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SURVEY

Social Recommendation for Social Networks Using Deep Learning Approach: A Systematic Review, Taxonomy, Issues, and Future Directions

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ABSTRACT Due to the rise of social media, a vast volume of information is shared daily. Finding relevant and acceptable information has become more challenging as the Internet’s information flow has changed and more options have been available. Various recommendation systems have been proposed and successfully used for different applications. This paper presents a taxonomy of deep learning algorithms for social recommendation by examining selected papers using a systematic literature review approach. Forty-six publications were chosen from research published between 2016 and 2022 in six major online libraries. The main purpose of this research is to provide a brief review of published studies to assist future researchers in establishing new strategies in this field. The implantation of deep learning in recommender systems proved to be very effective and achieved competitive performance. Different methods and domains have been summarized to find the most appropriate method and domain.

INDEX TERMS Deep learning, recommendation system, social recommender.

I. INTRODUCTION

Recommendation systems (RS) bring value to businesses through applications and online platforms. Social networks like Twitter, Facebook, and LinkedIn use RS to assist users in finding additional related items such as friends, posts, and trends, resulting in an enjoyable user experience. Several prominent RSs are available today, such as movie recommendations on Netflix, and item recommendations on Amazon. Despite the potential benefit of RSs, a lot of research points to future obstacles in the field, including the issue of developing a hybrid model for social recommendations that combines diverse methodologies [1]. Therefore, a good RS uses various techniques to arrive at a reasonable conclusion for consumers [1].

Deep learning (DL) is a branch of artificial intelligence that has recently exploded in popularity. It has numerous processing stages, and each is used to extract increasingly sophisticated characteristics which are then provided as input to the next characteristics. DL algorithms learn and process information like the human brain does [2]. DL model training process is classed as supervised or unsupervised learning. Some of the most popular DL models for social media recommendation systems include autoencoders (AE), convolutional neural networks (CNN), restricted Boltzmann machines (RBM), and recurrent neural networks (RNN). DL recommender systems have recently been the subject of both significantly increased interest and research papers. Different studies were conducted to review DL-based

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RSs [3], [4], [5]. However, previous studies summarize and analyze the highest-quality academic papers based on DL-based RSs. Still, none of them look at the many characteristics of social networks that are important in generating practical recommendations. Consequently, there is a compelling need for a comprehensive study and examination of state-of-the-art publications focusing on social RSs and using DL to better understand these approaches' fundamental opportunities and drawbacks in assisting researchers in developing a RS for social media.

This research presents the articles published from 2016 to 2022 and presents a taxonomy of DL algorithms for social recommendations. As a result, this study aims to identify, summarize, and evaluate current research on social RSs that use DL models. We perform classification by application area, techniques, and datasets. We perform classification by user, item, and transaction. Additionally, we surveyed data sources that are utilized for the social media RS. Our intended outcomes are the identified research gaps and proposed research areas.

The primary contributions of the study are listed below, as assessed via data gathering and synthesis from 46 peer-reviewed studies.

The following are the most important contributions of this systematic literature review (SLR):

- To identify possible research gaps and future works in social RSs using DL models.
- This study presents a study of features of social RSs and data sources on social networks.
- Various social application domains, datasets, and evaluation metrics that are used in multiple social RSs are also discussed.
- We conduct an SLR of the existing social recommendations based on various techniques using DL.
- We propose a taxonomy of DL algorithms for social recommendation by examining selected papers.

The rest of the article is structured as follows. Section II presents related works to review the deep learning-based recommendation systems. Section III presents background information on RSs, social recommendations, the features of social RSs, and data sources on social networks. Section IV provides the SLR technique, which resulted in the selection of 46 reviewed publications. Section V provides results and a discussion summarizing the procedure used to answer research questions using data from selected studies. Section VI presents a taxonomy of DL algorithms for a social recommendation. Section VII shows potential study gaps and suggests future research directions. Finally, Section VIII concludes and suggests more work.

II. RELATED WORK

Recently, different studies have been conducted to review DL-based RSs. Reference [4] presented a review of a RS by describing its limitations and solutions. The presented review provides a DL-based RS as well as its challenges and solutions. The current systematic survey includes a time-limited publication that is not up-to-date and does not cover current challenges and methodologies. The implanted systematic review is for research recommendations using DL and is also compliant with social network recommendations. The systematic review includes research papers from 2007 to 2018. Scalability and accuracy are the main challenges that need to be addressed in upcoming research. The researchers [3] developed a SLR to summarize the most reliable properties and outcomes of DL-based RSs. The article presents the SLR of deep learning-based recommendation approaches and covers emerging trends and robust techniques for RS. The implanted SLR was initially based on 1480 research papers downloaded from different databases, 105 of which were published between 2017 and 2018 and selected for the SLR by removing duplicate and irrelevant articles. The study is purely based on selected academic articles and research papers from an academic database. Fine-tuning parameters and system configurations increased RS robustness and performance to implement DL methods better. Reference [5] presented a detailed review of DL-based RSs that is robust and efficient in its discussion of business and audience capitalization growth. The survey outlines current DL-based RSs. A comprehensive study has been presented to highlight the importance of DL in the existing systems. The publications utilized for this systematic review were classified into two categories: neural blocks and deep hybrid systems. Researchers developed a survey covering all RSs suitable for business and social networking. The main challenges of DL strategies include scalability, interoperability, and parameter fine-tuning, and challenges discussed in the survey can be reduced in the future to increase the DL-based system's performance and robustness. Reference [6] provides a detailed analysis and review of state-of-the-art techniques for implementing DL in RSs. The researcher developed an in-depth analysis of a user preferences-based RS based on DL. The survey article covers all the presented robust techniques and DL-based robust tools for RSs. The study encompasses articles covering social, economic, and traditional community domains for efficient RSs. Deep learning-based RSs behave like a black box because of initial parameter tuning, and different models lack interoperability. Scalable and interoperability-improved methods are necessary when utilizing big data for RSs.

Reference [1] conducted a study of social RSs using DL techniques. Aspects of social RSs that are conducive to the system's robustness are discussed. The researchers discussed DL-based social RSs. The selected articles elaborate on the robustness of the social recommendation models. The implanted survey covers social RSs based on deep learning, and the study includes the social network RSs' features, problems, and challenges. The presented challenges described in the study include semantic filtering; social connections; group, tag, and cross-social media information sharing; and the challenges presented by these issues occurring in combination. Cross-domain implementation of RSs for social networking with imbalanced data and a combination of different challenges need to be addressed in the future. The researchers [7] have compared DL-based and traditional method-based RSs. The survey evaluated the RS according to both user requirements and literature expressing the applications of RSs. A robust RS utilized DL instead of traditional approaches. The survey presents an overview of social recommendation applications based on DL approaches. DL implantation in an RS, which contains a large amount of data to extract the user experience, becomes efficient and cost-effective. Available options for big data processing using DL lead to accurate and robust recommendations. DL implementation in RSs has made the models robust but has limitations in terms of scalability and interoperability. Reference [8] has developed an overview of DL-based rating systems of online services. A review of DL-based techniques for online services and applications has been presented. The study has comprehensively analyzed DL-based rating predictions by retrieving large quantities of data. Systematic approaches were utilized to analyze the rating prediction models with the help of both state-of-the-art DL algorithms and classical methods. The articles selected for the presented survey include the following DL models: deep architecture, deep hybrid models, and neural attentional models for rating classification. The systematic survey covers the trends and robust applications of rating prediction for RSs. The limitations of DL rating prediction models include information sharing of different resources and cross-domain implementation. Reference [9] presented a survey of deep learning approaches, including autoencoder-based recommendation systems, and developed a comparison of classical and autoencoder-based RSs. This study discusses the methods of the autoencoder-based recommendation systems and presents a detailed analysis. Autoencoder-based recommendation systems that use either the classical or the DL model are surveyed for comparison. The systematic study shows the impact of a community's social activities on different social networks and provides a competitive analysis of suitable applications using RSs. Autoencoder-based RSs have multi-tasking, interoperability, and temporal dynamics compared to classical recommendation models. The limitations of autoencoder-based RSs include scalability, attention structure, auxiliary information integration, and new robust autoencoder development. Shokeen and Rana [2] compiled a survey of competitive social media RSs. RS implementation in different domains has been evaluated systematically. Both RS datasets and the performance of robust RSs have been expressed descriptively. The presented survey covers social media RSs. A comprehensive study was implemented to discuss the RS robustness in cross-domains. A brief description has been presented, which covers all social media platforms according to the RSs. The paper was selected based on metrics, datasets, and applications. The limitations of this survey of social media RSs include attributes of objects and correlations between different objects. DL can be utilized to reduce the challenges inherent in current social media RSs. Thus, even though there have been several research studies on DL-based recommendation systems that function in the most popular domains, the use of deep learning in the development of social recommendation systems has been unexplored. This study seeks to identify, summarize, and evaluate studies on the applications of DL-based RSs on social networks to provide a systematic review of recent studies and pave the way for future research to help enhance the development of DL-based RSs in the context of social media.

III. BACKGROUND

A. RECOMMENDER SYSTEMS

RSs help consumers by recommending services or items that may interest them [10]. The importance of RSs in the academic world and in the industry today cannot be overstated. Many businesses utilize RSs to promote their products and services through various channels. RSs, for example, are responsible for most videos viewed on YouTube and other video streaming platforms [11]. RSs offer natural protection against consumers' overabundance of options. Users are confronted with a large amount of merchandise, videos, or restaurants due to the exponential increase in material available on the internet. As a result, personalization is a critical tool for enhancing the customer experience. RSs are specifically aimed at people who lack personal knowledge or expertise to determine the seemingly daunting unseen products that a platform, for example, may include [12]. A book recommender scheme can aid consumers in choosing a book to read. Amazon.com uses an RS to customize the online shop for each user [13]. However, the issue of data overload has become more and more pressing as Internet technology and social media develop at a rapid speed. A successful recommendation framework can increase traffic and revenues for service providers and provide users with accessible resources to conveniently access the things they want [14], [15]. In addition, some significant challenges required for improving RSs are sparsity, cold-start, the trustworthiness problem, preference acquisition and profiling, interaction, and the new recommendation task [16].

1) COLLABORATIVE FILTERING METHODS

RSs are also known as data filtering schemes, which employ information filtering methods that depend on the user's connection to the object to try to overcome the issue of information overload [17]. The most commonly used RS methods are CF methods [18]. This recommendation system technique can find similar users and use either the interests or the rating patterns of these users to recommend items to other users [19]. This technique has been applied successfully within various domains, including restaurant, movie, and music recommendations. Collaborative-based RSs are classified as model- or memory-based recommendation systems [3], [4]. A recent study by [20] proposed a new collaborative filtering method based on DL that delivers recommendations with the best balance of fairness and accuracy. The researchers have suggested the use of an original loss function and input data to achieve a balance of fairness and accuracy. This technique includes various layers of abstraction and can be used as a starting point for future DL work on the topic. However, the results demonstrate sufficient trends in the quality measures tested: an increase in fairness at the expense of an expected decrease in accuracy. However, the collaborative filtering method has some disadvantages, such as the cold-start problem [21], data sparsity [22], and scalability [22]. Several experiments have been undertaken in recent years to study and survey the classical RS. Reference [23] introduced a study of collaborative filtering (CF) approaches for RSs, which was one of the first significant works on the topic. The investigators looked at various advisory methods and compared them in terms of their benefits and drawbacks. Different examination surveys have been conducted to enhance the efficiency of CF in the cold start challenge, including integrating multiple CF techniques [24] and working CF on minor data rather than large data [25].

2) CONTENT-BASED METHODS

The content-based recommendation system was designed to recommend items with the same user's historical preference. It aims to suggest things like those a user has liked previously. A collection of characteristics, also called attributes or properties, are represented by items [26]. For example, when the individual previously chose action films in a movie RS, the following time, the RS would probably recommend a recent action movie to that same individual [27]. In addition, for object suggestions, CB filtering strategies focus primarily on user/item descriptions [28]. Information extraction and web search mining are commonly used to generate similar user/item data [29]. Various learning methods are used to learn a user profile: SVM, neural network [30], and Bayesian classifiers [31] are commonly used. Even though they require content definition, CB filtering methods typically include clear recommendations [32]. However, despite some content-based recommendation systems effectively recommending new products due to insufficient user profile information, they cannot provide individualized predictions. Furthermore, because the algorithms do not employ group information from like-minded people, recommendations are limited in terms of diversity and innovation [4].

3) HYBRID RECOMMENDATION APPROACH

Hybrid-based recommendations can combine two or more approaches to generate an enhanced recommendation [3]. They blend techniques A and B to use A's strengths to compensate for the disadvantages of B [27]. Generally, the method combines CF and the CBF technique to address the cold-start problem best [1]. For example, collaborative filtering methods suffer from new-item problems; for products with no ratings, they do not produce evaluation predictions. This does not restrict content-based methods, as the prediction for new products is based on the characterization (feature) that is readily available [27]. Therefore, the disadvantages of a single strategy can be mitigated by combining multiple techniques. Hybridization of RSs can be accomplished using a variety of approaches [33].

B. SOCIAL RECOMMENDATION

RSs and social networks support each other. They provide new possibilities for companies to consider the social impact of their product marketing. Furthermore, the increasing popularity of social networks means that the vast amounts of data within them could be useful for various implementations, including RSs.

However, information overload makes making decisions even more difficult for social media users. Therefore, social RSs are intended to help people better understand what they want on social networking sites by reducing information overload [34]. Social data is beneficial for three reasons in particular [35]. Firstly, it can be used to increase the accuracy of predictions. For example, the RS may deduce that, when two individuals are friends on a social media network, they may have similar tastes in products. Second, this can be applied to creating a modern recommender scheme. The third goal of social filtering is to investigate the connections between social data and collaborative institutions. For example, in issues of decision-making, the similarity between recommender and recommended can be significant. Intelligent recommendation systems and efficient search engines are helpful for users of social networks. Recommendation services including Amazon and Netflix take the opportunity to learn about their customers' interests and educate them about what they are interested in on their services. The latest research [36], [37], [38] has focused on social recommendations, and many e-commerce systems have attempted to use consumer social knowledge to increase the accuracy of their recommender systems [39], [40]. However, deep learning on social media can deliver insights from the brand's content, profiles, and audience. First, it can measure brands and trends across social media to help organizations measure and improve brand equity, detect consumer trends, and understand target audiences. Second, DL on social media can determine what to post for the most significant impact by analyzing both the brand itself and other companies' posts and can recommend post content, timing, and tone. Reference [41] examined the implementation domain for RSs and the use of machine learning approaches using a SLR process. Using machine learning approaches, the authors proposed various alternate validation steps and identified new research directions for RSs. Using proper DL techniques can in fact accomplish better performance than traditional techniques in terms of tag recommendation tasks for software information sites [42]. In addition, [43] used a SLR technique to study current approaches on the CF system, which uses social network data to solve the cold start challenge. The study focused on articles that were written between 2011 and 2017. Among the earliest methods in community recommendation analysis is to use "linked" consumers instead of "same" users in standard recommendation techniques. This means that the prediction of a consumer's ranking score for an object is dependent on the user's related friends rather than on all equivalent users [44].

C. FEATURES OF SOCIAL RECOMMENDER SYSTEM

Different aspects of a social RS can help improve the robustness of a system. A study of social RSs using DL techniques was conducted by [1]. The researchers discussed social RSs based on deep learning, and the study includes the social network RS's features. The survey classified different social RSs based on their selected features and attributes. The following additional features were identified for classifying different social RSs: context, group, trust, tag, temporal dynamics, semantic filtering, cross-social media data, and heterogeneous social connections. Although many studies have used these factors independently, none have used them simultaneously. In social commerce, a study by [45] suggested a social-hybrid RS recommending tourist attractions based on reputation, trust, social communities, and similarity. The study demonstrated that the proposed approach is superior to other commonly used approaches.

There has been an increasing number of studies on social recommendation, which indicates that social RSs has become a critical issue in recent years. However, there has not been a systematic review of social recommendation systems to study DL for social RSs. However, while computational difficulties may increase when these features are used to construct social recommendations, the results may be noteworthy. Therefore, we identified the need for a systematic review in the domain of social RSs.

In addition, one of the difficulties in presenting a social recommendation algorithm is determining the factors that influence suggestions. Because various criteria have varied effects on RSs, the appropriate weighting of features is a major issue in creating an algorithm [2].

D. DATA SOURCES ON SOCIAL NETWORKS

In this section, we survey the data sources utilized for the social media RS. According to [1], an additional area of investigation is identifying appropriate social media data for social RSs. RSs are data-gathering programs that actively collect various data to make recommendations. The data mainly concerns the things to recommend and the people to receive the recommendations. The data manipulated by RSs are divided into three objects: items, users, and transactions, which refers to the connections between the users and the items [16]. In accordance with the findings of [46], data sources are broadly classified into two basic categories: static and dynamic data. The phrase "static data" refers to information or properties that may be used to learn the utility of recommendations for a user but that do not change or that change slowly. The attributes of movie descriptions, such as action, drama, thriller, comedy, production date, cast, and director, are good examples of static data. Compared to static data, which usually remains the same, the attributes of dynamic data may change even in a very small amount of time. These attributes include social interactions, seasonal changes, the popularity of products, user preferences, etc.

1) USER

In online cultures, the user profile plays a critical role. According to [48], the user profile usually contains both the user's static personal information, such as name, gender, and email address, and the user's dynamic information, such as preferences and data needs. In general, user profiles vary from one form of media to the next, and users introduce themselves in many ways depending on the application's target audience (which is sometimes very specific). In addition, according to [16], the user model, which is stated to be made up of user data, represents the user's interests and needs. RSs can be considered a method for creating and manipulating user templates to create suggestions [47], [48]. Site searching habits in a web-based RS [49], and trip search patterns in a travel RS [50], can also be used to describe users. Therefore, user data may be found on social networking sites, including user profiles, social relationships, tags, comments, and postings. Recommendation systems use this information to provide relevant and effective recommendations [2].

2) ITEM

According to [51], interactions between users are influenced by shared social items. Static items, such as category and name, are common, whereas dynamic items, such as people's interests, are uncommon. In this case, an item has a tangible and/or numerical manifestation that is concrete and perceptible. Any items serve as dialogue starters and keepers of the group's attention. Moreover, according to [16], news, books, webpages, and films are low-difficulty and meaningful items. Digital cameras, smartphones, PCs, and other items of greater complexity and importance are examples. However, It has been discovered that under-contribution is a common issue in the online social context; i.e., individuals rarely want to share ideas and remarks [1]. Instead, consumers prefer to utilize prepared and processed data, referred to as social loafing. Research has shown that users are more likely to contribute when they believe their contributions are distinctive and valuable to communities or when they have a particular affinity for a specific group [1].

3) TRANSACTIONS

According to [16], the term "transactions" refers to the established relationships between a user and the RS, including the relationship between a user and a particular object, which could be explicit feedback, such as a user's rating of a particular item. Transactions are log-like data that are used by the system's suggestion generation algorithm to store valuable knowledge produced through human-computer interaction. A transaction log, for example, can provide a reference to the item chosen by the manipulator and a statement of the recommendation's context and the user's goal/question. If the transaction is accessible, it can also require direct input from the customer to rank the chosen item. Therefore, several authors propose to include additional information in future work to increase the performance of the RS model. This provides information on user profiles, social connections, and other session-related data [3]. In addition, it is easy to derive from the definition of social networking that recommendations play a key role in social networking services. In this arena, the vocabulary of recommendation includes terms such as user profiles, friends, likes, followers, tags, and comments [4].

E. DEEP LEARNING-BASED SOCIAL RECOMMENDATION SYSTEM

DL is a branch of artificial intelligence that has exploded in popularity recently. It has numerous processing stages, each of which is used to extract increasingly sophisticated characteristics, which are then provided as input to the next characteristic. DL algorithms learn and process information like the human brain does [2]. DL has improved recommendations within many domains and shows various learning methods that include autoencoders (AE), convolutional neural networks (CNN), restricted Boltzmann machines (RBM), recurrent neural networks (RNN) and others which are some of the most popular DL algorithms for social networks recommendation systems now in use. However, the creation of custom DL-based RSs has become a common theme. According to [3], various organizations have used DL approaches to improve the diversity and accuracy of their RSs in recent years [52], [53], for example, proposed a broad and deep framework for Google Play recommendation. Reference [11] suggested a movie suggestion system focused on DL. For news retweeting, [53] used an RNN.

A CNN is a feed-forward neural network with convolution layers and pooling processes. This method is adept at capturing global and local features and it can enhance accuracy and efficiency. The process also performs well during data processing with grid-like topology [54]. Reference [55] proposed a deep user-image feature (DUIF) model for extracting and learning the features of users and images from a wide range of both sparse and diverse social curation networks. The results of this work demonstrate the effectiveness of the DUIF model in extracting and learning image features for recommendations in social networks. However, privacy is the most significant limitation of this study because of the dependency on users' personal information. In addition, a customized tag suggestion model based on CNN was introduced by [56]. It employs the convolutional and max-pooling layers to extract visual features from videos. To create a customized suggestion, user information is injected. The proposed strategy improves accuracy by at least 2%.

The Recurrent Neural Network (RNN) is a method suitable for the sequential data modeling process. The loops and memories within the RNN serve the purpose of remembering the former computation. Variants that include long-short term memory (LSTM) and the gated recurrent network unit are deployed within the practice to overcome vanishing gradient [54]. Reference [57] proposed a deep RNN model for enhancing e-commerce recommendations by employing numerous layers to observe how people visit the website. To improve prediction performance, the authors combine the RNN with a feedforward network that depicts the user-item connection.

AEs are usually unsupervised neural networks trained to mirror their output as data. An AE usually consists of three layers: the layer of input, the hidden layer, and the layer of production. In the input layer, the number of neurons equals the number of neurons in the output layer [4]. The input layer is fed with the dataset's complex representations, and such complicated expressions are transformed into low-dimensional representations in the hidden layer. In essence, it mirrors the operation of an encoder, which encodes low-dimensional representations of complex, high-dimensional representations. The low-dimensional representations are transformed into high-dimensional representations by reverse mirroring the operations as the data moves from the hidden layer to the output layer. This can also be regarded as the operation of a decoder [6]. A deep learning-based matrix factorization (DLMF) was proposed by [58]. In DLMF, trust was considered as an input attribute for recommendations in social networks. In this study, the researchers employed deep encoders to train users' hidden attributes and items to maximize the objective function. As a result, recent studies indicate that the deep learning approach provides promising results in RS. Therefore, we conduct a SLR of existing social recommendations using DL in this study.

IV. SYSTEMATIC LITERATURE REVIEW

This SLR is conducted following the guidelines of [59] through the four-phase method of selecting relevant studies: research questions, search procedure, paper selection, and data synthesis. As mentioned earlier, different studies were conducted to review DL-based RSs. However, due to the growing amount of primary research on DL-based RSs, there have been relatively few additional research investigations on social DL-based RSs, and all of the current studies have relied only on the traditional research and analysis of the literature. Therefore, it is necessary to undertake the study using the SLR, which has been recommended as the method most suited for providing a thorough and objective analysis of published research.

This research provides a summary of the state of the art in the area from many vantage points, as well as an organized presentation of the topic into four main theoretical frameworks. The review provides the following contributions:

- Identified and classified essential DL algorithms and techniques applied to social RSs, and organized them into a taxonomy.

TABLE 1. Research questions.

RQ No.	Question	Motivation
RQ1	Which deep learning techniques have been implemented on social RSs in the previous studies?	Review the deep learning-based RS methods
RQ2	Which social networks dataset have been included in the study?	Identification of datasets utilized in RS.
RQ3	What are application domains used in the previous studies?	Analysis of classical RS techniques and applications.
RQ4	What are the metrics used for evaluating the performance of social RSs?	Analyze the performance evaluation measures used to evaluate the performance of RS techniques.

- Summarized the primary application domains of these DL-based social RSs.
- Current state-of-the-art implementations have been analyzed for existing obstacles and limitations.
- Identify possible future research directions in the field of DL-based social RSs.

1) PHASE 1: RESEARCH QUESTIONS

The following questions are limited to deep learning in social recommendation since the answers will allow us to do primary research and develop a new framework for some of the study's outstanding challenges. Table 1 represents the review questions that were prepared.

2) PHASE 2: SEARCH PROCEDURE

This study automatedly searched six major digital libraries to find the most relevant publications connected to the research issue, including Web of Science, Springer, IEEE, ACM, Scopus, and ScienceDirect. These libraries were chosen because of their popularity and because of the quantity of research articles contained therein. To narrow the search's scope, different combinations of keywords were used. Search terms were as follows:

"(“recommendation system” OR “recommender system” OR “recommendation” OR “recommender”) AND (“machine learning” OR “deep learning” OR “deep”) AND (“social”)"

For a study to be selected for further evaluation, a set of criteria must be completed to narrow down the search area. This study included articles that satisfied the following criteria:

- Papers that are published entirely in the English language.
- A research paper that answers at least one research topic.
- Papers published from 2016 to 2022 only.
- Only conference and journal papers are accepted for publication.

Articles that met the following criteria were excluded from the study:

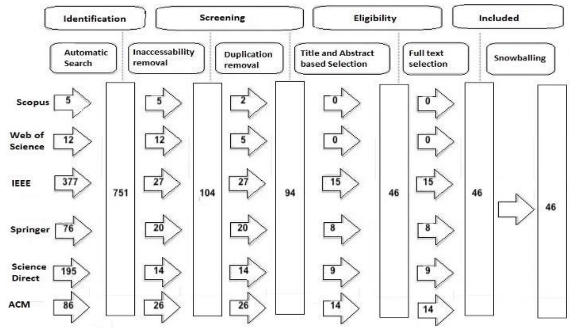

FIGURE 1. Paper selection process.

TABLE 2. Quality evaluation questions.

ID	Quantity
1	Is the paper's topic relevant to the study's research questions?
2	Is it obvious what the study's goal is?
3	What is the research methodology's level of rigor?
4	Is the data processing well described?
5	Is the deep model explained correctly?
6	Is there a concise summary of the findings?
7	Is there a clear description of the validity context?

- The paper is not related to DL-based social recommendations.
- The paper is not related to the topic of social recommendations.
- The paper does not discuss techniques that are directly related to DL-based social recommendations.
- The full text is not accessible.

In addition, the articles' keywords were evaluated and shown in Figure 3. The researchers extracted the relationship between the co-occurrence of terms linked to the study issue using VOSviewer software.

3) PHASE 3: PAPER SELECTION

Many publications were gathered from internet sources to engage in a comprehensive review of research in the field. Papers are written in English, and at least one research topic is selected. In addition, only articles published from 2016 to 2022 and conference and journal publications were included in this study. Figure 1 depicts the PRISMA guidelines-based paper selection procedure [61]. The articles were chosen from six international publications and four research questions. After reading each paper's abstract and methodology sections, the search results were filtered according to the selection criteria. The four steps of the selection process are identification, screening, eligibility, and inclusion. The first step is based on an automated search, yielding 590 people. After the screening, 94 articles remained after duplication and inaccessibility were removed. After completing all four steps depicted in Figure 1, 46 papers were obtained.

Quality evaluation: a quality assessment approach developed by [60] was used to grade the chosen papers. Reference [61] used a series of questions in Table 2 to assess the

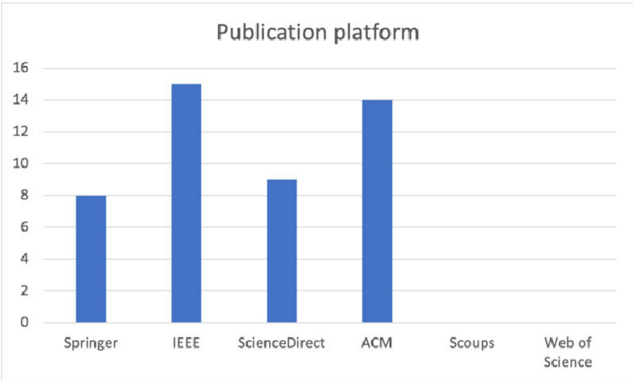

FIGURE 2. Publication platform.

TABLE 3. Data extraction method.

No.	Instance Name	Research Question
1	RS techniques and models.	RQ1
2	Analysis of Classical Methods	RQ3
3	Domains and application	RQ3
4	Datasets utilized	RQ2
5	Performance Evaluation measures	RQ4

quality of work. To narrow the search, each criterion was given a score of 2 (totally), 1 (partially), or 0 (not at all or none). For each criterion, a total score was generated for each study. Only studies with a score >=9 were considered. The final subset of papers has been found, which includes 46 studies. These articles have been thoroughly studied by the researcher, and all research issues have been addressed.

4) PHASE 4: DATA EXTRACTION

Different factors were evaluated in this study while selecting relevant research publications to be included. Various elements and qualities of the research articles were sorted into columns, and all these columns were combined to make a spreadsheet, which was used to finish the study. Examples of information clusters include: authors and year of publication, article title, application domain, social network dataset, DL model, RS method, and measures utilized. As indicated in Figure 2, the final selection of publications, which includes 46 papers, has been identified. The most common platform was IEEE, with 15 studies. Fourteen studies were published on ACM, nine on ScienceDirect, and eight on Springer.

The researcher has thoroughly examined these publications and addressed research questions. Table 3 shows the extraction data method, representing five data attribute names assigned to each study. The extraction data method covers RS techniques and models; analysis of classical methods, domains and applications; datasets utilized; and performance evaluation measures.

5) THREATS TO VALIDITY

One of the approaches for assuring the degree of empirical value of an SLR's results is to rigorously analyze its validity [12]. The four common kinds of TTVs given by [62] must be examined to support this SLR. These include constructing, internal, external, and conclusion validity. The initial stage was to establish validity through paper inspection and quality evaluation. The study topics, as well as the criteria for inclusion and exclusion, were explicitly defined. Internal Validity employed a human and automatic search strategy to discover publications that were exhaustively related to the themes of interest, ensuring that the paper-collecting procedure was neutral. In the third step, external validity was lowered by looking for publications published between 2016 and 2022 to generalize the study's findings. Finally, the validity of the conclusions was checked using the processes and techniques utilized in this study, which followed the principles of many writers [59], [63].

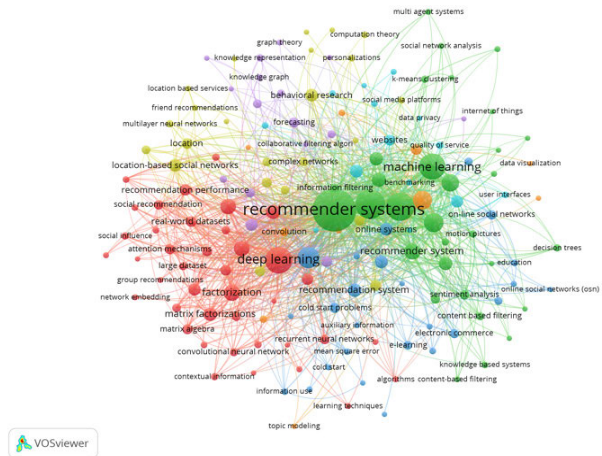

FIGURE 3. Frequency of keywords in the publications.

V. RESULTS AND DISCUSSION

This section summarizes the results of the procedure used to answer research questions using data from the chosen studies.

A. PRIMARY STUDIES (PS)

This section is divided into four subsections, the first of which explains the various DL techniques utilized in social RSs. The second section includes several datasets, while the third portion delves into DL techniques used in RSs. The final part discusses the various assessment criteria used to determine the accuracy of DL-based RSs. Table 4 shows a list of selected primary studies (PS) with the reference number of each study.

1) DEEP LEARNING-BASED SOCIAL RS

This part identifies the RQ1 result, which aids in categorizing the research that is part of this review and is based on SRS using DL. From 2016 through 2022, Figure 4 depicts the distribution of journal articles by publishing year. Many studies identified the DL techniques used for RSs through a graph. Table 10 presents the selected studies based on DL methods.

A lot of research employed various DL algorithms for RSs; for example, [64] offers SN-CFM, a DL-based model for predicting highly recommended consumer products based on customer and product similarity in the neighborhood. The

TABLE 4. Selected primary studies (PS).

Study No.	Paper	References	Study No.	Paper	References
PS01	Wan 2020	[68]	PS17	Lu 2018	[88]
PS02	Tahmasebi 2020	[69]	PS18	Malte 2018	[98]
PS03	Pan (2020)	[70]	PS19	Neamanee 2018	[75]
PS04	Gao 2020	[91]	PS20	Niu 2018	[100]
PS05	Pramanik 2020	[82]	PS21	Liang 2018	[67]
PS06	Zhang 2019	[66]	PS22	Wei 2017	[71]
PS07	Mohan 2019	[97]	PS23	Deng 2017	[58]
PS08	Lei 2019	[95]	PS24	Dang 2017	[81]
PS09	Zhang 2019	[80]	PS25	Nguyen 2017	[56]
PS10	Shamsoddin 2019	[64]	PS26	Zheng 2017	[87]
PS11	Garg 2019	[72]	PS27	Wang 2017	[101]
PS12	Chen 2019	[73]	PS28	Cao 2017	[79]
PS13	Lemei 2019	[93]	PS29	Hidasi 2016	[99]
PS14	Song 2019	[65]	PS30	Tan 2016	[103]
PS15	Wu 2019	[74]	PS31	Lee 2016	[92]
PS16	Qu 2018	[76]	PS32	Zhou 2016	[104]

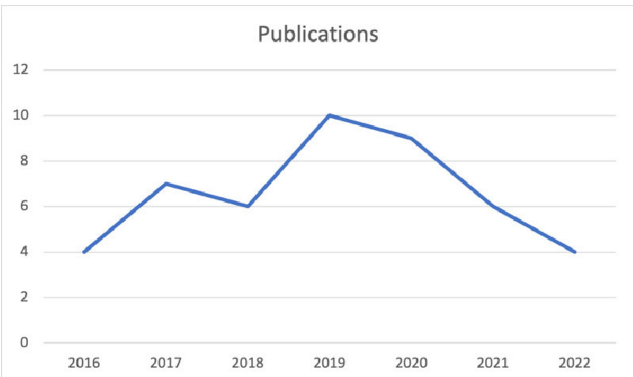

FIGURE 4. Distribution of studies per Year.

authors [65] propose a session-based RS based on RNN, KNN, and Neural Attentive Recommendation Machine DL algorithms.

The study [67] proposed a MARS by using a CNN for learning item representations. The CNN method is a specific feed-forward neural network with convolution layers and pooling operations. This method is effective at capturing global and local features, and it enhances accuracy and efficiency. A study by [56] proposes a tailored DL approach to picture tag suggestion that consider the user's preferences and visual data. The study uses the CNN approach to gather visual characteristics from photographs, providing excellent image classification performance. Another study by [66] provides a personalized social picture recommendation approach for extracting deep features from a trained model.

The AE method usually consists of three layers: the layer of input, the hidden layer, and the layer of output. In the input layer, the number of neurons equals the number of neurons in the output layer. The study [67] defines variant AEs using a deep latent Gaussian model. One study [68] suggested the use of a trust-based RS using the matrix factorization technique. The study employs an AE to recover the latent representation in the hidden layer from the trust relationship matrix to estimate the user factor matrix factorized from the user-item rating matrix. The authors [69] propose a deep AE-based hybrid social RS to address data sparsity. It uses an auto-encoder approach to extract complicated relationships between the target user's unrated items and is expected to deliver correct recommendations to the target user. The authors [70] focus on this challenge and offer a deep autoencoder model to train deep social representations for recommender systems to model social information more accurately and efficiently. The researchers [71] suggest using an AE to extract item attributes from content descriptions, which are then employed in a collaborative filtering model to estimate cold-start item ratings

DeepVenue is a deep learning-based venue recommendation system proposed by [74] that gives context-driven venue choices for Meetup event presenters to conduct their events. The work used RNN-based LSTM cells to efficiently store and learn long temporal sequence representations. The RNN method can handle the temporal dependencies and sequential features in RS.

Another study [72] recommends sequence and time-aware methods using session-based k-nearest-neighbors. According to the review's findings, AE algorithms are the most extensively used DL method for a social recommendation system, followed by CNNs. However, even though RSs have gained much attention in recent years, various challenges and possibilities will influence the future of RSs for academics, such as using DL techniques in constructing social recommendation systems.

In conclusion, deep learning recommendation models employ neural networks trained on huge amounts of user data to find patterns, discover hidden characteristics, and eventually predict tailored suggestions. They offer several benefits and are being utilized more often by businesses with significant amounts of user data. Deep learning is capable of detecting complicated interactions and patterns. Deep models can identify nonlinear data relationships. The model discovers representations and characteristics that summarize the essential aspects of users and products. Deep models benefit from enormous amounts of data and scale effectively in comparison to other models. Moreover, deep models can utilize heterogeneous data types, such as text, images, and more, in addition to ratings and interactions.

TABLE 5. Selected studies of social RS using deep leaning.

References	Authors and year of publication	Application Domains	Social network Dataset	Deep learning Model	Additional RS technique	Metric used
[68]	Wan, 2020	Social Recommendation	Epinions, Flixter	Deep Learning	Matrix Factorization	(Root Mean Squared Error) RMSE, F1score, Coverage (COV)
[69]	Tahmasebi et al (2020)	Movie	Twitter	autoencoder	Collaborative filtering and content-based filtering	Mean Absolute Error (MAE), and RMSE
[70]	Pan et al (2020)	learning social representations	Epinions and Ciao datasets	autoencoder	Collaborative filtering	MAE and RMSE
[91]	Gao et al(2020)	microblogs and social network	Sina Weibo and Twitter	DNN	Collaborative filtering	precision and recall
[82]	Pramanik 2020	Venue Recommender	Meetup and Yelp	DeepCoNN	Collaborative Topic Regression based Ranking (CTR) Matrix Factorization based Ranking (MFR)	Recall and Mean Inverse Rank (MIR)
[66]	Zhang 2019	Social Images	NUS-WIDE object + Flickr	CNN	Tag tree	precision and recall
[97]	C C, N. and Mohan, A (2019)	semantic social information	Github	autoencoder	Collaborative filtering	MAE and RMSE
[95]	Lei,2019	Attention-Aware Recommendation	Yahoo Movies, Amazon Video Games and Amazon Movies and TV	Deep Learning	Collaborative Filtering	Mean Average Precision (MAP), Recall@N
[80]	Zhang,2019	Movie Recommendation	MovieLens	Bayesian network	Matrix Factorization, collaborative filtering	RMSE, Precision@10
[64]	Shamsoddin, 2019	Product Prediction	Amazon	Deep Learning	Collaborative Filtering	MAE, RMSE, Positive Predictive Rate (PPV), Recall, Accuracy (ACC) and Mathew's Correlation Coefficient (MCC).
[72]	Garg,2019	Session-based Recommendation	Yoochoos, Diginetica, RetailRocket	Deep Learning	neighborhood -based methods	MRR@K (Mean Reciprocal Rank) and Recall@K,
[73]	Chen,2019	Context-ware Recommendation	MovieLens, Last.fm	Deep Learning	Collaborative filtering	F1-score
[93]	Lemei,2019	Personalized news recommendation	Adressa, Last.fm and Weibo-Net-Tweet	Deep neural Network	user interests modelling	MRR@K, Recall@K, Precision@K, F1 score
[65]	Song,2019	Social Recommendation	Douban, Delicious, Yelp	Deep Learning	Matrix Factorization	Recall@K and Normalized Discounted Cumulative Gain (NDCG)

TABLE 5. ***(Continued.)*** **Selected studies of social RS using deep leaning.**

[74]	Wu,2019	recurrent recommender systems	Netflix and MovieLens	Deep Learning	Collaborative Filtering	RMSE, MAE
[76]	Qu,2018	Friend recommendation	Sina Weibo	DNN		RMSE
[88]	Lu,2018	Reviews	Yelp, Amazon	Deep Learning	Matrix Factorization	MSE
[98]	Malte,2018	session-based recommendation	E-commerce Datasets, Media Datasets	Deep Learning	Matrix Factorization	Hit rate, MRR, catalog COV, and average popularity (POP)
[75]	Neamanee,2018	Time-Aware	MovieLens	Deep Learning		MAE, COV
[100]	Niu,2018	Image Recommendation	Flickr YFCC100M	Deep Learning	Matrix Factorization	Precision@K, Recall@K
[67]	Liang, 2018	Implicit Feedback	MovieLens-20M, Netflix-price, Million Song	Deep Neural Network	Collaborative filtering	Recall@K, NDCG@K
[71]	Wei,2017	Movie	Netflix	autoencoder	Collaborative filtering	RMSE
[58]	Deng,2017	trust-aware recommendation	Epinions and Flixster	autoencoder	Matrix Factorization	RMSE
[81]	Dang and Ignat,2017	user trust relations	Epinions and Ciao	DNN		MAE and RMSE
[56]	Nguyen,2017	Tag Recommendation	NUS-WIDE and Flickr-PTR	Deep Neural Network	Content-base	F1@K, AUC
[87]	Zheng,2017	Reviews Recommendation	Yelp, Beer, Amazon	Deep Learning	Collaborative filtering	MSE
[101]	Wang, 2017	Article Recommendation	Own dataset Created	Deep Learning	Content-base	AUC, Precision, Recall, F1 Score
[79]	Cao,2017	Top-N Recommendation	MovieLens, Netflix and Yelp	Deep Learning	Collaborative Filtering	Accuracy, Precision, Recall
[99]	Hidasi,2016	Session-based Recommendations	VIDXL, CLASS	Deep Learning	matrix Factorization	Recall@K, MRR@K
[103]	Tan,2016	Quote Recommendation	Quote dataset	Deep Learning	Content-base	MRR, Recall@K, NDCG@K
[92]	Lee, 2016	Quote Recommendation	real twitter dialogue	Deep Neural Network	Content-base	MRR, Recall@K, NDCG@K, Hit@K
[104]	Zhou,2016	Profile recommendation	ILSVRC-2012	Deep Learning	Content-Base	Distance
[102]	Youcef,2022	recommendation Multimedia data	Tweet dataset	Deep Learning	Collaborative Filtering	Mean Average Precision
[89]	Aminu,2021	Item recommendation	Yelp and Amazon	CNN	Mutual attention network	RMSE, MAE
[83]	SOHEILA,2021	Items' prediction	Epinions, FilmTrust, Ciao, and Flixster1	Deep Learning	collaborative filtering	precision, and recall.
[77]	Sunny,2021	Social Recommendaion	Movie Lens	Deep Learning	collaborative filtering	Predictive Accuracy Metrics, precision, recall, f-measure, and mean reciprocal rank (MRR),
[90]	Mourad,2020	knowledge-driven modeling	Yelp and Beer	deep neural networks	Generalized distillation principle	MSE
[106]	A. Razia, 2020	RS with the visual features of products	UTZappos 50 k	CNN+ Deep learning	PCA, t-SNE, UMAP	cosine distance and Euclidean distance.
[84]	Yu,2020	products, information or services	LastFM, Ciao, and Epinions	Social Attentive Deep Q-network	Collaborative Filtering	Hit Ratio (HR) and Normalized Discounted Cumulative Gain (NDCG).

TABLE 5. ***(Continued.)*** **Selected studies of social RS using deep leaning.**

[78]	Snehal,2021	User and Item prediction	Movie Lens	Deep Learning	Collaborative filtering	RMSE
[107]	Wylin,2020	Social recommendation	Advogato, Pretty-Good-Privacy (PGP)	Graph Convolutional Networks	Matrix factorization-based	F1-score, MAE
[108]	Farzaneh, 2022	Social Media recommendation	Flickr and Twitter.	Deep Learning	Collaborative filtering	Fitness Scores
[94]	Vedavathi, 2022	Movies in ecommerce websites	Twitter API	Deep reinforcement learning	Matrix Factorization	Accuracy, precision, recall, F1-score.
[85]	Amirreza,20 21	Social Networks Recommendations	Ciao, Douban and Epinions	graph-based neural networks	Matrix Factorization	Hit Ratio
[86]	Milad,2022	Trust-aware RS	Epinions and Flixster.	Deep learning	Deep representation learning	(MAE), precision, recall, and normalized discounted cumulative gain (NDCG). hit ratio
[96]	Yu,2021	Trust RS	FilmTrust and CiaoDVD	Deep Gradient Algorithm	Deep reinforcement learning	precision@k and ndcg@k

2) DATASETS

In some studies, an evaluation can make use of many datasets. Table 5 shows the 46 datasets we found in the selected papers. Each dataset's domain and the research that utilized it is listed. Each of the research found utilized at least one dataset.

MovieLens is a web platform that suggests movies to users and then utilizes their ratings to create a personalized user profile for future suggestions. MovieLens datasets come in a variety of sizes: 100K, 1M, 10M, and 20M. Table 5 demonstrates that the Movie Lens [67], [73], [74], [75], [76], [77], [78], [79], [80]; Epinions [58], [70], [81], [82], [83], [84], [85], [86]; and Yelp [79], [87], [88], [65], [82] [89] [90] datasets were the most often used datasets, based on the articles reviewed; however, Epinions is a consumer review platform where users may choose the reviewers they can trust. In this study, Twitter [69], [91], [92], [93] [94] and Amazon [64], [88], [87] [89], [95] were also widely utilized datasets in a lot of research. Furthermore, Table 5 further illustrates that multiple publicly available databases were utilized for the DL-based RS evaluation. Finally, most of the studies used publicly available datasets to conduct their research. In conclusion, most studies relied on publicly accessible datasets for their research, with most researchers also focusing on creating or extracting their own datasets. However, although the public datasets are big achievements for the evaluation of the proposed recommendation systems in the state-of-the-art review, new datasets must be collected to take advantage of RSs proposed in the future that may utilize social information from social media. The Twitter and Facebook APIs provide many features for collecting social information that can be useful in the research.

3) DOMAINS

In recent years, RSs have been applied to various domains that are gaining in popularity. For the RS, further research introduces distinct areas. Many application domains are provided with the dataset shown in Table 5, which spans from 2016 to 2022. According to the study, most research articles focused on adopting SRS in movie recommendations.

Several features such as context [73], [82]; trust [58], [68], [58], [81], [86], [96]; tag [91], [66], [73], [56]; semantic filtering [97]; and social connections were identified in this study for classifying different social RSs.

Other parameters are identified, such as session-based recommendations presented by [65], [72], [93], [98], and [99]; attention-aware recommendations [95]; friendship-aware recommendations [76]; and time-aware recommendations [75], [72].

Several studies employed distinct datasets for the corresponding domain, while others used comparable datasets and domains but different methodologies. Finally, this shows that the field is vibrant and attracts an increasing number of researchers and practitioners. However, tag and trust were social features used in social RSs.

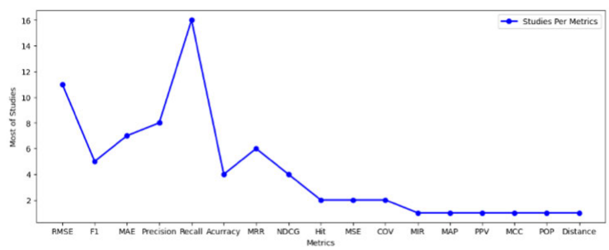

FIGURE 5. **Distribution of Studies per Metrices.**

4) EVALUATION METRICS

The key goals of any recommendation system are efficiency and high performance. Several measures have been devised and employed to quantify the efficiency of an RS. This section lists the parameters used to evaluate the DL algorithms included in this analysis. Figure 5 shows the distribution of prediction metrics of the studies that were analyzed in this research. It considers the number of studies that utilized a variety of measures between 2016 and 2022, with recall being the most commonly used indicator. Figure 5 is based on 17 metrics for categorization, rating prediction, ranking, and other recommendations.

Another form of measurement used to verify the precision [66], [77], [79], [80], [83], [91], [93], [94], [96], [100], [101], [102] of the RS is classification metrics, which effectively calculate the accurately classified degree objects based on the user's interest. In these measurements, the extent of the error in the users' ranking projection is usually ignored. The recall [66], [64], [65], [67], [72], [79], [82], [83], [86], [91], [92], [93], [94], [100], [101], [99], [103] shows how many of the user's favorite things are still available. Simply defined, accuracy is a representation of the user's preferred items. The F1 [56], [73], [101] calculation strikes a balance between recall and precision. The ACC [64] method compares actual positive and negative rates.

Rating prediction metrics mainly aim to see how effectively the RS can anticipate users' ratings. On the other hand, one can identify which algorithm has the lowest errors by comparing several algorithms using ranking predictive metrics. These measuring measures determine the accuracy of the device in terms of error. The three-evaluation metrics we found in this review were MSE [87], [88], [90]; RMSE [58], [64], [68], [70], [76], [71], [80], [89], [97]; and MAE [64], [70], [74], [75], [81], [89], [97]. These parameters are used to calculate the difference between predicted and actual ratings. As a result, higher performance is associated with lower metrics values.

The accuracy meter is a ranking metric that measures how well RSs perform when proposing user-ordered lists of objects where the elements' order is crucial. The following are the rating parameters for the RS assessments used in the review papers: NDCGs [65], [67], [86], [92], [96], [103] reveal that items with higher rankings offered users more satisfaction than items with lower ratings. The Hit ratio parameter [84], [85], [96], [98], [104] is a measure that determines how often a customer goal choice appears in a top-ranked list of recommendations. Mean reciprocal ranks assess the rating positions of consumers' preferred choices in the RS, whereas MAP [95] measures the precisions of the first K-graded items. The performance evaluation measures (PEMs) utilized in the research are listed in Table 6. However, RMSE and recall were the most used evaluation metrics in the domain of social RSs.

B. TOP STUDIES BASED ON PERFORMANCE EVALUATION MEASURES

The studies mentioned in Table 7 are top ranked in our SLR according to the knowledge garnered from our research. The researcher utilized different evaluation measures to gauge the performance of their studies.

TABLE 6. Performance evaluation measures (PEMs) used in the studies.

PEMs	Selected Studies
RMSE	PS01, PS02, PS03, PS07, PS09, PS10, PS15, PS16, PS22, PS23, PS24
Precision	PS04, PS06, PS09, PS13, PS20, PS27, PS28
Recall	PS04, PS05, PS06, PS08, PS11, PS13, PS14, PS20, PS21, PS27, PS28, PS30, PS31
F1_Score	PS01, PS12, PS13, PS25, PS27
MSE	PS17, PS26
MAE	PS02, PS03, PS07, PS10, PS15, PS19, PS24
AUC	PS25, PS27
MRR	PS11, PS13, PS18, PS30, PS31
COV	PS18, PS19,
Distance, NDCG	PS30, PS31, PS32
Accuracy, MIR, MAP	PS28, PS05, PS08

The researchers [70] implemented the deep matrix factorization (DMF) method to improve the user experience initialization performance. This make the model robust: a deep CNN-based attention-aware model was adopted to reduce the initialization delays. DMF and CNN-based techniques are embedded in a hybrid model to enhance the recommendation performance of the presented technique. A summary of the top selected studies is discussed below.

The deep venue RS [82] model offered robust venue suggestion. The model assigns a score to the venue-based reviews, and a ranking is initialized for all the venues. The ranking and scores enable the model to find the top venues. The presented model was implemented on a challenging venue dataset and robustly predicted the correct event venues. Tahmasebi et al. [69] proposed a method that is also a top-performing technique in our SLR. The researcher utilized the deep AE model to create a RS for movies. Both content and the collaborative masking method are employed in creating user interest predictions. The computation of user activity on different platforms and the deployment of AE on extracted information helped to create a robust model robust for movie suggestions, and it achieved competitive performance.

A deep hybrid AE [97] model is presented by researchers in combination with the modeling of the joint selection function. The semantic activity of users on social media platforms is extracted by employing the AE network model. The optimization function selected the most relevant information and predicted user interests in a competitive way.

A user review-based [87] model is presented to recommend the products to a user based on their studies and interests. The deep CNN model extracts information from user reviews and comments on different platforms. The deep model utilized the review text data to extract information. The model source extracted information from user-written comments. The text data processing of user comments and reviews to a specific network layer is designed for textual data input and processed using factorization machine learning methods. The deep model presented here achieved robust performance and outperformed the baseline method.

VI. TAXONOMY

A total of 46 selected studies were analyzed and classified into different categories. DL was divided into several categories based on application areas, techniques, and datasets. Specifically, data sources on social networks were classified according to various attributes.

A. DEEP LEARNING

1) CLASSIFICATION BY APPLICATION AREAS

DL has been widely implanted in different domains of different research areas. DL has been used to enhance and improve RSs. The researchers [68] presented a trust-aware RS to decrease the dependencies of the user on the factorization of the matrix for priming. Matrix factorization was embedded with a DL model for efficient user endorsements. RS follows the user's interest and behavior while performing suggestions and relevant predictions. Researchers [69], [80] developed a movie RS based on user interests and reviews. User reviews and social influencers' posts are utilized for successful movie recommendations.

A study by [82] devised an efficient venue RS using user requirements for different venue platforms. Different users' interests [95] are mapped for selecting different products, movies, and applications. Several cross-domain reviews and suggestions are utilized to predict users' requirements efficiently. Online stores provide user production recommendations by using [64] the IoT to provide the most relevant product suggestions to users. Customer history and social networks activity is processed to predict required items in online stores. Several online product stores and social networks [72] records users' sessions and activities to recommend relevant items available on online platforms. User sessions on online stores and social media platforms play a vital role in efficiently recommending items and specific products. News recommendation is a challenging task in the domain of news RSs. News stories are recommended [93] using user sessions on specific interests, but interests may vary; this issue can be tackled by suggesting the news pool incorporates variations such as user interests and affiliations. Friend RSs [76] normally use people's often incomplete profile information to find a perfect friend match. Comprehensive user information extraction is utilized to find the closest and best match in a partner. Online sessions [98] are key in recommending products, friends, news, and articles [101]. Traditional methods typically rely on user profile information, which is outdated. The online session records user activity across multiple platforms, from social media to news, articles, products, and venue recommendations.

2) CLASSIFICATION BY TECHNIQUES

Several techniques have been adopted for robust recommendations of products, friends, venues, and articles according to user requirements. Due to robustness and efficiency, DL has a good reputation in different domains. Researchers [69], [70], [97] utilized AEs in combination with matrix factorization [100] and content-based collaborative filtering for the robust recommendation of movies [79], social presence [65], information sharing on social media, and sentiment recommendation. A study by [68] utilized a fused matrix factorization method with a pre-trained deep neural network model to create a deep factorization method for movie recommendations. A deep neural network [91] is utilized to create unique features from search tags and user search history to create a hybrid RS for microblogging content suggestions. Deep learning [92] methods are used to create quotation and phrase recommendations by implementing a recurrent neural network. The network understands semantic phrases and creates threads according to quotes and phrases used on Twitter. Authors [104] extracted visual features from users' profiles to recommend products, venues, and matching profiles. The best application researchers presented is hotel suggestion using the implanted deep learning technique. Article selection [101] is a hectic practice that is performed manually by researchers. The editor behavior utilized—and embedded in—a DL model with the matrix factorization method for robust article selection using keywords, phrases, taglines, and writing styles. A deep cooperative neural network [87] was presented to extract data from the text of user comments and reviews on products. The presented deep model contains two parallel layers joined by shared layered, including users interacting with different products and suggestions. A time-aware RS [75] was presented for rating prediction. The user intentions are determined using entropy and a FCM algorithm to calibrate the ups and downs of the rating. Information about the old and new user rating was utilized to assign a new rating to the item. The presented method was compared with state-of-the-art methods, and it achieved competitive performance. Implicit feedback [67] was utilized in the RS through the use of variational AEs. Different learning methods were adopted by researchers to access information for robust recommendation and feedback. Maximum discrimination entropy was utilized to find the probability of likelihood among different reviews. The current method utilized the Bayesian model for parameter tuning to make the necessary positive feedback. Product ratings [81] are a very important part of e-commerce. The researchers developed a novel method called dTrust that does not rely on user information. The presented mechanism analyzes user interactions and trust levels on various platforms and utilizes that score to predict ratings. User information is input into a deep neural network model to predict and implant the rating in the real world. A study by [73] presented a tensor factorization method to map the relationship between users' tags and products. Tensor factorization creates a relationship in a contextual way between users and products. The presented method follows the adversarial tensor factorization technique to perform recommendations based on context-aware representation.

3) CLASSIFICATION BY DATASETS

Several datasets are utilized in the RSs according to their applications. Researchers used Epinions [68], Flixter [91], and Ciao [81] for social presence and suggestions, social interaction, and trust-aware recommendations. Several datasets are used for the different domains mentioned in Table 8.

B. DATA SOURCES ON SOCIAL NETWORKS

We survey the data sources that are utilized for the social media RS. The data manipulated by RS is divided into three types of objects: items, users, and transactions, which seem to be the relationships between the users and the items.

1) CLASSIFICATION BY USER

Data sources can be classified based on user characteristics. Characteristics that may be included to represent this data source include: age, gender, profession, location, etc. Chen et al. [73] conducted their experiments on the Last.fm dataset. This is an online music system. This dataset contains 1892 users, 1853 items, and 11946 tags. A study by [80] collected artist information using the Last.fm API to enhance the performance of their recommendation model. Researchers [65] utilized three data sources to gather the datasets. They collected user information from Douban, Delicious, and Yelp based on item (movie) consumption. They divide user behavior (movie consumption) into weekly and monthly sessions for Douban and Yelp. Reference [67] selected the Million Song Dataset for evaluation. This data consists of users' song play counts. They kept and used data for users who played songs at least 20 times.

2) CLASSIFICATION BY ITEM

The social recommendation data sources can be classified into items. Different properties that represent an item include: category, content, date of item, and popularity. Researchers in [91] collected datasets from Twitter and Sina Weibo. The datasets comprise microblogs as well as social networks. Each microblog post consists of text, timestamps, links, etc. The Weibo dataset consists of 216,176 microblogs and 2792 users. A study by [95] evaluated their technique using publicly available real-world datasets containing three different types of items. Three datasets used were Yahoo! Movies, Amazon Video Games, and Amazon Movies and TV.

Multiple datasets were utilized according to the RS domain. Researchers [104] utilized ILSVRC-2012 for profile suggestions. A quote dataset was used for the evaluation of the quote RS [103]. Yelp, Beer, and Amazon datasets were utilized for review predictions of specific products [87]. Movie reviews and recommendation models utilized Netflix and Amazon movies datasets. NUS-WIDE and Flickr object datasets were used for social image recommendations [66]. Venue RS utilized Meetup and Yelp datasets to validate venue RSs [82].

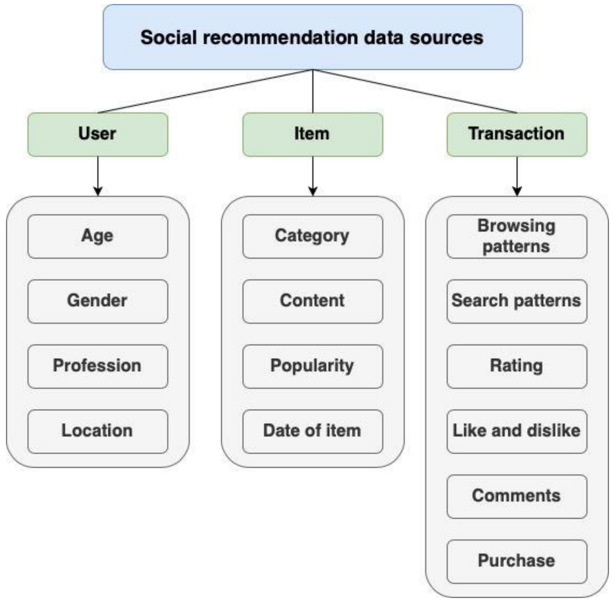

FIGURE 6. Data sources that are being utilized for social media recommendation systems.

3) CLASSIFICATION BY TRANSACTION

The SocialCDL model [72] was evaluated using real-world datasets, including ratings and social information. Social recommendation data sources were categorized based on transactions including ratings, comments, search patterns, browsing patterns, likes, and dislikes. The authors of [67] utilized the MovieTweetings dataset, which contains movie ratings and includes well-structured tweets. These data were collected from two websites—Epinions.com and Ciao.com—well-known consumer review sites.

In [97], the performance of the recommendation system was evaluated using three datasets, including Epinion, Film Trust, and MovieLens 10M. The Epinion rating data consist of 664824 ratings. The Film Trust includes 35497 ratings. At the same time, the MovieLens 10M consists of a total of 10,000,054 ratings. Researchers in [93] perform experiments using two datasets named MovieLens-1M, and MovieLens-20M. The MovieLens-1M dataset comprises one million ratings of 4000 movies, and MovieLens-20M consists of 20 million ratings of 27000 movies.

The authors evaluated their technique using three rating datasets: Netflix, MovieLens, and Github archive data. In [100], authors utilized Flickr YFCC100M dataset data. They select images that have geo-coordinates located in contiguous United States. Further, they crawl to trace image "likes" using the Flickr API.

Figure 6 shows the types of data sources utilized for social media recommendation systems and their specific features and attributes.

VII. ISSUES, RECOMMENDATIONS AND FUTURE DIRECTION

This section covers a wide range of SRS's issues and future works. User happiness is the fundamental goal of any RS

TABLE 7. Top studies based on performance evaluation measures.

PS	Performance	Performance	Remarks
PS05: Pramanik 2020	Recall	0.86	The researcher computed Precision and MIR for the evolution of model.
	MIR	0.81	
PS01: Wan 2020	RMSE	0.80	F-measure, RMSE and Coverage used to validate the model performance.
	Coverage	98.88%	
	F-Measure	0.89	
PS26: Zheng 2017	MSE	0.99	The researchers achieved MSE of 99% which higher than any other model in our study.
PS02: Tahmasebi 2020	RMSE	1.41	This study achieved higher PMSE as compared to relevant studies.
	MAE	0.73	
PS07: Mohan 2019	RMSE	0.92	The study indicates the researchers best score of RMSE.
	MAE	0.73	
	AUC	0.79	

TABLE 8. Social dataset that done on previous studies.

Reference	Domain	Social network Dataset
[68] [70] [81]	Social Recommendation	Epinions, Flixter
[69] [93] [91]	Micro bogging, news, and quote recommendation	Twitter, Sina Weibo, Adressa, Last.fm
[82]	Venue Recommender	Meetup and Yelp
[97]	semantic social information	Github
[95]	Attention-Aware Recommendation	Yahoo Movies, Amazon Video Games and Amazon Movies and TV
[80] [95] [100] [79] [73] [71]	Movie and Top-N Recommendation	MovieLens, Last.fm, Netflix,Yelp, yahoo movies
[64]	Product Prediction	Amazon
[72]	Session-based Recommendation	Yoochoos, Diginetica, RetailRocket
[65]	Social Recommendation	Douban, Delicious, Yelp
[76]	Friend recommendation	Sina Weibo
[88]	Reviews	Yelp, Amazon
[98]	session-based recommendation	E-commerce Datasets, Media Datasets
[100]	Image Recommendation	Flickr YFCC100M
[67]	Implicit Feedback	MovieLens-20M, Netflix-price, Million Song
[87]	Reviews Recommendation	Yelp, Beer, Amazon
[101]	Article Recommendation	Own dataset Created
[99]	Session-based Recommendations	VIDXL, CLASS
[103]	Quote Recommendation	Quote dataset
[104]	Profile recommendation	ILSVRC-2012

that is meant to consider a variety of user experiences. Even though RSs have been the subject of a lot of press in recent years, a few challenges and possibilities will influence the future of the discipline for researchers. Some examples of the challenges faced by RSs include: user profile drift, item demand drift, changes in the quality management system and games, a revolution in material precepts of objects, energetic attention within the communal, seasonality, user-object favoritism unstable, vagaries in measurement tools, permanent and temporary churning, and high volatility. The state-of-the-art historical algorithms used by RSs have not been adaptable enough to handle all the dynamic issues that have arisen. Furthermore, a variety of strategies must be used to develop a high-accuracy social RS in SRS. It is preferable to implement a solution that can cater to long-term and short-term customer preferences. Some RS temporal models can only forecast customer behavior for prospective recommendations based on their preferences at a given time. Fewer studies ignore the value of prior experiences, which may have an impact on the creation of recommendations in many cases. Techniques for identifying shift points must be explored, with observed adjustments simply requiring the use of those techniques and the execution of the relevant processes.

TABLE 9. Issues, recommendation and future direction.

Issue/Challenge	Recommendation	Future research direction	References
Trust Information	collaborating filtering	DMF and collaborating filtering for robust RS	[68]
Interest aware RS	Hybrid auto encoder	Deep learning for robustness	[69]
Movie Recommendation	Markovian Factorization	Textual information processing	[80]
Event based social recommendation	Deep venue based on contest	Recommendation based on history	[82]
Mapping of user interests	MARS	Interoperability and scalability	[95]
Robust venue recommendation	Deep learning with collaborative filtering	Enhanced metaheuristic method	[95]
Consumer preference prediction	Deep learning with collaborative filtering	Enhanced metaheuristic method	[64]
Session based suggestions	SKNN with sequence and time aware neighborhood	Baseline for RS methods analysis.	[72]
User behavior in a session	Novel deep attention aware and graph-based CNN model	Addition of model information Image information	[93] [76]
User interest prediction	Session based algorithm	Domain specific recommendations	[98]
Article collection	Automated article selection	Image based article selection	[101]

TABLE 10. The selected papers based on Deep learning algorithm.

Deep learning Algorithm	Advantages	References
CNN	Allows Extracting latent features. Feature representation learning from a variety of sources, including text, picture, voice, and video.	[66] [95] [56] [89] [106]
RNN	Handling the temporal dependencies and sequential features.	[82]
Autoencoder	Appropriate for reducing feature dimensionality and extracting hierarchical features.	[68] [69] [70] [97] [71] [58] [58] [79] [67]

There is a demand to evaluate the point identification techniques for alterations that can be assessed by utilizing specific means and by executing a comprehensive test; then, the necessary action can occur by updating or rejecting the model when the modification is certain. Another unsolved issue in modeling idea drifts in RSs is concept drifts occurring in various ways and at different periods; various approaches are needed to deal with this issue. Consequently, it is necessary for one avenue of research to be a rigorous evaluation of the ability of DL approaches to create existing RS models. An additional point to consider is the type of evaluation utilized to determine the effectiveness of RS programs, as virtually all the trials examined were evaluated using offline techniques, even though offline assessment is meant to be less expensive and has no bias in response to dynamic user engagement; this is in contrast to web and user trials, in which the results are paradoxical when employed in real-life applications. Thus, further study on assessment techniques is needed to evaluate outcomes based on multiple evaluation characteristics—such as real-time, innovation, COV, luck, and variety, among others [105]—rather than just on a fine estimate. Despite the fact that there have been several studies on DL-based RSs in the most popular domains, such as e-commerce and movie recommendations, the use of DL to develop a social RS has yet to be examined. One possible research direction is a study of CNN-based recommendation techniques. One proposed research area for improving the accuracy of social RSs is a Twitter-based social RS.

Several challenges exist in the implementation of any RS, including user interest, product description, user behavior, and session-based activities across platforms. Implementing recommendations in various domains will necessarily come with various challenges. In movie RSs, user interest and sessions on various social media platforms and reviews play a vital role in suggesting movies according to users' taste. Social media recommendations require user interest in different social media platforms and user profile information utilized to predict activities. Sessions, tags, and reviews play a vital role in suggesting products, movies, articles, and movies. Several DL-based methods were adopted for robust recommendations in combination with collaborative filtering and matrix factorization. DL has transformed RSs into robust and precise models. Still, challenges such as cross-domain recommendation, interoperability, and scalability must be addressed to perform accurate and relevant recommendations on social media platforms, online stores, products, and articles.

Furthermore, the recent surge in the amount of research on social recommendations in different aspects indicates that social RSs have become an essential topic in recent years. Many social features such as trust, tag, context, group, semantic filtering, and cross-social media have been discussed individually in SRS studies. As a result, in the future, a hybrid social recommendation that integrates a set of essential features while employing a variety of approaches should be addressed. In addition, in the social context, to better understand users' interests, more contextual factors such as time, place, and the users' social networks should be included. Table 9 includes information about issues, recommendations, and future directions.

VIII. CONCLUSION

A thorough literature review was undertaken to assess and discuss the latest works on social RSs employing DL models in this study. The primary online databases were searched to gather the relevant papers for this study, including Web of Science, Springer, IEEE, ACM, Scopus, and ScienceDirect. Key findings were reviewed and presented. This article presented a SLR to review and examine current RS approaches that are DL-based models based solely on publications from between 2016 and 2022. This study aimed to assist academics and researchers in the relevant domains to gain a complete grasp of social DL-based RSs. The current research examines some of the most pressing outstanding topics and potential future developments. DL and RSs have become popular topics of research in recent decades. In addition, this study proposes a taxonomy of DL algorithms for social recommendation by examining the selected papers using a SLR approach. Every year, innovative tactics and models are developed. We hope this study will provide readers with a complete overview of significant aspects of this field and an explanation of key advancements and that it will shed light on future research. In addition, RSs have been widely utilized in the modern era, playing a significant role in domains including social media, news, movies, articles, venue recommendations, and many others. Several RSs have been analyzed to determine challenges and solutions. Different methods and models have been adopted for strong recommendations by predicting user intentions and interests. The implantation of DL in RS has proved to be very effective and achieved competitive performance. Different methods and domains have been summarized to find the most appropriate method and domain. The challenging datasets of RSs have also been discussed and investigated categorically. DL has shown robust performance by performing suggestions according to user interests. Interoperability, scalability, and cross-domain implementation are persistent challenges that can be addressed by incorporating novel methods like textual and visual information processing into robust models in order to create robust recommendations.

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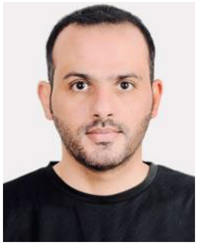

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