IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received 5 September 2023, accepted 2 October 2023, date of publication 10 October 2023, date of current version 19 October 2023.

Digital Object Identifier 10.1109/ACCESS.2023.3323353

TOPICAL REVIEW

Deep Learning-Based Recommendation System: Systematic Review and Classification

CAIWEN LI[1], ISKANDAR ISHAK[1], HAMIDAH IBRAHIM[1], (Member, IEEE), MASLINA ZOLKEPLI[1], FATIMAH SIDI[1], (Member, IEEE), AND CAILI LI[2]

[1]Department of Computer Science, Faculty of Computer Science and Information Technology, Universiti Putra Malaysia (UPM), Serdang, Selangor 43400, Malaysia
[2]College of Art and Design, Heilongjiang Institute of Technology, Daowai, Harbin, Heilongjiang 150050, China

Corresponding author: Iskandar Ishak (iskandar_i@upm.edu.my)

This work was supported in part by Universiti Putra Malaysia through the Putra Grant Scheme under Grant GP/2020/9692500, and in part by the Ministry of Higher Education Malaysia through the Fundamental Research Grant Scheme under Grant FRGS/1/2020/ICT06/UPM/02/1.

ABSTRACT In recent years, recommendation systems have become essential for businesses to enhance customer satisfaction and generate revenue in various domains, such as e-commerce and entertainment. Deep learning techniques have significantly improved the accuracy and efficiency of these systems. However, there is a lack of literature regarding classification in systematic review papers that summarize the latest deep-learning techniques used in recommendation systems. Moreover, certain existing review papers have either overlooked state-of-the-art techniques or restricted their coverage to a narrow spectrum of domains. To address these research gaps, we present a systematic review paper that comprehensively analyzes the literature on deep learning techniques in recommendation systems, specifically using term classification. We analyzed relevant studies published between 2018 and February 2023, examining the techniques, datasets, domains, and measurement metrics used in these studies, utilizing a thorough SLR strategy. Our review reveals that deep learning techniques, such as graph neural networks, convolutional neural networks, and recurrent neural networks, have been widely used in recommendation systems. Furthermore, our study highlights the emerging area of research in domain classification, which has shown promising results in applying deep learning techniques to domains such as social networks, e-commerce, and e-learning. Our review paper offers insights into the deep learning techniques used across different recommendation systems and provides suggestions for future research. Our review fills a critical research gap and offers a valuable resource for researchers and practitioners interested in deep learning techniques for recommendation systems.

INDEX TERMS Deep learning, term classification, recommendation system, systematic review, state-of-the-art techniques.

I. INTRODUCTION

As data becomes more readily available, recommendation systems are gaining popularity in e-commerce. In today's business world, data-driven decisions are crucial, and many companies are incorporating recommendation system features into their websites and apps to enhance user experience and increase revenue [1], [2], [3], [4], [5]. The purpose of recommendation systems is to provide personalized and relevant suggestions to users based on their past behavior, preferences, and interests [6], [7], [8], [9], and to solve the problem of information overload in various domains such as e-commerce [10], [11], [12], e-learning [13], [14], [15], social networks [16], [17], [18], [19], [20], [21], and entertainment [22], [23], [24], [25].

However, recommendation systems face challenges such as data sparsity, cold start, and the need for collecting past user feedback [26], [27]. Researchers are developing more effective recommendation algorithms to overcome these challenges and improve accuracy and user satisfaction [28],

The associate editor coordinating the review of this manuscript and approving it for publication was Vlad Diaconita.

[29]. As the amount of data being collected continues to increase due to technological advances, there is a growing need for techniques that can efficiently handle large amounts of data [30], [31].

Deep learning techniques based on artificial neural networks have proven exceptionally effective in accurately predicting outcomes for big data applications, particularly for recommendation systems [32], [33]. Deep learning models can learn and extract relevant features from raw data, making them highly effective in handling complex and high-dimensional datasets [34]. This capability is particularly relevant in recommendation systems, where personalized recommendations can be made to users based on their behavior and preferences [35], [36].

Given the considerations mentioned above, there is a need for a comprehensive and practical guide to deep learning-based recommendation systems. No systematic review has been conducted that focuses explicitly on deep learning-based recommendation systems using broad search terms that cover a wide range of recommendation domains. Furthermore, there is a lack of recent literature reviews that include the most advanced deep learning techniques developed within the last five years. Most importantly, no systematic study classifies deep learning techniques and domains into more appropriate categories based on the terms used in existing research articles. Such categorization would significantly expedite the summarization of future research in this field.

A. RESEARCH AIM AND OBJECTIVES

In summary, our research objectives are outlined as follows:

1) **Systematic Literature Review (SLR):** Conduct a systematic literature review on deep learning-based recommendation systems, summarizing insights from articles published within the last five years.
2) **Summarize State-of-the-Art Techniques:** Analyze and summarize the most recent and advanced deep learning techniques developed in the past five years and their applications in recommendation systems.
3) **Domain Categorization:** Categorize deep learning techniques and their application domains into relevant and meaningful groups based on terminologies used in the studies.
4) **Classification Using Search Terms:** Develop a term classification system to assist researchers in effectively targeting specific terms within the related field.
5) **Summarize Datasets and Metrics:** Summarize the datasets and metrics commonly utilized in the reviewed papers to help future researchers understand the prevalent dataset choices and metrics employed in the field.

By addressing these objectives, we aim to contribute to understanding and advancing deep learning-based recommendation systems by providing a consolidated and accessible overview of the latest developments and trends in this rapidly evolving domain.

B. ARTICLE STRUCTURE AND SECTIONS

The article is structured as follows:

- **Section I: Introduction** establishes the context and objectives of the research and provides an overview of the article's organization.
- **Section II: Related Work** provides a comprehensive survey of relevant research, including surveys, studies, and reviews, and summarizes and discusses their key contributions and limitations.
- **Section III: Background** presents the essential competencies, techniques, approaches, and challenges in recommendation systems.
- **Section IV: Research Method** outlines the systematic process followed in conducting the research, including research questions, article search strategies, screening procedures, quality assessment outcomes, and article selection based on the data extraction form.
- **Section V: Methodological Approach** details the research methodology, including data collection and analysis, article selection and review, publication trend identification, and classification methodology. The section connects methodological choices to the research process and results.
- **Section VI: Results Interpretation and Discussion** furnishes the analysis outcomes from the reviewed literature, encapsulating classification strategies for each category, underlying insights, comprehensive summary of findings, and gaps in research within each category.
- **Section VII: Limitations and Future Work** critically examines the study's limitations, addresses challenges encountered by deep learning recommendation systems, and proposes avenues for future research to tackle them.
- **Conclusion** synthesizes the study's outcomes into a coherent summary, providing meaningful conclusions from the findings and rounding off the study's comprehensive exploration.

This article thoroughly analyzes current research on recommendation systems using deep learning. It covers an introduction, related studies, background information, methodology specifics, discoveries, and potential avenues for future research.

II. RELATED WORK

Recently, recommendation systems have seen a surge in the use of deep learning techniques. This has resulted in numerous research studies in the field [37], [38]. Relevant articles have been categorized into three types, including literature surveys, research studies, and systematic literature reviews, based on keywords found in their titles. These categories are chosen because they provide a comprehensive overview of related works and guide future research directions. Similarly,

[39] have also identified these three categories as related works.

Our objective is to recognize the distinct research methodologies employed by each category, promote a better understanding of deep learning-based recommendation systems, and enable researchers to search for related articles more efficiently. Researchers can better understand the current state-of-the-art and identify future research directions by thoroughly analyzing the literature.

A. LITERATURE SURVEY

We analyzed several survey articles on deep learning-based recommendation systems covering deep reinforcement learning, graph neural networks, and autoencoder-based models. These surveys provide insights into the current state-of-the-art field, guiding the development of more effective recommendation systems.

Chen et al. [40] classified existing deep reinforcement learning-based recommender systems into model-based and model-free reinforcement learning. In contrast, Marinó et al. [41] compared lossy and structure-preserving approaches to compress pre-trained convolutional neural networks. Furthermore, Wu et al. [42] provide a thorough review and classification of the literature on the advances of graph neural network (GNN)-based recommender systems. They offer an in-depth explanation of each technique's architecture and summarize the datasets and metrics utilized in each study. The authors also discuss the challenges facing the field and point out that dynamic graphs in the recommendation are a largely under-explored area that deserves further study. Given the prevalence of the sparsity issue in recommender systems, the authors believe that self-supervised learning in GNN-based recommender systems is a promising direction for future research.

Wu et al. [43] conducted a systematic review of neural recommender models, categorizing them based on data usage into collaborative filtering, content-enriched recommendation, and temporal/sequential recommendation–the paper aimed to summarize the neural recommender model field and discuss promising future research directions. Ali et al. [44] classified deep learning models that provide citation recommendations based on six criteria, presenting a comparative analysis of these models and examining popular datasets, evaluation metrics, challenges faced, and upcoming issues and solutions.

Zhang et al. [45] reviewed recent research on autoencoder-based recommender systems, highlighting their advantages in data dimensionality reduction, feature extraction, and reconstruction. The paper discussed potential research directions for autoencoder-based recommender systems and presented differences between these systems and traditional recommender systems. The article by Zhang et al. [46] offers a comprehensive overview of the latest research on deep learning-based recommender systems. It delves into the architecture of deep learning algorithms and provides an in-depth analysis of advanced recommendation systems. Although the article does not cover a review of recommendation domains, it provides valuable insights into the current trends and emerging perspectives on the technical side of development.

Mu et al. [47] provided a systematic review of deep learning-based recommender systems, introducing the basic terminologies and concepts of recommender systems and deep learning technology, describing current research on deep learning-based recommender systems, and providing possible research directions for the future. Alahmadi et al. [48] investigated deep learning techniques to enhance MOOC-based course recommendation results, examining recent research on MOOC-based recommendation systems and highlighting the benefits of using deep learning techniques.

In addition, some of the surveys in our review examine the potential of deep learning-based recommender systems in e-learning and point-of-interest recommendation. For example, Salau et al. [49] discussed the potential of deep learning-based recommender systems in e-learning to enhance learning practices. In contrast, Islam et al. [50] surveyed deep learning-based point-of-interest recommendation techniques that use users' historical check-ins and other data.

These papers thoroughly explore the current state of research on recommender systems, with a particular emphasis on approaches leveraging deep learning. The topics covered include data usage, citation recommendations, autoencoder-based systems, and the impact of deep learning. Additionally, the papers delve into applying these techniques to Massive Open Online Courses (MOOCs).

1) COMPARISON

Taken as a whole, these surveys provide valuable insights and offer promising directions in recommender systems. However, it is important to note that these surveys have certain limitations. They do not fully explore the range of techniques, domain applications, data collections, and measurements contributing to recommender systems' bigger picture.

There is still much more to discover from these surveys. To address this, we expanded our approach by incorporating various techniques, domains, data collection methods, and measurements. Our ultimate goal is to comprehensively analyze recommender systems, encompassing recent articles and all perspectives. This will provide future researchers with a holistic understanding of the subject matter.

B. RESEARCH STUDY

We reviewed several research studies on using deep learning techniques in recommendation systems. For example, De et al. [4] proposed using feed-forward neural networks as advanced frameworks for designing collaborative filtering engines, which consolidate and improve upon previous work. Dai et al. [51] introduced a personalized recommendation algorithm for online learning resources based on an improved backpropagation neural network algorithm. Dang et al. [52] discussed session-based recommendation, a recently proposed approach that reduces dependence on user profiles while maintaining high accuracy. The paper used real-world datasets and evaluation metrics to compare the performance of various session-based recommendation algorithms, including the deep learning approach named GRU4Rec. Additionally, Anantha et al. [2] discussed how deep learning techniques are used in various domains, including recommender systems, and compared the performance of traditional recommender systems with deep learning-based recommender systems.

1) COMPARISON

Various efforts have been made to enhance recommendation quality, including developing innovative frameworks and algorithms. While certain studies focus on specific recommendation types, such as the research conducted by Anantha et al. [2], it is worth noting that this study did not consider articles published within the last five years. Thus, our study is particularly significant as it fills this gap and advances our understanding of this field.

C. SYSTEMATIC LITERATURE REVIEW (SLR)

The aim of conducting a literature review on recommendation systems based on deep learning is to provide a comprehensive analysis and synthesis of existing research to offer a complete overview of the field's current state [53]. This review aims to summarize and compare various deep learning techniques used in recommendation systems, highlight current systems' primary challenges and limitations of current systems, and suggest potential research directions for the future.

Our systematic review serves as a literature review. While other similar reviews exist, they either focus on a specific deep learning technique or review articles from beyond the last five years, with a different classification structure and selection strategy.

Starting with a systematic literature review (SLR) of specific deep learning techniques for recommender systems, this area of artificial intelligence provides personalized recommendations to users based on their behavior and preferences. Liu et al. [13] explore deep learning techniques for course recommendations in e-learning environments. Doh et al. [54] investigate deep knowledge graph-based recommender systems, and Safavi et al. [55] examine deep learning-based point-of-interest recommender systems.

In our anchor paper, Batmaz et al. [56] analyzed compiled studies within four dimensions, including deep learning models utilized in recommender systems, remedies for the challenges of recommender systems, awareness and prevalence over recommendation domains, and the purposive properties. They summarized deep learning techniques, including state-of-the-art techniques, and classified the techniques based on the purpose of data modeling. Additionally, they summarized specialized recommendation systems. Da'u et al. [57] conducted a comprehensive literature review on deep learning-based recommender systems, with a detailed review of deep learning techniques, comparing their advantages and disadvantages and evaluation metrics and datasets.

1) COMPARISON

In comparison to Batmaz et al.'s review of thesis, journal, workshop, and conference papers from 2007 to 2017 [56] and Da'u et al.'s selection of 99 studies published from 2007 to 2018 [57], our review focuses exclusively on peer-reviewed journal articles published within the last five years (2018-2022), including some articles from 2023. This timeframe allows us to analyze the most current literature and provide insights into the latest developments in the field. Our review prioritizes peer-reviewed journal articles for their high-quality research and reliability, as they undergo rigorous evaluation by experts and provide detailed analyses.

A significant benefit of our approach is broad search keywords, enabling us to cast a wide net and identify a broad range of research studies that may have been overlooked in previous reviews. By utilizing this strategy, we can provide a comprehensive and up-to-date analysis of the latest research on deep learning-based recommendation systems.

Our review offers a valuable resource for researchers and practitioners interested in understanding the latest developments in this rapidly evolving deep learning-based recommendation systems field.

The following Table 1 displays detailed information for each article, including category, publication year, journal, domain, and technique, in addition to the comparison with our article.

III. BACKGROUND

The utilization of deep learning techniques in recommendation systems is prevalent, mainly due to their ability to extract relevant features from complex data and detect intricate user behavior patterns [59]. Deep learning has exhibited superior performance across various domains, including computer vision, video processing, and natural language processing, compared to conventional machine learning methods [47], [60], [61].

A. RECOMMENDATION SYSTEM CHALLENGES

Deep learning techniques are beneficial for developing recommendation systems, but organizations may face challenges such as data sparsity, the cold start problem [62], overfitting [63], scalability [64], and ethical concerns. Data sparsity occurs due to limited data available for the recommendation system to train on, and the cold start problem arises when insufficient data is available for accurate recommendations for new users or items [65]. Overfitting can occur when the model becomes too specialized to the training data and cannot generalize to new data.

TABLE 1. Comparison with related work.

Category	Reference	Year	Journal Index	Domain	Reviewed Technique	Comparison with Our Review
Survey	[40]	2023	J1	General	Deep Reinforcement Learning	Diverse DL techniques
Survey	[41]	2023	J2	General	Deep Neural Networks	Various techniques beyond NN
Survey	[42]	2022	J3	General	Graph Neural Networks	Expands beyond GNN techniques
Survey	[49]	2022	J4	E-learning	Deep Learning	Broad E-learning spectrum
Survey	[50]	2022	J2	Point-Of-Interest	Deep Learning	Wider range beyond POI
Survey	[43]	2022	J5	General	Deep Neural Networks	Not confined to NN techniques
Survey	[44]	2020	J6	Citation	Deep Learning	Focuses on diverse domains
Survey	[45]	2020	J7	General	Autoencoder-Based	Encompasses various DL techniques
Survey	[46]	2019	J3	General	Deep Learning	Focuses on recent 5 years
Survey	[47]	2018	J8	General	Deep Learning	Focuses on recent 5 years
Survey	[48]	2021	J9	Course	Deep Learning	Explores beyond a single domain
Survey	[58]	2022	J10	Trust-Aware	Deep Learning	Not confined to one type of RS
Study	[4]	2022	J11	Service	Neural Collaborative	Broad domains and techniques
Study	[51]	2021	J12	E-Learning	Neural Network	Covers diverse domains
Study	[52]	2020	J13	Session-Based	Deep Learning	Focuses on various applications
Study	[2]	2018	J14	General	Deep Learning	Encompasses wider domains and includes recent articles
Review	[13]	2022	J15	E-learning	Deep Learning	Broad domains and techniques
Review	[54]	2022	J1	General	Deep Knowledge Graph	Not confined to embedding techniques
Review	[55]	2022	J2	Point-Of-Interest	Deep Learning	Explores beyond Point-Of-Interest
Review	[56]	2019	J15	General	Deep Learning	Covers recent articles from the last 5 years

Journal Index: J1: Knowledge-Based Systems; J2: Neurocomputing; J3: ACM Computing Surveys; J4: Applied Sciences (Switzerland); J5: IEEE Transactions on Knowledge and Data Engineering; J6: Expert Systems With Applications; J7: Frontiers of Computer Science; J8: International Transaction Journal of Engineering Management & Applied Sciences & Technologies; J9: Pacific Asia Journal of the Association for Information Systems; J10: International Journal of Embedded Systems; J11: SN Computer Science; J12: Advances in Modelling and Analysis B; J13: Artificial Intelligence Review; J14: Data; J15: Electronics (Switzerland)

As the dataset size and number of users and items increase, the computational resources required to train and deploy the recommendation system may become a bottleneck, which can limit scalability [47]. Deep learning techniques may raise ethical concerns, such as privacy violations or bias in recommendations [66].

To best utilize deep learning techniques, it is important to understand their strengths in each application field and make the best selection throughout the implementation stages. Overcoming these challenges requires expertise in deep learning techniques and a strong understanding of the domain and business requirements of the recommendation system. Organizations can develop effective recommendation systems that provide valuable insights and enhance customer engagement.

For further information on the challenges associated with recommendation systems, consult the article [67], which offers detailed reviews.

B. CLASSIFICATION OF RECOMMENDATION SYSTEM CATEGORIES

We categorize recommendation systems based on their functionalities and applications, extending beyond conventional methods to highlight the data types that work effectively with distinct deep-learning techniques, underscoring their pivotal role in recommendation systems.

Recommendation systems are a type of technology that can be used in a variety of ways, such as suggesting movies [65], [68], [69] or products to customers, recommending articles to readers, or suggesting friends on POI [17], [70] and social media [71]. These systems can differ significantly in terms of their purpose, the algorithms and techniques they use, their functionality, and how they are implemented. While researchers generally categorize recommendation systems into three traditional categories, there is a need to understand them in more detail and with greater functional accuracy to keep up with the growing popularity of these systems in e-businesses.

To understand them better, we classify recommendation systems into three categories: traditional, application, and functionality. The traditional category includes collaborative filtering, content-based filtering, and hybrid systems. The functionality category involves various tasks the recommendation system performs, such as predicting user preferences based on contextual information or explaining recommended items using existing knowledge. Finally, the application category pertains to the particular implementation of the recommendation system, such as a mobile app or a website. Understanding these categories can better understand recommendation systems and their capabilities.

These three factors give us a more comprehensive understanding of recommendation systems and their applications.

Please refer to Table 2 in our research for more information on our classification approach.

C. KEY TECHNIQUES AND APPROACHES IN RECOMMENDATION SYSTEMS

Developing effective recommendation systems can be a challenging task involving combining various techniques and carefully considering the specific requirements of the system and data involved. Foundational deep-learning techniques and key data components are essential to this complex process. Therefore, it is crucial to understand the importance of these components and how they interact to develop a clear understanding of recommendation system development.

Modern deep-learning recommendation systems strategically combine techniques that span a wide range of methodologies to achieve accuracy and personalization. These strategic approaches encompass various techniques, each contributing uniquely to the system's effectiveness and performance.

In the following sub-subsections, we logically introduce key techniques and approaches, starting with foundational techniques and gradually moving towards more specialized and advanced approaches. This provides clear connections between the subsections, illustrating how different techniques can complement or build upon each other to enhance recommendation systems.

1) EMBEDDINGS

Start with embeddings, as they are a foundational technique used in various recommendation systems. Embeddings capture the underlying representations of users and items, which often serve as inputs to other deep-learning architectures.

Recommendation systems heavily rely on embeddings, which are low-dimensional vector representations of users, items, and other features, obtained by training the model on user behavior data such as clicks, ratings, and purchases [107]. Embeddings capture the relationships between users and items, enabling the model to make more accurate recommendations. Advanced deep-learning recommendation systems may incorporate different types of embeddings, including contextual embeddings [108] that capture additional information about users or items, allowing for more personalized recommendations based on the user's current situation. Word embedding methods, commonly used in NLP, involve encoding words from a vocabulary into vectors to capture syntactic and semantic information [54]. Graph embedding methods represent graphs or network structures as low-dimensional vectors and have applications in tasks such as link prediction and community detection [54].

Various deep learning algorithms have been developed to learn low-dimensional embeddings of users, items, and other features, such as DeepFM [38], [109], [110], [111], [112], [113]. DeepFM combines factorization machines with deep neural networks to model feature interactions. Overall, embeddings and deep learning algorithms have revolutionized recommendation systems, enabling the generation of more accurate and personalized recommendations for users [54]. These techniques have shown promising results in various machine learning tasks, including recommendation systems, text classification, and image recognition [54]. Thus, embedding techniques have become a fundamental component of state-of-the-art deep-learning recommendation systems, enabling the modeling of complex and dynamic user-item interactions.

2) NEURAL NETWORKS

Move on to neural networks, which are widely employed in recommendation systems. Neural networks can include feedforward, convolutional, and recurrent networks, each serving a unique purpose in recommendation tasks.

Recommendation systems based on deep learning have transformed the field of recommendation systems by incorporating neural networks to process embeddings and provide highly personalized recommendations based on user behavior. Careful selection of the neural network architecture is crucial for developing these systems, with popular choices including multi-layer perceptrons (MLPs) [114], [115], convolutional neural networks (CNNs) [20], [70], [116], [117], [118], and recurrent neural networks (RNNs) [119], [120], [121], [122]. These deep-learning recommendation systems have demonstrated outstanding performance in various domains, such as e-commerce, entertainment, and social media.

By leveraging neural networks, recommendation systems can effectively capture complex patterns and relationships in user behavior data that were previously challenging to model [123]. MLPs, CNNs, and RNNs have emerged as the preferred neural network architectures for recommendation systems due to their ability to model various data types and interactions between users and items. Using these neural networks in deep learning recommendation systems has led to more precise and personalized recommendations, greatly enhancing the overall user experience [124].

The choice of neural network architecture depends on the data and task at hand, and a combination of different types of neural networks can be used for improved performance. Table 3 provides an overview of commonly used types of neural networks and their techniques and potential applications based on their strengths.

We will discuss enhanced neural networks in separate subsections, including deep reinforcement learning, collaborative filtering neural networks, generative models, and attention mechanisms, as their technique applications in recommendation systems differ, and we consider them distinct components of such systems.

3) GENERATIVE MODELS

Generative models, such as variational autoencoders (VAEs) [133], [134] and generative adversarial networks (GANs) [135], constitute powerful deep-learning techniques with

TABLE 2. Categories of recommendation systems.

Classification	Category	Definition	Application
Traditional	Content-Based	Uses item metadata such as descriptions, tags, and categories to make recommendations [67], [72].	Convolutional neural network for image and video recommendations; Graph-based methods for item similarity-based recommendations [57].
Traditional	Collaborative Filtering	Uses neural networks to learn from user-item interactions to make personalized recommendations [67].	Deep matrix factorization for explicit user-item interactions data [73]; Deep neural networks for implicit interactions data [74].
Traditional	Hybrid	Combines multiple data types and techniques to make recommendations, such as using user behavior and item metadata [67].	Deep neural networks for feature learning [75]; Deep reinforcement learning for adaptive recommendations [76].
Application	Web-Based	Uses web data such as user behavior on websites, search queries, and social media activity to make recommendations.	Neural net time series for time-aware web services recommendation [77]; Deep collaborative filtering for web-service recommendations [78].
Application	App-Based	Uses data from mobile apps such as user actions within the app, app usage patterns, and app reviews to make recommendations.	Deep reinforcement learning for content pushing on mobile [79]; Context-aware deep interaction learning for app recommendations [80].
Application	Cross-Domain	Makes recommendations across multiple domains, such as recommending products in one category based on user behavior in another category [81].	Transfer learning for solving the aforementioned problems [62]; Graph-based methods for similarity analysis across domains [82], [83].
Application	Session-Based	Uses data from a user's current session to make recommendations, such as items they have recently viewed or added to their cart [84].	Recurrent neural network for sequence modeling [85], [86]; Transformer-based models for attention-based recommendations [87].
Functionality	Context-Aware	Uses contextual data such as reviews, ratings, demographics, and location to make recommendations [88].	Autoencoder for text data [88], [89]; Long short-term memory for time series data [90], [91].
Functionality	Interactive	Allows users to provide feedback during the recommendation process, such as rating items or indicating preferences [92].	Deep collaborative filtering for item and feedback data [93], [94]; Natural language processing techniques for sentiment analysis and feedback analysis [95]–[97]
Functionality	Knowledge-Based	Uses explicit knowledge about items, such as product features or user preferences, to make recommendations [54], [98].	Neural networks for feature extraction and similarity analysis [99]; Knowledge graphs for explicit knowledge representation [100].
Functionality	Social	Uses social network data such as user profiles, connections, and activity to make recommendations [101], [102].	Graph-based methods for community detection and node embedding [103]–[106]; Graph neural network for interest data [16], [102], [103].

substantial applicability in recommendation systems. They offer a distinct perspective by enabling the system to generate fresh recommendations based on learned data patterns. These models are proficient in generating new recommendations or creating items akin to existing ones, augmenting the catalog, and enhancing recommendation diversity.

Variational autoencoders (VAEs) and generative adversarial networks (GANs) are examples of generative models that exhibit proficiency in generating new content by discerning patterns and structures within existing data. Generative models can be trained on user behavioral data in recommendation systems to formulate novel recommendations tailored to each user's preferences [134]. Additionally, these models can generate new items that closely match existing ones, thus expanding users' recommended options.

In recommendation systems, generative adversarial networks (GANs) excel at generating user-item interactions. The GAN loss function is designed to train a generator network (G) to produce recommendations that closely resemble authentic user-item interactions. Simultaneously, a discriminator network (D) is employed to distinguish between real and generated interactions. The primary objective of this adversarial game in GANs for recommendation can be articulated as follows:

$$\min_G \max_D \big[\mathbb{E}_{(u,i)\sim p_{\text{data}}(u,i)} (\log D(u, i)) + \mathbb{E}_{z\sim p_z(z)} (1 - \log D(G(z, i)))\big]$$

In the above equation, (u, i) represents a user-item interaction sampled from the actual data distribution, and $G(z, i)$ signifies the generation of user-item interactions based on latent variables z and i (the item). The primary goal is to make the generated interactions indistinguishable from genuine ones.

Variational autoencoders (VAEs) have found application in recommendation systems, particularly in collaborative filtering and personalized recommendations. These models map user and item interactions into a latent space, facilitating a more profound comprehension of user preferences.

The application of generative models in recommendation systems has resulted in a broader range of user recommendations, enhancing their experience and increasing engagement [136]. This approach has gained popularity in modern recommendation systems, leading to the creation of more sophisticated and efficient recommendation platforms.

TABLE 3. Neural network techniques in recommendation systems.

Neural Network Name	Technique	Application
Recurrent Neural Network (RNN)	RNNs model sequential data, such as time series or clickstream data, by maintaining a hidden state that summarizes previous inputs and captures long-term dependencies [50].	Used for recommendation systems analyzing user behavior over time, such as session-based recommendations [57].
Long Short-Term Memory (LSTM)	LSTMs address the vanishing gradient problem in RNNs by selectively updating and forgetting information with memory cells and gates [17].	Applied in tasks such as speech recognition, machine translation, and sentiment analysis [125].
Graph Neural Network (GNN)	GNNs model graph-structured data by learning representations of users and items based on their relationships in the graph [42].	Utilized for node classification, link prediction, and community detection in complex network structures [126].
Autoencoder	Autoencoders are neural networks that learn compact representations of input data by encoding it into a lower-dimensional latent space and then decoding it back to the original space [57].	Applied in dimensionality reduction, feature learning, and denoising tasks across various domains [26].
Transformers	Transformers use self-attention mechanisms to capture long-range dependencies and relationships between items in modeling user-item interactions and generating recommendations [52].	Employed for other natural language processing tasks, including language translation and text generation [52].
Radial Basis Function Network (RBFN)	RBFNs employ radial basis functions as activation functions in their hidden layers and calculate their output by computing a weighted sum of these radial basis functions [127].	Used for function approximation tasks, such as regression, interpolation, and time-series prediction [128].
Memory-Augmented Neural Network (MANN)	MANNs store and retrieve information from external memory during computation [57].	Beneficial for recommendation systems storing user preferences or context information and handling complex queries [129].
Deep Belief Network (DBN)	DBNs learn hierarchical representations of input data by stacking Restricted Boltzmann Machines to extract complex features [57].	Applied in recommendation systems needing to learn complex patterns and features from input data [57].
Multilayer Perceptron (MLP)	MLPs learn complex relationships between input and output variables using multiple layers of interconnected nodes and non-linear activation functions [44].	Commonly used in supervised learning tasks, like classification and regression [130].
Convolutional Neural Network (CNN)	CNNs analyze visual data, such as images or videos, using convolutions to extract features and classify them [57].	Frequently used in recommendation systems for processing visual information associated with items [131].
Self-Organizing Maps (SOM)	SOMs learn low-dimensional representations of input data through unsupervised learning and preserve topological relationships between input data points [72].	Utilized for anomaly detection, data exploration, and visualization [132].

4) COLLABORATIVE FILTERING

Collaborative filtering neural network (CFNN) is a key element of deep learning methods used in recommendation systems. Collaborative filtering, for example, is a popular technique that makes recommendations based on similarities between users or items [137]. It delivers personalized recommendations by studying how users behave and what they prefer [138]. This review specifically explores how neural networks and filtering techniques work together, emphasizing collaborative filtering.

Collaborative filtering involves using data about users to uncover similarities between them and the items they are interested in. This is done through embeddings, like condensed representations of important features. Neural networks then use these embeddings to create recommendations that consider the common characteristics among users. For instance, researchers like Zhang et al. [139] have combined embeddings and paragraph representations to enhance collaborative filtering.

A significant advancement in building effective collaborative recommender systems is the use of latent factor models [113]. These models are crucial in personalized recommendation setups. They capture user preferences based on past interactions, like ratings and clicks. By identifying similar users based on their preferences, collaborative filtering effectively suggests items that align with individual tastes [140]. For example, Ullah et al. [141] applied deep neural collaborative filtering to improve personalized educational service recommendations. Similarly, Yang et al. [142] refined user-generated list recommendations through gated and attentive neural collaborative filtering. In addition to the terms mentioned earlier, there are other commonly used terms in recommendation systems.

Many researchers have combined the data sparsity problem in traditional collaborative filtering algorithms with various neural networks in recommendation systems to overcome the data sparsity problem. For instance, Nassar et al. [143] proposed a novel multi-criteria collaborative filtering model based on deep learning. In contrast, Yu et al. [144] proposed a contextual-boosted deep neural collaborative filtering (CDNC) model that utilizes item introductions and user ratings to alleviate the cold-start problem and provide interpretable item recommendations.

We better understand complex user-item dynamics by integrating collaborative filtering into deep learning models. This leads to recommendations that are deeply rooted in user interactions. This approach is gaining considerable momentum, becoming a foundational aspect of recommendation systems and yielding highly accurate, tailored recommendation platforms.

5) ATTENTION MECHANISMS

Transition to attention mechanisms, which enhance understanding user preferences and item characteristics. Attention mechanisms can complement both neural networks and collaborative filtering.

Attention mechanisms have emerged as a powerful tool within deep learning recommendation systems, allowing models to focus selectively on specific input components during prediction [46]. Typically implemented with recurrent neural networks (RNNs) in recommendation systems, attention mechanisms enable models to adapt to individual user behavior and preferences, leading to more precise and personalized recommendations [145]. For example, these mechanisms weigh the relevance of various items based on user context and history, enhancing recommendation accuracy. Widely employed in natural language processing, computer vision, and recommendation systems, attention mechanisms track component importance [46].

The landscape of attention-based neural network techniques is diverse, each category offering unique advantages for improving recommendation quality. Here are some example articles we have reviewed:

- **Time-Aware Self-Attention Models:** Incorporating temporal dynamics, these models capture evolving user preferences over time. Zhang et al. introduced a "Time-Aware Self-Attention Based Neural Network Model" [146] that optimizes sequential recommendations using self-attention mechanisms.
- **Knowledge-Aware Attentional Models:** Exploiting domain knowledge, these models provide informed suggestions. Liu et al. proposed a "Knowledge-Aware Attentional Neural Network" [147], enhancing review-based movie recommendations with explanations through attention mechanisms.
- **Graph Neural Network Models:** Excelling in modeling user-item interactions, these models capture collaborative filtering dynamics. Chen et al. presented a "Multi-Head Attention Graph Neural Network" [148] for session-based recommendations, tapping into multi-dimensional interests.
- **Dual Attention Models:** Adapting to local and global patterns in user preferences, these models offer a comprehensive perspective. Heidari et al. addressed cold-start and sparsity challenges with an "Attention-Based Deep Learning Method" [149], employing attention mechanisms.
- **Dynamic Attention Models:** Tailoring to changing user behavior, these models employ dynamic attention mechanisms. Zhang et al. proposed a "Dynamic Attention-Integrated Neural Network" [150] for session-based news recommendation.

These attention-based techniques enrich recommendation systems by capturing intricate patterns and relationships, enhancing user experiences.

6) TRANSFER LEARNING

Move to transfer learning techniques. These can benefit from the foundation of previously discussed techniques and leverage knowledge from related domains.

Transfer learning is a popular technique in deep learning that has been widely adopted in various domains, including recommendation systems. This approach involves using pre-trained models or embeddings from related tasks to enhance the performance of a model on a new task [151]. In recommendation systems, transfer learning is particularly valuable as it incorporates insights from diverse domains, such as image or text classification, resulting in improved accuracy and efficiency [47]. To ensure a successful transfer, it is important to carefully select and transfer relevant user or item information from auxiliary domains to the target domain [83], [152]. By strategically incorporating transfer learning, recommendation systems can achieve superior performance, efficient training, and reduced data requirements [62], [82].

Transfer learning can bring several benefits to recommendation systems. One of them is the ability to extract features from user profiles or items using pre-trained image or text models. These extracted features can be used as input for the recommendation model. Furthermore, transfer learning allows existing models to be fine-tuned with a small dataset specific to the recommendation task, which can help them adapt and specialize. By leveraging external knowledge, recommendation systems can improve their capabilities and make better recommendations through knowledge transfer.

7) SIDE INFORMATION

After addressing the core techniques, consider incorporating side information like user demographics and item attributes. This can provide a more comprehensive understanding of how deep learning techniques handle diverse data types.

Deep learning recommendation systems are empowered to incorporate diverse forms of side information, including textual descriptions, images, and other item-associated features. This integration enhances prediction accuracy and facilitates the delivery of personalized recommendations [153], [154], [155]. The central challenge within recommendation systems lies in learning effective user and item representations from interactions and side information [42]. This approach has gained widespread adoption in state-of-the-art recommendation systems, significantly contributing to the evolution of advanced platforms capable of harnessing multiple information sources for tailored and relevant recommendations [155], [156].

Side information is a fertile ground for deep learning models to glean insights. Incorporating such data has demonstrated tangible enhancements in recommendation system performance [155], [156]. Hybrid deep neural networks, for instance, embed user attributes like age, location, occupation, zip code, and user ratings as input, thereby enhancing recommendation precision [157]. Deep learning principles extend beyond recommendation domains, extracting latent features across diverse scientific disciplines such as image, video, and signal processing [158].

Here are some examples of how side information can enhance recommendations:

- **Enriching Recommendations with Context:** Side information, encompassing user attributes and item features, amplifies recommendations through nuanced preference comprehension [156], [159].
- **Addressing Cold Start Challenges:** Integrating side information alleviates cold start issues for new users/items [160], [161].
- **Topic Modeling and Contextual Data:** Techniques like topic modeling distill themes from side information, bolstering recommendations [162].
- **Hybrid Approaches for Improved Results:** Hybrid methodologies fusing user-item ratings and side information surmount sparsity challenges [163].
- **Taxonomy-Aware Recommendations:** Models incorporating taxonomic side information augment accuracy [164].
- **Sentiment and User Interactions:** User sentiments enhance recommender systems [96].
- **Personalization through Deep Learning:** Deep learning models leverage side information for personalized recommendations [75], [159].
- **Deep Matrix Factorization for Versatile:** Deep matrix factorization integrates varied side information, enhancing collaborative filtering [165].

8) REINFORCEMENT LEARNING

Conclude with reinforcement learning, which optimizes recommendations based on user interactions and rewards. This demonstrates its ability to improve recommendations.

Deep reinforcement learning (DRL) is a potent deep learning technique harnessed by state-of-the-art recommendation systems to optimize user recommendations. RL enables the system to enhance the relevance and engagement of recommendations over time by learning to optimize a reward function based on user interactions with the recommendations [40].

In recommendation systems, RL entails training an agent (the recommendation algorithm) to make decisions in an environment (user behavior) to maximize a cumulative reward. For instance, a reward function can be formulated based on user interactions like click-through rates, culminating in a personalized and effective recommendation strategy [40], [166].

However, it's important to note that while RL offers promising benefits, it comes with challenges. Adopting RL can demand substantial data and computational resources, potentially limiting its applicability in certain scenarios [167].

This approach of RL has been applied extensively within the domain of recommendation systems. Some notable examples include:

- **Challenges in User Behavior Modeling [79]:** Liu et al. propose an RL framework that decomposes the complexities of modeling user behavior into two distinct RL tasks.
- **Optimizing Recommendation and Caching Policies [124]:** Guo et al. leverage deep reinforcement learning to optimize recommendation and caching policies.
- **Hierarchical Dialogue Management [11]:** Basile et al. introduce a hierarchical RL framework for dialogue management within conversational recommender systems.
- **Federated Learning for Daily Schedule Recommendations [168]:** Huang et al. address the challenge of daily schedule recommendations using deep RL within a federated learning framework.
- **E-commerce Information Retrieval [169]:** The application of deep reinforcement learning extends beyond recommendation systems to e-commerce information retrieval.

Summary: Deep learning techniques provide a powerful set of tools for recommendation systems, and many different approaches can be used depending on the data and the application. State-of-the-art deep learning recommendation systems use techniques such as embeddings, neural networks, generative models, collaborative filtering, attention mechanisms, transfer learning, side information, and reinforcement learning to provide users with highly accurate and personalized recommendations. The specific techniques used depend on the data and the application. Still, the core idea is to use deep learning to capture the complex relationships between users, items, and other features and to provide highly relevant and engaging recommendations. For instance, graph neural networks are just one example of a technique that can provide highly accurate and personalized recommendations in session-based scenarios. Overall, these techniques have greatly improved the quality of recommendations and enhanced the user experience.

IV. RESEARCH METHOD

In this section, we provide an overview of our detailed and structured analytical review process for assessing advanced deep-learning-based recommendation systems. Using specific search terms, our findings are categorized based on various aspects, such as techniques, domains, and types of recommendation systems.

Our goal is to systematically review the current state of deep-learning-based recommendation systems and highlight key findings in each category. To achieve this, we follow a systematic literature review (SLR) process similar to the one used in the article by Alabadla et al. [170]. We adhere to the guidelines from Kitchenham et al. [171], [172] and follow the best practices recommended in Wang et al.'s study [39] to ensure the rigor and validity of our review.

We include research questions and sub-questions, search strategy, literature search, screening process, quality assessment, data extraction, and data synthesis, all of which we describe in detail. Our systematic review is conducted using specific search terms, and we assess the quality of the studies included in the review using appropriate quality assessment tools.

Our review process helps identify research gaps and provides a better understanding of the key concepts and variables associated with deep-learning-based recommendation systems, contributing to future research in this area.

To better understand our research flow, please refer to Figure 1 before delving into the details of our study.

A. RESEARCH QUESTION

Our objective is to investigate various aspects of deep learning-based recommendation systems, such as their fundamental concepts and variables. Moreover, we are dedicated to equipping future researchers with useful information on search terms related to deep learning techniques and application domains. To achieve this, we formulated the following research questions and relevant sub-questions, adopting a similar approach to that described in Gema et al.'s study [173].

- **RQ1:** What deep learning techniques are commonly used in recommendation systems, and how do different evaluation metrics compare?
  1) What are the state-of-the-art deep learning techniques for recommendation systems, and what are their strengths?
  2) What evaluation metrics are commonly used to assess deep learning-based recommendation systems?
  3) What popular datasets are used for testing deep learning-based recommendation systems?
- **RQ2:** What are the various applications of deep learning techniques in recommendation systems, and how can we categorize them based on their domains?
  1) How can deep learning recommendation systems be categorized based on domains?
  2) How do domain-specific needs and requirements impact the choice of deep learning techniques used in recommendation systems?
  3) What are the commonly used datasets for testing deep learning-based recommendation systems across different domains?
- **RQ3:** How can deep learning techniques in recommendation systems be effectively classified to facilitate quick searches for relevant keywords?
  1) What search terms are commonly employed in recommendation system research?
  2) How have previous studies classified deep learning techniques in recommendation systems and informed research directions?
  3) How do researchers categorize deep learning techniques in recommendation systems across different domains?

TABLE 4. Search keywords for literature review.

KCO1 - RS: "recommendation system" OR "recommender system" OR "recommendation"
KCO2 - DL: deep* OR neural* OR "autoencoder" OR "multilayer perceptron" OR "radial basis" OR "restricted Boltzmann" OR "memory-augmented" OR "generative adversarial" OR "self-organizing" OR "long term" OR CNN OR RNN OR LSTM OR GAN OR MLP OR RBFN OR SOM OR DBN OR RBM

We use these research questions and sub-questions to guide our literature review and data collection process. The search terms relevant to our study are identified based on these questions. They retrieve relevant literature from various sources, such as online databases and search engines.

This systematic review poses important research questions on deep learning-based recommendation systems. RQ1 identifies popular deep learning techniques, such as autoencoder, CNN, RNN, and MLP, along with their evaluation metrics, such as accuracy, precision, and recall. It also highlights the datasets used in previous research, such as MovieLens, Amazon, and Yelp, providing researchers with insights into potential gaps and opportunities for future research. RQ2 categorizes the different applications of deep learning techniques, providing valuable guidance on how to apply these techniques in various domains, such as e-commerce, social networks, and e-learning. It also helps researchers choose the appropriate datasets for their experiments and provides insights into the limitations of these datasets, allowing for more efficient experimental designs. RQ3 identifies the most effective way to classify deep learning techniques and recommendation terms, aiding researchers in quickly searching for relevant keywords and discovering new research opportunities.

B. SEARCH STRATEGY

To conduct a comprehensive literature review, we develop a search strategy to identify relevant keywords and synonyms for two key concept areas: recommendation systems (KCO1) and deep learning techniques (KCO2). We established inclusion and exclusion criteria aligned with our research objectives to ensure a thorough search considering various aspects of deep learning algorithms, techniques, and recommendation system terms.

The search keywords we used to refine our search are shown in Table 4.

To ensure a targeted selection of articles that are directly relevant to our study, we adopted a more restrictive search strategy by focusing on searching for our keywords only in

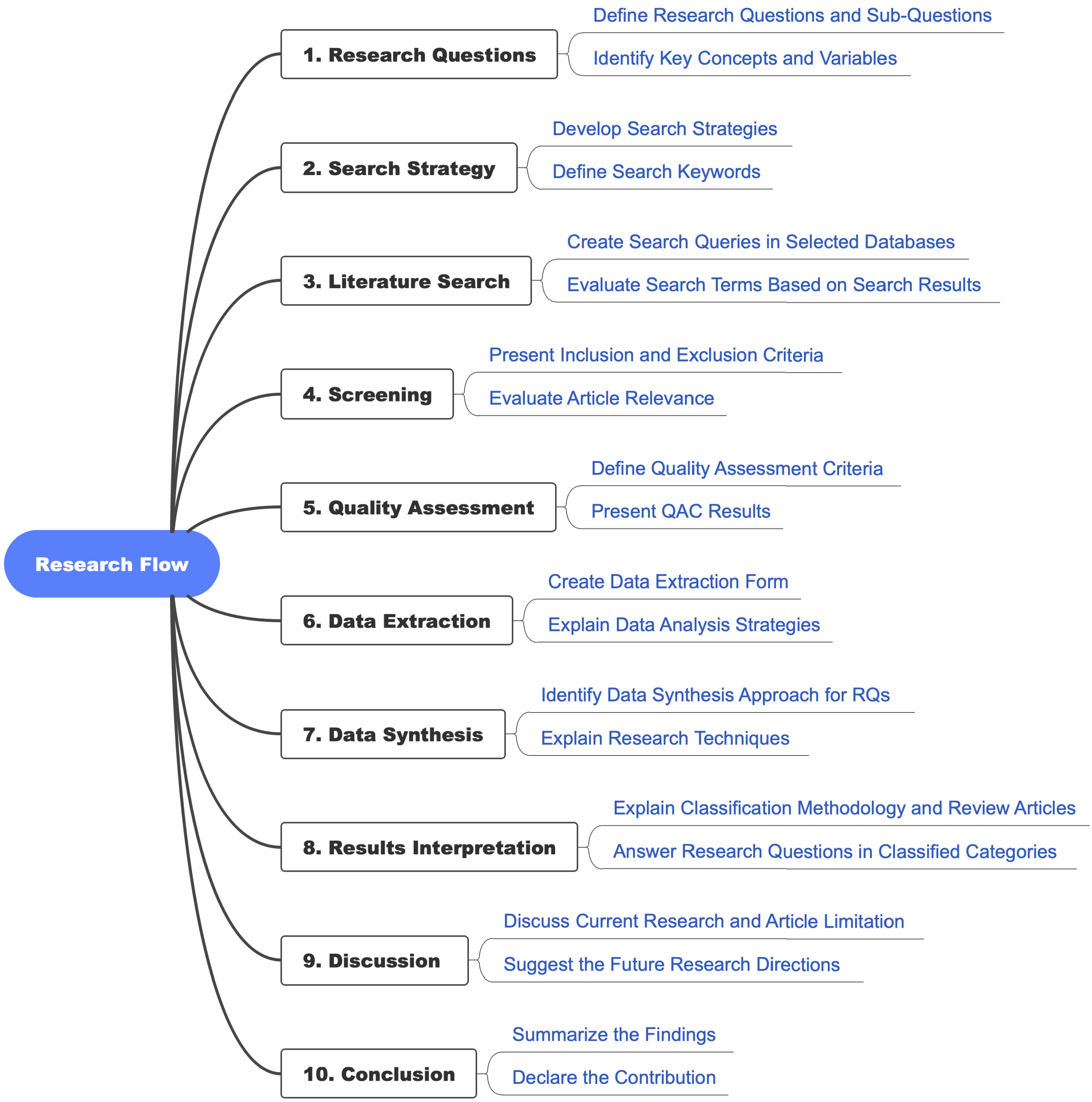

FIGURE 1. Research flow overview (Steps 1-10).

the article titles, depending on the availability of the database. This approach enables us to obtain more specific and targeted information that is narrowed down to what we are looking for despite potential variations in abstract structure across different journals.

In our article selection process, we included popular and advanced deep learning techniques as search terms and articles that mention the terms "deep" or "neural" in the title for the technique keywords target. On the recommendation system side, we deliberately included more general terms rather than limiting ourselves to "recommendation system" or "recommender system." This approach allows us to capture a wider range of research that utilizes deep learning techniques for recommendations and encompasses various frameworks or systems designed for recommendation purposes. By adopting this strategy, we aim to explore potential opportunities for applying deep learning techniques in different domain applications, making our literature review more comprehensive and relevant. Overall, our search strategy is designed to efficiently and effectively identify relevant articles for our review, ensuring we cover a wide range of research in recommendation systems that utilize deep learning techniques.

C. LITERATURE SEARCH

This subsection covers our literature search process, including the inclusion and exclusion criteria for studies and the reasons for these criteria. We also describe the search queries used in each database. We aim to conduct a thorough search to retrieve relevant studies from various databases. To achieve this, we utilized a combination of keywords and search operators that allowed us to consider various study designs and research questions.

To conduct our search, we utilized controlled vocabulary and extended search terms across six major databases: Scopus, Web of Science, IEEE Xplore, EBSCOHost, SpringerLink, and ScienceDirect. As mentioned in the last subsection, our search string included terms related to deep learning and recommendation systems. We applied filters to exclude irrelevant studies such as conference papers, dissertations, textbooks, unpublished working papers, and non-English papers. We only considered peer-reviewed research articles between 2018 and February 2023 that focused on recommendation systems using deep learning techniques. Our search covered 67 publishers and 239 journals.

To simplify the search process, we used a query that extracted all the necessary articles from one query to avoid overlapping. We implemented this approach for databases such as IEEE, Web of Science, and Scopus, as detailed in Table 5. However, our queries have limitations and may not cover all the advanced naming techniques in deep learning. Nonetheless, we strive to follow best practices for our study.

We applied similar queries for searching for other databases such as ScienceDirect, SpringerLink, and EBSCOhost. However, these databases have limitations regarding search query functions, so we had to break the queries into multiple parts to best match with other databases. Additionally, we manually applied filters after extracting the list of articles to overcome these limitations.

Regarding technique terms, we include all ‘‘neural’’ and ‘‘deep’’ related techniques. Despite the various naming conventions researchers use, their main techniques often tie back to deep learning. As mentioned in the last section, we included recommendation terms to cover a wider domain for our domain classification and summary analysis. Overall, we strived to employ best practices in our search process while acknowledging the limitations of different databases and naming conventions.

We applied a more aggressive filter across all the outputs from our literature search to ensure we selected highly relevant articles for our study. Firstly, we re-filtered the search terms for ‘‘RS & DL’’ across all the databases, focusing on article titles and author keywords. We also applied filters to exclude articles that did not have a DOI number and only considered articles that were related to our categories and written in English.

TABLE 5. Search queries for academic databases.

IEEE: (("Document Title": "recommendation system") OR ("Document Title": "recommender system") OR ("Document Title": "recommendation")) AND (("Document Title": deep) OR ("Document Title": neural) OR ("Document Title": "autoencoder") OR ("Document Title": "multilayer perceptron") OR ("Document Title": "radial basis") OR ("Document Title": "restricted boltzmann") OR ("Document Title": "memory-augmented") OR ("Document Title": "self-organizing") OR ("Document Title": "generative adversarial") OR ("Document Title": CNN) OR ("Document Title": RNN) OR ("Document Title": "long short") OR ("Document Title": LSTM) OR ("Document Title": GAN) OR ("Document Title": MLP) OR ("Document Title": RBFN) OR ("Document Title": SOM) OR ("Document Title": DBN) OR ("Document Title": RBM))
Web of Science: TI = (("recommendation system" OR "recommender system" OR “recommendation”) AND (deep* OR neural* OR "autoencoder" OR "multilayer perceptron" OR "radial basis" OR "restricted Boltzmann" OR "memory-augmented" OR "generative adversarial" OR "self-organizing" OR "long term" OR CNN OR RNN OR LSTM OR GAN OR MLP OR RBFN OR SOM OR DBN OR RBM))
Scopus: (TITLE ("recommendation system" OR "recommender system" OR recommendation) AND TITLE (deep OR neural OR "autoencoder" OR "multilayer perceptron" OR "radial basis" OR "restricted Boltzmann" OR "memory-augmented" OR "generative adversarial" OR "self-organizing" OR "long-short" OR CNN OR RNN OR LSTM OR GAN OR MLP OR RBFN OR SOM OR DBN OR RBM))

We cleaned and filtered the data using R code, resulting in a final list of DOIs/articles from different databases, as shown in Figure 2.

D. SCREENING

The screening aims to identify relevant articles on recommendation systems that utilize deep learning techniques. We utilize a two-stage screening process that involves multiple criteria, including the title, author keywords, index keywords, abstract, and full-text review.

Initially, we started with 2171 articles that we obtained from various databases. To eliminate potential duplicates, we removed articles that appeared in multiple databases and articles with the same title and DOI. After this initial step, we were left with unique articles.

To narrow the set of unique articles, we compiled a list of excluded terms irrelevant to our research focus. These excluded terms covered agriculture, fashion, highway, marine, pharmacology, radiology, and transportation. We also excluded cryptocurrency, fund, and legal terms as they were not directly related to our research on recommendation systems using deep learning techniques. Additionally, we excluded terms related to specific medical conditions and equipment or tools irrelevant to our research focus.

With this list of excluded terms, we screened the remaining articles based on their titles, authors, and index keywords. This initial screening process helped us identify potentially relevant articles.

However, to ensure that only relevant articles were included, we conducted a more in-depth analysis of the remaining articles in the second stage of our screening process. We excluded articles not aligning with our research focus on recommendation systems using deep learning techniques. Some articles required a full-text review to determine their relevance. Independent reviewers conducted this stage of the screening process to minimize bias.

After implementing the two-stage screening process, we had a collection of articles that met the selection requirements for our research. Our research focused on fields of study with practical applications in different industries, such as engineering, technology, information systems, applied mathematics, business & management, and information science. Our selection criteria allowed us to limit our analysis to areas more applicable to real-world challenges, enabling us to explore new perspectives and potential solutions to problems.

Summary: The screening process ensured that only relevant articles were included in our study. The two-stage process using text mining models and independent reviewers helped us to minimize bias and focus on our research objectives.

E. QUALITY ASSESSMENT

We conduct a quality assessment using text-mining techniques and manual review terms to analyze recent deep learning-based recommendation systems thoroughly. We select terms to identify relevant factors, such as recommendation terms, deep learning techniques, and application domains.

Our quality assessment framework was designed to include easily measurable and well-defined factors by combining traditional quality assessment questions related to article design (as outlined by Kitchenham et al. [172]) with QACs tailored to the article classifications. This approach allowed us to be more flexible in our paper selection and cover many articles across various categories, making the quality assessment more practical and efficient.

We categorized the articles into two groups: domain-specific and non-domain-specific. Our classification strategies were developed based on the term scores, which served as indicators of highly relevant factors (Detailed explanations of the terms can be found in the result section). Afterward, we subjected both recommendation systems to quality assessment criteria (QACs). These QACs included:

- **QAC1:** Involvement of deep learning techniques - This criterion evaluated whether the articles utilized deep learning-based techniques or algorithms.
- **QAC2:** Application in a specific domain - This criterion assessed the article's application in a specific domain or application.
- **QAC3:** Use of alternative recommendation terms - This criterion evaluated whether the articles used recommendation terms other than "recommender system/engine" or "recommendation system/engine."

TABLE 6. Quality assessment results for total articles.

Criteria	Score Formula	Total Article
QAC 1	0:NO; 0.5: PARTLY; 1: YES	759/799
QAC 2	0:NO; 1: YES	416/799
QAC 3	0:NO; 0.5: PARTLY; 1: YES	501/799

The quality assessment results in Table 6 are based on the term mapping process. QAC1 was assessed using a two-layer scoring strategy. If the article title or keywords mentioned specific technical terms such as "variational autoencoder," "convolutional neural network," or "matrix factorization," it received a score of 1. If only general terms like "deep learning" were mentioned, it scored 0.5. Otherwise, it received a score of 0. QAC2 only had two possible scores: 1 if the article mentioned domains in our categories in the title or keywords (see the Results section for a detailed list) and 0 if it did not mention any specific domains. QAC3 scored articles based on whether they mentioned "recommender system/engine," "recommendation system/engine," or "rs" terms, with a score of 1. Articles that mentioned terms related to recommendation systems but not the exact terms mentioned above received a score of 0.5. In contrast, those not mentioning relevant terms received a score of 0.

Our QACs were applied to evaluate the quality of the articles and identify the strengths and weaknesses of current research in deep-learning recommendation systems. We determined the percentage of articles falling into each category using these criteria. Please note that we only removed a few articles at this stage. However, this quality assessment process gave us a general direction for selecting primary studies and creating structured guidelines for measuring the selected articles based on our research objectives. We aimed to summarize the current state of research in deep-learning recommendation systems, and this process allowed us to do so without eliminating studies from the outset.

F. DATA EXTRACTION

This subsection describes our methodology for extracting data from our selected studies using a standardized data extraction form [172]. We created a standardized data extraction form to gather crucial information about each study, such as the specific deep learning techniques, the data sets utilized, and the domain applied to the recommendation systems. We had two independent reviewers complete the form to ensure accuracy and consistency. Whenever there were any discrepancies, we resolved them through discussion and consensus.

We analyzed the studies at an aggregated level to gain insights into the advanced deep-learning techniques employed in recent years and to provide a detailed overview of domain-specific applications. Our data extraction form for domain-focused articles included criteria such as domain clarity and relevance, technique robustness and validity, and

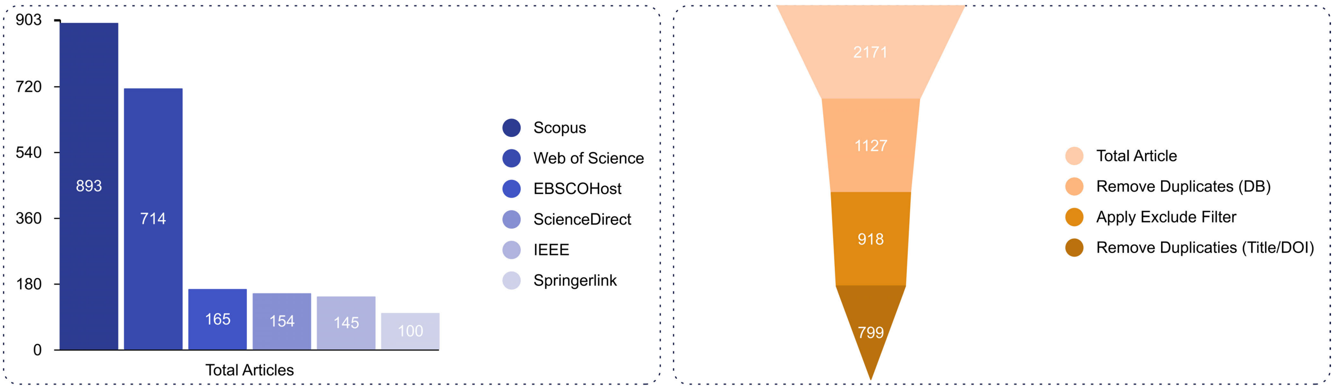

FIGURE 2. **Extracted articles by database & article extraction funnel.**

dataset diversity. We assessed the clarity of the article's presentation on the deep learning-based recommendation system in a specific domain, the validity and reliability of the techniques used, and the adequacy of the dataset used to support the claims made in the article.

We examined technique-focused articles, which are partly from non-domain-specific (semi-primary) articles. These articles focused on enhancing specific aspects of deep learning techniques or recommendation systems, providing valuable insights into our research inquiries. As our primary research sources, these articles were crucial in addressing most of our research questions. To extract relevant information, our data extraction form included specific criteria, such as the employed techniques, dataset preference, and performance metrics. This assessment focuses on evaluating recommendation systems' replication, effectiveness, and popularity metrics using deep learning techniques. We also scrutinized the details of the techniques employed and the appropriateness of the chosen datasets.

Using our data extraction form, we effectively collected the relevant information needed to conduct a detailed analysis of the main features and results of studies related to deep learning-based recommendations. The extracted data can be found in Table 7.

G. DATA SYNTHESIS

We utilized quantitative and qualitative methods to synthesize the extracted data from the included studies to answer our research questions. For **RQ1-1** and **RQ2-1**, we used a quantitative meta-summary [39] approach to identify the frequency of each discovery and construct a frequency matrix for deep learning-based techniques. By analyzing the higher frequency of recommendation system domains, we aimed to identify application patterns for different techniques and understand the usage of these techniques in recommendation systems.

To address **RQ1-2,3** and **RQ2-2,3**, we employed a qualitative narrative synthesis method to summarize the defining characteristics of each study's results in a narrative to identify consistency across studies [174]. We extracted information related to the dataset and metrics from each study. We mapped the information back by domain and techniques to understand the trends in the field's different types of dataset usage.

For **RQ3**, we used descriptive analysis techniques to aggregate and present the data quantitatively [170]. We described the current status of classification strategies and the strengths and limitations of recommendation systems. To ensure the reliability of our findings, we conducted subgroup analyses and developed a classification strategy that future researchers could use for their search strategies. This comprehensive approach ensures that our findings are clear, robust, relevant to the intended audience, and can guide future research.

V. METHODOLOGICAL APPROACH

After conducting quantitative and qualitative analyses on data gathered from various studies, we addressed our research questions and sub-questions. We also presented our detailed classification strategy, which aided in summarizing the insights obtained through our research methodology. Additionally, we outlined our data collection, analysis, classification methodology, and the significant findings obtained through these methods.

A. DATA COLLECTION AND ANALYSIS

We initiated our study by searching databases using specific keywords related to deep learning-based recommendation systems. From this search, a total of 799 papers were identified. These papers were categorized into domain-specific studies (416) and non-domain-specific studies (362). Within the non-domain-specific studies, also considered semi-primary, 139 primary studies were identified based on specific search terms. The detailed list of these articles can be found in [175].

These papers were published across 239 journals from 67 publishers, covering various science, engineering, and business fields. These fields included computer science (with a focus on artificial intelligence, information systems, software engineering, hardware & architecture, and theory

TABLE 7. Data extraction form.

Category	Data Extraction Criteria	Data Extraction Question	Research Question
Technique-Focused	Detail of Techniques	Is the article detailed enough to comprehend the technique of the recommendation system based on deep learning?	RQ 1-1
Technique-Focused	Metric Preference	What are the most commonly used evaluation metrics in the field of recommendation systems?	RQ 1-2
Technique-Focused	Dataset Preference	What types of datasets, in terms of data source, data size, and data format, are typically used for testing recommendation system techniques?	RQ 1-3
Domain-Focused	Technique Robustness	How reliable and supportive are the techniques used for the research question?	RQ 2-1
Domain-Focused	Clarity and Relevance	Does the article clearly explain the use of deep learning-based recommendation systems within a particular domain?	RQ 2-2
Domain-Focused	Diversity in Dataset	What types of datasets have been used in various domains of recommendation systems?	RQ 2-3

& methods), electrical and electronic engineering, materials science, applied physics, telecommunications, mathematics, multidisciplinary biology, neurosciences, operations research & management science, instruments & instrumentation, business, and multidisciplinary sciences. Some of these categories also involved automation & control systems, cybernetics, and library science.

1) ARTICLE SELECTION AND REVIEW

During the quality assessment process, two review stages were conducted to select primary articles, which formed the basis of the quality assessment score. For non-domain-specific (semi-primary) articles, an additional scoring system was established based on specific techniques and recommendation system terms to ensure comprehensive coverage. To be considered a primary study, articles had to score 2.5 or higher, mention the specific techniques, discuss deep learning, and use exact naming for recommendation systems.

2) PUBLICATION TRENDS AND DISTRIBUTION

Our investigation involved analyzing publication trends across publishers and journals over the past five years until February 2023. The aim was to identify the leading contributors to research in deep learning-based recommendation systems. As of February, 53 articles related to deep learning-based recommendation systems have been published this year, although our data for 2023 remains incomplete.

The COVID-19 pandemic has accelerated the growth of digital applications across various domains, significantly utilizing recommendation systems [64], [176]. Coping with the increasing complexity and diversity of data within these systems has necessitated the adoption of deep learning techniques. Consequently, there has been a surge in articles related to deep learning-based recommendation systems across major journals.

Figure 3 visually represents the distribution of articles by year and journal, providing insights into the evolution of publication trends. Elsevier emerged as the leading contributor among the publishers, with 181 articles in our research, closely followed by IEEE. Regarding journal rankings, IEEE Access stands out with the highest number of articles in the field, totaling 68, followed by Expert Systems With Applications.

Although 2022 witnessed the highest number of publications across all journals, specific journals experienced peaks in 2020. IEEE Access, Neurocomputing, and Knowledge-Based Systems had significant numbers of related articles during that year. For a comprehensive list of included venues, please refer to [175], which is publicly accessible.

B. CLASSIFICATION METHODOLOGY

This subsection describes our approach to classifying articles based on techniques and domains. We grouped relevant keywords into higher-level technique categories to categorize articles according to technique terms. These categories aligned with the implementation of recommendation systems and components outlined in the background section. Domain information was classified based on industry and data type, facilitating future research utilization.

We focused on primary studies for the classification analysis while considering domain-specific and semi-primary articles for specific research questions. This approach allowed us to provide a thorough overview of the field by analyzing classification summarization and insight sharing.

1) TECHNIQUE CLASSIFICATION AND COMPARATIVE ANALYSIS

In our approach to technique classification, we aim to comprehensively understand the various techniques used in deep learning-based recommendation systems. Instead of traditional systematic literature reviews (SLRs) and classification studies, we use search keyword analysis to categorize 140 different technique terms into 27 categories. This unique strategy helps us recognize terminology across various articles and disambiguate interchangeable terms.

For example, in the realm of graph neural network techniques, terms like "knowledge graph," "graph embedding,"

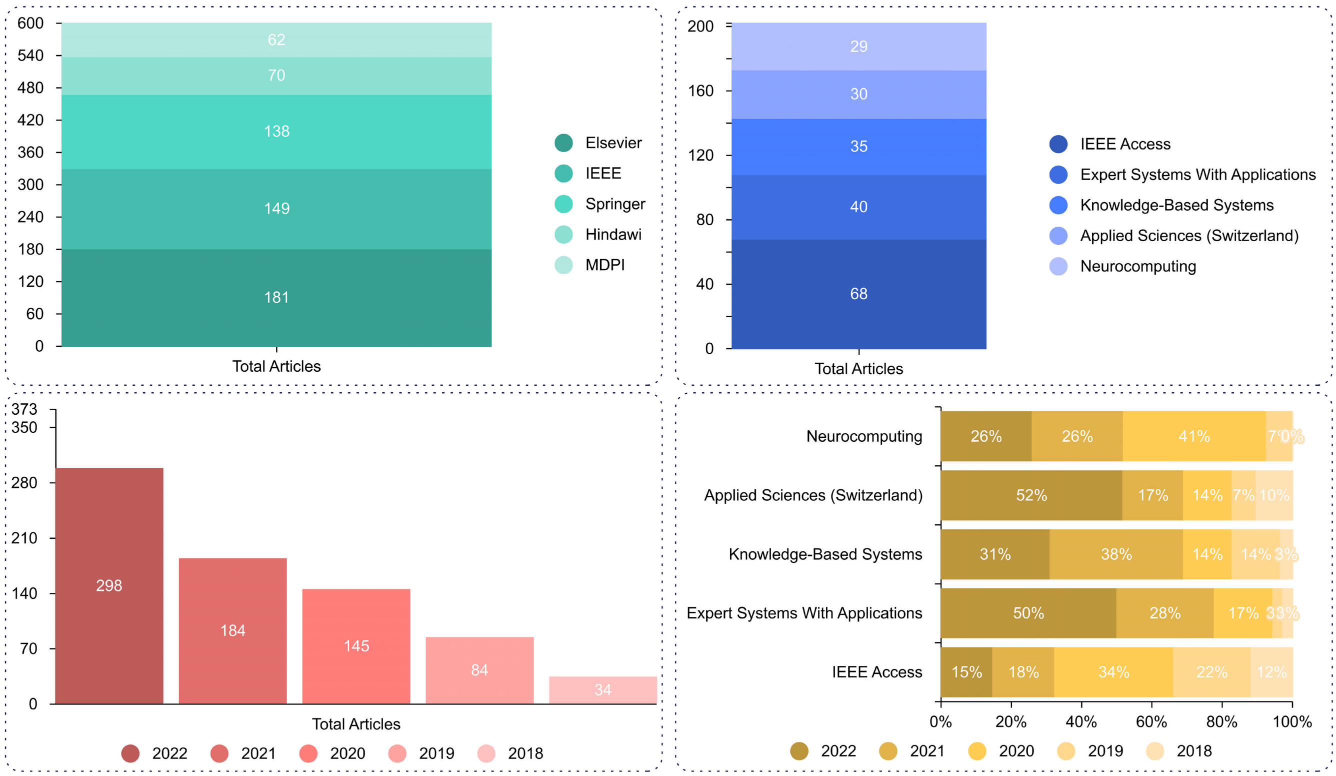

FIGURE 3. Publication trends and article distribution.

"graph attention," "graph convolutional networks," "bipartite graph," and "neural graph" may seem synonymous. However, our categorization is grounded in the different facets of recommendation systems - algorithm, functionality, application, and data model - which helps to clarify these terms.

As a result, we have created a taxonomy of higher-level technique categories that align with the implementation of recommendation systems and relate seamlessly to the component and recommendation system categories discussed in the background section.

Moreover, compared with related works, our approach notably bridges the gap between techniques and recommendation system components, offering a panoramic view of their symbiotic relationship. While conventional studies may classify techniques based on broad domains or generalized methods, our methodology intricately binds techniques to their practical application in recommendation systems. This provides a more profound comprehension of their contexts, applications, and capabilities.

2) DOMAIN CLASSIFICATION AND COMPARATIVE ANALYSIS

Our approach to domain classification involves extracting and categorizing domain-specific information using rigorous strategies. We extract relevant terms from various sources, such as article titles, authors, and index keywords, to classify 58 domains into eight categories based on industries and data types. This categorization can be a valuable resource for future researchers.

In addition, we have identified nine variant terms for recommendation systems, demonstrating our contextual understanding of each article. Our approach is more comprehensive than previous methodologies, as we holistically integrate domain-specific and variant-specific terms. This contrasts existing works that may categorize domains through limited criteria or overlook a myriad of recommendation system variants.

Our exhaustive classification endeavor, intertwined with meticulous quality assessment, ensures the inclusivity and representativeness of our primary studies. This enables us to tackle specific research questions with unparalleled depth and accuracy. By highlighting the comparative aspects, we also emphasize the distinctive features and merits of our classification strategies, elucidating their uniqueness and substantial value in comprehending deep learning-based recommendation systems.

Our holistic approach significantly contributes to systematic quality assessment, helping us select our primary studies. It assures the accuracy and representativeness of our research, making it an essential contribution to the field.

C. INTEGRATION OF METHODOLOGY AND RESULTS

We have summarized domain-specific articles that focus specifically on techniques for RQ2, which is our secondary research question. However, for our primary research question, RQ1, we conducted a more comprehensive examination of the primary studies. We paid particular attention to the term review, dataset, and metrics. For dataset-related questions about RQ1-3 and RQ2-3, we reviewed studies from domain-specific and semi-primary articles, but we only performed a detailed analysis of the primary studies. In addressing RQ3, we considered all the studies about classification summarization and insight sharing, covering both domain and techniques, to provide a thorough overview of the field.

To facilitate a thorough understanding of our research strategy, please refer to Figure 4 for our analytical diagram. This diagram outlines our overall research approach, encompassing two primary objectives: conducting a systematic literature review (SLR) and performing a classification analysis. Examining the diagram enables us to revisit our research strategy and understand how these objectives align with our research goals.

VI. RESULTS INTERPRETATION AND DISCUSSION

In this section, we have answered the research questions that were previously formulated to help us analyze the latest research on recommendation systems based on deep learning. Our focus was on the state-of-the-art deep learning techniques identified from the term summary, along with their corresponding performance metrics and the datasets used in the studies. We also explored the different domains where deep learning techniques have been applied in recommendation systems and categorized them accordingly. Additionally, we examined the datasets that researchers used to evaluate these techniques across various recommendation domains. Finally, we investigated the most effective approach for classifying deep learning techniques and analyzed the strengths and limitations of each technique based on deep learning.

A. TERM CLASSIFICATION AND ANALYSIS

Our goal is to assist researchers in comprehending the distinct deep-learning techniques employed in various recommendation system publications and identifying the particular purpose of each term.

1) COMPARATIVE ANALYSIS OF PRIOR CLASSIFICATION APPROACHES

In addressing Research Question 3 (RQ3), which focuses on refining search terms and keywords, we review how various articles have categorized techniques. This groundwork lays the foundation for tackling the sub-questions within RQ3. We then dive into the specifics of our term classification approach, explaining why it stands out and how it can benefit future research endeavors.

a: TECHNIQUE TAXONOMY IN PRIOR RESEARCH

Researchers' categorization of deep learning techniques plays a crucial role in shaping research directions. It is imperative to thoroughly investigate the various methods utilized for this categorization and their effects on the field.

RQ3-2: *How have previous studies classified deep learning techniques in recommendation systems and informed research directions?*

Numerous articles have explored deep learning techniques within recommendation systems, categorizing them based on specific algorithms or applications. For instance, Zhang et al. [46] presented a classification encompassing multilayer perceptron (MLP), deep structured semantic model (DSSM), autoencoder-based collaborative filtering, convolutional neural networks (CNNs), graph convolutional networks (GCNs), recurrent neural networks (RNNs), restricted Boltzmann machine (RBM), neural attention mechanisms, deep reinforcement learning (DRL), and deep hybrid models. However, this classification primarily centered around neural networks, overlooking other pertinent components associated with deep learning techniques in recommendation systems.

Another survey by Mu et al. [47] categorized deep learning techniques into autoencoders, restricted Boltzmann machines, recurrent neural networks, convolutional neural networks, and deep belief networks. The survey also outlined hybrid collaborative filtering techniques, including recurrent neural network-based, restricted Boltzmann machine-based, autoencoder-based, and generative adversarial network-based collaborative filtering methods. It delved into deep learning applications in content-based, context-aware, social network-based recommender systems and deep learning-based hybrid recommender systems.

While there are well-established deep learning-based recommendation techniques, it's important to note that new categories of these techniques have emerged. These emerging categories are gaining attention and require consideration in addition to the established techniques. It's important to keep up-to-date with the latest advancements in recommendation systems to ensure that the most effective techniques are utilized.

b: DIVERSITY IN RECOMMENDATION SYSTEM DOMAINS

The realm of recommendation systems extends across diverse domains, including e-commerce, entertainment, education, and social media. Nevertheless, consolidating this diversity within a coherent classification framework presents a significant challenge. Accordingly, we tackle a crucial sub-question of our research question (RQ3):

RQ3-3: *How do researchers categorize deep learning techniques in recommendation systems across different domains?*

Numerous studies on recommendation systems categorize domains by assessing available articles and determining their applicability to specific domains. The domains are often labeled using standardized terms from prior studies or authors' definitions. While some studies have identified prevalent application domains like sequential information, text, images, audio, video, networks, check-ins, points of interest (POI), hashtags, news, review text, quotes, visuals,

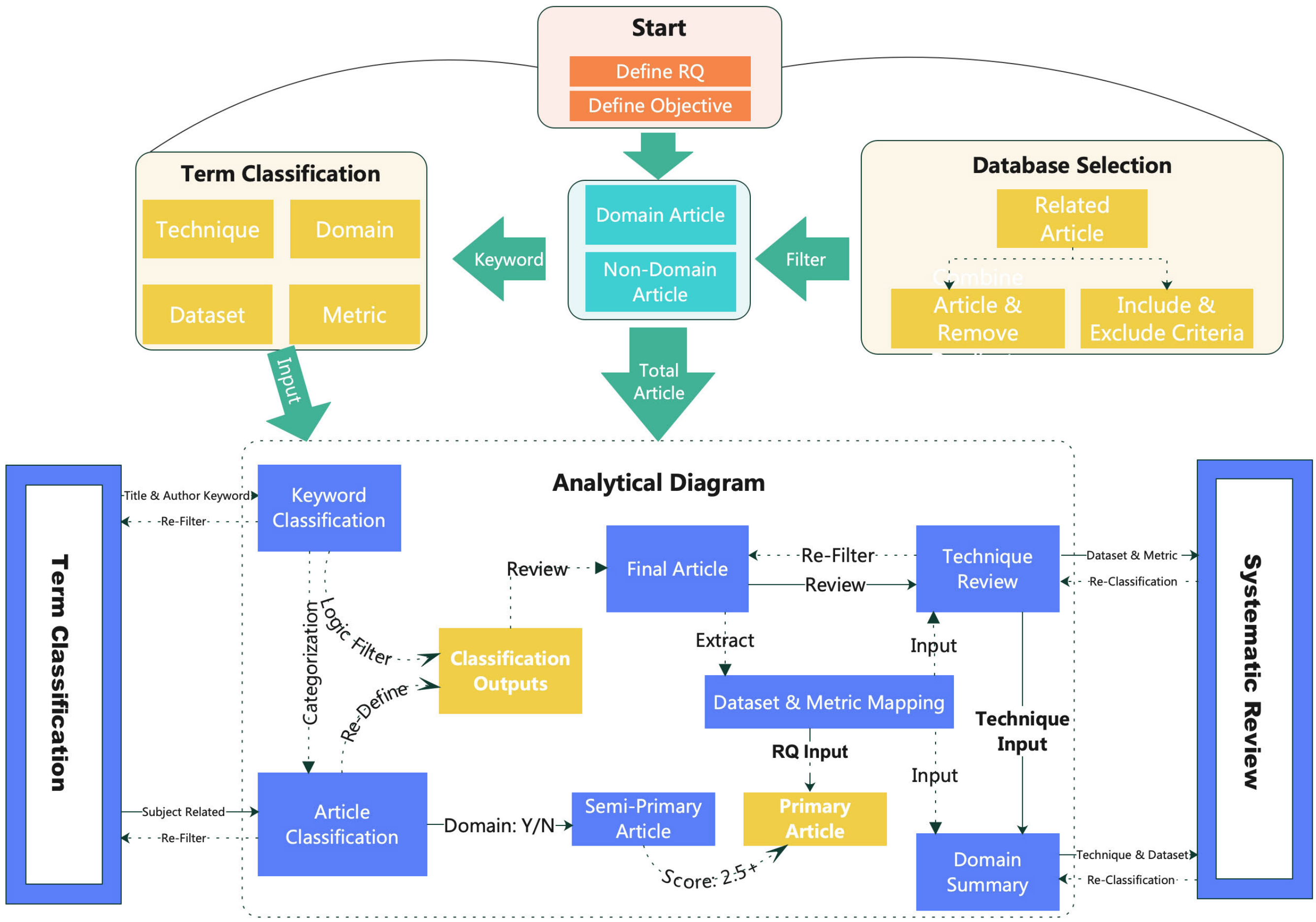

FIGURE 4. **Diagram of analytical process: Classification and systematic review.**

features, music, videos, citations, social, and cross-domain interactions [46], these classifications might not fully equip future researchers to grasp the breadth of recommendation system applications comprehensively.

Recommendation systems have become integral to our daily lives, supporting decision-making by offering personalized recommendations based on past behaviors and preferences. These systems find utility across various domains, including e-commerce, entertainment, education, and social media. Categorization should account for different criteria, such as data sources, models, and application domains, to capture the diverse landscape of recommendation systems.

2) CATEGORIES OF TERM CLASSIFICATION AND CLASSIFICATION RESULTS

Classifying terms in the context of deep learning-based recommendation systems is a fundamental aspect of our article. Through a comprehensive categorization process, we aim to provide a structured understanding of the various terms used in this field. This sub-subsection outlines our classification strategies for technique, domain, and data/model terms and aims to answer our research question:

RQ3-1: *What search terms are commonly employed in recommendation system research?*

a: CATEGORIES OF TECHNIQUE TERMS

Our article presents an updated and comprehensive perspective on the techniques employed in deep learning-based recommendation systems. Departing from predefined categories, we adopted a dynamic approach by extracting terms from selected articles and organizing them based on their usage patterns.

This process involved employing advanced text mining techniques on a final list of 787 carefully curated articles to ensure relevance. Prominent terms from article titles, keywords, and manual inputs were scrutinized to construct these categories. The resulting term list was validated by two reviewers, focusing on recommendation system components, algorithms, applications, and terminologies.

For clarity and ease of reference, we introduced index labels for each category:

1) **TCF** for the technique category functionality group
2) **TCC** for the technique category components group
3) **TCA** for the technique category applications approach

This classification scheme empowers us to analyze articles from varied perspectives, gaining insights into diverse aspects of deep learning-based recommendation systems. Our extensive classification effort yielded 27 categories across the three-technique groups (TCF, TCC, TCA).

- **Technique Category Functionality (TCF):** The TCF group includes techniques like NLP, sentiment analysis, computer vision, feedback, user behavior modeling, context-based analysis, social network analysis, content-based analysis, aware-based analysis, and sequential modeling to enhance recommendation systems.
- **Technique Category Components (TCC):** The TCC group develops key components for recommendation systems, including collaborative filtering, matrix factorization, neural networks, adversarial techniques, autoencoder, graph-based filtering, and attention-based techniques.
- **Technique Category Applications Approach (TCA):** The TCA group uses various techniques, including hybrid-based, session-based optimization, factor analysis, and rate prediction.

This detailed categorization provides insights into deep learning-based recommendation systems' functionality, components, and applications, enhancing our understanding of their diverse aspects.

b: TECHNIQUE CLASSIFICATION RESULTS

We classified the categories of deep learning-based recommendation techniques and their corresponding top usage terms in Table 8.

c: CATEGORIES OF DATA & MODEL TERMS

Although not directly involved in recommendation system techniques, the terms related to data and model components play a vital role in the implementation process of the recommendation system. This category focuses on identifying and extracting such terms, making it easier for future researchers to identify precise terms for data processing and model enhancement.

This category was created using advanced text-mining techniques on a final list of 787 selected articles. Prominent terms from article titles, keywords, and additional manual inputs were methodically examined to construct these categories.

Our classification spans several key aspects:

- **Data Source:** Capturing the origins and management of data used in recommendation systems.
- **Data Preprocessing:** Addressing techniques that refine raw data for analysis.
- **Data Representation:** Focusing on structured portrayals of data used in modeling.
- **Data Terms:** Covering analysis and treatment of data in recommendation systems.

Furthermore, we explore categories revolving around model construction and evaluation:

- **Modeling:** Addressing techniques for constructing recommendation system models.
- **Machine Learning:** Encompassing established machine learning techniques for recommendation systems.
- **Deep Learning**: Incorporating deep learning techniques for improved recommendation models.
- **Model Development:** Covering techniques for refining recommendation models.
- **Model Optimization:** Including techniques to optimize and refine recommendation models.
- **Evaluation:** Encompassing methodologies for assessing recommendation model performance.

d: DATA & MODEL CLASSIFICATION RESULTS

Table 9 categorizes and presents the most frequently used terms related to data and model aspects in the context of recommendation systems. These terms encompass data sources, preprocessing techniques, data representations, and various modeling and optimization methods commonly employed in research and development.

e: CATEGORIES OF DOMAIN TERMS

Our article aims to synthesize the latest applications of deep learning techniques in recommendation systems across diverse domains. Achieving this goal necessitated a hybrid approach, combining the extraction of terms from selected articles with manual summarization alongside established classifications.

Conventional domain classification categorizes deep learning-based recommendation systems based on data types, industries, and application contexts. However, these traditional classifications may not fully align with the most influential articles shaping the field.

We thoroughly analyzed 416 domain-specific articles to overcome this limitation and extracted 58 domain-related terms from article titles and keywords. Using these terms, we categorized domains into eight distinct categories and introduced a new category specifically for cross-domain applications. We aim to utilize this categorization to address the following research question:

RQ2-1: *How can deep learning recommendation systems be categorized based on domains?*

Our categorization uses **D** for domain category and **do** for domain application. Additional details can be found in the classification result subsection. Below are explanations of the domain categories:

- **Application:** This category encompasses domains where recommendations are integrated into applications, including web, mobile apps, APIs, and cross-domain scenarios.
- **Entertainment & Media:** Deep learning techniques are extensively used in domains such as books, movies, music, news, and streaming services.
- **E-commerce & Retail:** E-commerce and retail domains benefit from deep learning-based recommendations for products, services, and items.

TABLE 8. Technique term classification: Categories and top terms.

Technique Category	Technique: Top Terms
$TCF01$ Natural Language Processing	Task Analysis, Topic Modeling, Word Embedding, Text Mining, Text Similarity, Gated Recurrent Unit, Textual Information, Topic Model
$TCF02$ Sentiment Analysis	Sentiment Analysis, Sentiment Classification, Review Helpfulness, Review Process, Review Text
$TCF03$ Computer Vision	Face Attribute, Visual Contents, Visual Feature
$TCF04$ Feedback	Implicit Feedback, Negative Feedback, Explicit Feedback
$TCF05$ User Behavior	User Preference, User Review, Behavior Modeling, User Behavior, Behavioral Science, User Profiling, User Rating
$TCF06$ Context-Based	State Representation, Content Embedding, Context Awareness, Temporal Context, Point Of Interest, Next POI
$TCF07$ Social Network Analysis	Social Network, Social Influence, Social Trust, Geo-Social Relationship, Social Analysis, Social Dual, Social Networking
$TCF08$ Content-Based	Multi-Dimension Interest, Multi-Label Classification, Content-Aware, Multi-Criteria Recommender
$TCF09$ Aware-Based	Context-Aware, Trust-Aware, Time-Aware, Tag-Aware, Session-Aware, Knowledge-Aware, Content-Aware, Emotion-Aware, Text-Aware
$TCF10$ Sequential	Sequential Recommendation, Sequence Recommendation, Sequential Behavior, Deep Sequential, Non-Sequential Interaction
$TCC01$ Collaborative Filtering	Deep Collaborative, Collaborative Filtering, Multi-Criteria Collaborative, Reciprocal Recommendation
$TCC02$ Matrix Factorization	Deep Matrix, Deep Matrix Factorization, Deep Factorization, Matrix Completion, Matrix Factorization Attention, Probabilistic Matrix, Variational Matrix, Variational Matrix Factorization
$TCC03$ Factorization	Factorization Machine, Factorization Attention, Factorization Attention Mechanism, Factorization Initialization
$TCC04$ Neural Network	Neural Collaborative, Neural Network Model, Neural Attention, Neural Graph, Neural Recommendation, Neural Model, Neural Collaborative Filtering, BP Neural Network, Capsule Network
$TCC05$ Adversarial	Generative Adversarial Network, Adversarial Learning, Adversarial Network, Generative Adversarial, Loss Function
$TCC06$ Autoencoder	Autoencoder Framework, Variational Autoencoder, Deep Autoencoder, Autoencoder Training, Auto Encoder, Heterogeneous Autoencoder
$TCC07$ Convolution Neural Network	Deep CNN, Convolutional Neural Network, CNN Compression, Convolution Neural Network, Convolutional Network
$TCC08$ Recurrent Neural Network	Recurrent Neural Network, Recurrent Unit, Boltzmann Machine, Long-short-term memory
$TCC09$ Graph-Based Filtering	Recommendation With Graph, Bipartite Graph, Random Walk
$TCC10$ Graph Neural Network	Knowledge Graph, Graph Neural Network, Heterogeneous Graph, Graph Neural Network For Session, Graph Embedding, Graph Attention, Graph Convolutional Networks
$TCC11$ Multi-Layer	Multilayer Perceptron, Multi-Layer Perceptron
$TCC12$ Attention-Based	Attentional Mechanism, Attention Mechanism, Attention Model, Attention Network
$TCA01$ Hybrid-Based	Hybrid Recommendation, Hybrid Recommender, Hybrid Model, Deep Hybrid, Hybrid Deep, Hybrid Approach
$TCA02$ Session-Based	Network For Session, Neural Network For Session, Model For Session, Neural Model For Session, Session Recommendation, Session Dependency
$TCA03$ Optimization	Genetic Algorithm, Adaptive Deep, Adaptive Learning, Gradient Problem, Steiner Tree, Taylor Series
$TCA04$ Factor Analysis	Factor Analysis, Factor Model, Latent Analysis
$TCA05$ Rate Prediction	Rating Prediction, Rate Prediction, Rate Matrix

- **Education & Learning:** In the education sector, deep learning techniques contribute to personalized course recommendations, e-learning platforms, and learning resources.
- **User Information:** Deep learning techniques enhance recommendation systems based on user interests, feedback, and interactions. This category includes domains like fitness, careers, and point-of-interest recommendations.
- **Scholarly Research:** Academic and research domains benefit from deep learning-based scholarly papers, journals, and citation recommendations.
- **Social & Social Media:** Social media platforms leverage deep learning recommendations for user interactions, group dynamics, event recommendations, and more.
- **Tourism:** Deep learning techniques are applied to tourism, travel, and hotel recommendations.

Each domain category represents a context where deep learning techniques are harnessed to provide relevant, personalized, and effective recommendations, catering to users' diverse needs and preferences.

f: DOMAIN CLASSIFICATION RESULTS

Table 10 categorizes recommendation system domains grouped by specific application categories. A unique term identifies each domain, and these classifications encompass a wide range of application areas where recommendation systems play a pivotal role. These categorizations help understand the diverse landscape of recommendation system usage across various domains.

TABLE 9. Data & model term classification: Categories and top terms.

Data & Model Category	Data & Model: Top Terms
^{DM01}Data Source	Category Information, Information Site, Information Sites, Multi-Criteria Rating, Demographic Information, Information System
^{DM02}Data Preprocessing	Information Fusion, Huffman Coding, Incremental Input, Information Integration, Interests Extraction
^{DM03}Data Representation	Metadata Information, Item Representation, Information Network, Item Attribute, Item Correlations, Item Description, Item Interaction, Item Metadata
^{DM04}Data Terms	Data Analysis, Data Noise, Auxiliary Information, Co-Occurring Item, Negative Sampling, Binary Code, Co-Occurrence Pattern, Data Mining, Data Model
^{DM05}Modeling	Predictive Model, Preference Modeling, Preference Relation, Correlation Mining, Memory Network, Latent Dirichlet, Latent Dirichlet Allocation, Manifold Regularization
^{DM06}Machine Learning	Dirichlet Allocation, Nearest Neighbor, Decision Tree, Document Similarity, Embed Propagation, Evolutionary Computation, Heterogeneous Data, K-Nearest Neighbor, Variational Inference
^{DM07}Deep Learning	Deep Reinforcement, Deep Neural Network, Deep Representation, Deep Ensemble, Deep Collaborative, Deep Latent, Deep Matrix
^{DM08}Model Development	Time Series, Learning Approach, Knowledge Engineering, Knowledge Transfer, Similarity Measure, Vector Representation, Bayesian Inference, Causal Inference, Feature Extraction, Feature Selection, Feature Embedding, Feature Interaction
^{DM09}Model Optimization	Knowledge Distillation, Loss Function, Model Compression, Weight Quantization, Weight Sharing
^{DM10}Evaluation	Comparative Survey, Fault Diagnose, Performance Evaluation, Quantile Loss

TABLE 10. Recommendation system domains by category.

Category	Domains
^{D1} Application	Web$_{do1}$, App$_{do2}$, Mobile$_{do3}$, Page$_{do4}$, Session$_{do5}$, Pop-ups$_{do6}$, API$_{do7}$, Cross-Domain$_{do8}$
^{D2} Entertainment & Media	Book$_{do9}$, Movie$_{do10}$, Music$_{do11}$, News$_{do12}$, Streaming$_{do13}$, TV Program$_{do14}$, Smart TV$_{do15}$, Video$_{do16}$, Celebrity$_{do17}$, Film$_{do18}$, Recipe$_{do19}$
^{D3} E-commerce & Retail	E-commerce$_{do20}$, Product$_{do21}$, Service$_{do22}$, Item$_{do23}$, Human Resource$_{do24}$, Store$_{do25}$
^{D4} Education & Learning	Course$_{do26}$, E-learning$_{do27}$, Library$_{do28}$, Project$_{do29}$, Course Resource$_{do30}$, Learning Resource$_{do31}$, Education$_{do32}$, Student$_{do33}$, College$_{do34}$, Question$_{do35}$
^{D5} User Information	Interest$_{do36}$, Feedback$_{do37}$, Point-Of-Interest (POI)$_{do38}$, Fitness$_{do39}$, Job$_{do40}$, Career$_{do41}$
^{D6} Scholarly Research	Citation$_{do42}$, Journal$_{do43}$, Paper$_{do44}$, Text$_{do45}$
^{D7} Social & Social Media	Call$_{do46}$, Group$_{do47}$, Hashtag$_{do48}$, Text Interaction$_{do49}$, Reciprocal$_{do50}$, Social$_{do51}$, Tag$_{do52}$, Location-Based$_{do53}$, Event$_{do54}$, Friend$_{do55}$
^{D8} Tourism	Tourist$_{do56}$, Travel$_{do57}$, Hotel$_{do58}$

The terms mentioned above generally relate to various types of data utilized based on their functionalities within recommendation systems. Those data can be summarized into categories such as text, user, item, social, time, and location, and the terms mentioned are commonly used in each of these categories.

g: CATEGORIES OF RECOMMENDATION TERMS

During the article selection process, general keywords were utilized to encompass a broad range of articles on recommendation systems that utilize deep learning techniques. This section offers a classification of terms that are frequently linked with recommendation systems, thereby aiding in the comprehension of various aspects of recommendation technology.

- **Recommendation System Terms:** This category encompasses fundamental terms commonly used to denote recommendation systems in a general sense. These terms collectively form the foundational vocabulary for understanding different aspects of recommendation technology. The terms include: *Recommendation System*, *Recommendation Engine*, *Recommender System*, *Recommender Engine*, and the abbreviation *RS*.
- **Recommendation System Terms Variant:** Within this category, we present synonyms and variations of recommendation system terms that provide nuanced perspectives on distinct elements of recommendation systems. The terms in this category encompass *Recommendation Algorithm*, *Recommendation Analysis*, *Recommendation Framework*, *Recommendation Method*, *Recommendation Model*, *Recommendation Strategy*, *Recommendation Technique*, *Recommendation Technology*, and *Recommendation Domain*.

These terms collectively furnish a vocabulary that researchers, practitioners, and enthusiasts can use to communicate proficiently within recommendation systems. They encapsulate the diverse dimensions of recommendation systems, from their core components to advanced strategies and technologies.

h: RECOMMENDATION CLASSIFICATION RESULTS

Figure 5 illustrates the distribution stemming from our analysis. Despite alternative terms such as "framework" or "model," the majority of articles still lean towards the usage of "Recommendation/Recommender System & Engine." Nevertheless, certain researchers use "Recommendation" directly with the domain application or application term.

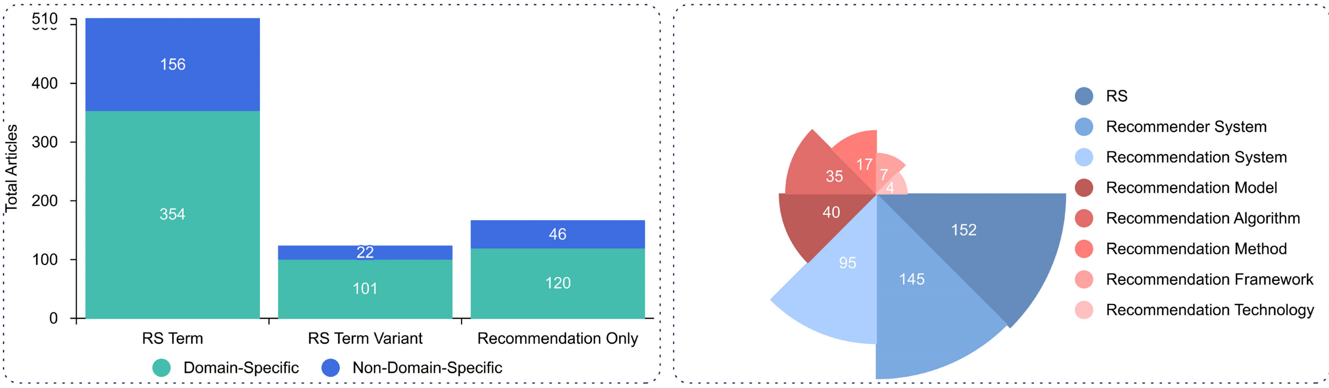

FIGURE 5. Terms of recommendations (domain vs non-domain) & top 8 classified terms.

Based on our analysis, it has become apparent that many terms are utilized within the realm of recommendation systems, showcasing the diverse perspectives of researchers. These terms not only aid in comprehending the field but also contribute to addressing our research inquiry.

Summary: Our classification method aims to review selected studies and their utilization of advanced terms within these categories. Through this structured approach, we contribute to a deeper understanding of the terminology associated with deep learning-based recommendation systems.

B. TERM CLASSIFICATION FINDINGS AND DISCUSSION

In this subsection, we analyze the implications of our classification results on deep learning-based recommendation systems. We thoroughly discuss the trends and focus within each category while addressing unexpected findings or patterns.

1) ANALYSIS AND COMPARISON OF STATE-OF-THE-ART TECHNIQUES

In this sub-subsection, we explore advanced techniques for recommendation systems, focusing on the latest deep-learning approaches that power these systems. We aim to answer the research question RQ1-1. We avoid duplicating the background information in the introduction to ensure clarity and conciseness.

RQ1-1: *What are the state-of-the-art deep learning techniques for recommendation systems, and what are their strengths?*

a: NATURAL LANGUAGE PROCESSING (NLP) AND TEXT ANALYSIS

Thanks to natural language processing (NLP) research advances, recommendation systems are continuously improving. Techniques like task analysis, topic modeling, word embedding, and text mining are utilized to enhance the accuracy and effectiveness of recommendation systems.

For example, Liu et al. [177] created a DYSR model that utilizes a dynamic graph neural network and task analysis to bridge the semantic gap between services and mashups. Similarly, Hong et al. [178] applied word embedding techniques to view a user's interaction as a document composed of items as words.

By using NLP techniques, researchers can analyze text data more efficiently and gain insights into user preferences and needs, ultimately improving recommendation systems' overall performance.

b: SENTIMENT ANALYSIS FOR ENHANCED RECOMMENDATIONS

The field of sentiment analysis plays a crucial role in text mining and holds significant importance in recommendation systems [15]. For instance, Alatrash et al. [15] introduced a recommendation approach that combines sentiment analysis and genre-based similarity in collaborative filtering methods. Dang et al. [29] suggested the use of BERT for genre preprocessing and feature extraction, along with hybrid deep learning models for sentiment analysis of user reviews. Moreover, Liu et al. [95] proposed a novel multilingual review-aware deep recommendation model (MRRec) for rating prediction tasks.

c: COMPUTER VISION FOR PERSONALIZED INSIGHTS

Deep learning has shown promising results in various fields, including image processing, computer vision, pattern recognition, and natural language processing [46], [156], [179], [180].

By utilizing computer vision methods, it is possible to analyze and extract valuable insights from visual content like images or videos. This information can provide personalized recommendations based on users' visual preferences and interests. One example is face attribute analysis, which uses computer vision algorithms to identify and analyze specific facial features such as age, gender, facial expression, and ethnicity [181].

Researchers have explored various applications of visual content and sequential patterns for point of interest (POI) recommendations. Sang et al. [182] leveraged users' photos and check-in patterns for their recommendations. Markapudi et al. [183] suggested using low-level visual features from videos to generate relevant recommendations.

Meanwhile, Messina et al. [184] examined the impact of artwork metadata, neural visual features, and manually engineered visual features like naturalness, brightness, and contrast on content-based artwork recommendations.

d: IMPLICIT AND EXPLICIT FEEDBACK FOR BETTER PRECISION

Feedback is the information that users provide about their interactions with items and their preferences. There are various types of feedback, including implicit, explicit, and negative.

Implicit feedback refers to user behavior and actions that can be inferred from their interactions with a system, such as clicks, purchases, or views [185]. Explicit feedback refers to the user's direct and explicit input about their preferences and opinions [75]. To utilize implicit feedback information, collaborative filtering, matrix factorization, neural network, and other techniques are commonly combined [186], [187], [188].

For example, Gong et al. [189] proposed a new top-N recommendation method called MFDNN for heterogeneous information networks (HINs), considering both explicit and implicit feedback information to determine the potential preferences of users and the potential features of the product. Liu et al. [97] used explicit feedback to accurately reflect users' explicit preferences and potential preferences to build a recommendation model. A new loss function is designed based on explicit-implicit feedback to obtain the best parameters through neural network training to predict users' preferences for items.

Negative feedback refers to the user's dissatisfaction or dislike of an item [190]. In our selected studies, it has been applied in the news [92] and TV recommendations [191].

e: USER BEHAVIOR AND PREFERENCES FOR PERSONALIZATION

Understanding user behavior and preferences is pivotal. User interactions like item views, clicks, purchases, and ratings provide rich insights, particularly in session-based recommendations [192], [193]. User profiling, aided by techniques like graph neural networks [194] and social graph neural networks [195], captures preferences. Feature-level preferences extracted from reviews [196] further enrich user profiles.

User behavior and preference are important factors in recommendation systems. User behavior refers to the actions and interactions of users within the recommendation system, such as the items they view, click, purchase, or rate. These behaviors are commonly used in session-based recommendations [87], [192], [197], [198], and can provide rich information for understanding user preferences [193].

User reviews and ratings are often used to capture user preferences and feedback [199]. Behavioral science techniques, such as the use of graph neural network [82], [194] and social graph neural network [195], can be applied to understand and model user behavior in recommendation systems.

User profiling is another technique to capture user preferences and interests [199]. For example, [200] utilized deep reinforcement user profiling for recommendations in heterogeneous information networks. Other methods for comprehensive user profiling include extracting feature-level preferences from review information [196].

f: CONTEXT-BASED APPROACHES FOR ENHANCED PERSONALIZATION

Personalized recommendations in context-based recommendation systems involve user context information such as location, time, and day. To incorporate context information, context embedding is a commonly used technique, as demonstrated by models such as Tkg2Vec and Traj2Vec developed by Bin et al. [201]. Liu et al. [202] suggested four state representation schemes for learning recommendation policies. In contrast, Zhang et al. [203] designed a state representation module using a dynamic recurrent mechanism that integrates concept information and exercise difficulty level to generate a continuous state representation of the student.

Location-based context information is particularly important in personalized recommendations. Recurrent neural network (RNN)-based POI recommendation techniques consider similar users' location interests and contextual information such as time, current location, and friends' preferences [204]. Extreme sparsity in user-point-of-interest (POI) matrices presents a challenge in context-based recommendation systems, as discussed by Xing et al. [205]. To address this challenge, the authors propose a content-aware POI recommendation technique based on convolutional neural networks (CPC). The approach utilizes a unified framework incorporating POI properties, user interests, and sentiment indications, demonstrating the effectiveness of CPC in capturing semantic and sentiment information from review content to enhance POI recommendations on location-based social networks.

g: SOCIAL-BASED AND LOCATION-AWARE PERSONALIZATION

There are also social-based POI recommendations, which involve concepts like geo-social relationships. Cui et al. [206] proposed a dual geo-social relationship and deep implicit interest topic similarity mining approach, DDR-PR, recommending POIs within a reachable region. Pan et al. [207] proposed DPGSR-PR, which personalizes geographical features by estimating and considering kernel density towards determining user check-in behaviors and choices in specific domains.

Social is also commonly used in recommendation systems. Deep learning has been applied to model the social network-enhanced collaborative filtering problem [208]. Social-network-based recommendation algorithms leverage rich social network information to alleviate the problem of data sparsity and improve the recommendation performance [101]. Wu et al. [102] argue that neglecting the latent collaborative interests of users hidden in the user-item interest network by only modeling the influence diffusion process in the social network.

h: SEQUENTIAL BEHAVIOR FOR PERSONALIZED SUGGESTIONS

Sequential recommendation, also known as sequence recommendation, is a vital component of modern recommender systems that tailors item suggestions to users based on their sequential behavior over time [209]. This approach is particularly valuable in contexts where user preferences evolve dynamically, making historical interactions a valuable resource for generating personalized recommendations.

A significant trend in sequential recommendation revolves around incorporating interactive features, which enhance the quality of recommendations [210]. Researchers have turned to deep learning models to tackle challenges like sparsity and the cold-start problem. For example, Ma et al. [211] introduced DeepAssociate, a deep learning model designed to capture both sequential influence and history-candidate association. This innovation is instrumental in improving recommendation performance by leveraging the correlation between user behaviors and item characteristics.

Temporal information has emerged as a critical aspect of sequential recommendation models. Zhang et al. [146] introduced a time-aware transformer model that employs self-attention mechanisms to capture temporal dependencies within user-item interactions. This approach significantly enhances recommendation accuracy by considering when interactions occurred.

Deep learning techniques have played a pivotal role in modeling complex user-item interactions. DSER, introduced by Hong et al. [178], utilizes deep neural networks to capture the non-linear relationships inherent in sequential interactions. By treating user-item interactions as sequences and applying doc2vec techniques, DSER achieves substantial improvements in recommendation accuracy, particularly in scenarios with sparse data.

i: CONTENT-BASED STRATEGIES FOR PERSONALIZATION

Content-based recommendation systems have emerged as indispensable tools for delivering personalized content suggestions across diverse transactional contexts. Recent studies underscore the adoption of multi-dimensional approaches in cutting-edge models. Markapudi et al. [183] introduced a pioneering approach known as the content-based video recommendation system (Cbvrs). This system adeptly addresses the semantic gap inherent in video recommendations by harnessing low-level visual features and employing pre-processing techniques such as motion-adaptive Gaussian denoising filtering, thereby enhancing video quality and efficiency.

In music recommendation, Magron et al. [23] addressed the perennial challenge of the ‘‘cold-start problem’’ by introducing neural content-aware collaborative filtering. This innovative approach integrates content information derived from low-level acoustic features with deep learning methodologies. As a result, it has demonstrated remarkable performance, particularly in scenarios where initial user data is limited. Furthermore, the domain of hybrid recommendation systems has garnered substantial attention. Behera et al. [69] proposed a weighted hybrid collaborative filtering (CF) system that effectively amalgamates content k-nearest neighbors (KNN) and the restricted Boltzmann machine (RBM). This hybrid strategy has proven particularly potent in enhancing movie recommendations, especially when confronted with sparse datasets.

In the domain of location-based social networks (LBSNs), Lu et al. [20] addressed the challenges associated with sparse data through the introduction of a content-aware point-of-interest (POI) recommendation method. This innovative approach leverages deep convolutional neural networks (CNN) in conjunction with multi-objective immune optimization techniques to generate diverse and precise POI recommendations. Furthermore, for mobile networks, Liu et al. [79] proposed a groundbreaking deep reinforcement learning approach for proactive content pushing and recommendation. This approach effectively mitigates user demand uncertainty and has yielded substantial net profit improvements for mobile network operators.

j: INCORPORATING KNOWLEDGE AND TRUST FOR ACCURACY

Recent developments in content-based recommendation systems have introduced advanced techniques, mainly driven by deep learning, to enhance both recommendation accuracy and interpretability [212]. These techniques fall into two major categories: knowledge-aware and trust-aware approaches.

In the knowledge-aware domain, researchers have been integrating user-generated content and knowledge entities to capture meaningful user-item interactions. For instance, Liu et al. [147] introduced the knowledge-aware attentional neural network (KANN), and Zhang et al. [213] proposed the aggregating knowledge-aware graph neural network (KGARA). These methods prioritize user knowledge integration to deliver personalized recommendations. Moreover, Wang et al. [103] introduced the quaternion-based knowledge graph neural network (QSOR), utilizing quaternion-based embeddings and double-end attention mechanisms, while Lyu et al. [28] presented knowledge-enhanced graph neural networks (KEGNN), leveraging semantic knowledge for improved interpretability and accuracy. Additionally, Zhang et al. [214] introduced a bilinear knowledge-aware graph neural network with text information (BKGNN-TI).

Conversely, trust-aware recommendation systems take into account factors like time, location, trust levels, and sentiment analysis to offer context-aware recommendations.

Ahmed et al. [81] presented the trust-aware denoising autoencoder with spatial-temporal activity (TSTDAE), addressing these considerations. Liu et al. [215] applied deep learning-based initialization techniques to handle initialization and trust-related challenges. These models are designed to provide recommendations that are both reliable and contextually relevant.

k: MATRIX FACTORIZATION FOR RECOMMENDATION

Matrix factorization has been widely adopted in recommendation systems to model latent user-item interactions, enabling personalized recommendations. Several recent advancements in this domain have contributed to improving recommendation accuracy and efficiency.

Liu et al. [216] introduced efficient deep matrix factorization (EDFF), which effectively utilizes user-item interaction reviews, incorporating convolutional neural networks (CNNs) with word-attention mechanisms. The method addresses data sparsity issues and demonstrates effectiveness in industrial applications. Shen et al. [217] presented DVMF, a deep learning-based Bayesian recommendation framework that employs variational inference and reparameterization techniques. DVMF introduces deep neural networks to infer hyper-parameters from user and item information, achieving superior prediction accuracy across multiple datasets.

In addition to traditional matrix factorization methods, advanced techniques have been proposed to enhance recommendation systems. Wan et al. [21] addressed trust-aware recommendations in social networks using DMF techniques. They introduced both linear and non-linear DMF methods, enhancing matrix initialization accuracy, and integrated deep marginalized denoising autoencoders to improve recommendation performance, especially for cold-start users. Chen et al. [187] proposed ENMF, an efficient neural matrix factorization framework that eliminates the need for sampling. ENMF offers lower time complexity and consistently outperforms state-of-the-art methods in top-k recommendations, making it suitable for real-world, large-scale systems.

To address data sparsity and improve recommendation accuracy, researchers have explored the incorporation of auxiliary information into matrix factorization. Zhang et al. [218] introduced a probabilistic matrix factorization recommendation method incorporating self-attention mechanism CNNs. This approach captures long-distance dependencies within auxiliary information components and achieves superior accuracy in rating prediction. Xiao et al. [219] presented neural variational matrix factorization (NVFM), a deep generative model that effectively incorporates side information for improved collaborative filtering recommendations. Yi et al. [165] introduced deep matrix factorization (DMF), a deep learning-based collaborative filtering framework that effectively integrates various types of side information, with implicit feedback embedding (IFE) mitigating model complexity and improving training efficiency.

l: ADVERSARIAL TECHNIQUES FOR IMPROVED PERFORMANCE

Adversarial techniques mainly involve generative adversarial networks (GANs), which have gained significant attention in various fields due to their ability to learn complex real data distributions [220].

In the context of recommendation systems, Zheng et al. [221] proposed an adversarial training framework to learn a hybrid recommendation model, where a generator model is trained to learn the distribution over pairwise ranking pairs. In contrast, a discriminator is trained to distinguish between generated (fake) and real item pairs. Similarly, Zhang et al. [222] introduced a novel deep neural network called Dual Adversarial Network for cross-domain recommendation. In contrast, Liu et al. [223] proposed a domain-adversarial training paradigm for cross-domain recommendation, the first deep model to consider domain-specific and domain-shared knowledge across domains.

m: NEURAL GRAPH TECHNIQUES AND EMBEDDINGS

Neural graph and graph embedding techniques have gained much attention for their ability to provide accurate and precise recommendations in various application scenarios. In particular, knowledge graph embedding (KGE) has been effective in this regard [98]. A recent study by Qi et al. [104] proposed a model that employs a graph embedding algorithm to extract static features of users and movies. These features are then fed as input to a gated recurrent unit (GRU), enabling the model to consider the static features while modeling the user's dynamic behavior.

In another work, Zhang et al. [139] introduced paragraph embeddings to represent user reviews and item descriptions. They designed two neural networks to capture the sentiment of user reviews and the content features of items, respectively. Additionally, Sang et al. [224] proposed a knowledge graph-enhanced neural collaborative recommendation (K-NCR) framework. This framework combines user-item interaction and auxiliary knowledge information for the recommendation task. Specifically, it learns the representation of item entities through a proposed propagating model. This approach presents a new synchronized heterogeneous autoencoder (SHAE) for a top-N recommendation, considering both the features learned by the item autoencoder (IAE) and user autoencoder (UAE) models [225].

n: HYBRID APPROACHES IN RECOMMENDATION SYSTEMS

One of the pivotal categories extracted from the selected articles pertains to various application approaches for recommendation systems. In recommender systems, hybrid approaches play a significant role in enhancing recommendation performance by combining multiple techniques. These approaches encompass a wide range of strategies and models, including "hybrid-based," "hybrid model," and "hybrid deep," each offering unique contributions to the field [75], [184], [226], [227].

Researchers have explored various approaches to improve recommendation systems, such as the "Hybrid Model" developed by Huang et al. [226]. This model combines matrix factorization and deep learning to address challenges related to data sparsity and model expressiveness, leading to improved recommendation performance. Similarly, Liu et al. [75] investigated the "Hybrid Deep" approach, which combines traditional recommendation techniques with deep learning methods. This approach has proven effective in enhancing recommendation accuracy by using neural networks to capture complex patterns and user preferences. Additionally, Kang et al. [227] proposed a "Hybrid-Based Collaborative Filtering Model" that leverages the strengths of both user-based and item-based collaborative filtering to overcome the cold start problem.

o: ADVANCEMENTS IN SESSION-BASED RECOMMENDATION SYSTEMS

The session-based recommendation is a critical task in recommender systems, focusing on providing personalized suggestions based on short-term user interactions within a session [52]. Unlike traditional recommendation systems that rely on long-term user profiles, session-based methods excel in scenarios where interactions are fleeting or dynamic.

Session-based recommendations have been significantly improved thanks to the implementation of deep learning techniques. Recurrent neural networks (RNNs), such as those in the "SGPD" model, are commonly employed to model sequential behaviors and capture user preferences within sessions [228]. Graph neural networks have also made significant strides. "ReGNN" introduces a repeat-exploration mechanism within a graph neural network to effectively handle repeat recommendations, recognizing their importance in session-based scenarios [145]. Furthermore, leveraging neighborhood session information with dual attentive neural networks, as proposed by Wu et al. [229], offers a promising approach to enhancing session-based recommendation.

Handling the lack of interactions for specific target behaviors is another crucial aspect. Memory-augmented meta-learning frameworks, exemplified by "MMFSR," use meta-learning to generalize recommendations across sessions, addressing the cold-start problem by deriving personalized parameters based on multi-behavior characteristics [230].

Temporal information is key in the session-based recommendation, as highlighted by models like the "time-aware neural attention network." These models incorporate interaction timing to create more accurate user preference models, leveraging global session graphs, graph neural networks, and attention mechanisms to capture evolving user preferences over time [192].

p: VARIED DATA APPROACHES IN RECOMMENDATION SYSTEMS

The optimization category contains terms related to optimization techniques used in recommendation systems, such as genetic algorithm [231], [232], [233] and Taylor series [234]. The factor analysis category includes terms related to factor analysis techniques for recommendation systems, such as factor analysis [235], [236] and factor model [18], [59], [237], [238]. Lastly, the rate prediction category encompasses terms related to rate prediction techniques, such as rating prediction [239], [240]. These categories provide a means to classify articles in recommendation systems that utilize deep learning techniques.

q: COMPARISON OF TECHNIQUES

When comparing these techniques, it's clear that each category addresses specific aspects of recommendation systems. While NLP and text analysis enhance understanding, sentiment analysis captures user emotions. Computer vision enables visual personalization, and context-based approaches tailor recommendations to situations. Social-based, location-aware, and content-based strategies focus on different data sources, while knowledge and trust techniques enhance accuracy. Sequential behavior, matrix factorization, attention mechanisms, and adversarial techniques make predictions more precise. Neural graph techniques and hybrid approaches offer comprehensive solutions.

In conclusion, recommendation systems benefit from a wide range of deep learning techniques. The choice of technique depends on the application's nature, available data, and desired outcome. Combining these approaches can lead to innovative and powerful recommendation systems that cater to diverse user preferences and requirements.

2) EXPLORATION OF ADVANCED DATA & MODELING TECHNIQUES

This sub-subsection provides a detailed analysis of the advanced data and modeling techniques utilized in recommendation systems. These modeling techniques showcase the complex nature of recommendation systems, where predictive models, machine learning techniques, and deep learning strategies intersect to offer accurate and personalized recommendations to users. The integration of these methodologies plays a crucial role in shaping the future of recommendation systems, ultimately providing users with customized and relevant suggestions. Within this context, we delve into our research question (RQ3), denoted as:

RQ3-1: *What search terms are used in recommendation system research?*

a: DATA SOURCE, PREPROCESSING, AND REPRESENTATION

Effective recommendation systems rely on well-managed data sources, thoughtful preprocessing, and structured data representation. Techniques such as category information, information sites, metadata extraction, interests extraction, and item metadata contribute to organized data for analysis. Additionally, user profiling techniques that capture preferences from reviews [199] and feature-level preferences extracted from review information [196] provide valuable insights into user preferences.

b: PREDICTIVE MODELS AND PREFERENCE MODELING

Preference modeling is essential for recommendation systems, involving predictive models anticipating user behavior and preferences. Techniques such as memory networks leverage memory to store and retrieve information [209], [241]. These preference relations model the intricate connections between users and items [242] and correlation mining techniques that uncover patterns in user-item interactions [242], all contribute to building accurate predictive models. Furthermore, latent Dirichlet and latent Dirichlet allocation techniques aid in identifying latent topics within data [243], [244].

c: MACHINE LEARNING APPROACHES

Machine learning techniques play a prominent role in recommendation systems. Nearest neighbor methods [245], decision trees [246], and document similarity measures [247] are frequently employed. K-nearest neighbor techniques [245] and variational inference strategies [219] also come into play. For instance, Wang et al. [246] devised a hybrid algorithm combining gradient-boosting trees and deep-learning models for feature regularization and recommendation. Hamada et al. [245] proposed a multi-criteria recommender system integrating k-nearest neighborhood collaborative filtering for predicting unknown criteria ratings. As seen in Shen et al.'s work [217], variational inference optimizes models like DVMF through reparameterization tricks and stochastic gradient-based optimization.

d: ENHANCING APPROACHES FOR MODEL DEVELOPMENT

Enhancing recommendation models encompasses a range of techniques, including time series analysis, knowledge-based systems, and cross-domain recommender systems. For instance, recent advancements have seen the rise of knowledge-based systems in the recommendation, such as the approach proposed by Ning et al. [248], which leverages past news click data and the neural knowledge DNA (NK-DNA). Cross-domain recommender systems have also gained traction, effectively supplementing sparse data with knowledge transferred from related domains [222]. These innovative approaches contribute to the evolution of recommendation systems.

e: FEATURE ENGINEERING AND EMBEDDINGS

Feature engineering is a crucial component of recommendation systems, enabling the extraction of valuable insights from user preferences and item characteristics. For example, Ma et al. [211] explored the association between user preferences and candidate items using sequential influence extraction and association feature extraction. In another study, Wen et al. [249] delved into the local feature extraction of algorithms like scale-invariant feature transformation (SIFT) and the classification performance of support vector machines (SVM). This knowledge was then applied to design an intelligent background music system based on deep learning and Internet of Things (IoT) technology.

In pursuit of better performance, studies have introduced innovative methods that combine different techniques to enhance recommendation models. Gong et al. [189] introduced a fusion approach that combines matrix factorization (MF) and deep neural networks (DNN) to learn independent feature embeddings, effectively capturing both linear and non-linear user-object relationships. Additionally, they proposed a shared feature embedding layer to reduce learning parameters and computational complexity. Another study by Huang et al. [250] focused on training two closely related modules: vector representation for group features and preference learning for groups on items. These integrated approaches showcase the potential for synergistic enhancements in recommendation systems.

f: LEVERAGING DEEP LEARNING STRATEGIES

Deep learning techniques have revolutionized recommendation systems, with diverse methodologies underpinning model development. Deep reinforcement methods [202], [251], [252], [253], [254] are prominent, embedding reinforcement learning in deep learning models. Deep representation learning [238], [255], [256], [257], [258] uncovers intricate user-item relationships. Additionally, deep ensemble models [259], deep collaborative approaches [260], [261], [262], and deep latent techniques [238], [263], [264], [265] contribute to recommendation enhancement. Deep matrix factorization [216], [266], [267] techniques provide effective solutions as well.

Deep reinforcement involves incorporating reinforcement learning in deep learning models, while deep neural networks model complex relationships between user and item features [268]. For instance, Liu et al. proposed a hybrid neural recommendation model that uses ratings and reviews to learn deep representations for users and items [269]. Roy et al. aimed to design an improved deep ensemble learning model (ID-ELM) for group recommender systems using various application-oriented datasets [259]. Meanwhile, Liang et al. introduced DeepLtrs, a deep latent recommender system that utilizes observed user ratings and product review texts to provide high-quality recommendations [263]. Xu et al. addressed the inefficiency of deep neural networks in capturing low-rank relations between users and items by combining SDNN with an improved deep matrix factorization model to form a unified framework named DualCF [266]. These studies demonstrate the importance and potential of deep learning in recommendation systems.

g: MODEL OPTIMIZATION AND EVALUATION

Optimizing recommendation models involves diverse techniques, including knowledge distillation [225] that transfers knowledge between models. Loss functions, like the one designed by Xia et al. [270] for holistic training and model compression approaches [271], enhance model efficiency. Evaluation techniques such as performance evaluation [272] and quantile loss [226] provide insights into model effectiveness.

The model optimization category encompasses terms related to techniques utilized to optimize recommendation system models. These techniques include knowledge distillation, where the work of Pan et al. [225] developed two novel heterogeneous knowledge distillation methods, namely feature-level and label-level, to build relations between IAE and UAE models. Additionally, the category includes loss functions, such as the one designed by Xia et al. [270] for the holistic training of the model, which consists of three parts representing the effects of different factors on rating predictions and model compression as outlined in the work of Zhao et al. [271]. These techniques aim to enhance the performance of recommendation systems by simplifying the models and improving their efficiency.

The evaluation category pertains to terms related to techniques employed to assess the performance of recommendation system models. These techniques include performance evaluation and quantile loss, as exemplified by the studies of Ludewig et al. [272] and Huang et al. [226], respectively. These methods aid in determining the effectiveness of recommendation systems and identifying areas for improvement.

In conclusion, advanced data management and modeling techniques play a crucial role in shaping the landscape of recommendation systems. These techniques offer insights into user preferences, optimize models, and evaluate their performance, resulting in more accurate and personalized recommendations.

3) CATEGORIZED DOMAINS AND ANALYSIS

Deep learning-based recommendation systems have become prevalent in various domains and industries. Researchers have classified them into specific domains to provide tailored recommendations that cater to distinct contexts. However, concerns have arisen regarding the adequacy and accuracy of existing classifications due to the rapid evolution of this field.

The pursuit of categorization has yielded insights that enable researchers to explore specific applications, refine and improve domain-specific recommendations, and identify the complex relationships between data types, industries, and application forms.

This article explores the various domains that have emerged from this categorization, including application, entertainment and media, e-commerce and retail, education and learning, scholarly research, user information, social media, and tourism. Each of these domains represents a unique aspect of the recommendation system landscape, and the aim is to unveil their inherent intricacies and potential future directions.

Accurate and pertinent terms in these categorizations are crucial, as they can refine and optimize the effectiveness of domain-specific recommendation systems. These terms are often extracted from the content of articles, and researchers can continue to seek improved classifications and harness the power of precise terminology to enhance the future of deep learning-based recommendation systems.

The following paragraphs explore the key domains identified in the classification of these recommendation systems, highlighting their implications and potential trajectories for further advancement. This helps provide an answer to the research question.

RQ2-2: *How do domain-specific needs and requirements impact the choice of deep learning techniques used in recommendation systems?*

a: APPLICATION DOMAINS

The first category in classifying domain terms for recommendation systems is "Application." This category covers web, app, mobile, page, and session domains commonly used in recommendation systems. For instance, in one study, a Laplace correction-based k-nearest neighbor (LKNN) model was applied to suggest suitable web pages to users based on their queries [234]. In another study, mobile-edge networks (MENS) were explored for edge intelligence in wireless communication networks [273]. The session-based recommendation is also a popular application. It aims to predict the next item a user will likely interact with within a session based on their behavior (e.g., click or purchase) [230]. Various techniques have been used to enhance session-based recommendation, such as graph neural networks, attention models, behavior modeling, sequence enhancement, disentangled representation learning, hypergraph neural networks, knowledge distillation, deep learning, and recurrent neural networks. More details about these techniques and their classifications can be found in [175].

b: CROSS-DOMAIN AND API RECOMMENDATIONS

The cross-domain recommendation has recently gained popularity, especially with the graph approach. For example, Guo et al. [82] proposed a new graph-based solution called time interval-enhanced domain-aware graph convolutional network (TIDA-GCN) to address the challenges of cross-domain recommendation. Quyang et al. [83] constructed a multi-graph based on users' behaviors from different domains and then proposed a multi-graph neural network to learn cross-domain app embedding.

In addition to the commonly used applications, there are recommendations for pop-ups and APIs. However, with the rapidly increasing number of APIs, choosing suitable APIs for a mashup becomes challenging, particularly when the historical relationships between APIs and mashups are sparse [274]. Using the neural graph collaborative filtering technique, Lian et al. [275] proposed an API recommendation method that exploits the high-order connectivity between APIs and API users.

c: ENTERTAINMENT & MEDIA

The ''Entertainment & Media'' category was one of the first categories to introduce recommendation systems, such as Netflix movie recommendations. This category includes books, movies, music, news, streaming, TV, and video. Some studies in this category include personalized book recommendation algorithms based on deep learning models [276], efficient movie recommendation lists on mobile apps [277], improving recommendation accuracy for live streaming recommendations by modeling both viewer and anchor's dynamic behaviors [278], applying sentence BERT to news titles and contents [279], and proposing a viewing environment model that considers viewing behavior records and electronic program guides [191].

d: E-COMMERCE & RETAIL

The ''E-commerce & Retail'' category comprises recommendation systems for e-commerce and retail platforms, such as product and service recommendations. These systems use various techniques, such as collaborative filtering, content-based filtering, and hybrid filtering, to improve sales and user engagement. For instance, many e-commerce sites use recommender systems as business tools to increase their sales productivity and help customers find suitable products [280]. To address the problem of sparse log data affecting the accuracy of model recommendation, a personalized product recommendation method was proposed, which uses a deep factorization machine (DeepFM) to analyze user behavior [111]. Moreover, Liu et al. [281] predicted the consumption level of different users at the store based on multisource data, which can help with store placement and analyze customer behavior in the store at different periods. In another study, various neural network models such as Levenberg-Marquardt (LM), Bayesian-regularization (BR), and scaled-conjugate-gradient (SCG) were experimented with the input time series to find the best-fit model for the prediction of personalized QoS-based web service recommendation [77].

The use of recommendation systems in e-commerce and retail has significantly increased due to the rapid growth of online shopping. However, compared to other categories, this remains an underdeveloped category, and there is a need for more advanced recommendation techniques to be applied in this area. As e-commerce and online retail continue to expand, there will be a greater need for more effective and personalized recommendations to improve user experience and increase sales.

e: EDUCATION & LEARNING

The ''Education & Learning'' domain application category is a popular research field encompassing recommendation systems applied to various education and learning platforms, including e-learning, libraries, and course resources. These systems use personalized learning, learning analytics, and recommendation algorithms to enhance the learning experience and outcomes. For instance, course recommendation has been studied extensively, with over ten studies in our article pool. Shen et al. [282] found that using traditional recommendation algorithms to solve problems such as data sparsity and cold start does not significantly improve recommendation performance. To address this, Alahmadi et al. [48] proposed an online course recommendation model based on autoencoder that utilizes long-term and short-term memory (LSTM) networks to improve the autoencoder's ability to extract the temporal characteristics of data.

Additionally, MOOC-based recommendation systems provide suggested quality courses to learners. Liu et al. [283] found that hybrid prediction models can be used to predict student performance in each course by ranking prediction. Yuan et al. [284] conducted a study that focused on link prediction methods in online education and established appropriate models for online education, addressing the gap in the relatively few studies on online education resources. Other related terms in this category include Student, College, and Question. Kurniadi et al. [285], Wu et al. [286], and Tu et al. [287] have explored these topics in their studies. Mishra et al. [288] proposed a deep semantic structure algorithm that overcame the existing system's issue. Wan et al. [289] used the hybrid convolutional neural network, and a career recommendation model for college students based on deep learning and machine learning is proposed. Simulation experiments are carried out on it.

f: SCHOLARLY RESEARCH

''Scholarly Research'' is a popular research field that focuses on citation and text recommendations to aid researchers in discovering relevant papers, authors, and research topics. One of the popular domains in this category is citation recommendation. The cumulative citation recommendation (CCR) system is designed to identify noteworthy documents from a large volume of stream data for a given target entity in knowledge bases [290]. Another promising approach in this field is using relational topic models (RTMs) for citation prediction. This method jointly models document contents and citations [291]. Additionally, SBERT has been used for journal recommendation. It measures the similarity of journal scopes with articles and performs better than other methods such as word2vec, glove, and fasttext [292].

g: USER INFORMATION-BASED

Under the ''User Information'' category, various recommendation techniques generate personalized suggestions based on user feedback, interests, careers, and Point of Interest (POI) data. One approach involves feedback-based recommendations, where a dual closed-loop structure is utilized to train the encoder and decoder simultaneously. This unique design allows for sharing feedback signals between these components, ultimately leading to more refined and effective recommendations [293].

In contrast, interest-based recommendations take advantage of an attention-based memory network to understand how users' interests impact their interactions with friends. This method helps distinguish key factors that influence the relationships between users and their friends, contributing to more tailored recommendations [294].

For POI-based recommendations, an innovative approach is employed, integrating auxiliary attribute information using neural matrix factorization. This technique combines convolutional neural networks and attention mechanisms to enhance recommendation accuracy, particularly in scenarios involving Points of Interest [295]. Moreover, a novel POI recommendation model designed for fitness enthusiasts considers both temporal and spatial preferences. This model incorporates a fusion method that combines similarity and spatial factors in the calculation of the final recommendation similarity [296].

In job recommender systems, there are two primary approaches: content-based filtering, which extracts profile content, and collaborative filtering, which relies on user behavior in the form of ratings [288]. Additionally, a specialized career recommendation model tailored for college students employs a hybrid convolutional neural network to provide valuable career guidance [289].

h: SOCIAL MEDIA RECOMMENDATIONS

Recommendation systems often include a "Social Media" category, which focuses on improving user engagement and social interactions by providing personalized recommendations. This category typically includes friend, group, and location-based recommendations. Kang et al. [297] used a random forest method to analyze call logs, an important feature of personalized data, to identify highly correlated data between call data and new outgoing calls. This information was then learned using a neural network. To address the cold-start problem of group event recommendation, Li et al. [298] proposed a new hybrid deep framework. Yang et al. [299] proposed a hybrid neural network approach that extracts features from both text and images to incorporate them into a sequence-to-sequence model for hashtag recommendation. Gong et al. [71] proposed DFRec++, a hybrid deep neural network framework that combines attribute attention and network embeddings to provide social friend recommendations using interactive semantics and contextual enhancement.

i: TOURISM RECOMMENDATIONS

Tourism is a category that focuses on recommendation systems applied to tourism platforms, such as travel websites and tourist attractions. These systems aim to provide personalized travel recommendations to improve user satisfaction and retention. Fang et al. [300] proposed and evaluated BERT-based baseline models for the travel conversational recommender system and compared them with several representative non-conversational and conversational recommender system models. Zhu et al. [301] proposed a novel model named neural attentive travel package recommendation (NATR) for tourism e-commerce by combining users' long-term and short-term preferences. Xia et al. [302] developed a deep neural network recommendation model with three modalities that utilized an embedding layer, pooling layer, and fully connected layer.

4) DATASET AND PERFORMANCE MEASUREMENT METRICS

This sub-subsection discusses two crucial aspects for evaluating recommendation systems based on deep learning techniques. These aspects are the collection of datasets and the variety of performance measurement metrics commonly used to evaluate such systems. Together, they provide a solid foundation for accurately evaluating and benchmarking deep learning-based recommendation techniques.

a: DATASET COMPILATION

We conducted an exhaustive analysis of 787 articles to curate a meticulously selected collection of 81 datasets labeled as da1 to da81. We aimed to provide valuable insights into dataset analysis and recommendation system research for researchers and practitioners.

These datasets are publicly available real-world datasets commonly used in recommendation systems research. They cover various domains, including e-commerce, social media, music, movies, books, etc. Our selection process was rigorous, with each dataset being reviewed and selected based on relevance, diversity, and usefulness.

RQ1-2: *What popular datasets are used for testing deep learning-based recommendation systems?*

Table 11 presents a comprehensive list of commonly used datasets in recommendation system experiments. These datasets can be specific to particular geographic regions, such as Brazilian E-Commerce, Chengdu, and Chinese Capital, or they can be global platforms like Amazon, Google Play, and YouTube. The table contains associated details for each dataset.

Our curated collection of datasets serves as an invaluable resource for researchers and practitioners looking to explore, experiment, and innovate across diverse domains. These datasets provide a rich landscape for researchers to conduct experiments and analyze data across domains and industries. We believe that our selection of datasets will help advance the field of recommendation systems research and provide valuable insights into dataset analysis for years to come.

b: PERFORMANCE MEASUREMENT METRICS

The evaluation of recommendation systems involves the use of a variety of performance measurement metrics. These metrics help to quantify the effectiveness and accuracy of such systems. They are derived from the analysis of 787 articles and provide standardized benchmarks for assessing different recommendation algorithms. The metrics can be categorized into standard and non-standard, each with unique features for evaluating recommendation system performance.

TABLE 11. List of datasets used in studies.

Dataset Names
da1: ABHR-1, **da2**: ACM, **da3**: AliExpress, **da4**: All the News, **da5**: Amazon, **da6**: Korea Enterprise Data (KED), **da7**: Apple, **da8**: Automotive, **da9**: Book-Crossing, **da10**: LDOS-CoMoDa, **da11**: Card Transactions, **da12**: Careerbuilder, **da13**: DePaul, **da14**: Chinese Capital, **da15**: CIFAR-10, **da16**: CIKM Cup, **da17**: Citation, **da18**: CiteSeer, **da19**: CiteULike, **da20**: ColdGAN, **da21**: Criteo, **da22**: DBLP, **da23**: Diginetica, **da24**: Epinions, **da25**: FilmTrust, **da26**: Flixster, **da27**: Foursquare, **da28**: GANDI, **da29**: GeoLife, **da30**: Good Books, **da31**: Google Play, **da32**: GroupLens, **da33**: GTZAN Music, **da34**: IMDb, **da35**: iOS, **da36**: IPTV, **da37**: Iris, **da38**: Jester, **da39**: Jingdong, **da40**: KDD2012-Cup, **da41**: Kindle Store, **da42**: Last.fm, **da43**: LBSNs, **da44**: MNIST, **da45**: Movielens, **da46**: Moviepilot, **da47**: MSNBC, **da48**: Naukari, **da49**: Netflix, **da50**: PatentNet, **da51**: ProgrammableWeb, **da52**: Travel-STS, **da53**: RecSys Challenge, **da54**: InCarMusic, **da55**: Tijuana-Restaurant, **da56**: Taobao, **da57**: Titanic, **da58**: Tmall, **da59**: TripAdvisor, **da60**: Twitter, **da61**: Web API, **da62**: Weblog, **da63**: Weibo, **da64**: CARSKit, **da65**: Yelp, **da66**: YouTube, **da67**: EachMovie, **da68**: Ciao, **da69**: Douban, **da70**: MXPlayer, **da71**: DePaulMovie, **da72**: ReDial, **da73**: OpenDialKG, **da74**: Beer, **da75**: EasyMovide, **da76**: Jaccard, **da77**: Levenshtein, **da78**: WISDOMAIN Patent, **da79**: DePaulMovie, **da80**: Frappe, **da81**: Retailrocket

RQ1-3: *What evaluation metrics are commonly used to assess deep learning-based recommendation systems?*

Table 12 summarizes these performance metrics. The standard metrics include accuracy, F-measure, hit ratio (HR), mean average precision (MAP), precision, recall, and root mean square error (RMSE), among others. Each metric measures a different aspect of recommendation system performance.

Non-standard metrics, such as the area under the curve (AUC), mean reciprocal rank (MRR), and standardized discount cumulative return (SDCR), offer different perspectives for evaluating recommendation systems. The choice of metric depends on the specific context of evaluation and the goals of the recommendation system.

The full list of metrics includes accuracy, advanced loss function, F-measure, F1 score, hit ratio, mean absolute error, mean average precision, mean absolute percentage error, mean square error, normalized discounted cumulative gain, precision, recall, root mean square error, click-through rate, conversion rate, and F1 score. Each metric serves as a unique benchmark that caters to the specific demands of recommendation systems and their applications.

For example, hit ratio (HR) measures the ratio of selected recommended items, while mean average precision (MAP) calculates the average precision across relevant items. Normalized discounted cumulative gain (NDCG) accounts for item positioning in recommendation lists, whereas root mean square error (RMSE) measures the deviation between predicted and actual rating values. Metrics such as click-through rate (CTR) and conversion rate gauge user engagement and revenue generation efficacy but are less frequently used due to complexity.

In summary, the critical assessment of deep learning-based recommendation systems relies on carefully examining datasets and a comprehensive range of performance measurement metrics. These metrics guide the selection of evaluation criteria and facilitate comparative analyses and the evolution of recommendation algorithms.

C. DATASET AND METRIC OVERVIEW

The insights gleaned from an analysis of 787 studies shed light on the landscape of deep learning techniques, the choice of datasets, and the prevalent evaluation metrics in recommendation systems. The summarized findings, along with an illustrative overview in Figure 6, provide valuable insights into researchers' preferences in this field.

During this extensive examination, it was observed that approximately 22% of the analyzed articles gravitated toward well-established and readily accessible datasets. Among these datasets were Movielens, with 54 articles utilizing it, and Amazon, featured in 40 articles. This inclination towards widely recognized datasets underscores their popularity among researchers, likely owing to their benchmark status and familiarity within the community.

Regarding evaluation metrics, the analysis unveiled the consistent use of metrics such as recall, precision, mean average precision (MAP), mean absolute error (MAE), root mean square error (RMSE), and normalized discounted cumulative gain (NDCG) across studies. Impressively, these core metrics constituted around 36% of the articles, indicating the enduring significance of traditional model-based evaluation methods in recommendation systems. Notably, recall (59 articles) and precision (57 articles) emerged as the top two commonly employed metrics for evaluating recommendation system performance.

However, a notable disparity was observed in adopting online metrics like click-through rate (CTR) and conversion rate. While these metrics hold significant value in assessing user engagement and revenue generation, they appeared less frequently in the studies. This discrepancy can be attributed to the inherent challenges associated with implementing online metrics, which often require access to online platforms for data collection.

It is essential to recognize that the dataset and metric names were primarily extracted from abstracts, with some articles undergoing a manual collection process for full-text screening. Despite the potential limitations in data collection, the overarching trends provide valuable insights into the popularity and prominence of specific datasets and evaluation metrics in the recommendation system research landscape.

D. TECHNIQUES & DATASET SUMMARIZATION BY DOMAINS

In this subsection, we delve into the domain-specific landscape of recommendation systems, categorizing them

TABLE 12. Recommendation system performance measurement metrics.

Metric Names
m1: Accuracy, **m2**: Advanced Loss Function, **m3**: F-Measure, **m4**: R-Squared, **m5**: Hit Ratio (HR), **m6**: Mean Absolute Error (MAE), **m7**: Mean Average Precision (MAP), **m8**: Mean Absolute Percentage Error (MAPE), **m9**: Mean Square Error (MSE), **m10**: Normalized Discounted Cumulative Gain (NDCG), **m11**: Precision, **m12**: Recall, **m13**: Root Mean Square Error (RMSE), **m14**: Click-Through Rate (CTR), **m15**: Conversion Rate, **m16**: F1 score
Non-Standard Metrics
m17: Area Under the Curve (AUC), **m18**: Receiver Operating Characteristic (ROC), **m19**: Mean Reciprocal Rank (MRR), **m20**: Standardized Discount Cumulative Return (SDCR), **m21**: Normalized Root Mean Square Error (NRMSE), **m22**: Average Precision (AP)

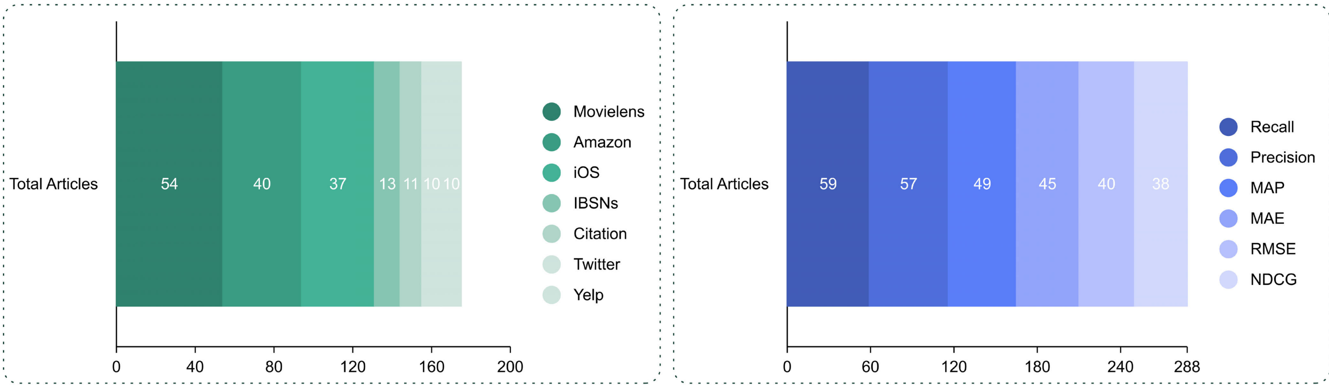

FIGURE 6. Dataset and evaluation metrics in recommendation system.

based on the terms extracted from the selected articles. This approach provides a nuanced understanding of the industries and data types underpinning recommendation systems.

Unlike traditional research domain classifications [46], our method offers a term-based categorization that spans a wide range of domains, ensuring comprehensiveness and facilitating future research in similar domains.

The two tables below offer insights from two perspectives: techniques and datasets. We summarize and share insights since domain-specific articles are our secondary sources. We aim to address the research questions RQ2-2 and RQ2-3.

1) TECHNIQUES BY DOMAINS

This sub-subsection delves into the influence of domain-specific needs and requirements on the selection of deep learning techniques in recommendation systems, addressing the research question:

RQ2-2: *How do domain-specific needs and requirements impact the choice of deep learning techniques used in recommendation systems?*

Table 13 provides a detailed classification of techniques utilized in recommendation systems, categorized by domain. The table is ordered by the total number of articles associated with each domain, including mappings for the top 20 domains. This presentation offers insights into the prevalent techniques within each domain, shedding light on trends and avenues for future research.

The analysis of the table reveals that the domain of **Social (do51)** boasts the highest number of articles (66). The most frequently employed techniques in this domain encompass recurrent neural networks (RNN), social network analysis (SNA), attention-based models, collaborative filtering, and factor Analysis.

In the **Session-based (do5)** recommendation system domain, which is often applied in e-commerce, prevalent techniques include graph neural networks (GNN), attention-based models, feedback mechanisms, adversarial approaches, and recurrent neural networks (RNN).

Other domains like **Point-of-Interest and Interest** also display a diverse array of techniques, including convolutional neural networks (CNN), recurrent neural networks (RNN), and graph neural networks (GNN). For a comprehensive breakdown of techniques in each domain, please refer to the classification table in [175].

It's crucial to note that the choice of recommendation system techniques depends on each application's unique demands and contexts. While some domains exhibit more research articles, selecting the most appropriate techniques should align with the application's requirements.

2) DATASETS BY DOMAINS

This sub-subsection explores the commonly used datasets for evaluating deep learning-based recommendation systems across various domains.

TABLE 13. Classification of recommendation techniques by domains.

Domain Index	Total Article	Technique Category
do51	66	TCC08, TCF07, TCC12, TCC10, TCC04, TCC01, TCC09, TCF09, TCC07, TCA01, TCC06, TCA04, TCF02, TCC02, TCF01
do5	52	TCC10, TCF09, TCC12, TCC04, TCF01, TCC05, TCC08, TCF06, TCF10, TCC07, TCC09, TCC06, TCA01
do36	38	TCC08, TCF07, TCC10, TCC12, TCF08, TCC04, TCF09, TCC07, TCA01, TCF10, TCC01, TCF02
do38	31	TCC08, TCF07, TCC04, TCC07, TCA01, TCC10, TCF09, TCF10, TCA04, TCC01, TCF02
do11	22	TCC07, TCF09, TCC04, TCC12, TCA01, TCC10, TCC08
do37	18	TCC12, TCC01, TCC03, TCC05, TCC04, TCC06, TCA01, TCC09, TCC10, TCF04, TCF09, TCC08
do21	14	TCC04, TCF02, TCC01, TCA01, TCC12, TCF01, TCC07, TCC03, TCC05, TCC08, TCA05
do1	13	TCA03, TCC01, TCC07, TCC04, TCF06, TCC10, TCF07, TCF09, TCC08, TCA01
do10	13	TCC04, TCC01, TCA01, TCC08
do16	13	TCC04, TCC10, TCF07, TCC07, TCF01, TCC06
do26	13	TCC01, TCC04, TCC12, TCC10, TCF02, TCC07
do12	12	TCC10, TCC07, TCA03, TCC12, TCC04, TCF01, TCF04, TCC08, TCF09, TCA01
do27	12	TCC11, TCC04, TCC07, TCF01, TCF02, TCC01, TCC08, TCA01, TCC06, TCA05, TCA03, TCF07
do52	12	TCC02, TCC01, TCC04, TCF09, TCC07, TCC10, TCC12, TCA05
do32	11	TCC07, TCC04, TCC01, TCA03, TCC08
do42	11	TCC01, TCC10, TCF01, TCC05, TCC04, TCC07
do47	11	TCC04, TCF07, TCC10, TCC09, TCC01, TCC12, TCC07, TCA01, TCF02
do53	11	TCF07, TCC04, TCC07, TCA01, TCC10, TCA04, TCF02, TCC08
do8	10	TCC01, TCF02, TCF06, TCC12, TCC06, TCF10, TCF01, TCC10, TCC05, TCC07, TCA05, TCC04
do3	9	TCF06, TCC04, TCC10, TCF07, TCC08

TABLE 14. Classification of datasets by domains for recommendation.

Domain Index	Total Articles	Datasets
do51	22	da60, da24, da42, da65, da43, da26, da35, da22, da27, da66, da45, da25, da63, da2
do38	16	da65, da43, da5, da27, da63
do36	15	da65, da43, da53, da23, da16, da63, da60, da27, da2
do42	11	da17, da2, da22, da18, da50
do5	11	da23, da58, da53, da16, da24, da35, da19
do52	7	da45, da63, da60, da35, da66
do10	7	da45, da32, da34, da5, da60
do21	6	da5, da34, da65, da7, da52, da21, da40
do53	6	da65, da43, da27, da63
do8	5	da35, da5, da46, da45, da3
do7	4	da61, da51
do55	3	da65, da43, da63
do1	3	da61, da47, da32, da5
do11	3	da35, da33
do37	3	da19, da45, da5

RQ2-3: *What are the commonly used datasets for testing deep learning-based recommendation systems across different domains?*

Table 14 provides an in-depth classification of datasets organized by domain and the corresponding number of articles that reference them. This analysis is based on data extracted from 416 domain-specific articles.

The table highlights the following key findings:

- **Social** (do51) stands out as the domain with the most classified datasets, featuring 22 datasets. Prominent datasets in this domain include Twitter, Epinions, and Last.FM, and Weibo.
- **Point-Of-Interest** (do38) closely follows, with 16 articles referencing datasets such as Yelp, LBSN, Amazon, and Foursquare.
- **Interest** (do36) is another popular domain, with commonly used datasets including Yelp, Diginetica, Weibo, Twitter, and ACM.
- **Citation** (do42) recommendation systems are gaining traction, with datasets like Citation, ACM, DBLP, CiteSeer, and PatientNet frequently employed.
- **Session-based** (do5) recommendation systems, commonly applied in e-commerce, utilize datasets like Diginetica, Tmall, RecSys Challenge, CIKM Cup, and Epinions.
- **Tag** (do52) recommendation systems, fueled by the growth of social networks and entertainment, rely on datasets including Movielens, Weibo, Twitter, and YouTube.
- **Movie** (do10) recommendation systems are in high demand, with commonly used datasets being Movielens, GroupLens, IMDb, and Amazon.

These insights underscore the diverse dataset choices tailored to specific domains, reflecting the varied needs and applications of recommendation systems across different industries. Please refer to [175] for a comprehensive dataset-technique mapping.

E. INSIGHTS FROM PRIMARY STUDIES: TECHNIQUES, DATASETS, AND METRICS

In this subsection, we explore the main findings obtained from the primary studies, as well as the techniques, datasets, and evaluation metrics that characterize the field of deep learning-based recommendation systems.

Our selection process was guided by the quality assessment criteria (QAC), which led us to identify 139 primary studies. The main focus was on state-of-the-art deep learning techniques with broad applications beyond specific domains. However, to ensure a manageable scope for the article, we selected studies that integrate at least two technique groups: TCF, TCA, and TCC. This criterion enabled us to explore advanced and multifaceted approaches commonly used in recommendation systems.

Table 15 provides an overview of the top 41 selected articles, while the complete list of primary studies can be found in [175].

1) TECHNIQUE DIVERSITY AND INTEGRATION

The analysis of selected articles points to a diverse range of techniques utilized in deep learning-based recommendation systems. Notably, some techniques have garnered more attention due to their effectiveness in addressing specific challenges. There are several popular techniques in deep learning-based recommendation systems. For instance, the NLP-based technique (TCF01) has been hybridized with deep learning techniques in studies such as Lee et al. [304], Qiu et al. [33], and Hong et al. [309], which improved text analysis performance.

Attention-based techniques (TCC12) have also gained popularity in recommendation systems. Liu et al. [307] proposed the DARMH model, integrating sentiment analysis (TCF02), attention-based (TCC12), convolution neural network (TCC07), and multi-layer (TCC11) techniques. Da'u et al. [313] proposed the MDRR model, incorporating rate prediction (TCA05), collaborative filtering (TCC01), and attention-based (TCC12) techniques. Both studies evaluated their models on Amazon (da5) and Yelp (da65) datasets using metrics RMSE (m13), MAE (m6), and Precision (m11).

Furthermore, mixed techniques combining TCF & TCC or TCA & TCC techniques are commonly used. For instance, Ahmadian et al. [305] proposed the DTRR model, incorporating collaborative filtering (TCC01), neural network (TCC04), and trust aware-based (TCF09) technique. Ouyang et al. [315] presented the two-char review model, combining neural network (TCC04), collaborative filtering (TCC01), and rate prediction (TCA05) techniques.

In summary, the recommendation system process is complex and involves multiple steps. Due to the diversity of datasets and their challenges, combining various techniques to build effective recommendation systems is necessary. Employing various techniques or hybrid approaches makes it possible to address specific limitations and side effects of individual techniques. This diversity and flexibility in techniques contribute to overall performance improvement and enhance the quality of recommendations generated by the system.

2) KEY FINDINGS: TECHNIQUES, DATASETS, AND METRICS

Our analysis of recommendation system research has led us to uncover several core findings. We have explored the various techniques researchers employ, identified the datasets commonly used in their studies, and highlighted the evaluation metrics critical for assessing recommendation system performance.

a: TECHNIQUE LANDSCAPE

Collaborative filtering (TCC01) emerges as the standout technique, finding its place in 15 articles, signifying its enduring relevance in recommendation research. Close behind is natural language processing (TCF01) and neural network (TCC04), which feature prominently in 13 articles each. Sentiment analysis (TCF02) and hybrid-based approaches (TCA01) are noteworthy inclusions in 8 articles, demonstrating their utility in diverse recommendation scenarios. Techniques like aware-based (TCF09) and convolutional neural networks (TCC07) each appear notable in 6 articles. Rate prediction (TCA05) and attention-based mechanisms (TCC12) exhibit their prowess in 5 articles, further enriching the tapestry of techniques.

b: DATASETS OF CHOICE

In recommendation system research, selecting appropriate datasets is pivotal for evaluating proposed algorithms. Certain datasets are preferred among researchers, each offering distinct advantages for experimentation.

- **Amazon's Dataset (da5)** stands out prominently, appearing in 29 articles. Its extensive collection comprises 142.8 million reviews on Amazon products spanning nearly two decades. This dataset encompasses user profiles, item metadata, and user-generated reviews. Researchers like Serrano et al. [329] and Shoja et al. [243] have harnessed this data source to fuel their investigations, demonstrating its value in assessing recommendation algorithms.
- **MovieLens (da45)**, with its comprehensive MovieLens-100K, MovieLens-1M, and MovieLens-20M datasets, plays a significant role in recommendation system research [42]. These datasets encompass user-item rating pairs, timestamps, movie attributes, tags, and user demographic features. With 18 articles utilizing MovieLens, including Yu et al. [144], it is evident that these datasets offer a versatile benchmark for evaluating collaborative filtering and knowledge graph-based recommendation systems.
- **Yelp's Dataset (da65)** assumes significance in nine articles. Like Amazon's dataset, Yelp's offering includes reviews, user ratings, and other contextual information. Researchers have leveraged this dataset to explore user-item collaborative filtering and Point of Interest (POI) recommendation tasks [42].
- **Book-Crossing (da9)** has provided a solid foundation for six research endeavors. This dataset focuses on book-related data, including user ratings and book attributes,

TABLE 15. Summary of selected primary studies on deep learning-based recommendation systems.

Article	Year	Technique	Model Name	Dataset	Metric
[303]	2022	TCC10, TCF10	Sirius	da5, da45, da70	m12, m14, m18
[304]	2022	TCF01, TCC04	DBR	da6	m1, m16, m17
[305]	2022	TCC01, TCC04, TCF09	DTRR	da24, da26	m6, m10, m11, m12
[306]	2022	TCF02, TCC08, TCA03	Adaptive LSTM	da5	m1, m6, m10, m11, m13
[307]	2022	TCF02, TCC12, TCC07, TCC11	DARMH	da5	m9
[308]	2022	TCC01, TCA01, TCC04	User-User Network with DNN	da26, da34, da45	m1, m13, m6, m15
[33]	2022	TCF01, TCF02, TCA01	MHRM	da5	m6, m5, 19
[155]	2022	TCF09, TCC10	cGCMC and cGCMCF	da10, da13, da52, da54, da55	m6, m13
[309]	2023	TCF01, TCC11	TPEDTR	da11	m12, m15, m10, m18, m6
[113]	2023	TCC01, TCA04	Dual DMF	da45	m6, m8
[89]	2022	TCC04, TCC06, TCF09	Context-Aware with NN & AE	da55, da64, da71, da54	m7, m11
[310]	2023	TCF01, TCC04	ASR	da72, da73	m12, m18
[311]	2021	TCC01, TCF01	Two-Phase DL	da5	m13, m15, m1
[312]	2021	TCC01, TCA01, TCA04, TCF06	HBSADE	da5, da9	m10, m11, m12, m15, m20
[313]	2021	TCA05, TCC01, TCC12	MDRR	da5, da65	m13, m6, m11
[95]	2021	TCF01, TCF02, TCC04, TCA05	MrRec	da5	m9
[314]	2021	TCF01, TCC07	DL Architecture	No Specific	m11, m12, m15
[157]	2021	TCC01, TCC04, TCA01	Privacy Hybrid RS	da9, da25, da45	m1, m13, m6, m9, m11, m12
[254]	2021	TCF09	DDPG	da45	m6, m13
[315]	2021	TCC04, TCF01, TCA05	Two-Char Review	da5, da65	m10, m13
[316]	2023	TCF02, TCF01, TCC04	SARWAS	da5	m11, m6, m13
[317]	2020	TCC04, TCA01	NeuralPSL	da65, da74	m9
[318]	2020	TCC12, TCC08, TCF10	Attention GRU	da53	m12, m18
[235]	2020	TCC01, TCC04, TCA04, TCC06	FDAE and FAE	da45, da75	m6, m13
[319]	2022	TCC04, TCC07, TCF10	DACNN	da5, da45, da65	m21, m7, m12, m11
[320]	2020	TCC07, TCA05	JDRM	da65	m13
[321]	2020	TCC02, TCA01	DUPIA	da5, da45	m13
[322]	2020	TCF06, TCC03, TCF01, TCA01	DST-HRS	da5, da45	m13, m11, m12
[154]	2020	TCF01, TCC01	DCC-PersIRE	da76, da77	m3, m13, m12, m11
[160]	2020	TCC04, TCA01	DNNRec	da45, da25, da9	m1, m9, m13, m6
[323]	2020	TCC07, TCC12, TCA03	ADLFM	da5	m6, m9
[236]	2020	TCA04, TCFO1, TCC01	CF Factor M&A Framework	da78	No Specific
[324]	2020	TCC07, TCA05, TCF02	REAO	da5, da65	m6, m15
[325]	2020	TCC01, TCC07, TCA05	AODR	da5, da65	m13, m6, m11, m7
[326]	2020	TCC01, TCF06	CA-NCF	da45, da59, da79	m6, m11
[221]	2020	TCC07, TCC05, TCA01, TCF09	ADHR	da5, da45	m10, m12
[237]	2019	TCA04, TCC07	DLFM-HSM	da5, da45	m6, m9
[226]	2019	TCA01, TCC04, TCC11	DMFL	da9, da45	m12, m16
[327]	2018	TCC01, TCC11, TCC07, TCF09	WDMMA	da80, da45	m13, m16, m17
[328]	2022	TCC06, TCC03, TCA01	Autoencoder Hybrid	da9, da45	m13, m6
[210]	2022	TCF10, TCC12	DeepInteract	da27, da5, da81	m18, m10, m16

making it a valuable resource for evaluating book recommendation systems [330].

In summary, choosing a dataset is critical in recommendation system research. The preference for specific datasets, such as Amazon, MovieLens, Yelp, and Book-Crossing, reflects their suitability for various recommendation tasks. Researchers harness these datasets to assess collaborative filtering, sequential recommendation, and other recommendation system paradigms, ultimately advancing the field's understanding and capabilities. For more information regarding the recommendation system datasets, please refer to [331].

c: EVALUATION METRICS

Several important metrics are used to assess recommendation systems' performance. One such metric is the Mean Absolute Error (MAE) (m6), a popular choice used in 17 articles. MAE is calculated in the following way:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|r_i - \hat{r}_i|$$

where: n is the total number of ratings, r_i represents the actual rating given by the user for item i, $\hat{r}_i$ denotes the predicted rating for item i.

Similarly, Root Mean Square Error (RMSE) (m13) is another widely adopted metric featured in 18 articles. RMSE is computed as:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(r_i - \hat{r}_i)^2}$$

Precision (m11) and Recall (m12) are also significant contributors to the evaluative landscape, with 14 and 15 articles, respectively, employing them. Precision and Recall are defined as:

$$Precision = \frac{TP}{TP + FP}$$
$$Recall = \frac{TP}{TP + FN}$$

where: TP is the number of true positives, FP is the number of false positives, FN is the number of false negatives.

Normalized Discounted Cumulative Gain (NDCG) (m10) is a trusted metric in 11 articles, demonstrating its continued relevance in assessing recommendation system performance. The formula for NDCG has been previously provided:

$$nDCG@k = \frac{1}{IDCG@k}\sum_{i=1}^{k}\frac{2^{rel_i} - 1}{\log_2(i+1)}$$

where $nDCG@k$ is the normalized discounted cumulative gain at a given cutoff k, $IDCG@k$ is the ideal discounted cumulative gain at cutoff k, and rel_i represents the relevance score of the item at position i in the ranked list of recommendations.

These metrics collectively serve as valuable tools for evaluating and comparing recommendation system performance, aiding researchers and practitioners in pursuing effective recommendation algorithms.

Please refer to [175] for a comprehensive breakdown and further analysis.

VII. LIMITATION AND FUTURE WORK

This section discusses the limitations of our study and outlines avenues for future research. Despite the valuable insights gained, it's essential to acknowledge the constraints within our approach.

A. LIMITATIONS IN OUR STUDY AND FUTURE WORK

Our analysis offers a comprehensive examination of deep learning-based recommendation systems. However, it's important to consider some limitations that could affect the interpretation of our findings. These limitations create opportunities for future research and refinement of our methodology.

One limitation is that we only focused on peer-reviewed articles, meaning we may have missed out on state-of-the-art techniques published in other forms. It may be worth exploring non-traditional publication sources to gain additional insights. Furthermore, we selected articles based on title keywords, which could have limited their inclusion. Future studies could consider broader inclusion criteria.

Additionally, our analysis provides a broad overview of the techniques' application, popularity, and categorization, rather than an in-depth evaluation of each technique. Future studies could delve deeper into each category of techniques and evaluate their performance in greater detail.

Lastly, due to the large number of articles in the domain-based category, we extracted information from abstracts, titles, and keywords, potentially missing relevant data in datasets and metrics.

Despite these limitations, our findings still provide significant value in understanding the employed techniques and dataset preferences, offering an overview of the field of recommendation systems. This information can serve as a foundation for further investigations and guide researchers and practitioners in their work. Therefore, even with the limitations mentioned above, this practice provides worthwhile insights for those involved in recommendation systems research and application.

B. CURRENT STUDY LIMITATIONS AND SUGGESTIONS

Deep learning-powered recommendation systems possess immense potential in different domains. However, they confront challenges that need addressing to boost their performance and reliability. These challenges extend beyond typical problems such as cold-start and data sparsity, which researchers have been dealing with. It is essential to recognize that enhancing performance requires more than just refining the techniques themselves.

Firstly, the selection of techniques should be tailored to the specific characteristics of the application domain. Researchers must carefully evaluate which techniques are most suitable for their particular problem and establish a clear classification strategy to ensure consistency and facilitate the discovery of related work.

Secondly, recommendation systems have been developed and tested in specific domains like e-commerce or entertainment. To enhance recommendation models, exploring their potential application in a broader range of domains and utilizing diverse data sources, including industry data, e-commerce data, publication sources, and contextual data like census data for point-of-interest recommendations, is necessary.

Lastly, while offline metrics like recall and precision are commonly used to evaluate recommendation systems, online metrics that measure real-time performance are necessary to reflect system performance in actual deployment settings. By addressing these challenges, we can improve the reliability and performance of deep learning-based recommendation systems across diverse domains.

On the other hand, based on our analysis, we suggest the following strategies to enhance the performance and reliability of deep learning-based recommendation systems:

1) **Clear Classification Criteria**: Develop precise classification criteria for recommendation systems based on hybridity and specific techniques to enhance consistency and clarity. A new classification system should cater to the evolving needs of recommendation systems research.
2) **Utilize Novel Techniques**: Explore innovative techniques within recommendation systems, including new neural network architectures and embedding methods, to push the boundaries and enhance performance. Adapt these architectures to diverse recommendation scenarios.
3) **Specialize Techniques**: Carefully select techniques for recommendation systems based on domain-specific characteristics to improve relevance and performance. Researchers should consider the appropriateness of techniques across various application domains.
4) **Expand Application Across Domains**: Extend the application of recommendation systems to diverse domains such as healthcare, finance, or education, broadening the impact of recommendation technologies.
5) **Utilize More Data**: Incorporate more data sources, including industry-specific datasets, to enhance recommendation accuracy and relevance, reflecting real-world usage more accurately.
6) **Develop Online Metrics**: Create online metrics that enable real-time assessment of recommendation system performance, providing more timely and relevant feedback on system behavior.
7) **Increase Interpretability**: Improve the interpretability of deep learning-based recommender systems by integrating attention mechanisms and visualization techniques, offering deeper insights into system operations.
8) **Address Bias and Transparency**: Mitigate biases in training data through data cleansing or augmentation methods and enhance transparency by providing explanations for recommendations.
9) **Improve Personalization**: Explore techniques for enhancing personalization in deep learning models by incorporating user feedback and advanced feature engineering methods, utilizing user and contextual information for tailored recommendations.

Implementing these strategies will contribute to developing more effective and adaptable recommendation systems and address the challenges currently in the field.

VIII. CONCLUSION

Our research focused on analyzing recommendation systems that utilize deep learning techniques. We found that neural collaborative filtering was the most commonly used technique across various domains, although the popularity of specific techniques varied depending on the domain. This highlights the importance of considering domain-specific traits when selecting an appropriate technique.

In our analysis, we discovered that matrix factorization was the most frequently utilized technique in the primary studies we examined, followed by graph neural networks and attention mechanisms. Other techniques, such as convolutional neural networks, deep reinforcement learning, knowledge graphs, and sequential recommendation, were also frequently employed. Among the different domains, social, session-based, and point-of-interest (POI) recommendation systems were the most popular, with numerous articles mentioning their use.

Our analysis made significant contributions to the field of deep learning-based recommendation systems. Our systematic literature review (SLR) provided a comprehensive understanding of the state of deep learning-based recommendation systems, summarizing insights and trends from recent articles. We also successfully analyzed and summarized the latest advanced deep learning techniques developed in the past five years, highlighting their applications in recommendation systems. Additionally, we categorized deep learning techniques and their application domains into meaningful groups based on study terminologies, facilitating better understanding and navigation. Our creation of a term classification system is a valuable resource, helping researchers effectively target specific terms within the field. Furthermore, we provided a summary of the datasets and metrics commonly used in the reviewed papers, serving as a reference for future researchers.

In conclusion, our research has played an important role in advancing the field of deep learning-based recommendation systems. Our work has enhanced our understanding of current trends, clarified domain-specific terminology, and provided valuable tools for researchers to navigate and contribute to this evolving and crucial study area.

REFERENCES

[1] G. Bathla, R. Rani, and H. Aggarwal, "Improving recommendation techniques by deep learning and large scale graph partitioning," *Int. J. Adv. Comput. Sci. Appl.*, vol. 9, no. 10, pp. 403–409, 2018.
[2] N. L. Anantha and B. Bathula, "Comparative study on traditional recommender systems and deep learning based recommender systems," *Adv. Model. Anal. B*, vol. 61, no. 2, pp. 64–69, Jun. 2018.
[3] A. Akbar, P. Agarwal, and A. Obaid, "Recommendation engines-neural embedding to graph-based: Techniques and evaluations," *Int. J. Nonlinear Anal. Appl.*, vol. 13, no. 1, pp. 2411–2423, Mar. 2022.
[4] P. D. Rosa, M. Deriaz, M. D. Marco, and L. Laura, "Service recommendations with deep learning: A study on neural collaborative engines," *Pacific Asia J. Assoc. Inf. Syst.*, vol. 14, pp. 59–70, Jan. 2022.
[5] Z. Batmaz and C. Kaleli, "AE-MCCF: An autoencoder-based multi-criteria recommendation algorithm," *Arabian J. Sci. Eng.*, vol. 44, no. 11, pp. 9235–9247, Nov. 2019.
[6] Y. Geng, Y. Zhu, Y. Li, X. Sun, and B. Li, "Multi-feature extension via semi-autoencoder for personalized recommendation," *Appl. Sci.*, vol. 12, no. 23, p. 12408, Dec. 2022.
[7] N. Chizari, N. Shoeibi, and M. Moreno-García, "A comparative analysis of bias amplification in graph neural network approaches for recommender systems," *Electronics*, vol. 11, no. 20, p. 3301, Oct. 2022.
[8] Z. Qiu, Y. Hu, and X. Wu, "Graph neural news recommendation with user existing and potential interest modeling," *ACM Trans. Knowl. Discovery Data*, vol. 16, no. 5, pp. 1–17, Oct. 2022.
[9] Z. Huang, Y. Liu, C. Zhan, C. Lin, W. Cai, and Y. Chen, "A novel group recommendation model with two-stage deep learning," *IEEE Trans. Syst., Man, Cybern., Syst.*, vol. 52, no. 9, pp. 5853–5864, Sep. 2022.

[10] S. Bandyopadhyay and S. Thakur, "Product prediction and recommendation in e-commerce using collaborative filtering and artificial neural networks: A hybrid approach," in *Intelligent Computing Paradigm: Recent Trends*, vol. 784. Singapore: Springer, 2020.

[11] P. Basile, C. Greco, A. Suglia, and G. Semeraro, "Deep learning and hierarchical reinforcement learning for modeling a conversational recommender system," *Intelligenza Artificiale*, vol. 12, no. 2, pp. 125–141, Jan. 2019.

[12] N. Hanafi, E. Pujastuti, A. Laksito, R. Hardi, R. Perwira, A. Arfriandi, and N. Asroni, "Handling sparse rating matrix for e-commerce recommender system using hybrid deep learning based on LSTM, SDAE and latent factor," *Int. J. Intell. Eng. Syst.*, vol. 15, no. 2, pp. 379–393, Jan. 2022.

[13] T. Liu, Q. Wu, L. Chang, and T. Gu, "A review of deep learning-based recommender system in e-learning environments," *Artif. Intell. Rev.*, vol. 55, no. 8, pp. 5953–5980, Dec. 2022.

[14] P. Balasamy and K. Athiyappagounder, "An optimized feature selection method for e-learning recommender system using deep neural network based on multilayer perceptron," *Int. J. Intell. Eng. Syst.*, vol. 15, no. 5, pp. 461–472, Jul. 2022.

[15] R. Alatrash, R. Priyadarshini, H. Ezaldeen, and A. Alhinnawi, "Augmented language model with deep learning adaptation on sentiment analysis for e-learning recommendation," *Cogn. Syst. Res.*, vol. 75, pp. 53–69, Sep. 2022.

[16] W. Chang, D. Sun, and Q. Du, "Intelligent sensors for POI recommendation model using deep learning in location-based social network big data," *Sensors*, vol. 23, no. 2, p. 850, Jan. 2023.

[17] S. Safavi and M. Jalali, "DeePOF: A hybrid approach of deep convolutional neural network and friendship to Point-of-Interest (POI) recommendation system in location-based social networks," *Concurrency Comput., Pract. Exper.*, vol. 34, no. 15, Jul. 2022, Art. no. e6981.

[18] L. Sun, "POI recommendation method based on multi-source information fusion using deep learning in location-based social networks," *J. Inf. Process. Syst.*, vol. 17, no. 2, pp. 352–368, 2021.

[19] Y. Liu and A.-B. Wu, "POI recommendation method using deep learning in location-based social networks," *Wireless Commun. Mobile Comput.*, vol. 2021, Jul. 2021, Art. no. 9120864.

[20] X. Lu and H. Zhang, "A content-aware POI recommendation method in location-based social networks based on deep CNN and multi-objective immune optimization," *J. Internet Technol.*, vol. 21, no. 6, pp. 1761–1772, 2021.

[21] L. Wan, F. Xia, X. Kong, C.-H. Hsu, R. Huang, and J. Ma, "Deep matrix factorization for trust-aware recommendation in social networks," *IEEE Trans. Netw. Sci. Eng.*, vol. 8, no. 1, pp. 511–528, Jan. 2021.

[22] C. Tang and J. Zhang, "An intelligent deep learning-enabled recommendation algorithm for teaching music students," *Soft Comput.*, vol. 26, no. 20, pp. 10591–10598, Oct. 2022.

[23] P. Magron and C. Févotte, "Neural content-aware collaborative filtering for cold-start music recommendation," *Data Mining Knowl. Discovery*, vol. 36, no. 5, pp. 1971–2005, Sep. 2022.

[24] P. Linlin, "Tchaikovsky music recommendation algorithm based on deep learning," *Mobile Inf. Syst.*, vol. 2022, Sep. 2022, Art. no. 1265451.

[25] H. Xia, K. Huang, and Y. Liu, "Unexpected interest recommender system with graph neural network," *Complex Intell. Syst.*, vol. 9, no. 4, pp. 3819–3833, Aug. 2023.

[26] A. M. Al-Sbou and N. H. A. Rahim, "An improved hybrid semi-stacked autoencoder for item-features of recommendation system (iHSARS)," *Indonesian J. Electr. Eng. Comput. Sci.*, vol. 30, no. 1, pp. 481–490, Apr. 2023.

[27] W. Jing, A. K. Sangaiah, L. Wei, L. Shaopeng, L. Lei, and L. Ruishi, "Multi-view fusion for recommendation with attentive deep neural network," *Evol. Intell.*, vol. 15, no. 4, pp. 2619–2629, Dec. 2022.

[28] Z. Lyu, Y. Wu, J. Lai, M. Yang, C. Li, and W. Zhou, "Knowledge enhanced graph neural networks for explainable recommendation," *IEEE Trans. Knowl. Data Eng.*, vol. 35, no. 5, pp. 4954–4968, May 2023.

[29] C. Dang, M. Moreno-García, and F. De la Prieta, "Using hybrid deep learning models of sentiment analysis and item genres in recommender systems for streaming services," *Electronics*, vol. 10, no. 20, p. 2459, Oct. 2021.

[30] F. Yang, H. Wang, and J. Fu, "Improvement of recommendation algorithm based on collaborative deep learning and its parallelization on spark," *J. Parallel Distrib. Comput.*, vol. 148, pp. 58–68, Feb. 2021.

[31] Y. Huo, "Talent management recommendation technology based on deep learning," *Math. Problems Eng.*, vol. 2022, Sep. 2022, Art. no. 7697192.

[32] V. Tapaskar and M. M. Math, "Deep recurrent Gaussian Nesterovs recommendation using multi-agent in social networks," *Evolving Syst.*, vol. 13, no. 3, pp. 435–452, Jun. 2022.

[33] G. Qiu, C. Song, L. Jiang, and Y. Guo, "Multi-view hybrid recommendation model based on deep learning," *Intell. Data Anal.*, vol. 26, no. 4, pp. 977–992, Jul. 2022.

[34] Y. Li and X. Tong, "Trust recommendation based on deep deterministic strategy gradient algorithm," *IEEE Access*, vol. 10, pp. 48274–48282, 2022.

[35] X. Huang and X. Liu, "Incorporating a topic model into a hypergraph neural network for searching-scenario oriented recommendations," *Appl. Sci.*, vol. 12, no. 15, p. 7387, Jul. 2022.

[36] D. H. Tran, Q. Z. Sheng, W. E. Zhang, N. H. Tran, and N. L. D. Khoa, "CupMar: A deep learning model for personalized news recommendation based on contextual user-profile and multi-aspect article representation," *World Wide Web*, vol. 26, no. 2, pp. 713–732, Mar. 2023.

[37] D. Wu, B. Sun, and M. Shang, "Hyperparameter learning for deep learning-based recommender systems," *IEEE Trans. Services Comput.*, vol. 16, no. 4, pp. 2699–2712, Jul./Aug. 2023.

[38] M. Ma, G. Wang, and T. Fan, "Improved DeepFM recommendation algorithm incorporating deep feature extraction," *Appl. Sci.*, vol. 12, no. 23, p. 11992, Nov. 2022.

[39] S. Wang, L. Huang, A. Gao, J. Ge, T. Zhang, H. Feng, I. Satyarth, M. Li, H. Zhang, and V. Ng, "Machine/deep learning for software engineering: A systematic literature review," *IEEE Trans. Softw. Eng.*, vol. 49, no. 3, pp. 1188–1231, Mar. 2023.

[40] X. Chen, L. Yao, J. McAuley, G. Zhou, and X. Wang, "Deep reinforcement learning in recommender systems: A survey and new perspectives," *Knowl.-Based Syst.*, vol. 264, Mar. 2023, Art. no. 110335.

[41] G. C. Marinó, A. Petrini, D. Malchiodi, and M. Frasca, "Deep neural networks compression: A comparative survey and choice recommendations," *Neurocomputing*, vol. 520, pp. 152–170, Feb. 2023.

[42] S. Wu, F. Sun, W. Zhang, X. Xie, and B. Cui, "Graph neural networks in recommender systems: A survey," *ACM Comput. Surv.*, vol. 55, no. 5, pp. 1–37, May 2023.

[43] L. Wu, X. He, X. Wang, K. Zhang, and M. Wang, "A survey on accuracy-oriented neural recommendation: From collaborative filtering to information-rich recommendation," *IEEE Trans. Knowl. Data Eng.*, vol. 35, no. 5, pp. 4425–4445, May 2023.

[44] Z. Ali, P. Kefalas, K. Muhammad, B. Ali, and M. Imran, "Deep learning in citation recommendation models survey," *Expert Syst. Appl.*, vol. 162, Dec. 2020, Art. no. 113790.

[45] G. Zhang, Y. Liu, and X. Jin, "A survey of autoencoder-based recommender systems," *Frontiers Comput. Sci.*, vol. 14, no. 2, pp. 430–450, Apr. 2020.

[46] S. Zhang, L. Yao, A. Sun, and Y. Tay, "Deep learning based recommender system: A survey and new perspectives," *ACM Comput. Surv.*, vol. 52, no. 1, pp. 1–38, Jan. 2020.

[47] R. Mu, "A survey of recommender systems based on deep learning," *IEEE Access*, vol. 6, pp. 69009–69022, 2018.

[48] D. Alahmadi and F. Alruwaili, "Deep learning for MOOCs course recommendation systems: State of the art survey," *Int. Trans. J. Eng. Manage. Appl. Sci. Technol.*, vol. 12, no. 11, 2021, Art. no. 12A11Q.

[49] L. Salau, M. Hamada, R. Prasad, M. Hassan, A. Mahendran, and Y. Watanobe, "State-of-the-art survey on deep learning-based recommender systems for e-learning," *Appl. Sci.*, vol. 12, no. 23, p. 11996, Nov. 2022.

[50] M. A. Islam, M. M. Mohammad, S. S. S. Das, and M. E. Ali, "A survey on deep learning based Point-of-Interest (POI) recommendations," *Neurocomputing*, vol. 472, pp. 306–325, Feb. 2022.

[51] Y. Dai and J. Xu, "Study of online learning resource recommendation based on improved BP neural network," *Int. J. Embedded Syst.*, vol. 14, no. 2, p. 101, 2021.

[52] T. K. Dang, Q. P. Nguyen, and V. S. Nguyen, "A study of deep learning-based approaches for session-based recommendation systems," *Social Netw. Comput. Sci.*, vol. 1, no. 4, p. 216, Jul. 2020.

[53] K. Barbara and C. Stuart, "Guidelines for performing systematic literature reviews in software engineering," Version 2.3, Dept. Comput. Sci., Keele Univ., Keele, U.K., Tech. Rep. EBSE-2007-01, 2007, pp. 1–26.

[54] R. F. Doh, C. Zhou, J. K. Arthur, I. Tawiah, and B. Doh, "A systematic review of deep knowledge graph-based recommender systems, with focus on explainable embeddings," *Data*, vol. 7, no. 7, p. 94, Jul. 2022.

[55] S. Safavi, M. Jalali, and M. Houshmand, "Toward point-of-interest recommendation systems: A critical review on deep-learning approaches," *Electronics*, vol. 11, no. 13, p. 1998, Jun. 2022.

[56] Z. Batmaz, A. Yurekli, A. Bilge, and C. Kaleli, "A review on deep learning for recommender systems: Challenges and remedies," *Artif. Intell. Rev.*, vol. 52, no. 1, pp. 1–37, Jun. 2019.

[57] A. Da'u and N. Salim, "Recommendation system based on deep learning methods: A systematic review and new directions," *Artif. Intell. Rev.*, vol. 53, no. 4, pp. 2709–2748, Apr. 2020.

[58] M. Dong, F. Yuan, L. Yao, X. Wang, X. Xu, and L. Zhu, "A survey for trust-aware recommender systems: A deep learning perspective," *Knowl.-Based Syst.*, vol. 249, Aug. 2022, Art. no. 108954.

[59] H. Huang, S. Luo, X. Tian, S. Yang, and X. Zhang, "Neural explicit factor model based on item features for recommendation systems," *IEEE Access*, vol. 9, pp. 58448–58454, 2021.

[60] Z. Wu, Y. Lu, and Z. Feng, "Application of deep learning technology in the recommendation system of constitutional and constitutional cases," *Wireless Commun. Mobile Comput.*, vol. 2022, Sep. 2022, Art. no. 8444672.

[61] J. Liu, W.-H. Choi, and J. Liu, "Personalized movie recommendation method based on deep learning," *Math. Problems Eng.*, vol. 2021, Feb. 2021, Art. no. 6694237.

[62] S.-T. Zhong, L. Huang, C.-D. Wang, J.-H. Lai, and P. S. Yu, "An autoencoder framework with attention mechanism for cross-domain recommendation," *IEEE Trans. Cybern.*, vol. 52, no. 6, pp. 5229–5241, Jun. 2022.

[63] F. Merabet and D. Benmerzoug, "QoS prediction for service selection and recommendation with a deep latent features autoencoder," *Comput. Sci. Inf. Syst.*, vol. 19, no. 2, pp. 709–733, 2022.

[64] Q. Li and J. Kim, "A deep learning-based course recommender system for sustainable development in education," *Appl. Sci.*, vol. 11, no. 19, p. 8993, Sep. 2021.

[65] A. C. Hansel and A. Wibowo, "Using movie genres in neural network based collaborative filtering movie recommendation system to reduce cold start problem," *Int. J. Emerg. Technol. Adv. Eng.*, vol. 12, no. 3, pp. 63–73, Mar. 2022.

[66] L. Zhang and L. Zhang, "Top-*N* recommendation algorithm integrated neural network," *Neural Comput. Appl.*, vol. 33, no. 9, pp. 3881–3889, May 2021.

[67] D. Roy and M. Dutta, "A systematic review and research perspective on recommender systems," *J. Big Data*, vol. 9, no. 1, p. 59, Dec. 2022.

[68] K. K. Jena, S. K. Bhoi, C. Mallick, S. R. Jena, R. Kumar, H. V. Long, and N. T. K. Son, "Neural model based collaborative filtering for movie recommendation system," *Int. J. Inf. Technol.*, vol. 14, no. 4, pp. 2067–2077, Jun. 2022.

[69] D. K. Behera, M. Das, S. Swetanisha, and P. K. Sethy, "Hybrid model for movie recommendation system using content K-nearest neighbors and restricted Boltzmann machine," *Indonesian J. Electr. Eng. Comput. Sci.*, vol. 23, no. 1, pp. 445–452, Jul. 2021.

[70] S. Safavi and M. Jalali, "RecPOID: POI recommendation with friendship aware and deep CNN," *Future Internet*, vol. 13, no. 3, p. 79, Mar. 2021.

[71] J. Gong, Y. Zhao, S. Chen, H. Wang, L. Du, S. Wang, M. Z. A. Bhuiyan, H. Peng, and B. Du, "Hybrid deep neural networks for friend recommendations in edge computing environment," *IEEE Access*, vol. 8, pp. 10693–10706, 2020.

[72] F. O. Isinkaye, Y. O. Folajimi, and B. A. Ojokoh, "Recommendation systems: Principles, methods and evaluation," *Egyptian Informat. J.*, vol. 16, no. 3, pp. 261–273, Nov. 2015.

[73] W. Zhang, X. Zhang, H. Wang, and D. Chen, "A deep variational matrix factorization method for recommendation on large scale sparse dataset," *Neurocomputing*, vol. 334, pp. 206–218, Mar. 2019.

[74] Y. Yu, L. Zhang, C. Wang, R. Gao, W. Zhao, and J. Jiang, "Neural personalized ranking via Poisson factor model for item recommendation," *Complexity*, vol. 2019, Jan. 2019, Art. no. 3563674.

[75] Y. Liu, S. Wang, M. S. Khan, and J. He, "A novel deep hybrid recommender system based on auto-encoder with neural collaborative filtering," *Big Data Mining Anal.*, vol. 1, no. 3, pp. 211–221, Sep. 2018.

[76] R. Han, K. Chen, and C. Tan, "Curiosity-driven recommendation strategy for adaptive learning via deep reinforcement learning," *Brit. J. Math. Stat. Psychol.*, vol. 73, no. 3, pp. 522–540, Nov. 2020.

[77] V. P. Singh, M. K. Pandey, P. S. Singh, and S. Karthikeyan, "Neural net time series forecasting framework for time-aware web services recommendation," *Proc. Comput. Sci.*, vol. 171, pp. 1313–1322, Jan. 2020.

[78] R. Xiong, J. Wang, N. Zhang, and Y. Ma, "Deep hybrid collaborative filtering for web service recommendation," *Expert Syst. Appl.*, vol. 110, pp. 191–205, Nov. 2018.

[79] D. Liu and C. Yang, "A deep reinforcement learning approach to proactive content pushing and recommendation for mobile users," *IEEE Access*, vol. 7, pp. 83120–83136, 2019.

[80] Q. Hao, K. Zhu, C. Wang, P. Wang, X. Mo, and Z. Liu, "CFDIL: A context-aware feature deep interaction learning for app recommendation," *Soft Comput.*, vol. 26, no. 10, pp. 4755–4770, May 2022.

[81] A. Ahmed, K. Saleem, O. Khalid, J. Gao, and U. Rashid, "Trust-aware denoising autoencoder with spatial–temporal activity for cross-domain personalized recommendations," *Neurocomputing*, vol. 511, pp. 477–494, Oct. 2022.

[82] L. Guo, J. Zhang, L. Tang, T. Chen, L. Zhu, and H. Yin, "Time interval-enhanced graph neural network for shared-account cross-domain sequential recommendation," *IEEE Trans. Neural Netw. Learn. Syst.*, early access, Sep. 7, 2022, doi: 10.1109/TNNLS.2022.3201533.

[83] Y. Ouyang, B. Guo, X. Tang, X. He, J. Xiong, and Z. Yu, "Mobile app cross-domain recommendation with multi-graph neural network," *ACM Trans. Knowl. Discovery Data*, vol. 15, no. 4, pp. 1–21, Aug. 2021.

[84] X. Zhu, G. Tang, P. Wang, C. Li, J. Guo, and S. Dietze, "Dynamic global structure enhanced multi-channel graph neural network for session-based recommendation," *Inf. Sci.*, vol. 624, pp. 324–343, May 2023.

[85] T. Wu, F. Sun, J. Dong, Z. Wang, and Y. Li, "Context-aware session recommendation based on recurrent neural networks," *Comput. Electr. Eng.*, vol. 100, May 2022, Art. no. 107916.

[86] Q. Li, X. Xu, J. Liu, and G. Li, "Learning sequential general pattern and dependency via hybrid neural model for session-based recommendation," *IEEE Access*, vol. 10, pp. 89634–89644, 2022.

[87] M. Zhang, S. Wu, M. Gao, X. Jiang, K. Xu, and L. Wang, "Personalized graph neural networks with attention mechanism for session-aware recommendation," *IEEE Trans. Knowl. Data Eng.*, vol. 34, no. 8, pp. 3946–3957, Aug. 2022.

[88] S. Abinaya, M. K. K. Devi, and A. S. Alphonse, "Enhancing context-aware recommendation using hesitant fuzzy item clustering by stacked autoencoder based smoothing technique," *Int. J. Uncertainty, Fuzziness Knowl.-Based Syst.*, vol. 30, no. 4, pp. 595–624, Aug. 2022.

[89] S.-Y. Jeong and Y.-K. Kim, "Deep learning-based context-aware recommender system considering contextual features," *Appl. Sci.*, vol. 12, no. 1, p. 45, Dec. 2021.

[90] M. A. Abbas, S. Ajayi, M. Bilal, A. Oyegoke, M. Pasha, and H. T. Ali, "A deep learning approach for context-aware citation recommendation using rhetorical zone classification and similarity to overcome cold-start problem," *J. Ambient Intell. Humanized Comput.*, 2022, doi: 10.1007/s12652-022-03899-6.

[91] J. Wang, L. Zhu, T. Dai, and Y. Wang, "Deep memory network with Bi-LSTM for personalized context-aware citation recommendation," *Neurocomputing*, vol. 410, pp. 103–113, Oct. 2020.

[92] C. Wu, F. Wu, Y. Huang, and X. Xie, "Neural news recommendation with negative feedback," *CCF Trans. Pervasive Comput. Interact.*, vol. 2, no. 3, pp. 178–188, Oct. 2020.

[93] I. Tanuma and T. Matsui, "Variational autoencoder-based hybrid recommendation with Poisson factorization for modeling implicit feedback," *IEEE Access*, vol. 10, pp. 60696–60706, 2022.

[94] F. Xue, X. He, X. Wang, J. Xu, K. Liu, and R. Hong, "Deep item-based collaborative filtering for top-*N* recommendation," *ACM Trans. Inf. Syst.*, vol. 37, no. 3, pp. 1–25, Jul. 2019.

[95] P. Liu, L. Zhang, and J. A. Gulla, "Multilingual review-aware deep recommender system via aspect-based sentiment analysis," *ACM Trans. Inf. Syst.*, vol. 39, no. 2, pp. 1–33, Apr. 2021.

[96] A. Da'u and N. Salim, "Sentiment-aware deep recommender system with neural attention networks," *IEEE Access*, vol. 7, pp. 45472–45484, 2019.

[97] H. Liu, W. Wang, Y. Zhang, R. Gu, and Y. Hao, "Neural matrix factorization recommendation for user preference prediction based on explicit and implicit feedback," *Comput. Intell. Neurosci.*, vol. 2022, Jan. 2022, Art. no. 9593957.

[98] N. Khan, Z. Ma, L. Yan, and A. Ullah, "Hashing-based semantic relevance attributed knowledge graph embedding enhancement for deep probabilistic recommendation," *Appl. Intell.*, vol. 53, no. 2, pp. 2295–2320, Jan. 2023.

[99] Y. Pan, F. He, and H. Yu, "A novel enhanced collaborative autoencoder with knowledge distillation for top-*N* recommender systems," *Neurocomputing*, vol. 332, pp. 137–148, Mar. 2019.

[100] S. Wang, C. Huang, J. Li, Y. Yuan, and F.-Y. Wang, "Decentralized construction of knowledge graphs for deep recommender systems based on blockchain-powered smart contracts," *IEEE Access*, vol. 7, pp. 136951–136961, 2019.
[101] Y. Yu, W. Qian, L. Zhang, and R. Gao, "A graph-neural-network-based social network recommendation algorithm using high-order neighbor information," *Sensors*, vol. 22, no. 19, p. 7122, Sep. 2022.
[102] L. Wu, J. Li, P. Sun, R. Hong, Y. Ge, and M. Wang, "DiffNet++: A neural influence and interest diffusion network for social recommendation," *IEEE Trans. Knowl. Data Eng.*, vol. 34, no. 10, pp. 4753–4766, Oct. 2022.
[103] C. Wang, L. Li, H. Zhang, and D. Li, "Quaternion-based knowledge graph neural network for social recommendation," *Knowl.-Based Syst.*, vol. 257, Dec. 2022, Art. no. 109940.
[104] W. Qi, Z. Huang, D. Zhu, and J. Yu, "Graph neural network social recommendation algorithm integrating static and dynamic features," *Int. J. Pattern Recognit. Artif. Intell.*, vol. 36, no. 9, Jul. 2022, Art. no. 2259019.
[105] W. Fan, Y. Ma, Q. Li, J. Wang, G. Cai, J. Tang, and D. Yin, "A graph neural network framework for social recommendations," *IEEE Trans. Knowl. Data Eng.*, vol. 34, no. 5, pp. 2033–2047, May 2022.
[106] C. Liu, Y. Li, H. Lin, and C. Zhang, "GNNRec: Gated graph neural network for session-based social recommendation model," *J. Intell. Inf. Syst.*, vol. 60, no. 1, pp. 137–156, Feb. 2023.
[107] V. Boppana and P. Sandhya, "Web crawling based context aware recommender system using optimized deep recurrent neural network," *J. Big Data*, vol. 8, no. 1, p. 144, Dec. 2021.
[108] O. Tal and Y. Liu, "A joint deep recommendation framework for location-based social networks," *Complexity*, vol. 2019, Mar. 2019, Art. no. 2926749.
[109] B. Cao, M. Peng, Y. Qing, J. Liu, G. Kang, B. Li, and K. K. Fletcher, "Web API recommendation via combining graph attention representation and deep factorization machines quality prediction," *Concurrency Comput., Pract. Exper.*, vol. 34, no. 21, Sep. 2022, Art. no. e7069.
[110] Y. Xiao, C. Li, and V. Liu, "DFM-GCN: A multi-task learning recommendation based on a deep graph neural network," *Mathematics*, vol. 10, no. 5, p. 721, Feb. 2022.
[111] J. Xu, Z. Hu, and J. Zou, "Personalized product recommendation method for analyzing user behavior using DeepFM," *J. Inf. Process. Syst.*, vol. 17, no. 2, pp. 369–384, Apr. 2021.
[112] L. Chen, X. Bi, G. Fan, and H. Sun, "A multitask recommendation algorithm based on DeepFM and graph convolutional network," *Concurrency Comput., Pract. Exper.*, vol. 35, no. 2, Jan. 2023, Art. no. e7498.
[113] A. Tegene, Q. Liu, Y. Gan, T. Dai, H. Leka, and M. Ayenew, "Deep learning and embedding based latent factor model for collaborative recommender systems," *Appl. Sci.*, vol. 13, no. 2, p. 726, Jan. 2023.
[114] P. Sahu, S. Raghavan, and K. Chandrasekaran, "Ensemble deep neural network based quality of service prediction for cloud service recommendation," *Neurocomputing*, vol. 465, pp. 476–489, Nov. 2021.
[115] B. Ahirwadkar and S. Deshmukh, "Deep neural networks for recommender systems," *Int. J. Innov. Technol. Exploring Eng.*, vol. 8, no. 12, pp. 4838–4842, Oct. 2019.
[116] M. Huang and G. Sun, "Research on cross-hierarchical graph network recommendation algorithm based on random walk and convolutional neural network," *Concurrency Comput., Pract. Exper.*, 2021, doi: 10.1002/cpe.6704.
[117] R. J. Ziarani and R. Ravanmehr, "Deep neural network approach for a serendipity-oriented recommendation system," *Expert Syst. Appl.*, vol. 185, Dec. 2021, Art. no. 115660.
[118] S. Tao, C. Shen, L. Zhu, and T. Dai, "SVD-CNN: A convolutional neural network model with orthogonal constraints based on SVD for context-aware citation recommendation," *Comput. Intell. Neurosci.*, vol. 2020, Oct. 2020, Art. no. 5343214.
[119] S. Bansal and N. Baliyan, "Remembering past and predicting future: A hybrid recurrent neural network based recommender system," *J. Ambient Intell. Humanized Comput.*, 2022, doi: 10.1007/s12652-022-04375-x.
[120] L. Zhang, P. Wang, J. Li, Z. Xiao, and H. Shi, "Attentive hybrid recurrent neural networks for sequential recommendation," *Neural Comput. Appl.*, vol. 33, no. 17, pp. 11091–11105, Sep. 2021.
[121] C.-M. Huang and C.-Y. Wu, "The point of interest (POI) recommendation for mobile digital culture heritage (M-DCH) based on the behavior analysis using the recurrent neural networks (RNN) and user-collaborative filtering," *J. Internet Technol.*, vol. 22, no. 4, pp. 821–833, Jul. 2021.
[122] Q. Cui, S. Wu, Q. Liu, W. Zhong, and L. Wang, "MV-RNN: A multi-view recurrent neural network for sequential recommendation," *IEEE Trans. Knowl. Data Eng.*, vol. 32, no. 2, pp. 317–331, Feb. 2020.
[123] N. Nelaturi and G. Devi, "A product recommendation model based on recurrent neural network," *J. Européen Systèmes Automatisés*, vol. 52, no. 5, pp. 501–507, Nov. 2019.
[124] K. Guo and C. Yang, "Temporal–spatial recommendation for caching at base stations via deep reinforcement learning," *IEEE Access*, vol. 7, pp. 58519–58532, 2019.
[125] Y. Wang, M. Huang, X. Zhu, and L. Zhao, "Attention-based LSTM for aspect-level sentiment classification," in *Proc. Conf. Empirical Methods Natural Lang. Process.*, 2016, pp. 606–615.
[126] J. Zhou, G. Cui, S. Hu, Z. Zhang, C. Yang, Z. Liu, L. Wang, C. Li, and M. Sun, "Graph neural networks: A review of methods and applications," *AI Open*, vol. 1, pp. 57–81, Jan. 2020.
[127] B. Howard, M. H. Demuth, O. D. J. Beale, and M. T. Hagan, *Neural Network Design*, 2nd ed. Stillwater, OK, USA: Martin Hagan, 2014.
[128] J. Park and I. W. Sandberg, "Universal approximation using radial-basis-function networks," *Neural Comput.*, vol. 3, no. 2, pp. 246–257, Jun. 1991.
[129] A. Kumar, A. Ganeshan, and A. Choudhary, "Memory augmented neural networks: A comprehensive survey," *IEEE Access*, vol. 9, pp. 45010–45030, 2021.
[130] A. Géron, *Hands-On Machine Learning with Scikit-Learn, Keras, and TensorFlow: Concepts, Tools, and Techniques to Build Intelligent Systems*. Sebastopol, CA, USA: O'Reilly Media, 2019. [Online]. Available: https://www.oreilly.com/library/view/hands-on-machine-learning/9781492032632/
[131] M. Sun, F. Li, and J. Zhang, "A multi-modality deep network for cold-start recommendation," *Big Data Cogn. Comput.*, vol. 2, no. 1, p. 7, Mar. 2018.
[132] T. Kohonen, *Self-Organizing Maps*. Berlin, Germany: Springer, 2001.
[133] T. Zhong, Z. Wen, F. Zhou, G. Trajcevski, and K. Zhang, "Session-based recommendation via flow-based deep generative networks and Bayesian inference," *Neurocomputing*, vol. 391, pp. 129–141, May 2020.
[134] L. Fang, B. Du, and C. Wu, "Differentially private recommender system with variational autoencoders," *Knowl.-Based Syst.*, vol. 250, Aug. 2022, Art. no. 109044.
[135] J. Sun, B. Liu, H. Ren, and W. Huang, "NCGAN: A neural adversarial collaborative filtering for recommender system," *J. Intell. Fuzzy Syst.*, vol. 42, no. 4, pp. 2915–2923, Mar. 2022.
[136] H. Chen, S. Wang, N. Jiang, Z. Li, N. Yan, and L. Shi, "Trust-aware generative adversarial network with recurrent neural network for recommender systems," *Int. J. Intell. Syst.*, vol. 36, no. 2, pp. 778–795, Feb. 2021.
[137] T. N. Duong, T. A. Vuong, D. M. Nguyen, and Q. H. Dang, "Utilizing an autoencoder-generated item representation in hybrid recommendation system," *IEEE Access*, vol. 8, pp. 75094–75104, 2020.
[138] L. N. Hoai Nam, "Profile aggregation-based group recommender systems: Moving from item preference profiles to deep profiles," *IEEE Access*, vol. 10, pp. 6218–6245, 2022.
[139] Y. Zhang, Z. Liu, and C. Sang, "Unifying paragraph embeddings and neural collaborative filtering for hybrid recommendation," *Appl. Soft Comput.*, vol. 106, Jul. 2021, Art. no. 107345.
[140] M. F. Aljunid and M. Dh, "An efficient deep learning approach for collaborative filtering recommender system," *Proc. Comput. Sci.*, vol. 171, pp. 829–836, Jan. 2020.
[141] F. Ullah, B. Zhang, R. U. Khan, T.-S. Chung, M. Attique, K. Khan, S. E. Khediri, and S. Jan, "Deep Edu: A deep neural collaborative filtering for educational services recommendation," *IEEE Access*, vol. 8, pp. 110915–110928, 2020.
[142] C. Yang, L. Miao, B. Jiang, D. Li, and D. Cao, "Gated and attentive neural collaborative filtering for user generated list recommendation," *Knowl.-Based Syst.*, vol. 187, Jan. 2020, Art. no. 104839.
[143] N. Nassar, A. Jafar, and Y. Rahhal, "A novel deep multi-criteria collaborative filtering model for recommendation system," *Knowl.-Based Syst.*, vol. 187, Jan. 2020, Art. no. 104811.
[144] S. Yu, M. Yang, Q. Qu, and Y. Shen, "Contextual-boosted deep neural collaborative filtering model for interpretable recommendation," *Expert Syst. Appl.*, vol. 136, pp. 365–375, Dec. 2019.
[145] X. Xian, L. Fang, and S. Sun, "ReGNN: A repeat aware graph neural network for session-based recommendations," *IEEE Access*, vol. 8, pp. 98518–98525, 2020.

[146] Y. Zhang, B. Yang, H. Liu, and D. Li, "A time-aware self-attention based neural network model for sequential recommendation," *Appl. Soft Comput.*, vol. 133, Jan. 2023, Art. no. 109894.

[147] Y. Liu and J. Miyazaki, "Knowledge-aware attentional neural network for review-based movie recommendation with explanations," *Neural Comput. Appl.*, vol. 35, no. 3, pp. 2717–2735, Jan. 2023.

[148] Y. Chen, Q. Xiong, and Y. Guo, "Session-based recommendation: Learning multi-dimension interests via a multi-head attention graph neural network," *Appl. Soft Comput.*, vol. 131, Dec. 2022, Art. no. 109744.

[149] N. Heidari, P. Moradi, and A. Koochari, "An attention-based deep learning method for solving the cold-start and sparsity issues of recommender systems," *Knowl.-Based Syst.*, vol. 256, Nov. 2022, Art. no. 109835.

[150] L. Zhang, P. Liu, and J. A. Gulla, "Dynamic attention-integrated neural network for session-based news recommendation," *Mach. Learn.*, vol. 108, no. 10, pp. 1851–1875, Oct. 2019.

[151] M. Hakim, A. A. B. Omran, A. N. Ahmed, M. Al-Waily, and A. Abdellatif, "A systematic review of rolling bearing fault diagnoses based on deep learning and transfer learning: Taxonomy, overview, application, open challenges, weaknesses and recommendations," *Ain Shams Eng. J.*, vol. 14, no. 4, Apr. 2023, Art. no. 101945.

[152] H. Liu, Q. Liu, P. Li, P. Zhao, and X. Wu, "A deep selective learning network for cross-domain recommendation," *Appl. Soft Comput.*, vol. 125, Aug. 2022, Art. no. 109160.

[153] D. Liu, J. Li, B. Du, J. Chang, R. Gao, and Y. Wu, "A hybrid neural network approach to combine textual information and rating information for item recommendation," *Knowl. Inf. Syst.*, vol. 63, no. 3, pp. 621–646, Mar. 2021.

[154] L. Chen, L. Zhang, S. Cao, Z. Wu, and J. Cao, "Personalized itinerary recommendation: Deep and collaborative learning with textual information," *Expert Syst. Appl.*, vol. 144, Apr. 2020, Art. no. 113070.

[155] A. Sattar and D. Bacciu, "Graph neural network for context-aware recommendation," *Neural Process. Lett.*, vol. 55, no. 5, pp. 5357–5376, Oct. 2023.

[156] B. Ahirwadkar and S. Deshmukh, "DeepAutoEnCF: A denoising autoencoder for recommender systems," *Indian J. Comput. Sci. Eng.*, vol. 11, no. 3, pp. 244–250, May/Jun. 2020.

[157] S. Selvaraj and S. S. Gangadharan, "Privacy preserving hybrid recommender system based on deep learning," *TURKISH J. Electr. Eng. Comput. Sci.*, vol. 29, no. 5, pp. 2385–2402, Sep. 2021.

[158] W. Yan, D. Wang, M. Cao, and J. Liu, "Deep auto encoder model with convolutional text networks for video recommendation," *IEEE Access*, vol. 7, pp. 40333–40346, 2019.

[159] W. Zhou, J. Li, M. Zhang, Y. Wang, and F. Shah, "Deep learning modeling for top-*N* recommendation with interests exploring," *IEEE Access*, vol. 6, pp. 51440–51455, 2018.

[160] R. Kiran, P. Kumar, and B. Bhasker, "DNNRec: A novel deep learning based hybrid recommender system," *Expert Syst. Appl.*, vol. 144, Apr. 2020, Art. no. 113054.

[161] C. C. Chen, P.-L. Lai, and C.-Y. Chen, "ColdGAN: An effective cold-start recommendation system for new users based on generative adversarial networks," *Int. J. Speech Technol.*, vol. 53, no. 7, pp. 8302–8317, Apr. 2023.

[162] H. Kanwal, M. Assam, A. Jabbar, S. Khan, and Kalimullah, "Convolutional neural network and topic modeling based hybrid recommender system," *Int. J. Adv. Comput. Sci. Appl.*, vol. 11, no. 7, pp. 627–635, 2020.

[163] M. He, Q. Meng, and S. Zhang, "Collaborative additional variational autoencoder for top-*N* recommender systems," *IEEE Access*, vol. 7, pp. 5707–5713, 2019.

[164] C. Zhang, T. Li, Z. Ren, Z. Hu, and Y. Ji, "Taxonomy-aware collaborative denoising autoencoder for personalized recommendation," *Appl. Intell.*, vol. 49, no. 6, pp. 2101–2118, Jun. 2019.

[165] B. Yi, X. Shen, H. Liu, Z. Zhang, W. Zhang, S. Liu, and N. Xiong, "Deep matrix factorization with implicit feedback embedding for recommendation system," *IEEE Trans. Ind. Informat.*, vol. 15, no. 8, pp. 4591–4601, Aug. 2019.

[166] Y. Xu, Q. Ni, S. Liu, Y. Mi, Y. Yu, and Y. Hao, "Learning style integrated deep reinforcement learning framework for programming problem recommendation in online judge system," *Int. J. Comput. Intell. Syst.*, vol. 15, no. 1, p. 114, Dec. 2022.

[167] R. Liu, D. Jiang, and X. Zhang, "A stable deep reinforcement learning framework for recommendation," *IEEE Intell. Syst.*, vol. 37, no. 3, pp. 76–84, May 2022.

[168] W. Huang, J. Liu, T. Li, T. Huang, S. Ji, and J. Wan, "FedDSR: Daily schedule recommendation in a federated deep reinforcement learning framework," *IEEE Trans. Knowl. Data Eng.*, vol. 35, no. 4, pp. 3912–3924, Apr. 2023.

[169] D. Ma, Y. Wang, J. Ma, and Q. Jin, "SGNR: A social graph neural network based interactive recommendation scheme for e-commerce," *Tsinghua Sci. Technol.*, vol. 28, no. 4, pp. 786–798, Aug. 2023.

[170] M. Alabadla, F. Sidi, I. Ishak, H. Ibrahim, L. S. Affendey, Z. Che Ani, M. A. Jabar, U. A. Bukar, N. K. Devaraj, A. S. Muda, A. Tharek, N. Omar, and M. I. M. Jaya, "Systematic review of using machine learning in imputing missing values," *IEEE Access*, vol. 10, pp. 44483–44502, 2022.

[171] B. Kitchenham and P. Brereton, "A systematic review of systematic review process research in software engineering," *Inf. Softw. Technol.*, vol. 55, no. 12, pp. 2049–2075, Dec. 2013.

[172] B. A. Kitchenham, "Systematic literature reviews in software engineering—A systematic literature review," *Inf. Softw. Technol.*, vol. 51, pp. 7–15, Jan. 2009.

[173] G. Rodríguez-Pérez, G. Robles, and J. M. González-Barahona, "Reproducibility and credibility in empirical software engineering: A case study based on a systematic literature review of the use of the SZZ algorithm," *Inf. Softw. Technol.*, vol. 99, pp. 164–176, Jul. 2018.

[174] X. Huang, H. Zhang, X. Zhou, M. A. Babar, and S. Yang, "Synthesizing qualitative research in software engineering: A critical review," in *Proc. IEEE/ACM 40th Int. Conf. Softw. Eng. (ICSE)*, May 2018, pp. 1207–1218.

[175] C. Li, May 2023, "Deep learning-based recommendation system: Systematic review and classification—Outputs," *Zenodo*, doi: 10.5281/zenodo.7935315.

[176] R. J. K. Almahmood and A. Tekerek, "Issues and solutions in deep learning-enabled recommendation systems within the e-commerce field," *Appl. Sci.*, vol. 12, no. 21, p. 11256, Nov. 2022.

[177] M. Liu, Z. Tu, H. Xu, X. Xu, and Z. Wang, "DySR: A dynamic graph neural network based service bundle recommendation model for mashup creation," *IEEE Trans. Services Comput.*, vol. 16, no. 4, pp. 2592–2605, Jul./Aug. 2023.

[178] M. Hong, C. Koo, and N. Chung, "DSER: Deep-sequential embedding for single domain recommendation," *Expert Syst. Appl.*, vol. 208, Dec. 2022, Art. no. 118156.

[179] Q. Shambour, "A deep learning based algorithm for multi-criteria recommender systems," *Knowl.-Based Syst.*, vol. 211, Jan. 2021, Art. no. 106545.

[180] R. A. E.-D. Ahmed, M. Fernández-Veiga, and M. Gawich, "Neural collaborative filtering with ontologies for integrated recommendation systems," *Sensors*, vol. 22, no. 2, p. 700, Jan. 2022.

[181] F. Liu, Z. Chen, Y. Ding, S. Yang, and T. Zhang, "A face attribute based recommendation system via integrating denoising autoencoder and hash coding," *Comput. Electr. Eng.*, vol. 90, Mar. 2021, Art. no. 107020.

[182] Y. Sang, H. Sun, C. Li, and L. Yin, "LSVP: A visual based deep neural direction learning model for point-of-interest recommendation on sparse check-in data," *Neurocomputing*, vol. 446, pp. 204–210, Jul. 2021.

[183] B. Markapudi, K. Chaduvula, D. N. V. S. L. S. Indira, and M. V. N. S. S. R. K. S. Somayajulu, "Content-based video recommendation system (CBVRS): A novel approach to predict videos using multilayer feed forward neural network and Monte Carlo sampling method," *Multimedia Tools Appl.*, vol. 82, no. 5, pp. 6965–6991, Feb. 2023.

[184] P. Messina, V. Dominguez, D. Parra, C. Trattner, and A. Soto, "Content-based artwork recommendation: Integrating painting metadata with neural and manually-engineered visual features," *User Model. User-Adapted Interact.*, vol. 29, no. 2, pp. 251–290, Apr. 2019.

[185] M. F. Aljunid and M. D. Huchaiah, "Multi-model deep learning approach for collaborative filtering recommendation system," *CAAI Trans. Intell. Technol.*, vol. 5, no. 4, pp. 268–275, Dec. 2020.

[186] T. Huang, D. Zhang, and L. Bi, "Neural embedding collaborative filtering for recommender systems," *Neural Comput. Appl.*, vol. 32, no. 22, pp. 17043–17057, Nov. 2020.

[187] C. Chen, M. Zhang, Y. Zhang, Y. Liu, and S. Ma, "Efficient neural matrix factorization without sampling for recommendation," *ACM Trans. Inf. Syst.*, vol. 38, no. 2, pp. 1–28, Apr. 2020.

[188] X. Deng, F. Zhuang, and Z. Zhu, "Neural variational collaborative filtering with side information for top-*K* recommendation," *Int. J. Mach. Learn. Cybern.*, vol. 10, no. 11, pp. 3273–3284, Nov. 2019.

[189] J. Gong, X. Zhang, Q. Li, C. Wang, Y. Song, Z. Zhao, and S. Wang, "A top-*N* movie recommendation framework based on deep neural network with heterogeneous modeling," *Appl. Sci.*, vol. 11, no. 16, p. 7418, Aug. 2021.
[190] W. Zhang, X. Zhang, and D. Chen, "Causal neural fuzzy inference modeling of missing data in implicit recommendation system," *Knowl.-Based Syst.*, vol. 222, Jun. 2021, Art. no. 106678.
[191] X. Zhu, J. Guo, S. Li, and T. Hao, "Facing cold-start: A live TV recommender system based on neural networks," *IEEE Access*, vol. 8, pp. 131286–131298, 2020.
[192] R. Wang, J. Lou, and Y. Jiang, "Session-based recommendation with time-aware neural attention network," *Expert Syst. Appl.*, vol. 210, Dec. 2022, Art. no. 118395.
[193] L. Xia, C. Huang, Y. Xu, P. Dai, and L. Bo, "Multi-behavior graph neural networks for recommender system," *IEEE Trans. Neural Netw. Learn. Syst.*, early access, Oct. 19, 2022, doi: 10.1109/TNNLS.2022.3204775.
[194] A. Li, Z. Cheng, F. Liu, Z. Gao, W. Guan, and Y. Peng, "Disentangled graph neural networks for session-based recommendation," *IEEE Trans. Knowl. Data Eng.*, vol. 35, no. 8, pp. 7870–7882, Aug. 2022.
[195] C. Wei, Y. Fan, and J. Zhang, "High-order social graph neural network for service recommendation," *IEEE Trans. Netw. Service Manage.*, vol. 19, no. 4, pp. 4615–4628, Dec. 2022.
[196] X. Chen, K. Xiong, Y. Zhang, L. Xia, D. Yin, and J. X. Huang, "Neural feature-aware recommendation with signed hypergraph convolutional network," *ACM Trans. Inf. Syst.*, vol. 39, no. 1, pp. 1–22, Jan. 2021.
[197] H. Wang, Y. Zeng, J. Chen, Z. Zhao, and H. Chen, "A spatiotemporal graph neural network for session-based recommendation," *Expert Syst. Appl.*, vol. 202, Sep. 2022, Art. no. 117114.
[198] T. R. Gwadabe and Y. Liu, "Improving graph neural network for session-based recommendation system via non-sequential interactions," *Neurocomputing*, vol. 468, pp. 111–122, Jan. 2022.
[199] L. Li, "Learning recommendation algorithm based on improved BP neural network in music marketing strategy," *Comput. Intell. Neurosci.*, vol. 2021, Nov. 2021, Art. no. 2073881.
[200] H. Liang, "DRprofiling: Deep reinforcement user profiling for recommendations in heterogenous information networks," *IEEE Trans. Knowl. Data Eng.*, vol. 34, no. 4, pp. 1723–1734, Apr. 2022.
[201] C. Bin, T. Gu, Z. Jia, G. Zhu, and C. Xiao, "A neural multi-context modeling framework for personalized attraction recommendation," *Multimedia Tools Appl.*, vol. 79, nos. 21–22, pp. 14951–14979, Jun. 2020.
[202] F. Liu, R. Tang, X. Li, W. Zhang, Y. Ye, H. Chen, H. Guo, Y. Zhang, and X. He, "State representation modeling for deep reinforcement learning based recommendation," *Knowl.-Based Syst.*, vol. 205, Oct. 2020, Art. no. 106170.
[203] X. Zhang, Y. Shang, Y. Ren, and K. Liang, "Dynamic multi-objective sequence-wise recommendation framework via deep reinforcement learning," *Complex Intell. Syst.*, vol. 9, no. 2, pp. 1891–1911, Apr. 2023.
[204] M. Chen, W.-Z. Li, L. Qian, S.-L. Lu, and D.-X. Chen, "Next POI recommendation based on location interest mining with recurrent neural networks," *J. Comput. Sci. Technol.*, vol. 35, no. 3, pp. 603–616, May 2020.
[205] S. Xing, F. Liu, Q. Wang, X. Zhao, and T. Li, "Content-aware point-of-interest recommendation based on convolutional neural network," *Appl. Intell.*, vol. 49, no. 3, pp. 858–871, Mar. 2019.
[206] L. C. L. Cui, C. W. L. Cui, Z. Z. C. Wang, X. Y. Z. Zhang, and F. Z. X. Yu, "Fusing dual geo-social relationship and deep implicit interest topic similarity for POI recommendation," *J. Internet Technol.*, vol. 23, no. 4, pp. 791–799, Jul. 2022.
[207] Z. Pan, L. Cui, X. Wu, Z. Zhang, X. Li, and G. Chen, "Deep potential geo-social relationship mining for point-of-interest recommendation," *IEEE Access*, vol. 7, pp. 99496–99507, 2019.
[208] X. Feng, Z. Liu, W. Wu, and W. Zuo, "Social recommendation via deep neural network-based multi-task learning," *Expert Syst. Appl.*, vol. 206, Nov. 2022, Art. no. 117755.
[209] B. Wang and W. Cai, "Knowledge-enhanced graph neural networks for sequential recommendation," *Information*, vol. 11, no. 8, p. 388, Aug. 2020.
[210] M. Gan and Y. Ma, "DeepInteract: Multi-view features interactive learning for sequential recommendation," *Expert Syst. Appl.*, vol. 204, Oct. 2022, Art. no. 117305.
[211] Y. Ma and M. Gan, "DeepAssociate: A deep learning model exploring sequential influence and history-candidate association for sequence recommendation," *Expert Syst. Appl.*, vol. 185, Dec. 2021, Art. no. 115587.
[212] D. Dang, C. Chen, H. Li, R. Yan, Z. Guo, and X. Wang, "Deep knowledge-aware framework for web service recommendation," *J. Supercomput.*, vol. 77, no. 12, pp. 14280–14304, Dec. 2021.
[213] Y. Zhang, M. Yuan, C. Zhao, M. Chen, and X. Liu, "Aggregating knowledge-aware graph neural network and adaptive relational attention for recommendation," *Int. J. Speech Technol.*, vol. 52, no. 15, pp. 17941–17953, Dec. 2022.
[214] Y. Zhang, C. Li, J. Cai, Y. Liu, and H. Wang, "BKGNN-TI: A bilinear knowledge-aware graph neural network fusing text information for recommendation," *Int. J. Comput. Intell. Syst.*, vol. 15, no. 1, Nov. 2022.
[215] T. Liu and Z. He, "DLIR: A deep learning-based initialization recommendation algorithm for trust-aware recommendation," *Appl. Intell.*, vol. 52, no. 10, pp. 11103–11114, Aug. 2022.
[216] H. Liu, C. Zheng, D. Li, X. Shen, K. Lin, J. Wang, Z. Zhang, Z. Zhang, and N. N. Xiong, "EDMF: Efficient deep matrix factorization with review feature learning for industrial recommender system," *IEEE Trans. Ind. Informat.*, vol. 18, no. 7, pp. 4361–4371, Jul. 2022.
[217] X. Shen, B. Yi, H. Liu, W. Zhang, Z. Zhang, S. Liu, and N. Xiong, "Deep variational matrix factorization with knowledge embedding for recommendation system," *IEEE Trans. Knowl. Data Eng.*, vol. 33, no. 5, pp. 1906–1918, May 2021.
[218] C. Zhang and C. Wang, "Probabilistic matrix factorization recommendation of self-attention mechanism convolutional neural networks with item auxiliary information," *IEEE Access*, vol. 8, pp. 208311–208321, 2020.
[219] T. Xiao and H. Shen, "Neural variational matrix factorization for collaborative filtering in recommendation systems," *Appl. Intell.*, vol. 49, no. 10, pp. 3558–3569, Oct. 2019.
[220] M. Gao, J. Zhang, J. Yu, J. Li, J. Wen, and Q. Xiong, "Recommender systems based on generative adversarial networks: A problem-driven perspective," *Inf. Sci.*, vol. 546, pp. 1166–1185, Feb. 2021.
[221] X. Zheng and D. Dong, "An adversarial deep hybrid model for text-aware recommendation with convolutional neural networks," *Appl. Sci.*, vol. 10, no. 1, p. 156, Dec. 2019.
[222] Q. Zhang, W. Liao, G. Zhang, B. Yuan, and J. Lu, "A deep dual adversarial network for cross-domain recommendation," *IEEE Trans. Knowl. Data Eng.*, vol. 35, no. 4, pp. 3266–3278, Apr. 2023.
[223] H. Liu, L. Guo, P. Li, P. Zhao, and X. Wu, "Collaborative filtering with a deep adversarial and attention network for cross-domain recommendation," *Inf. Sci.*, vol. 565, pp. 370–389, Jul. 2021.
[224] L. Sang, M. Xu, S. Qian, and X. Wu, "Knowledge graph enhanced neural collaborative recommendation," *Expert Syst. Appl.*, vol. 164, Feb. 2021, Art. no. 113992.
[225] Y. Pan, F. He, X. Yan, and H. Li, "A synchronized heterogeneous autoencoder with feature-level and label-level knowledge distillation for the recommendation," *Eng. Appl. Artif. Intell.*, vol. 106, Nov. 2021, Art. no. 104494.
[226] Z. Huang, C. Yu, J. Ni, H. Liu, C. Zeng, and Y. Tang, "An efficient hybrid recommendation model with deep neural networks," *IEEE Access*, vol. 7, pp. 137900–137912, 2019.
[227] G. Kang, J. Liu, Y. Xiao, B. Cao, Y. Xu, and M. Cao, "Neural and attentional factorization machine-based Web API recommendation for mashup development," *IEEE Trans. Netw. Service Manage.*, vol. 18, no. 4, pp. 4183–4196, Dec. 2021.
[228] J. Zhang, C. Ma, X. Mu, P. Zhao, C. Zhong, and A. Ruhan, "Recurrent convolutional neural network for session-based recommendation," *Neurocomputing*, vol. 437, pp. 157–167, May 2021.
[229] Y. Wu and J. Gou, "Leveraging neighborhood session information with dual attentive neural network for session-based recommendation," *Neurocomputing*, vol. 439, pp. 234–242, Jun. 2021.
[230] B. Yu, X. Li, J. Fang, C. Tai, W. Cheng, and J. Xu, "Memory-augmented meta-learning framework for session-based target behavior recommendation," *World Wide Web*, vol. 26, no. 1, pp. 233–251, Jan. 2023.
[231] B. Şeref, E. Bostanci, and M. Güzel, "Evolutionary neural networks for improving the prediction performance of recommender systems," *Turkish J. Electr. Eng. Comput. Sci.*, vol. 29, no. 1, pp. 62–77, 2021.
[232] I. Topalli and S. Kilinç, "User profiling for TV program recommendation based on hybrid television standards using controlled clustering with genetic algorithms and artificial neural networks," *Turkish J. Electr. Eng. Comput. Sci.*, vol. 28, no. 3, pp. 1567–1583, 2020.

[233] C. Selvi and E. Sivasankar, "A novel adaptive genetic neural network (AGNN) model for recommender systems using modified k-means clustering approach," *Multimedia Tools Appl.*, vol. 78, no. 11, pp. 14303–14330, Jun. 2019.

[234] N. Jayalakshmi, V. Sangeeta, and A. S. Muttipati, "Taylor horse herd optimized deep fuzzy clustering and Laplace based K-nearest neighbor for web page recommendation," *Adv. Eng. Softw.*, vol. 175, Jan. 2023, Art. no. 103351.

[235] J. Jiang, W. Li, A. Dong, Q. Gou, and X. Luo, "A fast deep AutoEncoder for high-dimensional and sparse matrices in recommender systems," *Neurocomputing*, vol. 412, pp. 381–391, Oct. 2020.

[236] H. J. Kim, T. S. Kim, and S. Y. Sohn, "Recommendation of startups as technology cooperation candidates from the perspectives of similarity and potential: A deep learning approach," *Decis. Support Syst.*, vol. 130, Mar. 2020, Art. no. 113229.

[237] J. Han, L. Zheng, H. Huang, Y. Xu, P. S. Yu, and W. Zuo, "Deep latent factor model with hierarchical similarity measure for recommender systems," *Inf. Sci.*, vol. 503, pp. 521–532, Nov. 2019.

[238] W. Cheng, Y. Shen, L. Huang, and Y. Zhu, "Dual-embedding based deep latent factor models for recommendation," *ACM Trans. Knowl. Discovery Data*, vol. 15, no. 5, pp. 1–24, Oct. 2021.

[239] T. Qian, Y. Liang, Q. Li, and H. Xiong, "Attribute graph neural networks for strict cold start recommendation," *IEEE Trans. Knowl. Data Eng.*, vol. 34, no. 8, pp. 3597–3610, Aug. 2022.

[240] Y. Du, L. Wang, Z. Peng, and W. Guo, "Review-based hierarchical attention cooperative neural networks for recommendation," *Neurocomputing*, vol. 447, pp. 38–47, Aug. 2021.

[241] Y. Guo, Y. Ling, and H. Chen, "A neighbor-guided memory-based neural network for session-aware recommendation," *IEEE Access*, vol. 8, pp. 120668–120678, 2020.

[242] A. Pujahari and D. S. Sisodia, "Modeling side information in preference relation based restricted Boltzmann machine for recommender systems," *Inf. Sci.*, vol. 490, pp. 126–145, Jul. 2019.

[243] B. M. Shoja and N. Tabrizi, "Customer reviews analysis with deep neural networks for e-commerce recommender systems," *IEEE Access*, vol. 7, pp. 119121–119130, 2019.

[244] T. Manojpraphakar and A. Soundarrajan, "Deep contextual learning for event-based potential user recommendation in online social networks," *Intell. Autom. Soft Comput.*, vol. 34, no. 2, pp. 699–713, 2022.

[245] M. Hamada and M. Hassan, "Artificial neural networks and particle swarm optimization algorithms for preference prediction in multi-criteria recommender systems," *Informatics*, vol. 5, no. 2, p. 25, May 2018.

[246] H. Wang, G. Liang, and X. Zhang, "Feature regularization and deep learning for human resource recommendation," *IEEE Access*, vol. 6, pp. 39415–39421, 2018.

[247] E. Gündoğan and M. Kaya, "A novel hybrid paper recommendation system using deep learning," *Scientometrics*, vol. 127, pp. 3837–3855, Jun. 2022.

[248] G. Ning, C. Wu, Y. Li, H. Zhang, and E. Szczerbicki, "Toward intelligent recommendations using the neural knowledge DNA," *Cybern. Syst.*, vol. 52, no. 5, pp. 419–428, Jul. 2021.

[249] X. Wen, "Using deep learning approach and IoT architecture to build the intelligent music recommendation system," *Soft Comput.*, vol. 25, no. 4, pp. 3087–3096, Feb. 2021.

[250] Z. Huang, X. Xu, H. Zhu, and M. Zhou, "An efficient group recommendation model with multiattention-based neural networks," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 31, no. 11, pp. 4461–4474, Nov. 2020.

[251] L. Huang, M. Fu, F. Li, H. Qu, Y. Liu, and W. Chen, "A deep reinforcement learning based long-term recommender system," *Knowl.-Based Syst.*, vol. 213, Feb. 2021, Art. no. 106706.

[252] X. Zhou, W. Liang, K. I. Wang, and L. T. Yang, "Deep correlation mining based on hierarchical hybrid networks for heterogeneous big data recommendations," *IEEE Trans. Computat. Social Syst.*, vol. 8, no. 1, pp. 171–178, Feb. 2021.

[253] K. Sakurai, R. Togo, T. Ogawa, and M. Haseyama, "Deep reinforcement learning-based music recommendation with knowledge graph using acoustic features," *ITE Trans. Media Technol. Appl.*, vol. 10, no. 1, pp. 8–17, 2022.

[254] Z. Zhao, X. Chen, Z. Xu, and L. Cao, "Tag-aware recommender system based on deep reinforcement learning," *Math. Problems Eng.*, vol. 2021, May 2021, Art. no. 5564234.

[255] J. Ni, Z. Huang, J. Cheng, and S. Gao, "An effective recommendation model based on deep representation learning," *Inf. Sci.*, vol. 542, pp. 324–342, Jan. 2021.

[256] B. T. Kieu, I. J. Unanue, S. B. Pham, H. X. Phan, and M. Piccardi, "NeuSub: A neural submodular approach for citation recommendation," *IEEE Access*, vol. 9, pp. 148459–148468, 2021.

[257] Y. Pan, F. He, and H. Yu, "Learning social representations with deep autoencoder for recommender system," *World Wide Web*, vol. 23, no. 4, pp. 2259–2279, Jul. 2020.

[258] Z. Huang, X. Lin, H. Liu, B. Zhang, Y. Chen, and Y. Tang, "Deep representation learning for location-based recommendation," *IEEE Trans. Computat. Social Syst.*, vol. 7, no. 3, pp. 648–658, Jun. 2020.

[259] D. Roy and M. Dutta, "An improved cat swarm search-based deep ensemble learning model for group recommender systems," *J. Inf. Knowl. Manage.*, vol. 21, no. 3, Sep. 2022, Art. no. 2250032.

[260] M. Ibrahim, I. S. Bajwa, N. Sarwar, H. A. Waheed, M. Zulkifl Hasan, and M. Z. Hussain, "Improved hybrid deep collaborative filtering approach for true recommendations," *Comput., Mater. Continua*, vol. 74, no. 3, pp. 5301–5317, 2023.

[261] G. Behera and N. Nain, "Handling data sparsity via item metadata embedding into deep collaborative recommender system," *J. King Saud Univ. Comput. Inf. Sci.*, vol. 34, no. 10, pp. 9953–9963, Nov. 2022.

[262] C. Cui, J. Qin, and Q. Ren, "Deep collaborative recommendation algorithm based on attention mechanism," *Appl. Sci.*, vol. 12, no. 20, p. 10594, Oct. 2022.

[263] D. Liang, M. Corneli, C. Bouveyron, and P. Latouche, "DeepLTRS: A deep latent recommender system based on user ratings and reviews," *Pattern Recognit. Lett.*, vol. 152, pp. 267–274, Dec. 2021.

[264] D. Wu, X. Luo, M. Shang, Y. He, G. Wang, and M. Zhou, "A deep latent factor model for high-dimensional and sparse matrices in recommender systems," *IEEE Trans. Syst., Man, Cybern., Syst.*, vol. 51, no. 7, pp. 4285–4296, Jul. 2021.

[265] T. Vaiyapuri, "Deep learning enabled autoencoder architecture for collaborative filtering recommendation in IoT environment," *Comput., Mater. Continua*, vol. 68, no. 1, pp. 487–503, 2021.

[266] R. Xu, J. Li, G. Li, P. Pan, Q. Zhou, and C. Wang, "SDNN: Symmetric deep neural networks with lateral connections for recommender systems," *Inf. Sci.*, vol. 595, pp. 217–230, May 2022.

[267] R. Wang, Z. Wu, J. Lou, and Y. Jiang, "Attention-based dynamic user modeling and deep collaborative filtering recommendation," *Expert Syst. Appl.*, vol. 188, Feb. 2022, Art. no. 116036.

[268] E. Y. Keat, N. M. Sharef, R. Yaakob, K. A. Kasmiran, E. Marlisah, N. Mustapha, and M. Zolkepli, "Multiobjective deep reinforcement learning for recommendation systems," *IEEE Access*, vol. 10, pp. 65011–65027, 2022.

[269] H. Liu, Y. Wang, Q. Peng, F. Wu, L. Gan, L. Pan, and P. Jiao, "Hybrid neural recommendation with joint deep representation learning of ratings and reviews," *Neurocomputing*, vol. 374, pp. 77–85, Jan. 2020.

[270] H. Xia and X. Hu, "Neural social recommendation with user embedding," *IEEE Access*, vol. 8, pp. 10222–10233, 2020.

[271] Y. Zhao, K. Wang, G. Guo, and X. Wang, "Learning compact yet accurate generative adversarial networks for recommender systems," *Knowl.-Based Syst.*, vol. 257, Dec. 2022, Art. no. 109900.

[272] M. Ludewig, N. Mauro, S. Latifi, and D. Jannach, "Empirical analysis of session-based recommendation algorithms: A comparison of neural and non-neural approaches," *User Model. User-Adapted Interact.*, vol. 31, pp. 149–181, Mar. 2021.

[273] Z. Guo, K. Yu, N. Kumar, W. Wei, S. Mumtaz, and M. Guizani, "Deep-distributed-learning-based POI recommendation under mobile-edge networks," *IEEE Internet Things J.*, vol. 10, no. 1, pp. 303–317, Jan. 2023.

[274] C. Su and D. Huang, "Hybrid recommender system based on deep learning model," *Int. J. Performability Eng.*, vol. 16, no. 1, p. 118, 2020.

[275] S. Lian and M. Tang, "API recommendation for mashup creation based on neural graph collaborative filtering," *Connection Sci.*, vol. 34, no. 1, pp. 124–138, Dec. 2022.

[276] D. Hou, "Personalized book recommendation algorithm for university library based on deep learning models," *J. Of Sensors*, vol. 2022, Jun. 2022, Art. no. 3087623.

[277] M. Ibrahim, I. S. Bajwa, R. Ul-Amin, and B. Kasi, "A neural network-inspired approach for improved and true movie recommendations," *Comput. Intell. Neurosci.*, vol. 2019, Aug. 2019, Art. no. 4589060.

[278] S. Zhang, H. Liu, J. He, S. Han, and X. Du, "A deep bi-directional prediction model for live streaming recommendation," *Inf. Process. Manage.*, vol. 58, no. 2, Mar. 2021, Art. no. 102453.
[279] B. Juarto and A. S. Girsang, "Neural collaborative with sentence BERT for news recommender system," *Int. J. Informat. Visualizat.*, vol. 5, no. 4, p. 448, Dec. 2021.
[280] A. Ahmed, K. Saleem, O. Khalid, and U. Rashid, "On deep neural network for trust aware cross domain recommendations in e-commerce," *Expert Syst. Appl.*, vol. 174, Jul. 2021, Art. no. 114757.
[281] Y. Liu, L. Yao, B. Guo, N. Li, J. Zhang, J. Chen, D. Zhang, Y. Liu, Z. Yu, and S. Zhang, "DeepStore: An interaction-aware wide & deep model for store site recommendation with attentional spatial embeddings," *IEEE Internet Things J.*, vol. 6, no. 4, pp. 7319–7333, Aug. 2019.
[282] D. Shen and Z. Jiang, "Online teaching course recommendation based on autoencoder," *Math. Problems Eng.*, vol. 2022, Aug. 2022, Art. no. 8549563.
[283] J. Liu, C. Yin, Y. Li, H. Sun, and H. Zhou, "Deep learning and collaborative filtering-based methods for students' performance prediction and course recommendation," *Wireless Commun. Mobile Comput.*, vol. 2023, Sep. 2023, Art. no. 2157343.
[284] Q. Yuan, "Network education recommendation and teaching resource sharing based on improved neural network," *J. Intell. Fuzzy Syst.*, vol. 39, no. 4, pp. 5511–5520, Oct. 2020.
[285] D. Kurniadi, E. Abdurachman, H. Warnars, and W. Suparta, "Predicting student performance with multi-level representation in an intelligent academic recommender system using backpropagation neural network," *ICIC Exp. Lett. B, Appl.*, vol. 12, no. 10, pp. 883–890, Oct. 2021.
[286] J. Wu and Q. Feng, "Recommendation system design for college network education based on deep learning and fuzzy uncertainty," *J. Intell. Fuzzy Syst.*, vol. 38, no. 6, pp. 7083–7094, Jun. 2020.
[287] H. Tu, J. Wen, A. Sun, and X. Wang, "Joint implicit and explicit neural networks for question recommendation in CQA services," *IEEE Access*, vol. 6, pp. 73081–73092, 2018.
[288] R. Mishra and S. Rathi, "Enhanced DSSM (deep semantic structure modelling) technique for job recommendation," *J. King Saud Univ. Comput. Inf. Sci.*, vol. 34, no. 9, pp. 7790–7802, Oct. 2022.
[289] Q. Wan and L. Ye, "Career recommendation for college students based on deep learning and machine learning," *Sci. Program.*, vol. 2022, Feb. 2022, Art. no. 3437139.
[290] L. Ma, D. Song, L. Liao, and Y. Ni, "A joint deep model of entities and documents for cumulative citation recommendation," *Cluster Comput.*, vol. 22, no. S3, pp. 5435–5446, May 2019.
[291] Q. Xie, Y. Zhu, J. Huang, P. Du, and J.-Y. Nie, "Graph neural collaborative topic model for citation recommendation," *ACM Trans. Inf. Syst.*, vol. 40, no. 3, pp. 1–30, Jul. 2022.
[292] E. Gündoğan, M. Kaya, and A. Daud, "Deep learning for journal recommendation system of research papers," *Scientometrics*, vol. 128, pp. 461–481, Jan. 2023.
[293] Q. Wan and C. Jiang, "Dual denoising autoencoder based on neighbor-attention module for implicit feedback recommendation," *J. Eng. Sci. Technol. Rev.*, vol. 14, no. 6, pp. 137–144, 2021.
[294] W. Qi, J. Yu, Q. Liang, Z. Huang, Z. Xu, and H. Jiang, "Design of graph neural network social recommendation algorithm based on coupling influence," *Int. J. Pattern Recognit. Artif. Intell.*, vol. 36, no. 14, Nov. 2022, Art. no. 2252024.
[295] X. Li, S. Xu, T. Jiang, Y. Wang, Y. Ma, and Y. Liu, "POI recommendation method of neural matrix factorization integrating auxiliary attribute information," *Mathematics*, vol. 10, no. 19, p. 3411, Sep. 2022.
[296] L. Li and A. Yang, "A recommendation method of national fitness items based on neural network algorithm," *Sci. Program.*, vol. 2022, Jan. 2022, Art. no. 1544767.
[297] S. Kang, "Outgoing call recommendation using neural network," *Soft Comput.*, vol. 22, no. 5, pp. 1569–1576, Mar. 2018.
[298] R. Li, H. Zhu, L. Fan, and X. Song, "Hybrid deep framework for group event recommendation," *IEEE Access*, vol. 8, pp. 4775–4784, 2020.
[299] Q. Yang, G. Wu, Y. Li, R. Li, X. Gu, H. Deng, and J. Wu, "AMNN: Attention-based multimodal neural network model for hashtag recommendation," *IEEE Trans. Computat. Social Syst.*, vol. 7, no. 3, pp. 768–779, Jun. 2020.
[300] H. Fang, C. Chen, Y. Long, G. Xu, and Y. Xiao, "DTCRSKG: A deep travel conversational recommender system incorporating knowledge graph," *Mathematics*, vol. 10, no. 9, p. 1402, Apr. 2022.
[301] G. Zhu, Y. Wang, J. Cao, Z. Bu, S. Yang, W. Liang, and J. Liu, "Neural attentive travel package recommendation via exploiting long-term and short-term behaviors," *Knowl.-Based Syst.*, vol. 211, Jan. 2021, Art. no. 106511.
[302] H. Xia, W. An, G. Liu, R. Hu, J. Z. Zhang, and Y. Wang, "Smart recommendation for tourist hotels based on multidimensional information: A deep neural network model," *Enterprise Inf. Syst.*, vol. 17, no. 4, Apr. 2023.
[303] X. Dong, B. Jin, W. Zhuo, B. Li, T. Xue, and J. Song, "Modeling user interactions by feature-augmented graph neural networks for recommendation," *CCF Trans. Pervasive Comput. Interact.*, vol. 4, no. 3, pp. 207–218, Sep. 2022.
[304] D. Lee and K. Kim, "Business transaction recommendation for discovering potential business partners using deep learning," *Expert Syst. Appl.*, vol. 201, Sep. 2022, Art. no. 117222.
[305] M. Ahmadian, M. Ahmadi, and S. Ahmadian, "A reliable deep representation learning to improve trust-aware recommendation systems," *Expert Syst. Appl.*, vol. 197, Jul. 2022, Art. no. 116697.
[306] I. Rabiu, N. Salim, A. Da'u, and M. Nasser, "Modeling sentimental bias and temporal dynamics for adaptive deep recommendation system," *Expert Syst. Appl.*, vol. 191, Apr. 2022, Art. no. 116262.
[307] Z. Liu, B. Yuan, and Y. Ma, "A multi-task dual attention deep recommendation model using ratings and review helpfulness," *Appl. Intell.*, vol. 52, no. 5, pp. 5595–5607, Mar. 2022.
[308] A. Tanwar and D. K. Vishwakarma, "A deep neural network-based hybrid recommender system with user-user networks," *Multimedia Tools Appl.*, vol. 82, no. 10, pp. 15613–15633, Apr. 2023.
[309] M. Hong, N. Chung, C. Koo, and S.-Y. Koh, "TPEDTR: Temporal preference embedding-based deep tourism recommendation with card transaction data," *Int. J. Data Sci. Anal.*, vol. 16, no. 2, pp. 147–162, Aug. 2023.
[310] J. Wu, B. Yang, D. Li, and L. Deng, "A semantic relation-aware deep neural network model for end-to-end conversational recommendation," *Appl. Soft Comput.*, vol. 132, Jan. 2023, Art. no. 109873.
[311] W. L. Leiva, M.-L. Li, and C.-Y. Tsai, "A two-phase deep learning-based recommender system: Enhanced by a data quality inspector," *Appl. Sci.*, vol. 11, no. 20, p. 9667, Oct. 2021.
[312] N. Sivaramakrishnan, V. Subramaniyaswamy, A. Viloria, V. Vijayakumar, and N. Senthilselvan, "A deep learning-based hybrid model for recommendation generation and ranking," *Neural Comput. Appl.*, vol. 33, pp. 10719–10736, Sep. 2021.
[313] A. Da'u, N. Salim, and R. Idris, "Multi-level attentive deep user-item representation learning for recommendation system," *Neurocomputing*, vol. 433, pp. 119–130, Apr. 2021.
[314] G. Noveski, T. Eftimov, K. Mishev, and M. Simjanoska, "Data-driven intelligence system for general recommendations of deep learning architectures," *IEEE Access*, vol. 9, pp. 148710–148720, 2021.
[315] S. Ouyang and A. Lawlor, "Improving explainable recommendations by deep review-based explanations," *IEEE Access*, vol. 9, pp. 67444–67455, 2021.
[316] C. Choudhary, I. Singh, and M. Kumar, "SARWAS: Deep ensemble learning techniques for sentiment based recommendation system," *Expert Syst. Appl.*, vol. 216, Apr. 2023, Art. no. 119420.
[317] M. Gridach, "Hybrid deep neural networks for recommender systems," *Neurocomputing*, vol. 413, pp. 23–30, Nov. 2020.
[318] D. Guo and C. Wang, "Sequence recommendation based on deep learning," *Comput. Intell.*, vol. 36, no. 4, pp. 1704–1722, Nov. 2020.
[319] Q. Chen, G. Li, Q. Zhou, S. Shi, and D. Zou, "Double attention convolutional neural network for sequential recommendation," *ACM Trans. Web*, vol. 16, no. 4, pp. 1–23, Nov. 2022.
[320] Z. Y. Khan, Z. Niu, and A. Yousif, "Joint deep recommendation model exploiting reviews and metadata information," *Neurocomputing*, vol. 402, pp. 256–265, Aug. 2020.
[321] X. Zhang, H. Liu, X. Chen, J. Zhong, and D. Wang, "A novel hybrid deep recommendation system to differentiate user's preference and item's attractiveness," *Inf. Sci.*, vol. 519, pp. 306–316, May 2020.
[322] Z. Khan, N. Iltaf, H. Afzal, and H. Abbas, "DST-HRS: A topic driven hybrid recommender system based on deep semantics," *Comput. Commun.*, vol. 156, pp. 183–191, Apr. 2020.
[323] J. Han, L. Zheng, Y. Xu, B. Zhang, F. Zhuang, P. S. Yu, and W. Zuo, "Adaptive deep modeling of users and items using side information for recommendation," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 31, no. 3, pp. 737–748, Mar. 2020.

[324] A. Da'u, N. Salim, I. Rabiu, and A. Osman, "Recommendation system exploiting aspect-based opinion mining with deep learning method," *Inf. Sci.*, vol. 512, pp. 1279–1292, Feb. 2020.
[325] A. Da'u, N. Salim, I. Rabiu, and A. Osman, "Weighted aspect-based opinion mining using deep learning for recommender system," *Expert Syst. Appl.*, vol. 140, Feb. 2020, Art. no. 112871.
[326] I. M. A. Jawarneh, P. Bellavista, A. Corradi, L. Foschini, R. Montanari, J. Berrocal, and J. M. Murillo, "A pre-filtering approach for incorporating contextual information into deep learning based recommender systems," *IEEE Access*, vol. 8, pp. 40485–40498, 2020.
[327] W. Yuan, H. Wang, B. Hu, L. Wang, and Q. Wang, "Wide and deep model of multi-source information-aware recommender system," *IEEE Access*, vol. 6, pp. 49385–49398, 2018.
[328] Y. Bougteb, B. Ouhbi, B. Frikh, and E. Zemmouri, "A deep autoencoder-based hybrid recommender system," *Int. J. Mobile Comput. Multimedia Commun.*, vol. 13, no. 1, pp. 1–19, Jun. 2022.
[329] W. Serrano, "Intelligent recommender system for big data applications based on the random neural network," *Big Data Cogn. Comput.*, vol. 3, no. 1, p. 15, Feb. 2019.
[330] K. Rama, P. Kumar, and B. Bhasker, "Deep autoencoders for feature learning with embeddings for recommendations: A novel recommender system solution," *Neural Comput. Appl.*, vol. 33, no. 21, pp. 14167–14177, Nov. 2021.
[331] J. McAuley. (2023). *Recommender Systems and Personalization Datasets*. [Online]. Available: https://cseweb.ucsd.edu/~jmcauley/datasets.html

CAIWEN LI is currently pursuing the Ph.D. degree with the Faculty of Computer Science and Information Technology, Universiti Putra Malaysia (UPM). With years of experience as a Data Scientist, she has worked in various roles, including her most recent position with Amazon Web Services. She specializes in business intelligence and digital marketing, leveraging her expertise in data science techniques, such as forecasting, feature/model selection, data mining, APIs, and cloud technologies. Her research interests include recommendation systems, business intelligence, deep learning, and data mining.

ISKANDAR ISHAK received the Bachelor of Information Technology degree from Universiti Tenaga Nasional, Malaysia, the Master of Technology degree in information technology from the Royal Melbourne Institute of Technology, Australia, and the Ph.D. degree in computer science from Universiti Teknologi Malaysia. He is currently a Senior Lecturer with Universiti Putra Malaysia. His research interests include database systems, big data, and data analytics.

HAMIDAH IBRAHIM (Member, IEEE) received the Ph.D. degree in computer science from the University of Wales, Cardiff, U.K., in 1998. She is currently a Full Professor with the Faculty of Computer Science and Information Technology, Universiti Putra Malaysia (UPM). Her current research interests include databases (distributed, parallel, mobile, biomedical, and XML) focusing on issues related to integrity maintenance/checking, ontology/schema/data integration, ontology/schema/data mapping, cache management, access control, data security, transaction processing, query optimization, query reformulation, preference evaluation—context-aware, information extraction, concurrency control, data management in mobile, grid, and cloud.

MASLINA ZOLKEPLI received the bachelor's and master's degrees in computer science from Universiti Putra Malaysia, in 2007 and 2010, respectively, and the Ph.D. degree in computational intelligence and systems science from the Tokyo Institute of Technology, Japan, in 2015. She is currently a Senior Lecturer with the Department of Computer Science, Faculty of Computer Science and Information Technology, Universiti Putra Malaysia. Her research interests include business analytics, fuzzy brake systems, and computational intelligence.

FATIMAH SIDI (Member, IEEE) received the Ph.D. degree in management information system from Universiti Putra Malaysia (UPM), Malaysia, in 2008. She is currently an Associate Professor in computer science with the Department of Computer Science, Faculty of Computer Science and Information Technology, UPM. Her research interests include knowledge and information management systems, data and knowledge engineering, databases, data warehouses, big data, and data analytics.

CAILI LI is currently pursuing the Ph.D. degree in design and architecture with Universiti Putra Malaysia. She is an Associate Professor at the Heilongjiang Institute of Technology in China, specializing in design art, visual arts, analytical visualization, integrated arts, and landscape design. With her background as a Visiting Scholar with Tsinghua University, she brings extensive expertise and insights to her work, aiming to advance the design field, and inspire innovative solutions. Her research interest includes the intersection of art and technology.