Revolutionizing recommendations a survey: a comprehensive exploration of modern recommender systems

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Article Info

Article history:

Received Mar 28, 2024
Revised Feb 21, 2025
Accepted Mar 15, 2025

Keywords:

Collaborative filtering
Content-based filtering
Deep learning
Hybrid systems
Recommendation system

ABSTRACT

The rapid proliferation of digital information and online services has fundamentally reshaped user interactions with websites, necessitating the evolution of recommender systems. These systems, crucial in domains such as e-commerce, education, and scientific research, serve to enhance user engagement and satisfaction through personalized recommendations. However, it comes up with new challenges, including information overload, prompting the development of recommender systems that can efficiently navigate this vast group to offer more personalized and relevant suggestions. This survey paper explores the dynamic opinion of recommendation systems, addressing the limitations of traditional approaches, the emergence of deep learning models, and the extended potential for additional data. By investigating various recommendation systems and the evolving role of deep learning, this paper illuminates the path toward more accurate, personalized, and effective recommender systems, considering challenges like sparse data and improved context-based recommendations. The study encompasses three primary recommendation approaches: collaborative filtering, content-based filtering, and hybrid systems. It further investigates into the transformation brought about by deep learning models, showcasing how these models intricate user-item interactions. This survey offers a comprehensive exploration of recommendation systems and their advancements in the digital era, providing insights into the future of personalized content delivery.

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1. INTRODUCTION

The rapid growth of digital information and the proliferation of online services have significantly transformed user interactions with websites. In this context, recommender systems have emerged as pivotal tools for enhancing user engagement and satisfaction by providing tailored recommendations [1]. The significance of these systems extends across various domains, including e-commerce, education, and scientific research. However, as the volume of digital information continues to expand, the effectiveness and adaptability of recommender systems face challenges. Users grapple with information overload, and thus, it is imperative to develop recommender systems that can navigate this vast digital landscape and offer more relevant and personalized suggestions [2].

Recommender systems primarily operate through two key approaches: collaborative filtering (CF) and content-based filtering (CBF), each with its unique strengths and limitations. To address these limitations and enhance recommendation accuracy, current research has seen a significant shift towards the adoption of deep learning models [3], [4]. Deep learning-based recommendation systems have demonstrated remarkable potential by uncovering intricate user-item interactions and patterns. Nevertheless, these models often neglect the valuable insights hidden within supplementary data, such as user reviews and ratings [5]. Ratings can be subjective and may not always reflect users' true sentiments, making the integration of implicit feedback from user reviews increasingly essential. Incorporating both explicit ratings and implicit feedback from reviews holds the promise of refining recommendation systems and tailoring them to individual preferences [6]. In this survey paper, we delve into the transformative landscape of recommendation systems, where we explore the challenges faced by conventional approaches, the surge in deep learning models, and the untapped potential of supplementary data. By examining various recommendation scenarios and the evolving role of deep learning, we aim to shed light on the path towards more accurate, personalized, and effective recommender systems [7]. This survey comprehensively examines the landscape of recommendation systems and their promising advancements in the digital era, offering insights into the future of personalized content delivery.

The problem at hand revolves around the challenges and limitations faced by traditional recommendation systems, which are increasingly vital in various domains. The rapid growth of digital information and the need for personalization have spurred interest in leveraging deep learning techniques to enhance recommendation systems. However, the adoption of deep learning introduces its own set of challenges, including the need for substantial training data, complex model architectures, and parameter tuning. To address these issues, a comprehensive survey paper is proposed. This survey aims to explore how deep learning can alleviate the limitations of traditional recommendation systems, providing more accurate and personalized recommendations. Key research questions involve the challenges faced by traditional systems, the role of deep learning algorithms, their adaptability to different recommendation scenarios, and addressing specific research gaps within this domain, including sparse data and improved context-based recommendations.

2. RELATED WORK

In this survey paper, we research into the various types of recommendation systems, considering the challenges and innovations in the field. This exploration encompasses traditional and emerging techniques, underscoring the evolution of recommendation algorithms and the quest for more precise and user-centric recommendations in an increasingly complex digital environment. The effectiveness of recommendation systems is contingent upon their ability to effectively navigate and address the complexities and challenges inherent in this domain. The task of predicting user preferences, whether they are expressed through ratings or purchasing decisions, poses a fundamental challenge [8]. The conventional approach often involves the laborious process of manually identifying users who share similar interests. Recommendation algorithms, such as CF, CBF, and hybrid models, often rely on manual construction. CF algorithms operate under the assumption that individuals with similar preferences for specific items will exhibit similar levels of interest in novel items. This assumption forms the basis for suggesting top-rated items that align with a user's previous engagements with content [9]. The user's profile, derived from accurate feedback assessing the appeal of previous products, plays a vital role in this procedure.

Several techniques, such as support vector machines, K-nearest neighbors (K-NN), neural networks, and logistic regression, have been employed to address these recommendation challenges in binary classification tasks. CF techniques have demonstrated efficacy in providing personalized recommendations within the context of e-commerce platforms [10]. In this document, we will introduce a behavior record module, followed by an analysis of the module and the utilization of a recommendation algorithm module. A customized recommendation method, known as maximum margin factorization, has been explored for users with semi-definite preferences. This method aims to provide recommendations that are both more accurate and suitable for these users [11]. The integration of social network data into CF has been implemented to enhance the effectiveness of recommendations [12]. To accomplish this task, it is necessary to collect user preference ratings and utilize data obtained from social media relationships sourced from social networking sites. The primary objective of this project has been to assess the efficacy of CF in various neighbor groups, such as friends and nearest neighbors [13].

This system will recommend highly ranked items to users based on CF algorithms. These algorithms assume that users with similar tastes will find the recommended items comparable to their own content [14]. This feature surpasses its predecessors by emphasizing newly available products that are similar to the ones the customer has previously encountered. The primary challenge lies in determining the user's profile by gathering accurate information regarding their level of interest in previous items. Various techniques, including support vector machines, K-NN, neural networks, and logistic regression, are commonly employed for binary classification tasks [15]. The CBF recommendation class is widely recognized as a popular and extensively studied approach. The user modeling process is an essential element of CBF. It involves extracting user interests from the various items that users interact with. Text-based "items" commonly include emails and web pages. Typically, "interaction" takes place when anything is downloaded, bought, created, or labeled. The representation is achieved through the utilization of a content model that encompasses all the characteristics of the object. The predominant attributes primarily consist of word-based elements, including single words, phrases, or n-grams. Recommender systems may utilize extensible markup language (XML) elements, layout specifics, and writing style as supplementary non-textual criteria [16]. In modeling an item, typically only the most descriptive aspects are utilized, and both the users and these features are frequently assigned weights.

Hybrid recommendation algorithms have been found to outperform other filtering methods by combining CF and CBF techniques [17]. To enhance prediction capabilities within the recommendation system, it is crucial to leverage a notable exception identified in this context and apply it across various categories. Customers have the option to express their preferences for the introduction of new customer items, thereby enhancing turnover, when new goods become available. The investigation of this information retrieval method is currently underway in various fields, such as e-commerce and distance learning [18]. The main responsibility entails providing a comprehensive description of the user's objectives, dietary preferences, and recreational activities. Recommendation systems play a crucial role in personalizing online content, enabling tailored browsing experiences based on users' individual interests, and facilitating communication interfaces across a wide range of diverse locations [19].

The relevant factors related to users' interests are prioritized in order to offer a customized viewpoint. Various AI strategies are utilized, including parameter satisfaction, user modeling, and machine learning data. In order to utilize AdaBoost machine learning algorithms, it is necessary to generate recommendations. In order to predict the previous likes and dislikes of users, a methodology called AdaBoost is employed. The process of comparative analysis involves the utilization of dependable and flexible techniques for training the classifiers. K-fold cross-validation is employed to evaluate the performance of the AdaBoost classifier. A state-of-the-art approach was employed to develop a tourist recommendation system that utilizes data mining techniques to provide personalized suggestions based on user preferences [20]. The reviews obtained from social media platforms provide a significant amount of data that can be utilized to extract user preferences in the field of tourism. Furthermore, the comments that have undergone semantic and emotional preprocessing are further processed to determine the preferences of the visitors. In a similar manner, the aggregated reviews are utilized to extract the features of the regions of interest. A comprehensive profile can be created for each individual, accompanied by a strategy for providing group recommendations. This study utilizes deep profiles that are derived from the cumulative sum of all group numbers, rather than relying on item preference profiles as seen in previous research. Table 1 shows the survey table for CBF. Table 2 shows the survey table for CF. Table 3 shows the survey table for hybrid recommendation system.

Table 1. Survey table for content-based filtering

Reference	Method	Advantages	Research gap
[17]	Supervised learning	- Improved healthcare recommendations based on patient profiles, medical history, and diseases. - Classifying patients into sub-classes. - Predicting medical conditions.	- Lack of consideration for patient allergies.
[18]	Association rule mining, K-NN	- Predicting ICU patients' health for urgent actions. - Automated health prediction for ICU patients.	- Ignored embedding a machine learning (ML) model for live readings from ICU machines.
[19]	Combination of association and clustering rules	- Successful approach to disease prediction using medical history.	- No comparison with other proposals in the literature. - Limited assessment of vast medical history datasets.
[20]	Ontology characteristics, disease text mining	- Efficient doctor recommendation system for online prediagnosis. - Utilization of word frequency statistics and word vectors.	- Limited description of the recommendation system's comprehensiveness and application of patient traits in the interface.
[21]	Content-based image retrieval	- Better image retrieval performance through user information and feedback.	- Not specified in the provided information.
[22]	Cross-industry data mining, data set segmentation, dynamic caching	- Improved performance, low processing time, low storage requirements, and scalability in healthcare recommendation systems.	- Not specified in the provided information.
[23]	Hybrid model	- Predicting disease occurrences for cardiac patients. - Adaptive intelligent RS for heart disease patients. - Quick medical decisions for doctors and patients.	- Missing consideration of individual traits (age, gender, weight) in recommendations and predictions for heart disease patients.

Table 2. Survey table for collaborative filtering

Study	Reference method	Advantages	Research gap
[24]	CF	- Coined the phrase "CF." - Assumption that users with similar ratings or behaviors will have similar preferences. - Helps users discover interesting and valuable items. - Can handle explicit and implicit indications of user preferences.	- May not explicitly collaborate with recipients. - Recommendations may not always suggest particularly interesting items.
[25]	Memory-based CF	- Uses user rating data to calculate similarity between users or items. - Easy-to-implement and highly effective. - Customization reduces search effort for users. - Promises greater customer loyalty and higher sales.	- Unreliable when data is sparse and common items are few.
[26]	Model-based CF	- Utilizes data mining or machine learning algorithms to estimate a model for predictions. - Can include Bayesian belief nets (BNs) CF, clustering CF, and latent semantic CF models. - Potential to improve prediction performance.	- Need for further investigation and comparison of different model-based CF techniques.
[27]	Markov decision process (MDP)-based CF	- Results in higher profits compared to systems without recommenders.	- Requires exploration of the specific mechanisms and benefits of MDP-based CF systems.

Table 3. Survey table for hybrid recommendation system

Reference	Method used	Advantages	Research gap
[18]	Traditional hybrid recommendation system.	- Addressed the cold start problem for movies and users. - Used two similarity matrices to make recommendations.	High memory usage due to multiple similarity matrices.
[19]	Neural network	- Reduced cold start issues for new users in movie recommendations. - Used the Jaccard similarity index.	Ignoring other challenges.
[20]	K-means clustering	- Recommended movies by clustering movies based on user comments. - Studied the movielens dataset.	Complex architecture.
[21]	Classification algorithms	- Used classification algorithms (naïve Bayes, decision tree, random classification) as similarity metrics. - Evaluated the movielens dataset.	More scope of enhancement.
[28]	Hybrid co-clustering algorithm	- Proposed a hybrid method combining CF and demographic information. - Used the hybrid co-clustering algorithm. - Evaluated multiple datasets (Movielens, Jester, Netfix).	Can further enhance the accuracy by combining different algorithms.
[29]	Social networking approach	- Developed a recommendation system for online social networks. - Exploited user interactions in online social networks. - Conducted experiments on data from online social networks.	Addressing the cold start problem not explicitly mentioned.
[30]	Social network data analysis	- Explored challenges and solutions for recommender systems in large social networks. - Focused on the heterogeneity, size, and dynamics of social network data.	Addressing the cold start problem not explicitly mentioned.

They summarize the principles and characteristics of current news recommendation systems and discuss “unexpected consequences” that might arise from these algorithms. Meta-interest, a personality-aware product recommendation system based on user interest mining and metapath discovery. Meta-interest predicts the user's interest and the items associated with these interests, even if the user's history does not contain these items or similar ones. They present a design that will expand on the opportunities for better data accessibility and use, by integrating the recommendation system into connected health [28], [31]–[33]. They combine the advantages of graph convolutional network (GCN) and sequential recommendation models by proposing a novel self-attention based sequential recommendation with graph convolutional networks (SASGCN). Modify the fusion recommendation algorithm and propose the neural networks fusion recommendation (NNFR) model. This model improves the structure of BP neural network by specially designing the structure of network layers. The relations between different time spans are adopted to construct the signed networks and imitate user’s interest changes [34], [35].

They propose hierarchical federated recommendation system (HFSA), a semi-asynchronous hierarchical federated RS. Here it is proposed deep edu a novel deep neural CF for educational services recommendation. Review existing solutions for these issues, and finally elaborate research challenges and future directions in this field. The proposed method, a deep residual bidirectional gated recurrent neural network is applied to obtain high activity recognition accuracy from accelerometer signals on the smartphone

[36]–[38]. Propose a nonlinearly attentive similarity model (NASM) for item-based CF via locally attentive embedding by introducing local attention and novel nonlinear attention to capture local and global item information, simultaneously. A hypergraph embedding's for music recommendation (HEMR), a novel framework for song recommendation based on hypergraph embedding [39]. A new end-to-end recommendation model called neighbor library-aware graph neural network (NLA-GNN).

Design a novel multimodal contrastive framework to facilitate item-level multimodal fusion by mining both modality-shared and modality-specific information. An online deep reinforcement learning-based order recommendation (DRLOR) framework to solve the decision-making problem in the scenario of online food delivery (OFD) [40]–[44]. They evaluate several existing approaches on a set of 8 Microsoft repositories of different sizes. A robustly co-learning model (RCoLM) that takes the incompleteness nature of KGs into consideration when incorporating them into recommendation. An efficient method for calculating the distance between process fragments and select candidate node sets for recommendation purpose. This paper addresses the dynamism of the order recommendation problem and proposes a reinforcement learning solution method [45]–[48]. Propose an effective neural recommender system, graph-convolved factorization machine (GCFM), with the spirit of the symbolic graph reasoning principle that provides lightweight and interpretable recommendation suggestions [49].

3. RECOMMENDATION SYSTEMS

In each industry, recommendation systems are utilized to give clients priority based on their previous preferences. There are two recommender problems in the recommendation problem. The ability to predict a user's preferences for a product or to rank and propose products to a user by creating a Top-N list. Three types of recommendation systems are recognized. one is systems for CF that make suggestions to users based on their interactions, either overtly (for example, past ratings) or covertly (e.g., user comments). The foundation of content-based recommender systems is the idea that items are suggested based on how much they resemble previous user favorites. Figure 1 shows the types of recommendation systems. These methods are frequently applied to make up for the shortcomings of one method that the other method corrects.

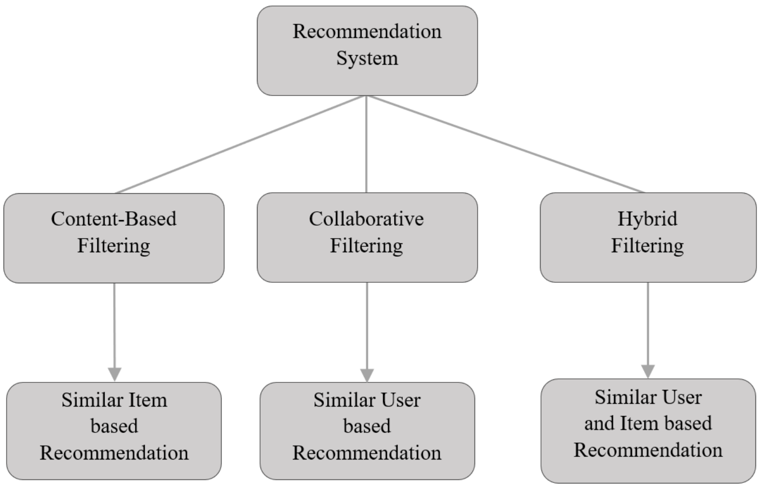

Figure 1. Types of recommendation systems

3.1. Content-based filtering recommender systems

CBF is a popular technique used in recommender systems to provide personalized recommendations to users. This approach is based on analyzing the content or attributes of items (e.g., products, articles, movies) and users' historical preferences to make recommendations. CBF systems focus on matching the characteristics of items to the user's profile or preferences. Here's how CBF recommender systems work:

- Item profile creation: each item in the system is represented by a set of descriptive features or attributes. For example, in a movie recommendation system, these features could include genres, actors, directors, and release year. The item profiles are created based on these attributes.
- User profile creation: a user's profile is constructed by analyzing their past interactions or preferences. For instance, in a movie recommendation system, the user's profile might include the genres, directors, or actors they have shown a preference for in the past.

- Recommendation generation: to generate recommendations for a user, the system compares the user's profile with the profiles of items. It calculates a similarity score between the user's profile and each item's profile. This score can be computed using various techniques such as cosine similarity, Jaccard similarity, or term frequency-inverse document frequency (TF-IDF) weighting. The items with the highest similarity scores are recommended to the user.
- Filtering and ranking: the system can apply additional filters or rules to refine the recommendations. For example, it may exclude items the user has already interacted with or limit recommendations to items that are currently available or popular. The recommended items are then ranked based on their similarity scores or other factors (e.g., release date, popularity) to present the most relevant items at the top of the list.

3.1.1. Advantages

Personalization: content-based systems provide personalized recommendations based on a user's historical preferences and the content attributes of items. Explanations: these systems can often provide explanations for why a particular item is recommended (e.g. "This book is recommended because you liked other books by the same author"). Cold start problem: CBF can make recommendations for new items or users with limited historical data, addressing the "cold start" problem to some extent.

3.1.2. Limitations

Limited serendipity: it tends to recommend items that are similar to what the user has already interacted with, which can lead to a lack of diversity in recommendations. Over-specialization: if a user's historical preferences are too narrow or if the item profiles are not diverse, the recommendations may become repetitive. Content quality: the quality of recommendations heavily depends on the quality and accuracy of the item profiles. Scalability: creating and maintaining detailed item profiles for a large catalog of items can be challenging.

3.2. Collaborative filtering

CF is a popular technique used in recommender systems to provide personalized recommendations to users. It is based on the idea that users who have agreed on or interacted with items in similar ways in the past are likely to agree on items in the future. CF can be broadly categorized into two main types: user-based CF and item-based CF. Item-based CF is less sensitive to the sparsity problem and can be more scalable since the number of items is typically smaller than the number of users.

- User-based CF: In user-based CF, the system recommends items to a user based on the preferences and behaviors of users who are similar to that user. User-based CF is sensitive to the "sparsity" problem, which occurs when most users have interacted with only a small subset of items. It may also suffer from scalability issues with a large user base. The process typically involves the following steps: i) create a user-item matrix where rows represent users, columns represent items, and the values represent user interactions (e.g., ratings, likes, purchase history). ii) calculate the similarity between the target user and other users in the system. iii) identify users who are most similar to the target user. iv) recommend items that these similar users have interacted with, but the target user has not.
- Item-based CF: in item-based CF, the system recommends items to a user based on the similarity between the items the user has interacted with and other items in the system. The similarity between items is determined based on how users have interacted with them. Similarity can be calculated using various metrics, such as cosine similarity or Jaccard index. Item-based CF is less sensitive to the sparsity problem and can be more scalable since the number of items is typically smaller than the number of users. The process typically involves the following steps: i) create an item-item similarity matrix, where each entry represents the similarity between two items. ii) for the target user, identify the items they have interacted with. iii) recommend items that are similar to the ones the target user has interacted with but have not been interacted with by the user.

3.2.1. Advantages

User-item independence: it doesn't require extensive information about items, making it suitable for a wide range of domains. Serendipity: it can discover hidden or unexpected connections between users and items. Scalability: its ability to function without detailed domain-specific data allows for effortless adaptation to new or expanding user-item datasets.

3.2.2. Limitations

Cold start problem: it can struggle to make recommendations for new users or items with limited interaction data (the "cold start" problem). Data sparsity: in systems with sparse data, it can be challenging to find similar users or items. Scalability: user-based CF may become inefficient as the user base grows, and item-based CF can face challenges with a large item catalog.

3.3. Hybrid recommendation system

Hybrid recommendation system is a recommender system that combines multiple recommendation techniques to provide more accurate, diverse, and effective recommendations to users. The goal of hybrid systems is to leverage the strengths of different recommendation approaches while mitigating their individual weaknesses. Hybrid recommendation systems are widely used in e-commerce, content platforms, and other domains where personalized recommendations are crucial for user engagement and satisfaction. The choice of hybrid approach and its components depends on the specific requirements and characteristics of the application. There are several common approaches to building hybrid recommendation systems:

- Weighted hybrid recommendation: in a weighted hybrid system, multiple recommendation algorithms (e.g., CF, CBF, and popularity-based recommendations) are employee. Each algorithm produces a set of recommendations, and the system assigns weights to these recommendations to indicate their relative importance. The final recommendation is generated by combining the weighted results from each algorithm.
- Switching hybrid recommendation: in a switching hybrid system, the recommendation algorithm is chosen based on certain conditions or user characteristics. For example, if the system determines that a user is a new user with limited interaction history (the "cold start" problem), it might use a content-based approach. For users with more historical data, CF could be employed.
- Cascade hybrid recommendation: a cascade hybrid system generates recommendations in stages, where each stage refines the results of the previous one. For example, in the first stage, a content-based approach might generate initial recommendations. In the second stage, CF could be applied to filter and refine these initial recommendations further.
- Feature combination hybrid recommendation: in a feature combination hybrid system, features from different recommendation approaches are combined into a single unified model. For instance, in a movie recommendation system, features from content-based (e.g., genre, actor, director) and CF (user-user or item-item similarities) approaches might be concatenated and used to predict user preferences.
- Meta-level hybrid recommendation: in a meta-level hybrid system, multiple recommendation algorithms operate independently and produce recommendations. A separate meta-level algorithm learns to combine and optimize the results of these base algorithms, potentially incorporating user feedback to determine the final recommendations.
- Parallel hybrid recommendation: in a parallel hybrid system, different algorithms run in parallel, and their recommendations are presented to the user simultaneously. Users can choose from among the recommendations, and the system may adapt its presentation based on user interactions and feedback.

3.3.1. Advantages

Enhanced recommendation quality: hybrid systems often provide more accurate and diverse recommendations by leveraging the strengths of different algorithms. Flexibility: they can handle various recommendation scenarios, including the cold start problem and sparse data. Personalization: they can cater to individual user preferences more effectively.

3.3.2. Challenges

Complexity: developing and maintaining hybrid systems can be more complex than single-method systems. Parameter tuning: determining the right weights, strategies, and algorithms can be challenging and may require ongoing tuning. Computational overhead: running multiple recommendation algorithms can be computationally intensive.

4. DEEP LEARNING BASED ALGORITHMS USED FOR RECOMMENDATION SYSTEMS

The deep learning-based algorithms can be used in various recommendation scenarios, such as CF, CBF, and hybrid systems. They often require substantial amounts of training data and can benefit from techniques like mini-batch training, regularization, and careful hyper-parameter tuning to achieve optimal performance. Additionally, deep learning models can be enhanced with techniques like attention mechanisms, reinforcement learning, and adversarial networks to further improve their recommendation capabilities. The choice of the algorithm depends on the specific requirements of the recommendation system, the type of data available, and the desired level of personalization and accuracy. Here are four common deep learning-based algorithms used for recommendation systems:

- Matrix factorization with deep learning (MF-DL): matrix factorization is a traditional technique in recommendation systems, but deep learning can enhance its capabilities. In MF-DL, deep neural networks are incorporated into matrix factorization to capture non-linear relationships between users and items. By combining CF with neural networks, MF-DL can model intricate user-item interactions and generate more accurate recommendations.
- Auto-encoders: auto-encoders are neural networks designed to learn a compact representation of the input data. In recommendation systems, they can be used to capture user and item embeddings. Variants like denoising autoencoders and variational autoencoders (VAEs) can be employed to model user preferences and item characteristics, respectively. Autoencoders can be stacked to create deep autoencoder models, which can capture higher-level abstractions in the data.
- Recurrent neural networks (RNNs): RNNs are well-suited for modeling sequential data and are used in recommendation systems when there is a temporal aspect to user interactions. Session-based recommendation systems often use RNNs to model user behavior sequences, taking into account the order and timing of interactions. Gated recurrent units (GRUs) and long short-term memory (LSTM) networks are popular RNN variants for recommendation.
- Convolutional neural networks (CNNs): CNNs are primarily known for their success in image processing, but they can be adapted for recommendation systems. In content-based recommendation systems, CNNs can be used to extract features from textual or image data associated with items. For example, in a movie recommendation system, a CNN could learn to extract features from movie posters or plot summaries for better recommendations. Table 4 shows the survey table on the deep learning algorithm used.

Table 3. Survey table on deep learning algorithms used

Reference	Algorithm used	Advantages	Research gap
[18]	Matrix factorization (MF)	- Utilized matrix factorization for recommendations in ClusterExplorer. - Addressed user control-related suggestions in the book field. - However, faced challenges with sparse data.	Research gap related to addressing sparse data and enhancing recommendation accuracy in ClusterExplorer.
[23]	Dual-headed attention fusion autoencoder	- Proposed a dual-headed attention fusion autoencoder model for context-based recommendations. - Fused user comments and implicit feedback. - Claimed superiority over multiple comparison algorithms.	Enhance the accuracy of the model developed further.
[24]	News recommendation model	- Introduced a news recommendation model learning from human editors. - Addressed the quality of candidate articles. - Captured the editor's selection criteria through article representation.	Research gap related to capturing context and editor preferences.
[25]	Asymmetric hierarchical network (AHN)	- Developed AHN, a flexible neural architecture for comment recommendation. - Utilized an asymmetric attention module to distinguish user and item embeddings. - Achieved superior performance.	Not specified in the provided information.
[26]	Various RS techniques for e-learning	- Presented a comprehensive review of technology-enhanced learning RSs. - Analyzed different recommendation techniques and sources of information.	Further could be explored by combining two algorithms to enhance accuracy

5. CONCLUSION

This survey paper has explored the various types of recommendation systems, underscoring their vital role to the users across diverse domains. Traditional methods, such as collaborative and CBF, have long been foundational, but the rise of deep learning models has introduced new possibilities by uncovering intricate user-item interactions. Deep learning's potential, however, underscores the importance of incorporating supplementary data like user reviews and implicit feedback. Beyond examining core approaches, this paper also examines into the existing work, addressing challenges and innovations, from manual user interest constructions to hybrid systems and even the utilization of stereotypes. This comprehensive survey underscores the need for integration of traditional and state-of-the-art techniques, resulting in more accurate, personalized, and effective recommender systems that continually adapt to the evolving digital paradigm, enriching user experiences across various domains.

ACKNOWLEDGEMENT

We would like to express our sincere gratitude to our guide for her unwavering guidance, invaluable insights, and encouragement throughout the research process.

FUNDING INFORMATION

No funding is raised for this research.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST

The author declares no conflict of interest.

DATA AVAILABILITY

No datasets utilized in this research.

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