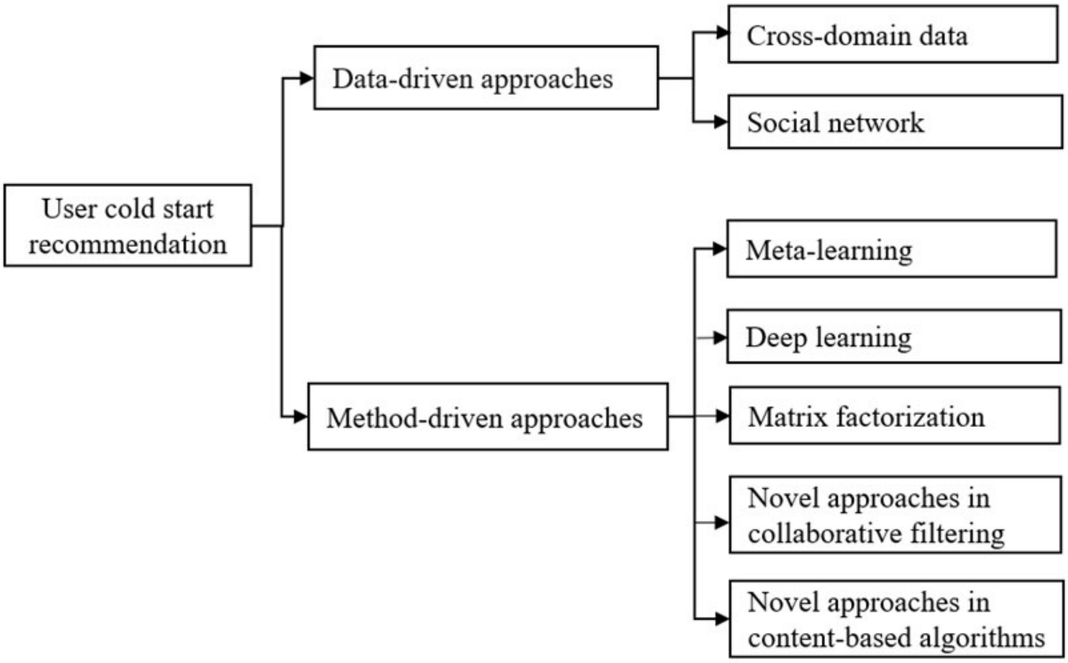

FIGURE 7. Classification of user cold start recommendation strategies.

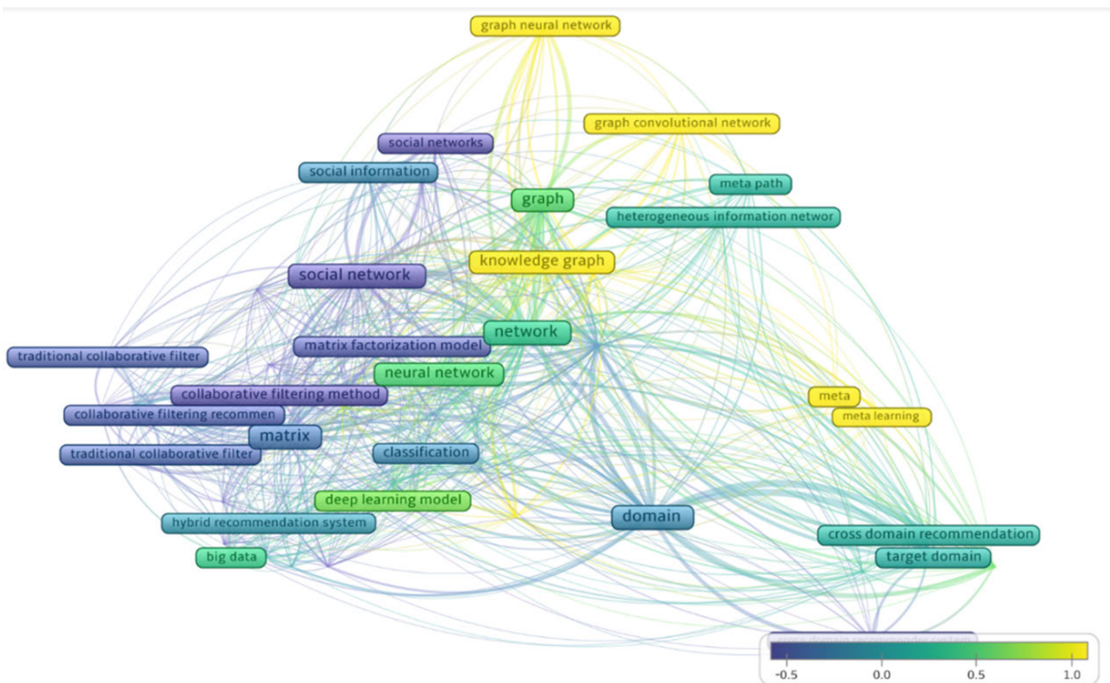

FIGURE 8. Time to solve the new users' problem. (Yellow indicates the nearest time, and purple indicates the farthest time.)

Both the cold start problem and the data sparsity problem are related to situations where there is insufficient information in a recommender system, but they occur at different times, on different scales, and with different solutions. Approaches to the cold-start problem typically focus more on obtaining additional information (e.g., user registration information or item metadata), while approaches to the data sparsity problem focus more on filling in the missing information by using data that already exists. However, approaches such as machine learning, meta-learning, and some hybrid approaches can address both the cold-start problem and the data sparsity problem.

Three main types of evaluation metrics are used for user cold start model evaluation: Rating prediction metrics,

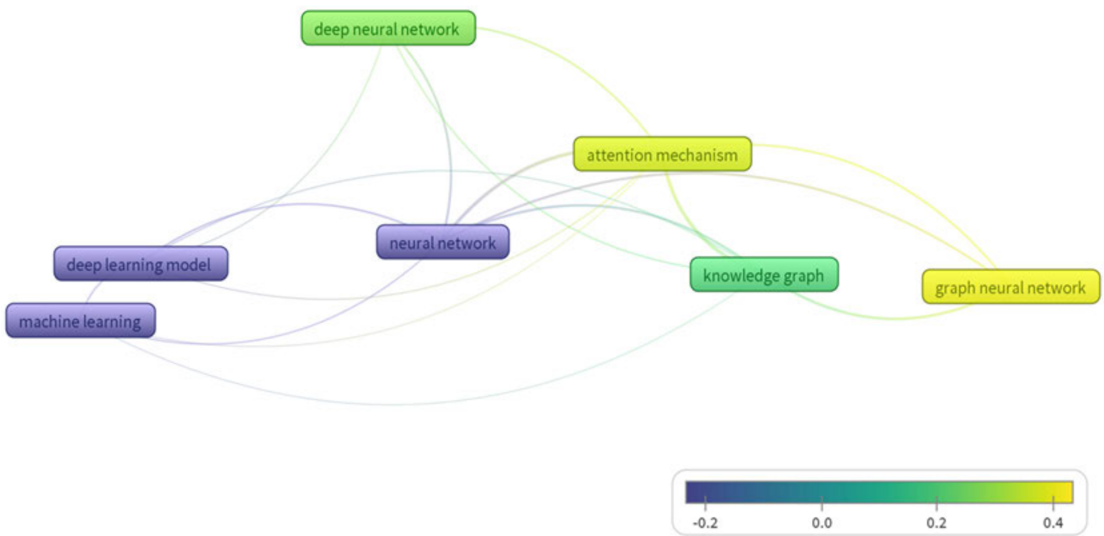

FIGURE 9. Deep learning algorithm overlay visualization. (Yellow indicates the closest to the current time, and purple indicates the farthest from the current time.)

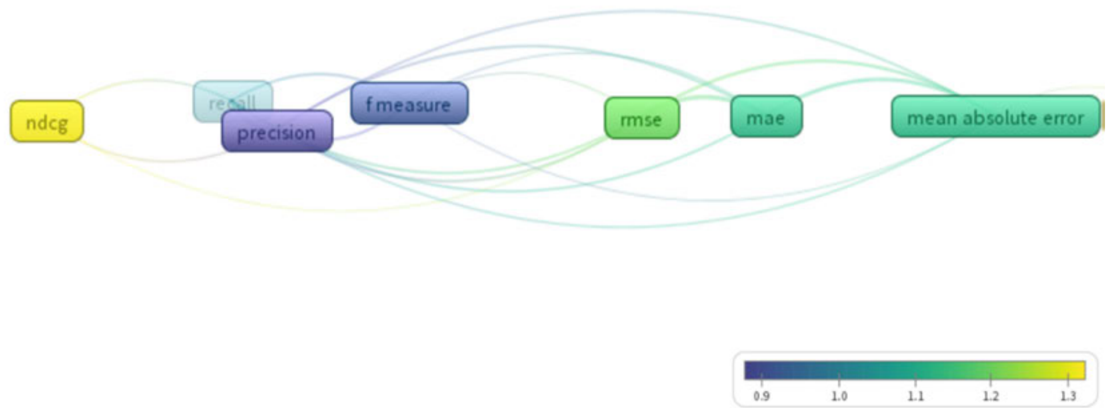

FIGURE 10. The evaluation metrics overlay diagram in the literature abstract. (Yellow indicates the closest to the current time, and purple indicates the farthest from the current time.)

Classification accuracy metrics, and Ranking Metrics. Most of the literature will choose different types of evaluation metrics for a comprehensive evaluation. Some papers use one type of evaluation metrics for evaluation. Most of the literature will adopt the Ranking Metrics type of evaluation metrics. Fig. 10 shows the evaluation metrics overlay diagram in the literature abstract. As can be seen from the figure, recently more and more scholars are using NDCG to analyze the performance of user cold start recommendation systems.

B. DIRECTIONS FOR FUTURE RESEARCH

In this research review, we survey the state-of-the-art literature addressing the user cold-start problem. Despite these advances, there are still many challenges that need to be addressed.

- *Collecting and utilizing additional information*

Researchers have found that using additional information about users and items can go a long way toward alleviating user cold-start problems. This additional information includes user profile information, social relationships, user behavior, and auxiliary information (e.g., knowledge base and time signals). However, there are great challenges in collecting implicit user data and processing real-time user feedback data, and it is a challenge to collect and utilize additional information effectively.

- *Multi-task learning*

Deep learning-based methods are more effective in solving the user cold start problem compared to single-task learning. Utilizing multi-task learning in deep neural networks can reduce the problem of having little data at the beginning of a new user through implicit data augmentation. Some researchers are looking to apply deeper architectures to user data to explore additional multitask learning.

- *Attention Mechanisms*

The attention mechanism enables neural networks to focus on a subset of features by selecting specific inputs, helping to alleviate the user cold-start problem in recommender systems. This is a mechanism that can be intuitively applied to many deep learning architectures such as CNNs and RNNs. For example, when applying attention techniques to CNN models, it can be utilized to select the most representative elements and filter out uninformative ones, while providing better interpretability. Thus, attention modeling is a promising research direction.

- *Harmonized indicators for evaluating user satisfaction*

It was observed in this review that although recent recommender systems have shown good performance. However, there is no single standardized criterion that can be used to evaluate the performance of all recommender systems. User satisfaction and personalization play a very important role in the success of such recommender systems. There is a need for some new standardized evaluation criteria to evaluate the level of user satisfaction in real-time.

- *Protecting users' private information*

Interaction information and incidental information (e.g., social networks) are commonly used for recommendations in solving the user cold-start problem. However, one may be reluctant to share it with the recommender system because his privacy may be compromised or even violated by others. How to better protect users' private information is an open issue.

VII. CONCLUSION AND LIMITATIONS

The focus of this paper is to analyze how the user cold start problem has been solved in literature during the last eight years. This study's primary contribution is a comprehensive analysis of 45 related literature. A thorough categorization of solutions for the user cold start issue is provided.

This study categorizes approaches to addressing the new user issue into data-driven and method-driven strategies. This study can provide a comprehensive guide for future research on solving the new user issue. It helps to understand the direction of research and studies on new user issues.

The investigation in this paper is based solely on a systematic literature review of 45 articles published in academic conferences and academic journals. Although this study has made a great endeavor to strive and collate the strategies proposed by quite a few researchers to alleviate the issue with user cold starts. However, no experimental validation has been carried out for comparative analysis. In the later phase of the study, the authors will typically focus on this issue.

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