IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received March 8, 2021, accepted March 30, 2021, date of publication April 9, 2021, date of current version April 20, 2021.

Digital Object Identifier 10.1109/ACCESS.2021.3072165

Context-Aware Recommender Systems for Social Networks: Review, Challenges and Opportunities

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This work was supported by the Research Center of College of Computer and Information Sciences, King Saud University.

ABSTRACT Context-aware recommender systems dedicated to online social networks experienced noticeable growth in the last few years. This has led to more research being done in this area stimulated by the omnipresence of smartphones and the latest web technologies. These systems are able to detect specific user needs and adapt recommendations to actual user context. In this research, we present a comprehensive review of context-aware recommender systems developed for social networks. For this purpose, we used a systematic literature review methodology which clearly defined the scope, the objective, the timeframe, the methods, and the tools to undertake this research. Our focus is to investigate approaches and techniques used in the development of context-aware recommender systems for social networks and identify the research gaps, challenges, and opportunities in this field. In order to have a clear vision of the research potential in the field, we considered research articles published between 2015 and 2020 and used a research portal giving access to major scientific research databases. Primary research articles selected are reviewed and the recommendation process is analyzed to identify the approach, the techniques, and the context elements employed in the development of the recommendation systems. The paper presents the detail of the review study, provides a synthesis of the results, proposes an evaluation based on measurable evaluation tools developed in this study, and advocates future research and development pathways in this interesting field.

INDEX TERMS Context-aware system, contextual factors, recommender system, social network.

I. INTRODUCTION

In recent years, online social networks became the natural way for users to socialize and search for information of interest. Mobile technologies have made these activities pervasive and accessible to any user, anytime and anywhere. Indeed, many mobile applications use recommender systems (RSs) to help users make various decisions such as which place to visit, which items to purchase, or which users to follow [1]. Recommendations provided by these systems certainly have an added value to users in guiding them through their needs. However, users are sometimes overwhelmed by masses of options making the recommendation task more complex and a real challenge for researchers.

In general, recommendation systems utilize feedback from users either explicitly by their rating or implicitly by their actions and behaviors. These systems analyze users' preferences but in many cases, they do not consider their context. There is a mutual relation between RSs and social networks (SNs). SNs benefit from RSs by increasing their users and their loyalty. For instance, SNs' users can find other like-minded individuals who share similar interests and subscribe to the same content. This allows them to share their views (such as on Twitter) or suggest other accounts with similar interests to follow (such as on Instagram). On the other hand, RSs benefit from the enormous data available on SNs in order to enhance the quality of recommendations. This is made possible through exploiting user-generated content in SNs such as user profile, the user network of friends, and the likes added by users. This enables RSs to understand topics attracting users and their communities, which contribute to enhancing their effectiveness [1].

RSs are the filtering engines that aggregate opinions to help decision-making processes. They are used broadly to influence almost everyone's daily life in various domains such as e-commerce, education, public health, and entertainment. The efficient generation of relevant recommendations in large-scale systems is a very complex task. In order to provide personalized recommendations, filtering algorithms need to capture users' varying interests and find relations

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

between them. The massive number of new users and items with no prior data recorded – the cold-start problem, the enormous data sparsity, the variety of dimensionality, and ambitious real-time requirements make such recommendations challenging in dynamic real-life situations [2].

This paper provides a thorough literature review of studies published between 2015 and 2020 on context-aware recommender systems for social networks. The main characteristics of this review are:

- It uses a methodology to determine, choose and synthesize the most relevant and cited works in context-aware recommender systems for social networks [3]. It then provides a classification of these works based on contextual factors, the recommended approach, and techniques used.
- It describes the development of context-aware recommender systems for social networks, which are used in many applications and fields such as tourism, entertainment, e-commerce, and friend-finding.
- It pinpoints research gaps and challenges in this field and proposes future directions and research opportunities to fulfill them.

Many surveys were published recently showing the increasing interest in this field. Some surveys carried out on RSs focus on a particular application field such as tourism [4], on a unique contextual factor such as location [5], on a particular environment like mobile [6], on specific social network platforms [7], or on given types of social media [8]. Other surveys are dedicated to context-aware recommendation systems focusing on showing the type of recommendations addressed by social-based recommender systems [9], on the different kinds of contexts and how context data is represented and used in the recommendation process [10]. Moreover, some surveys are designed to address the techniques used in the recommendation process to incorporate and exploit context information [11] or intelligent techniques used by recommendation systems to represent and process context information [12]. In this research, we systematically review recent studies which have focused on developing context-aware recommender systems for social networks. The particularity of these systems is that they are required to deal with dynamic and data-rich ecosystems SNs while they are expected to provide accurate, time-relevant and adaptive recommendations to users. This study, therefore has two main objectives: The first objective is to systematically collect, summarize, analyze and synthesize information related to research on context-aware recommender systems used in social networks published between 2015 and 2020. The second objective is to report on the findings and provide a broad picture of the current research state in this field and identify knowledge gaps that require further exploration. The following research questions (RQ) are put forward to achieve these objectives:

RQ1: Which context factors are used in context-aware recommendation systems for social networks?

RQ2: What approaches and techniques have been adopted for integrating contextual information in social network recommendations to enhance the quality of recommendations?

The paper is organized as follows: the next section provides a background of recommender systems and context in RSs. Section three describes the methodology that was used in the review process. The fourth section presents the literature review results, then the fifth section reports on the results fulfilling the research questions. The sixth section is a discussion about the results of the review. Section seven describes our survey's validity evaluation and proposes measurable validation tools developed for the present study. Finally, we present our conclusions and future challenges in the eighth section.

II. BACKGROUND

This section provides an overview of concepts related to context-aware recommender systems in social networks. It focuses on defining and analyzing the recommendation process and the context in these systems.

A. THE RECOMMENDATION PROCESS

The predominant approaches in the tradition of recommendation systems are collaborative filtering, content-based filtering, and hybrid filtering [7], [13]–[15]. Collaborative filtering (CF) provides users with items that other users liked in the past with similar interests and tastes. In this approach users' similarity is used rather than content similarity. Content-based filtering (CB) suggests items like those liked in the past by the same user with similar interests or features. A combination of CF and CB methods is known as hybrid filtering, which is an attractive approach that aims to eliminate the drawbacks of CF and CB.

The recommendation process determines the set of ratings R introduced by users or inferred by a system. RSs aim to assess the rating function f_R for the user U and item ($f_R : U \times I \rightarrow R$). Traditional RSs (i.e., collaborative filtering, content-based, and hybrid) deal with classical two-dimensional users and items [16], but they face many challenges to overcome. The most important of these challenges are the cold-start and data sparsity challenges. Cold-start is the problem of not knowing, ignoring, or the unavailability of the user needs and preferences, which may provide irrelevant recommendations. Data sparsity is related to the user feedback coverage where only a limited number of items are rated by users.

Traditional recommender systems have an inherent limitation as they do not consider explicit social relations between users [17]. Social networks provide additional information that improves understanding of the user behavior and ratings done by ranking algorithms [18]. In social networks, the homophily principle [19] assumes that if people are friends in social networks, they have something in common, creating natural correlations between users exploited by recommender systems. The main point of personalized recommendation is centered on the model analysis between users and items. This analysis can build models that reflect users' varying interests and help improve the quality of personalized recommendations. Some recommender systems based on social network data combine information affecting personal behaviors and interactive activities between users [18]. Many studies that have been done on the use of information derived from social networks [18], [19], [20] have proposed solutions to the two challenges mentioned above, cold-start and data sparsity. Some of these studies proposed a probabilistic model that can be used to deal with incomplete data [19]. Others integrated friendship and tag information and used them to analyze the social recommendation issue based on the matrix factorization technique (See Section V for more explanation) [14]. Other studies have proposed using a framework integrating several social networks to exploit the richness of data from these various sources to solve data sparsity [20].

B. CONTEXT AWARE RECOMMENDER SYSTEM

Context is essential in describing the environment surrounding the interaction between a user and an application [21], [22]. Context-aware systems have the ability to understand users' personal needs and provide them with tailored services. A context in RSs is a valuable addition to adapt information proposed to users. Integrating context extends the traditional two-dimensional RSs to three dimensions: user, item, and context C ($f_R : U \times I \times C \rightarrow R$). This addition means that the goal of context-aware recommender systems (CARSs) is to provide accurate recommendations for a specific user at the right time, in the specific location, using user-related information such as his/her current activity as well as the emotional state [3].

1) CONTEXT ACQUISITION

Context information can be acquired directly, indirectly, or by Inference [3]. Direct context acquisition is made through the user profile, which is provided directly by the user. The indirect acquisition consists of extracting implicit factors that affect the user. For instance, the user's location is acquired continuously by mobile devices. Most of the implicit factors are dynamic and hence change over time. They are more complex to handle and profoundly impact recommender systems' performance [2]. Acquisition by inference necessitates sophisticated methods such as data mining techniques, statistical calculations, and artificial intelligence algorithms to derive context variables. For example, association mining allows to infer what items are frequently bought by users during a specific time period.

2) CONTEXT INTEGRATION

Context integration approaches can be classified into three categories [23]: pre-filtering, post-filtering, and contextual modeling approach:

- Pre-filtering approaches are methods where the contextual information is combined with input data before calculating the recommendations list. The idea is to reduce the multidimensional matrix to a 2-dimensional user-item matrix in order to apply traditional recommendation algorithms. This approach, however, has low accuracy in some recommendation instances because extracting and selecting context proves to be a challenge. For example, when the system has insufficient information about the target user's past preferences and there are just a few ratings associated with this context. Many studies employ various contextual filters to increase efficiency. Different user-item matrices are merged into one single matrix to perform the recommendation process. Some studies recommend implementing contextual pre-filtering to reduce the number of events because events that are impossible to recommend should be excluded [24].
- Post-filtering approaches ignore contextual information when it is generating the list of recommended items. This approach adjusts the recommendation list for each user separately based on specific context information. The adjustment can be made either by sorting the list according to given context information as mentioned previously or by filtering out the irrelevant recommendations. Some studies recommend implementing post-filtering to reorder the recommendation list so that recommended information may be more suitable for the current circumstance 25].
- Contextual modeling approaches consider contextual information directly in the recommendation process. These approaches use both predictive models and heuristics to create multidimensional recommendation functions. Some studies advocate taking advantage of different contextual information by aggregating context's characteristics and adapting the random decision tree algorithm to split the contexts hierarchically to improve the recommendation quality [26].

3) CONTEXT MODELING

Different contextual information types are represented by a diversity of models such as logic-based model, graph-based model, ontology-based model, hierarchical model, and key-value model [27]. Logic-based models use facts, expressions, and rules to represent the context. Inference techniques such as fuzzy logic, which handles uncertain data or logical programming used to express rules are employed in these models. In graph-based models, the context is represented by nodes while links represent relations. This model adapts past similar contexts to solve the current one. In ontology-based models, the context is represented by classes, attributes, and relations. This type of model expresses semantic relations between concepts. In hierarchical models, the context is represented by hierarchical structures (i.e., tree), and each context is represented by a set of contextual dimensions shaped by a set of attributes. Another model which relies on a simple representation is the key-value model, which models context as key-value pairs (attribute, value).

III. REVIEW METHOD

A systematic literature review (SLR) is a process of interpreting and evaluating the findings in a specific domain of interest or research questions. According to Kitchenham and Charters [28], it must follow strict and predefined steps. For this reason, the present systematic review aims to identify gaps in research related to CARSs for social networks and provides a comprehensive review of studies published from 2015 till 2020. Moreover, the systematic review covers broader questions than single empirical studies can do [29].

A. INCLUSION CRITERIA

The aim of applying inclusion criteria is to ensure that all selected sources of information, whether primary or secondary, are related to the study topic. The purpose of this literature review is to analyze the aspects surrounding context-aware recommender systems for social networks. The data collected in this review is related to the research questions and was collected from journal articles, conference papers, and book chapters published between 2015 and 2020 and written in English. The following are the inclusion criteria:

- Only papers that propose new context-aware recommendation approaches are chosen – the primary studies. Therefore, surveys of CARSs are not considered among primary studies in this research.
- Only scientific journal papers, conference papers, and book chapters are included.
- Only papers written and published in English.
- Only papers published between 2015 till 2020.

B. SEARCH METHOD

The papers' search has been conducted in two phases: an automatic search phase and a manual search phase, where both were used to explore primary studies for the review. The automated search was conducted in online scientific databases by using specific keywords. The search has been done through our university access (at King Saud University) provided by the Saudi Digital Library (https://sdl.edu.sa/SDLPortal/en/A-ZDataBases.aspx), which grants unified access to almost all major scientific databases. The access includes ACM digital library, Cambridge University Press, EBSCO, Emerald, IEEE, IET digital library, IGI InfoSci Journals, Nature Journals, ProQuest, Sage Journals, ScienceDirect, Scientific American, Scopus, Springer Journals, Taylor & Francis, ISI Web of Knowledge, Wiley Online Library. The Saudi Digital Library gives access to conference papers, journal papers, theses, and eBooks. Common keywords related to context-aware recommender systems in several platforms such as (social network, microblog, Twitter) were used to search through the databases to match identified keywords with the published research and relevant literature. The following are some queries used in the search: "context-based recommend on online social network", "context-based recommend in microblog", and "context-based recommend in Twitter". (context including contextual, contextualization, contextualize) and (recommend including recommender, recommendation, recommended). A manual search was employed to include additional studies that provided a broader in-depth perspective on this paper's research questions. We used a forward and backward approach [24]. Bibliographies of all papers published in 2019 and 2020 were reviewed in the backward search to ensure that the review is exhaustive and no studies covering the same research topic within the same time scale were missed. By integrating these two types of search, we can be more confident that the systematic search is relatively inclusive. Microsoft Excel was used to organize and arrange all primary studies and helped in identifying duplicate studies so that they could be removed.

C. SELECTION PROCESS

The selection of the papers to consider in our literature review is illustrated in Fig. 1. First, the search was conducted according to the defined criteria, where 274 papers were retrieved. Second, 125 papers of these were removed for being duplicates (i.e., same paper) and have appeared in various databases. From the remaining 149 papers, 9 were removed because of being updates of existing papers written by the same authors. In this case, only the more comprehensive study describing the work is kept among the duplicates resulting in 140 papers. These papers' titles and abstracts were read to ensure that each paper is relevant to the present study. This step resulted in retaining 115 papers. Next, for these remaining papers, the full text was read, and those which are not in the domain or not related to the research questions are excluded. For instance, some papers

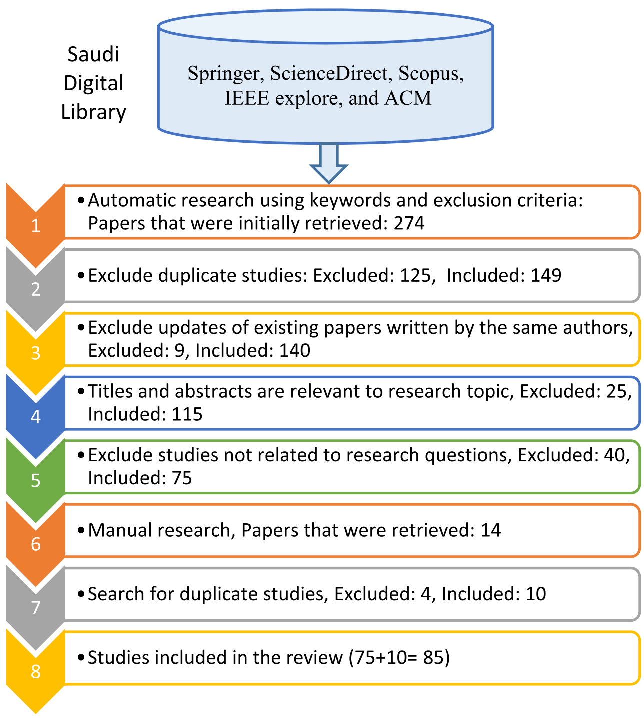

FIGURE 1. Search Method.

were excluded because they discuss group recommender systems but not personalized recommender systems that are the focus of our study. As a result, only 75 papers were remaining. Following that, a manual search was applied where all the references of studies published in 2019 and 2020 were reviewed to discover possible studies that explore the research topic in the required timescale from 2015 to 2020. As a result, 14 papers were identified. Among these 14 papers, four were excluded for being duplicates. Finally, 85 studies were selected and used in this literature review. It is worth mentioning that this process has been conducted through four search cycles detailed in Section VII.

IV. STUDIES CLASSIFICATION FOR SYSTEMATIC LITERATURE REVIEW

In this section, the primary studies for this literature review are discussed in terms of the study type (whether it is a journal article, a conference paper, or a book chapter), the year of publication, and the distribution of the papers according to the geographical area based on the affiliation of the first author and affiliation of all authors.

A. TYPES OF STUDIES

A total of 85 papers were finally selected as primary studies; these papers were relevant as they were published within our target field. The results comprised 43 journal articles, 40 conference papers, and 2 book chapters.

B. STUDIES DISTRIBUTION BY YEAR

Fig. 2 shows the distribution of publications related to context-aware recommender systems for social networks between 2015 and 2020. Among the 85 publications identified, there are 10 research papers published in 2015. A noticeable increase happened in 2016 and 2017, where 18 studies were published in both years. After a decrease of papers in 2018, a noticeable rise occurred with 12 studies in 2019 and 16 papers in 2020. We can say that this topic is regaining attention as there is an increased demand for the integration of sophisticated recommendation techniques specifically in the e-business field, which targets particularly social networks to advertise their products. Additionally, organizations that hold conferences and workshops related to recommender systems (like the RecSys Challenge series,[1] CARS series) are still very active.

C. STUDIES BY GEOGRAPHICAL AREA

Research from primary sources of information covered at least 24 different countries in the world spread out in 7 regions. As can be seen in Figure 3, The Asia Pacific region produced 56% of articles (48 in total). North America came second with 12 papers, Then Europe with 11 papers. The Middle East contributed with 8, while Africa contributed with 3, Latin America produced 2, and finally Oceania 1 paper. This geographical classification is based on the first author's affiliation country.

[1] https://recsys.acm.org/recsys19/challenge-workshop/
[1] https://cars-workshop.com/cars-2019-1

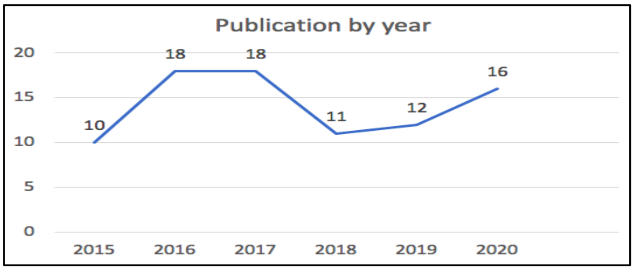

FIGURE 2. Number of articles by year.

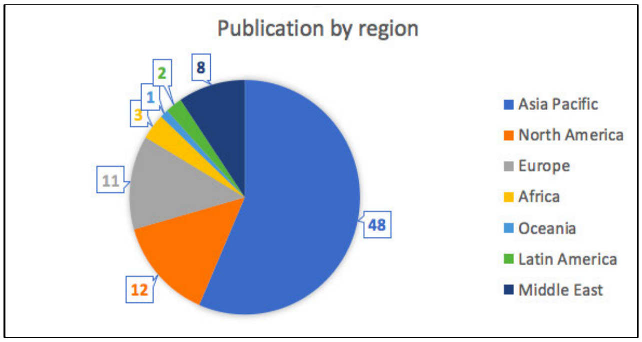

FIGURE 3. Distribution of articles by region.

As for the distribution by county in Fig. 4, two classifications are shown. The first one is based on the first author's affiliation country, and the second reports on all authors' affiliation countries for which the affiliation country of any co-author contributing to the paper is counted. Both bibliometric analysis show that the republic of China is the most active country with 32 papers, accounting for nearly 37% of the total number for first author's affiliation and 36% for all authors' affiliations.

V. RESEARCH QUESTIONS RESULTS

In the following subsections, we present our systematic review results in relation to the issues raised in our questions.

A. CONTEXT FACTORS

RQ1: Which context factors are used in context-aware recommendation systems for social networks?

Contextual information used in recommender systems can be categorized into four main dimensions, namely: environment, user, content, and a combination of the previous information, which we consider as an independent category named "Multidimensional", as shown in Figure 5. These dimensions are sometimes referred to as factors. Table 1 shows the context factors and recommendation approaches adopted in the articles used in this review.

1) ENVIRONMENT DIMENSION

The environment influences the state-of-mind or emotional state of users and therefore indirectly influences users'

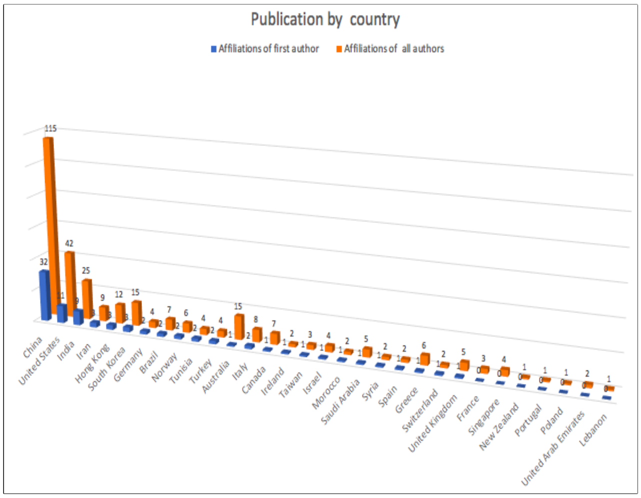

FIGURE 4. Distribution of articles by country (countries are ordered in increasing order by first author affiliation).

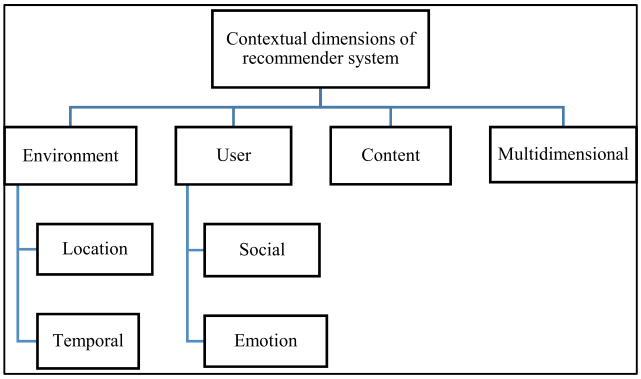

FIGURE 5. Context-aware recommender systems' dimensions.

preferences. For instance, people usually go to open places when the weather is sunny. They are more likely to read news related to their close geographical area (city, country, region), and they follow other users in some social networks based on interests' matching. The environment dimension includes location and time as basic ingredients characterizing the environment.

a: LOCATION-BASED RECOMMENDER SYSTEM

Obtaining the user's position in location-based social networks (LBSNs) is done through the global positioning system or sensors in urban areas or specific corporations' systems. Many studies [30], [31]–[34] interested in the travelling and point of interest (POI) research field have proposed location-based recommender systems. In LBSNs, users can share their check-in activities as they visit POIs. However, there is a sparsity of user check-in data. To cope with this issue, user preferences' spatial transfer is an important factor in improving recommendation performance by integrating users' long-term static and time-varying preferences [30], [31]. Taking local preferences and item content information into account facilitates people's travel not only near the area in which they live but also in a new area [32], [33]. In addition to spatial properties of geographical influence, Xu *et al.* [34] emphasized the sequence properties of exploiting implicit dependencies between POIs. Also, the location-based trending news feed is taken into consideration for recommending the news contents.

TABLE 1. Classification based on context factor and recommendation approach.

Context factor \ Recommendation Approach		Collaborative filtering	Content based filtering	Hybrid	Graph
Environment	Location	[30],[32]	[112]	[33],[34]	[114]
	Temporal	[35],[36], [105], [107]		[37],[38], [39]	
User	Social	[25],[42],[43], [45],[48],[49], [50],[52],[54], [55], [104], [109]		[40],[41], [47],[51], [56]	[44], [46], [53]
	Emotion	[58],[59],[60]			[57]
Content		[64],[71],[72]	[65],[66], [67],[68], [69],[70], [73],[111]	[31],[61], [63]	[62]
Multi-dimensional		[26],[75],[78], [82],[83],[90], [91],[94],[95], [97],[98],[99], [100],[101], [106]		[24],[74], [76],[79], [80],[81], [85],[86], [89],[92], [93],[96], [102], [115]	[77], [84], [87], [88]

b: TEMPORAL-BASED RECOMMENDER SYSTEM

Recommender systems have combined various temporal information with different granularities to be incorporated in the recommendation process [35]. Unlike some context data that is difficult to gather, time data, such as time of the day, day of the week, season, is easy to collect thanks to smartphones' recent development. Temporal information plays a significant role because users' life patterns vary greatly, and different locations have different proper visiting times [36]. In venue recommendation systems users visit historical sites, venue-related information, and contextual information like weather conditions, the season, the date, and the time of each visit are used as venue features, and the contextual similarities of venues will be utilized in the system [37]. User intrinsic interests and the temporal context are two important factors in user behavior modeling in a temporal recommendation. Considering the dynamic nature of social networks, a large part of the existing social recommendation methods are incapable of supporting real-time recommendations. The research proposed in [38] integrates the temporal semantic effects, social relationships, and user behavior sequential patterns into the process of network embedding. It can use the encoded representation of temporal contexts to generate news recommendations. The study presented in [39] examines the time feature to improve the recommendation accuracy by dynamically analyzing user's interests, preferences, and supplementary information to demographic data over time.

2) USER DIMENSION

Compared with the environment-related context, the user dimension has a closer relationship with users and can influence the users' preferences directly. The user dimension includes activity, demographical information, and emotional state.

a: SOCIAL-BASED RECOMMENDER SYSTEM

The user's social information including, individual interest, explicit and implicit social relations, and social explanations (feedback), e.g., likes, dislikes, etc., are extracted from online social networks. In social network-based recommendation systems, it is known that users have relevant knowledge or similar interest with users they are connected with. Event-based social networks (EBSNs) are examples of these networks consisting of online and offline social connections. In [40], the authors define online social connection as a common interest between the users, while offline social connection means they attend events together. Moreover, in [41], a heterogeneous social network is built to describe companies and researchers' relations. The relationships between them are extracted from their academic activities. Exploiting trust, distrust, and neutral relations based on users' latent features was effective in dealing with cold-start users' problems [42]. Once a trust relationship has been established, the ideas or behaviors of the trustee, i.e., the one who is being trusted, can influence the behavior of the trustor, i.e., the one who trusts. However, it is also generally agreed that people trusting each other may not always share similar preferences. The study proposed in [43] analyzes the relationships between trustees and trustors and establishes a deeper understanding of how users' online behaviors can be used for trust-aware recommendations. The social recommender system presented in [44] improves recommendation effectiveness by relying on the reliability of implicit relationships that integrates with explicit trust relationships and user-item interaction matrix. The work proposed by Nobahari *et al.* [45] enhances recommendations accuracy and obtains users, directors, and producers' satisfaction by combining synchronously user-item ratings based on trust, sequential interest, and user implicit interest. Also, the research in [46] illustrates how user's profile characteristics and social relationships effectively improve the recommendations' performance when constructing a user interest network. The technique proposed in [47] applies various interactive factors and tourists' relationships, such as their desires and interests, trust, reputation, affinities, and social community, to calculate the similarity and provide appropriate recommendations. Exploiting various social networks is proposed in [48] that can be very effective since it exploits every social network's richness. The technique examines more than a single social network and calculates user similarity to provide a unified recommendation model based on social networks.

For ridesharing services, the recommender system considers users' profile characteristics and preferences extracted from online social networks [49]. Another research proposed in [50] considers activity-partner recommendation utilizing attendance preference and social context based on past partner knowledge of users. On the other hand, with the percentage of passive use of SNs on the rise, some researchers investigated different types of information about followees. The investigation of followees from list memberships infer interest profiles for passive users [51]. Smart TV service has also been investigated to analyze watch-log. The idea is to collect sets of videos watched by each user with their corresponding timestamps. Based on that, the strong associations share their watching list according to their relevance [25].

Usually, users' implicit and explicit feedback information change over time. A modeling recommender system that incorporates the social popularity and temporal dynamics of explicit and implicit feedback information into the recommendation process outperform the conventional recommender system [52]. Also, exploiting diverse relations and asynchronous feedbacks in EBSNs was an efficient way to deal with the new event cold-start problem [53]. The technique proposed by Seo *et al.* [54] takes into account the contents generated by users along with their relationship and interaction information to measure the similarity between them, which improves recommendations in a multi-domain environment.

In [55], the authors integrated online user contexts clustering with online learning mechanisms for selecting highlighted news. Predicting the user's next click was proposed by authors in [56]. The suggested method combines user click events within-session and news contextual features to predict the following click behavior of a user in session-based news recommendations.

b: EMOTION-BASED RECOMMENDER SYSTEM

Emotions are particular feelings that characterize people's state of mind, such as happiness, sadness, and fear. The use of emotional information in the recommendation process has recently grasped researchers' attention. However, this has not yet been sufficiently explored due to the difficulty of emotion acquisition and incorporation. Wang *et al.* in [57] showed how users' emotional context extracted from their microblogs can affect the performance of music recommendations. In reality, the microblog users may share similar interests in certain topics but have different opinions on them. Sentiment analysis is an important part of personalized microblog recommendation. Cui *et al.* [58] proposed to incorporate the sentimental features into the traditional content-based microblog recommendation. They developed a graph-based emotion-aware music recommendation method to reveal the explicit and hidden associations between users and music items under certain emotional circumstances. This method extracts the users' music listening history along with the corresponding emotion from their microblog texts. The model presented in [59] enhances POI recommendation by integrating user sentiment information with spatial-temporal contexts. Wu *et al.* [60] proposed the technique for SNs in mobile media recommendation employing unique visual features, user's behaviors context, location context, and social context to model users' social media behaviors and identify its influence on the affective characteristics.

3) CONTENT DIMENSION

Content dimension includes all textual information related to users or items, for instance, messages posted by users and textual descriptions of films in film recommender systems. Over the past few years, the use of special user-defined keywords, called tags, to categorize or describe web and online SN contents has gained a lot of popularity. This user-driven phenomenon is known in the literature as folksonomy and it is a well-studied topic in both information retrieval and recommendation systems fields. Relationships are automatically built exploiting the tags created by the users and explicitly assigned to contents. Tags can be seen as generic features that can be used to create multi-domain recommender systems. The research work proposed in [61] focuses on the textual content of the digital traces for its availability in both social and personal contexts. Also, [62] proposes an extended graph representation that includes socio-demographic and personal traits extracted from the content posted by the user on social media. Predicting the contextual relevance of locations has been proposed by Aliannejadi and Crestani [63]. The method finds the mapping between user annotated tags and locations' taste keywords. By introducing a dataset on locations' contextual appropriateness, they showed the usefulness in predicting locations based on contextual relevance.

The profile users' interests are built based on tracing the users' textual contexts. Researchers in [64] integrate textual and contextual information of user and microtopic to generate a ranking list of microtopic. Wang *et al.* [65] propose to utilize the content of events from users' perspectives for event recommendation. This characterizes the latent preference of users by deeply exploiting the contextual information of events that users have attended, such as the time, location, and event host.

Many studies focused on extracting hidden content features. These studies were interested in discovering and analyzing features that, once revealed, may be of value for the recommendation. Authors in [66] used several semantic knowledge bases to fill the gap between the tweets' semantic context and the semantic meaning of hashtags. In [67] the authors propose a recommendation algorithm that matches user's interests and the content of the social networks. User's interests are expressed through a conceptual user model build using the concepts posted by the user. Concepts are identified from user posts using ConceptNet and are connected based on the textual context to form the contextual conceptual user model. This model is then extended with related concepts to build the augmented contextual conceptual model. Makki *et al.* [68] proposed a method centered around the models of word embedding because the context of the words is significant. In [69], the authors proposed two training procedures that were applied. In the first one, each hashtag is trained with a separate word embedding model applicable in the context of that hashtag. In the second procedure, each hashtag obtains its embedding from a global context. Gorrab *et al.* [70] proposed hashtags and users recommender system based on hashtags' semantic analysis. They built social user profiles, analyzed hashtags, and studied their contextual and temporal co-occurrence. In [71], the researchers proposed a tag-aware personalized recommendation system using a deep-semantic similarity model to extract recommendation-oriented representations for social tags achieving superior personalized recommendations. In [72], the solution lies in leveraging rich user attributes and matching them to event semantic knowledge accurately. The method is based on deep convoluted neural networks that take full context into consideration. Also, authors in [73] use a deep neural network model for quote recommendation in a given dialogue. This model learns the tweet features in a sequence by extracting the meaning of semantic features that exist in the sequential structure of dialogs.

4) MULTIDIMENSIONAL-BASED RECOMMENDER SYSTEM

In many cases, recommender systems aggregate different types of information to model a context due to the correlation between contextual factors. For example, combined social interactions of users, a textual description of a restaurant with its location for a restaurant recommendation system. Designing a recommender system that considers multiple contextual information may end with a complex recommendation algorithm due to the diverse nature of the information handled. Consequently, it is important to study the relevance of any contextual factor before using it to personalize recommendations.

In explicit rating, users explicitly provide input values that indicate their interest in particular items [74]. Rating should be adapted and dynamically modified based on the user's behavior and the context in general. In [75], the authors proposed a model that captures and exploits contextual information from the user's environment and employs collaborative social tagging to maximize the benefit of the extracted contextual information in the recommendation process. Wu *et al.* [76] proposed a mechanism that weighs the impact of the historical actions. The contextualized temporal attention learns what, when, and how these actions take place. Another model proposed in [26], named factorization machine, is used to partition the user-item-context interactions. The proposed model in [77] captures the temporal semantic effects, social relationships, and user behavior sequential patterns in a unified way by embedding the heterogeneous user-item network into a shared low dimensional space. This network was built in order to support a real-time social recommendation. The approach proposed in [78] combines multiple similarity matrices derived from a user-item bipartite graph, user-user social graph, and user-location bipartite graph. Spatial social union considers the relation between user and item as well as the social relationships between users, and the relationships between user and location. Finally, the technique proposed in [79] takes time, location, mood, and other contextual factors into consideration when recommending songs.

Many studies have been dedicated to the recommendation, which does not depend on explicit rating. These are based on the assumption that users have the same interests if their contexts are similar. The technique presented in [80] provides information filtering recommendations based on social relationships and tag-based interests. The model proposed in [81] takes the title and abstract of a research paper as inputs and recommends the potential top venues among journals and conferences to help researchers choose the suitable venue for publishing their research. The model relies on papers' and places' networks when providing recommendations. Authors in [82] proposed to store summary cluster information of users (i.e., demographic information, location, and behavior) instead of recording the whole history of contexts and user feedback. The research proposed in [83] predicts a proper item by utilizing the feedback reward of previous users in the nearby context region. Similar items can be amalgamated into a cluster to reduce the computing load. Yin *et al.* [84] embed all the observed relations among users, events, locations, time, and text content in shared low-dimension space, which is able to leverage the correlation between events and their associated content and contextual information. García-Sánchez *et al.* [85] proposed a framework that uses a shared ontological model to represent user interests and advertisements as vectors of concepts. The advertisement textual description is analyzed using natural language techniques to identify ontology concepts. The user registration information is used to identify the initial ontology concepts which represent user interests. The user concept vector is updated whenever the user clicks on some advertisements or interacts on the social network. User vector and advertisement vectors are matched using a similarity measure. The most similar advertisements are then recommended to the user. In [86], the authors exploited social signals based on group memberships, location signals based on the users' geographical preferences, and temporal signals derived from the users' time preferences. The approach proposed in [87] integrates the spatiotemporal, social, and popularity influences to find the personalized attractive force between a visited location of a user and a new location for the user as the weight of the visited location affecting the new location. They extracted sequential patterns from historical check-in location sequences of all users to know the effect of each visited location on the new location. In [88], the authors proposed to fuse the categorical, temporal, social, and spatial aspects in a single model to know the effect of each visited location on the new location. The rank of a location is influenced by the check-in history of the user at the time. Ogundele *et al.* [89] developed preference models built to compute geographical, categorical, social, and temporal influences of events on users based on their historical attendance records, and a personalized weight is estimated for each criterion. In [90], the authors proposed a travel recommendation model that exploits automatically mined knowledge from user-contributed photo tags and the detected people attributes, travel group types, and travel group season in photo contents. The work presented by Baral *et al.* [91] determines user preferences and POI sequences that match the locality preferences and user preferences through relying on various contextual information, such as social, temporal, categorical, and spatial contexts that are formulated and presented using a hierarchy aggregation technique. The proposed method in [92] suggests POI to users through grabbing the sentimental attributes for POIs. This is done by fusing the factors of sentiment similarity and geographical distance. Gong *et al.* [93] recommend friends for a user by applying a deep learning technique. Friends recommendation combines static attributes (e.g., the geographical location), dynamic behaviors (e.g., liking), and network structures (e.g., social relations).

Personalized recommendation through a tensor or matrix factorization exploration has been applied in many domains. The matrix factorization model is used to model interactions of users on items. For instance, Ge *et al.* [94] have developed an expert recommender system using geo-spatial, topical, and social context across users, experts, and topics. Authors in [95] first separately consider spatial and temporal features of user activity preference with sparse check-in data and then combine them together using a context-aware fusion framework. The method in [96] proposes to use six categories of features that represent the tendency of a user to attend the event using semantic information, geographical information, and online social network among users. In [97], matrix factorization utilizes the linear contextual features model to model explicit contextual features like semantic, spatial, temporal, user, event, group, and social features. The work proposed by Unger *et al.* [98] deals with explicit, unstructured, and structured context representations by adding numeric vectors to all available explicit contexts. Then, by adding compressed latent contextual embeddings extracted from an autoencoder (i.e., the nonlinear correlations between the original contextual features are represented as compressed and low-dimensional numerical values), and then utilizing hierarchical contextual information in a structured and latent manner. Authors in [99] studied how to treat contextual data in neural recommender systems effectively. Beutel *et al.* in [100] incorporated contextual data in the recurrent neural network by embedding the context feature first and then performing an element-wise product of the context embedding with the model's hidden states.

The work proposed in [101] collects cultural and artistic information, monitors and displays cultural heritage features in an easily understandable format by recording users' data and preferences, including important tourism features, weather conditions, and demographics to provide better recommendations. The work proposed by Sansonetti *et al.* [102] exploits liked open data sources using semantic technologies when considering users' activities and their friends in social networks.

B. APPROACHES AND TECHNIQUES IN CONTEXT-AWARE RECOMMENDER SYSTEMS

RQ2: What approaches and techniques have been adopted for integrating contextual information in social network recommendations to enhance the quality of recommendations?

SNs have rich contextual information, which allows recommendation systems to improve their overall performance and recommendation accuracy by integrating contextual factors such as location and time into their recommendation process. In doing so, they lead to mitigate some of the challenges such as cold-start and data sparsity problems. Table 2 shows the recommendation approaches that propose solutions to overcome the sparsity and cold-start problems. Moreover, additional information retrieved from social networks about users and their friends could promote the understanding of users' behaviors [17].

TABLE 2. References for recommendation approaches handling sparsity and cold-start problems.

Recom-mendation approach	Sparsity	Cold-start
Collaborative filtering	[25],[30],[32],[36],[42],[43],[52],[58],[59],[63],[71],[72],[94],[95],[97],[101],[106], [107],[109]	[42],[43],[52],[72],[75],[82],[83],[91], [97],[101],[104]
Content based filtering		[65],[112]
Graph	[88]	[44],[53],[62],[77], [84]
Hybrid	[24],[31],[33],[34],[37],[56],[74],[81],[85],[86],[93]	[24],[40],[56],[61], [81],[85],[86],[89]

Over the last years, CARSs have been a focus of attention for various research communities where enormous studies were proposed to enhance their efficiency. In this section, we briefly present context-based recommender system approaches and techniques and highlight recent developments in modern state-of-the-art techniques, including deep learning and hybrid techniques. Table 3 shows the distribution of studies based on the different techniques that are used in recommendation approaches.

Many researchers categorize approaches in recommender systems into at least three main approaches [8], [13]–[15] as presented in Section II. Following this tendency, in this research, we consider four main approaches for recommender systems, namely [2]: collaborative filtering, content-based filtering, graph-based filtering (GB), and hybrid-based filtering (HB). Besides, there is a wide range of techniques

TABLE 3. Recommendation techniques used in selected primary studies.

Techniques	References
Bayesian probability	[80], [90]
Bipartite graphs embedding	[84]
Clustering	[30], [60], [70], [91], [106]
Decision tree	[26], [38], [83]
Deep neural networks	[35], [56], [59], [65], [71], [72], [73], [76], [93], [98], [99], [100], [107]
Distance-based method	[88], [89]
Fuzzy clustering	[112]
K Nearest Neighbor	[24], [25], [44], [54], [75]
K-Means clustering	[55]
Learning to rank	[40], [49], [67], [86]
Markov chain	[87]
Matrix factorization	[33], [34], [39], [42], [43], [45], [48], [52], [58], [64], [82], [92], [97]
Mixture model	[32], [105]
Ontology model	[85], [111]
Random-walk	[53], [57], [62], [77], [81], [114]
Regression-based	[61]
Semantic similarity-based	[66], [68], [102]
Similarity-based method	[37], [41], [46], [47], [50], [51], [63], [69], [74], [78], [79], [101], [104], [115]
Tensor factorization	[31], [36], [94], [95], [109]

used to implement recommender systems described in this paper. These techniques are sometimes referred to as algorithms or methods.[3] Figure 6 depicts the approaches and techniques that are described in the following subsections.

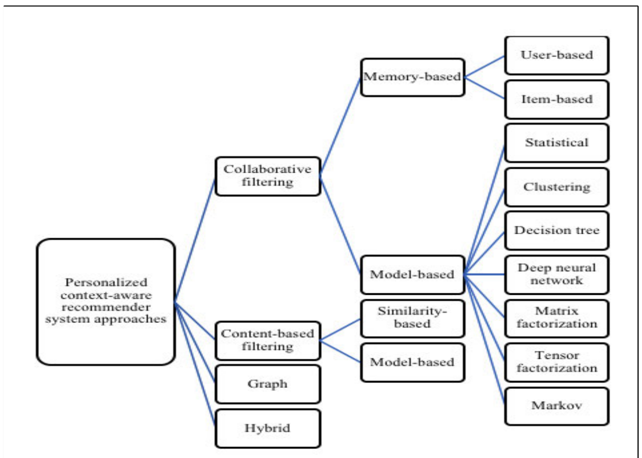

FIGURE 6. Classification of context-aware recommender systems' approaches and techniques.

1) COLLABORATIVE FILTERING APPROACH

The collaborative filtering approach provides users with widely used items as they allow an easy match between

[2]Some authors have more detailed categorizations such as Aggarwal [13] who considers that knowledge-based and demographic recommender systems as two independent categories of models.

[3]In Fig. 6, level 1 (next to root) represents the main approaches of recommender systems. Levels 2 and 3 show a classification of techniques used by some recommender systems presented in this study. It is noted that some techniques may be used by different approaches. Example: Clustering technique is used by model based in CF and CB approaches.

users with similar interests and tastes. It is a popular recommendation approach that specifies mainly two types of techniques: memory-based technique (neighborhood-based) and model-based technique [103].

Memory-based techniques infer missing values in the rating matrix by measuring the similarities between users' behaviors and preferences. Calculating similarities is essential for memory-based and used by user-based and item-based techniques. The user-based technique predicts a user's rating for an item through aggregating ratings for her most similar users who previously rated the same item. This prediction is formulated as follows:

$$\hat{r}_{u,j} = \frac{1}{n} \sum\nolimits_{k \in N_u} Sim\,(u, k) \cdot r_{k,j} \tag{1}$$

where n is the size of N_u that contains the most similar users to the target user u; $Sim\,(u, k)$ is the similarity score between users u and k, and $r_{k,j}$ is the user k rating's for the item j [14].

The work presented in [84] relies on collaborative filtering to study user's preferences and determine attributes that influence a ridesharing-based recommender system. The system applies a machine learning classification model to analyze the information of potential passengers. The potential passengers are ranked through a ranking procedure that depends on a similarity algorithm. A previous topic model-based presented in [25] aims to predict user's interests from users' watching lists of video co-occurrence. The model employs a user-based k-nearest neighbor collaborative filtering technique on the inferred user interest distributions. A prior work [50] defines a friends list based on their partners' activity candidate set and uses cosine similarity between activities' rated vectors. Another work proposed in [30] recommends top-k POIs for a user, where a personalized Hawkes process is applied to estimate probabilities of visiting POIs based on her historical check-ins. The system proposed by Ravi *et al.* [101] exploits user's activities, such as current location, comments, and reviews about the cultural heritage, to recommend interest heritage sites using a user-based collaborative filtering technique. The technique presented in [54] processes users' information and measures their friendship strength by calculating the similarity using k-nearest neighbors on users' interaction, personal, and group information. It then applies collaborative filtering on similarities and implicit preference values to generate personalized recommendations.

Item-based techniques concentrate on measuring the similarities between items, as a user who highly rated an item is assumed to like similar items. Under this assumption, item-based collaborative filtering techniques predict rates for items and rank them to a user by aggregating similarities between candidate items and items previously rated by the user. The prediction is formulated as follow:

$$\hat{r}_{u,j} = \frac{1}{n} \sum\nolimits_{k \in N_i} Sim\,(j, k) \cdot r_{u,k} \tag{2}$$

where n is the size of N_i that contains the neighbor items of item j; $Sim\,(j, k)$ is the similarity score between items j and k, and $r_{u,k}$ is the target user u rating's for the item k [14].

There are several collaborative filtering techniques to enhance the accuracy of user-item recommendations. In [75], the authors present a technique that uses extra contextual dimension and social tagging. Another method proposed in [96] amalgamates semantic content analysis and contextual event influence for user neighborhood selection in event recommendation. Another work presented in [104] recommends POIs through collaborative filtering by calculating the correlation between tags and locations. Similar to the work presented in [52], an effective preference-based technique using temporal dynamics examines the explicit and implicit feedback information provided by a customer through a user-item matrix factorization and pearson correlation measurement. Moreover, a study proposed in [78] develops a spatial social union-aware location-sensitive technique through analyzing the user-item bipartite graph, user-user social graph, and user-location bipartite graph similarity matrices. However, providing instant recommendations from different streams is challenging, particularly with the enormous number of messages describing user-item interactions. Hence, a study proposed in [38] addresses this challenge by enhancing memory-based implementations through developing various techniques, such as user-based, item-based, content-based, and most-popular technique to check which technique is suitable to solve the challenge.

Model-based techniques learn from exploiting the matrix values, then they apply classification techniques to train the model from the labeled data. By applying different data mining and machine learning techniques to the learning process's outcome, the model predicts the relevance of new items for the users through finding patterns from training data. The training process is then used to make predictions for unrated items and uncover latent features explaining observed ratings. Unlike the statistical models, which use machine learning to infer the relationships between variables. The model proposed in [105] simultaneously models the topics related to users' vital interests and a temporal context. Another model proposed in [32] focuses on spatial items and exploits their location and content information. In contrast, the latent factor model proposed in [58] retrieves sentimental features from a microblog and combines them with other types of information using sentiment classifiers based on contextual knowledge of microblogs.

Clustering techniques are viral for partitioning large dataset items based on users' rating data. A prior work presented in [55] partitions user context into clusters where independent clusters have their knowledge and maintain their online learning processes. Another work proposed in [106] inspects user's interest and clustering by using a cluster-of-bandit algorithm. The study took place in an online environment and aimed to share knowledge between the users. The work in [83] addresses the enormous amount of data by leveraging users' explicit and implicit information to formulate user's space using a tree-based model that enables efficient computations through analyzing large-scale items at the cluster level. The tree-based model can handle the cold-start problem and expiring new items by formulating the context space and partitioning users' explicit information dynamically in each round. The work proposed in [26] improves capturing the complex local interaction of sparse data by splitting the contexts hierarchically using random decision trees. Additionally, the technique presented by Baral *et al.* [91] aggregates multiple sets of users' preferences in a locality using locality-based hierarchical structures and exploit these preferences to provide contextual sequence recommendation. The work proposed in [60] applies a cluster-based machine learning technique that automatically studies relationships among content and context influences to provide recommendations for smart online social network media systems on smartphones.

In contrast, dimension disaster and data sparsity are examples of the challenges for traditional learning models. Though, neural network (NN) models became very popular as they can handle these challenges through a low dimensional representation of symbolic data. The neural network musical recommender system proposed in [107] aggregates the embeddings of music pieces in their complete listening records and active interaction session, respectively, to derive users' general and contextual preferences. Similarly, the recommender system proposed in [35] incorporated the embeddings of user and item in the NN model for better personalization to identify dynamic preferences based on user's interaction with items. The graph-attention neural network proposed in [99] relies on dynamic user's behaviors with recurrent neural network (RNN) and context-dependent social influence to model user's session-based interest and forceful social impacts. The technique presented in [71] maximizes the similarities between users and their target items by mapping the tag-based user and item's profiles to an abstract deep feature space using deep neural networks. A latent cross model presented in [100] integrates contextual features in the RNN-based recommender system used in YouTube. This model focuses on embedding the context feature and then performs an element-wise product of the context embedding with the model's hidden states. Another model proposed in [72] enables useful and accurate user-event matching features through considering the full context. The model projects any given user and event into the same latent space using deep convoluted neural network (CNN), which then passes matching features and other standard features to a gradient-boosting decision tree-based combiner model. The technique presented in [59] constructs a location sentiment rating matrix and user attention matrix based on the effects of geo-location, temporal contexts, and users' sentimental reviews on locations. The technique leverages RNNs to learn the embeddings of different factors by dividing users into several groups and training various neural networks for different groups, enhancing the pertinence. The work presented by Unger *et al.* [98] studies the methodology of including contextual information through three deep context-aware recommendation models into deep learning-based collaborative filtering approaches and utilizes them to learn a nonlinear function of user-item interaction.

Matrix factorization (MF) is an essential recommender system technique in discovering latent features and accommodating additional information like confidence level [78] that reveal interactions between users and items. This is due mainly to its ability to decompose a matrix into a product of two matrices with the capability to retain the original form back when multiplied. Consider a set of U users and a set of I items, and a rating matrix R of size $|U| \times |I|$, we can discover K latent features by finding two matrices $P\,(|U| \times K)$ and $Q(|I| \times K)$, such that their approximate is $R \approx P \times Q^T$ [108]. To apply matrix factorization on users' social context and find appropriate latent features, users who trust each other are brought together and separated from those who distrust and have different interests. A recent trust model presented in [43] improves memory-based and matrix factorization-based performance by incorporating these two models, while another model proposed in [42] concurrently mines users' trusts, distrusts, and neutral relationships in rankings. In contrast, the work proposed in [97] depends on six diverse sets of features extracted from semantic information, geographic information, online social network among users to model users' preferences and their willingness to attend events using a feature-based matrix factorization model.

A joint probabilistic latent factor model presented in the micro-topics recommendation [64] is built on top of collaborative filtering, content analysis, and feature regression to blend rich information into a matrix factorization-based solution. The unified model presented in [82] describes implicit feedbacks and explicit contextual features using a combination of matrix-factorization model and linear contextual features model. Moreover, the technique proposed in [48] uses joint probability distribution and matrix factorization to provide recommendations for multiple social networks.

Tensor factorization (TF) is an expansion to matrix factorization techniques that aim to diminish tensors into their lower-dimensional feature vectors. In [109], the authors propose enhancing the accuracy of recommendations and mitigating data sparsity problems by using the user's social trust information and his implicit feedback and expanding the bias tensor factorization. A prior work proposed in [94] personalizes expert recommendation using a tensor-based exploration of geo-spatial, topical, experts and topics, and social context across users. A previous work presented in [36] employs a context-aware tensor decomposition technique to retrieve user's rating for a given location and time relying on a user-user similarity matrix and a location feature matrix extracted from a three-dimensional tensor approach that shapes the relations between a user, location, and time. The non-negative tensor factorization technique presented in [95] recovers the latent correlation between a user, time, and activity factors to explain how to infer a user's temporal activity preference.

Under the assumption that future states are obtained from current states, A Markov model, a stochastic model, models sequential data and randomly changes states. The use of the Markov process in recommender systems is focusing on predicting effective items that users may pick in the near future. Whether it is a sequence-aware recommender system or a time-aware recommender system, both Markov models take an ordered or timestamped list of users' previous interactions as the main input. The gravity-model-based location technique proposed in [87] derives a user's probability of visiting new locations by analyzing her previously visited places and check-ins from the higher-order sequential influence based on the order additive Markov chain. The probability calculation considers the weight of each visited site on the new location by integrating the spatiotemporal, social, and popularity influences and determines the attractive force between locations. Table 4 presents a synthesis of context-aware recommender systems using the collaborative approach.

2) CONTENT-BASED APPROACH

The content-based approach suggests items similar to those liked in the past by the same user with similar interests or features to create a user profile. The term frequency-inverse document frequency (TF-IDF) is a popular technique used in information retrieval [110] that applies heuristic similarity for measuring item-to-item likeness. The model proposed in [70] adopts semantic analysis and clustering techniques on social user profiles for recommendations. Inspired by TF-IDF, the model proposed two hashtags' indexing schemes on hashtags in user's tweets based on ontology using hashtag indexing, filtering, and semantic analysis technique. Arafeh *et al.* [111] presented a recommender system that used ontology to improve the relatedness of nodes in the filtering step. Their algorithm assigns recommendation probability for each node in the knowledge graph through a given ontology model that decreases the budget and time required for mining. Another model presented in [90] provides travel recommendations by using Bayes technique that constructs statistical models from the latent information, and minds knowledge extracted from users' photo tags, people attributes, travel group types, and the season from photos' contents. Another work that targets social media content is proposed in [68] to return top-k tweets ranked by their relevance to the query. This retrieval model applies probabilistic language techniques, such as a unigram language model, bayesian smoothing, and dirichlet priors to answer a user's query. Another work that targets tweets and applies naïve Bayes and k-means clustering techniques is presented in [112], where tweets are combined and clustered using the fuzzy k-means technique. Eventually, each cluster is assigned a label through the naïve Bayes model, and the recommender system returns the top five categories matching the user's interests. Moreover, the probabilistic generative technique proposed in [63] maps location keywords to users' tags. Hence, enabling the recommender system to predict the user's tagging behaviors effectively. The model reveals that using machine learning techniques to predict contextually appropriate locations and re-rank suggestions improves location recommendations.

Although MF and TF are frequently used in contextual modeling techniques, recommender systems extensively apply latent dirichlet allocation (LDA) for contextual pre-filtering and post-filtering approaches. The task for LDA is to infer one matrix for the distribution over topics for a given document and a second matrix for topic-specific distribution over words in the vocabulary [113]. Regarding the context-aware LDA models, the first matrix for topic distribution is enhanced through various techniques, including a bag of concepts representing users' interests and DBpedia for their background knowledge base. The method proposed in [51] provides recommendations for passive users who do not generate content by inferring their interests from lists of followees that can provide quantitative and qualitative information. The work presented in [66] proposed a model that relies on the spreading activation technique as a matrix for topic-specific distribution over vocabulary words. The model measures the semantic similarity between a tweet and trending hashtags collected recently through applying WordNet, Wikipedia, and DBpedia semantic knowledge bases.

Even though the word frequency representation, like the bag-of-words model, is commonly used as a text representation technique for recommender systems, it ignores sentence structure and word orders of the content, making it unable to capture the contextual information of the content entirely. This challenge highlighted the need for alternative solutions capable of learning effective feature representation from text content. Recent deep learning techniques show great potential via applying RNN and CNN to capture semantic features, i.e., n-grams and the overall ordering of words in context, respectively. The RNN technique proposed in [69] applies skip-gram embedding on the suggested pre-hashtag word embedding for the added context. In addition, the work presented in [65] uses a probabilistic matrix factorization framework on users' events contextual information captured by CNN to recommend events. Lastly, the work introduced in [73] provides a quote recommendation by extracting a meaningful representation of the tweet context. Table 5 presents a summary of recommender systems using the content-based approach.

3) GRAPH-BASED APPROACH

Graph-based approach expresses social networks as graphs, where nodes represent users and items, and edges model the different relationships among user-user or user-item pairs (e.g., likes, follow). Graph-based recommender systems use relationship representations to identify similar users or items [53], [57], [62], [88], [114]. PageRank is one of the most popular GB techniques that produces a ranking of the nodes in a graph and finding popular nodes by applying a random-walk model to move through the directed graph. When the random-walk reaches a node that has no outgoing

TABLE 4. Context aware recommender systems using the collaborative approach.

Ref. ,Year	Application field	Recommendation technique	Contextual factor	Problems handled	Data set
[25], 2016	Videos	K-Nearest-Neighbor CF	Social	sparsity	JHKVoD dataset.
[26], 2016	Movies and menu items	Random decision trees	Multidimensional		Adom dataset, Food dataset, and Yahoo dataset.
[30], 2019	POI	Clustering with noise algorithm	Location	sparsity	Gowalla.
[32], 2016	Event, location	mixture model	Location	sparsity	DoubanEvent and Foursquare.
[35], 2020	Items (film)	Deep neural networks	Temporal		Movielens, Amazon, video game dataset.
[36], 2016	Location	Tensor decomposition	Temporal	sparsity	Foursquare.
[42], 2015	Items	Matrix factorization	Social	sparsity, cold-start	Epinions dataset.
[43], 2017	Items	Trust model incorporated into a memory-based and matrix factorization	Social	sparsity, cold-start	Epinions Dataset.
[45], 2019	Items	Matrix factorization	Social		Epinions.
[48], 2018	Items	Probabilistic matrix factorization	Social		Yelp and Douban Movie.
[49], 2019	Passengers	Machine learning model	Social		A database was created using subjective test results.
[50], 2015	Activity-Partner	Similarity scores	Social		Gowalla, Foursquare, and Brightkite.
[52], 2017	Products	User-item matrix factorization	Social	sparsity, cold-start	Rival Java evaluation toolkit
[54], 2017	Topics or interests related to (smartphone, music, movie, and drama)	Similarity measures and k nearest neighbors	Social		Twitter.
[55], 2016	News	K-Means clustering	Social		Synthetic dataset
[58], 2017	Microtopic	Matrix based on latent factor model	Emotion	sparsity	Weibo dataset.
[59], 2020	POI	Recurrent Neural Network	Emotion	sparsity	Yelp.
[60], 2017	Media	Cluster-based	Emotion		Flickr, Twitter.
[64], 2017	Microtopics (hashtag)	Matrix factorization	Content	cold-start	Sina Weibo and Twitter.
[71], 2016	Tag	Deep neural networks	Content	sparsity	Delicious bookmarking system and released in HetRec 201.
[72], 2017	Event	Convoluted neural networks	Content	sparsity cold-start	Largescale data set sampled from traffic in a real-world production system.
[75], 2016	Media category such as news, music, and movies	k nearest neighbors	Multidimensional	cold-start	last.fm
[78], 2015	Items (movies)	Similarity matrices	Multidimensional		MovieLens.
[82], 2016	Event	Linear contextual feature model and Matrix Factorization model	Multidimensional	cold-start	Meetup.
[83], 2018	Job or Candidate	Tree model	Multidimensional	cold-start	2017 ACM Conference on Recommender Systems Challenge
[90], 2015	Travel	Bayesian model	Multidimensional		Facebook and Flickr.
[91], 2019	Location	Clustering	Multidimensional	cold-start	Weeplace and Gowalla.
[94], 2016	Expert	Tensor-based	Multidimensional	sparsity	Twitter dataset.
[95], 2015	Location	Tensor model	Multidimensional	sparsity	Foursquare and Gowalla.
[97], 2018	Event participants	Feature-based Participant-Ranking Matrix Factorization	Multidimensional	sparsity, cold-start	Meetup, Plancast, and Twitter datasets.
[98], 2020	POI (restaurants)	Deep neural networks	Multidimensional		CARS, Frappe, and Yelp.
[99], 2019	Items	Recurrent neural network	Multidimensional		Douban, Delicious, and Yelp.
[100], 2018	Videos	Recurrent neural network	Multidimensional		YouTube.
[101], 2019	Cultural item	Similarity matrices	Multidimensional	sparsity. cold-start	Facebook, print media (encyclopedias), YouTube.
[104], 2017	New places to the user	Similarity scores	Social	cold-start	Location dataset.
[105], 2016	Items (News, movie, tag)	mixture model	Temporal		Digg, MovieLens, Douban, Delicious.
[106], 2020	Items (Music, news)	Clustering-Explorable Bandits	Multidimensional	sparsity	LastFM, WeChat
[107], 2018	Music	Neural network models	Temporal	sparsity	Xiami Music.
[109], 2020	Items	Trust tensor factorization	Social	sparsity	Ciao-DVD, Epinions

TABLE 5. Context aware recommender systems using content based approach.

Ref. ,Year	Application field	Recommendation technique	Contextual factor	Problems handled	Data set
[65], 2018	Event	Convoluted neural network with word embedding	Content	cold-start	Meetup.
[66], 2017	Hashtag	Spreading activation technique to calculate the semantic similarity	Content		Twitter and DBpedia.
[67], 2020	Textual content (tweet)	Conceptual user modeling	Content		Twitter.
[68], 2016	Tweet	Unigram language model with Bayesian smoothing and Dirichlet priors.	Content		Using the TREC 2015 Microblog track.
[69], 2017	Hashtag	Word embeddings	Content		Twitter.
[70], 2017	Hashtag	Clustering	Content		Twitter.
[73], 2016	Quote	Deep neural networks	Content		Wikiquote website, Oxford Concise Dictionary of Proverbs and Twitter.
[111], 2020	Items (movies)	Ontology enhance filtering	Content		MovieLens.
[112], 2018	News	Fuzzy clustering	Location	cold-start	Google News dataset

links, it employs a restart mechanism by either jumping to an arbitrary node of the network with a probability α or through following a random outgoing link connected to the current node with a probability (1- α). The probability at a node l is defined as follows:

$$\pi\,(l) = \frac{\alpha}{n} + (1-\alpha)\cdot \sum\nolimits_{j\in In(l)} \pi\,(j)\cdot p_{jl} \tag{3}$$

where $In(l)$ is the set of nodes that have outgoing links directed to l from total number of network's nodes n, and p_{jl} is the transition probability from node j to node l [14].

A limitation that the PageRank technique has is the inability to provide a personalized recommendation as it does not consider the user's preferences. Hence, a personalized PageRank (PPR) technique that altered the random-walk is developed to assess graph nodes relatedness concerning nodes of interests. This alteration enables the random-walk procedure to spread at each step of the walk a probability volume to neighboring nodes over outgoing edges while diverting a fixed ratio of the probability volume at each node to the initial node-set. When the random-walk terminates, the shortest paths in the graph-nodes will assign the highest weights indicating the highest relevancy to the initial query. The work presented in [62] uses the PPR technique to measure nodes' relevancy with respect to a target node. Another work that relies on the same probability technique is introduced in [114] to recommend friends for LBSNs using a specialized random walk with restart, where the random-walk starts from the current user and moves based on the uniformly computed probabilities through the graph until it ends when reaching a steady state. The work in [88] proposed a topic-sensitive PageRank model for LBSN, where representative topics are the spatial and the categorical aspects of the LBSN, such that locations are treated as nodes while users and times are the attributes of these nodes. Moreover, the work presented in [53] applies random walk with a restart to measure the similarity between users and future events. The initial graph gets updated with users and events at a time interval to capture the dynamic relations. The recommendation similarity for each user is calculated using graph entropy of all time intervals resulted in graphs. Randomly connected graph techniques apply to build a concept context graph that assigns a proper priority for each of the visited candidate users are proposed in [46] to determine the recommended candidate users' ranking. Using a random-walk technique, a relevance propagation technique that catches the overall user preference on music is presented in [57] to recommend appropriate music for users based on their emotional status.

A joint even-partner recommendation system presented in [84] inserts multiple heterogeneous relations into a shared low-dimensional space among various attributes like users, events, locations, time, and text content by deriving a bipartite graph-based embedding model. A dynamic graph-based embedding model introduced in [77] provides efficient instant relevant users and interested items recommendations via building a heterogeneous user-item network, where users and items are presented as vertices while semantic effects, social relationships, and user behavior sequential patterns are characterized as different types of edges respectively. The social recommender system presented in [44] focuses on the reliability of the implicit relationships between users, through constructing a graph hosing connection between them from the item-rating matrix and the explicit trust relationships. The system calculates the underlying users' relations using predictions on the graph. Table 6 presents recommender systems using the graph-based approach.

4) HYBRID APPROACH

Hybrid approaches are an integration of multiple approaches. As a result, using hybrid filtering systems enhance context filtering. Though, social network hybrid filtering systems overcome CB and CF's limitations by combining rating-feature data of user-item profiles. The social network recommender system presented in [80] is a hybrid system that applies collaborative filtering and content-based recommendation. The system uses the nearest neighbors' technique as

TABLE 6. Context aware recommender systems using graph based approach.

Ref. ,Year	Application field	Recommendation technique	Contextual factor	Problems handled	Data set
[44], 2020	Products (movies)	Neighborhood mechanism	Social	cold-start	Epinions, Flixster, and FilmTrust.
[46], 2015	Followees	Similarity	Social		TENCENT dataset.
[53], 2017	Event	Random walk with restart algorithm	Social	cold-start	Douban Event.
[57], 2016	Music	Propagation algorithm based on random walk	Emotion		Sina Weibo.
[62], 2017	Items	PageRank	Content	cold-start	MovieTweets dataset.
[77], 2019	Friends and items	Random walk	Multidimensional	cold-start	Twitter and Last.fm.
[84], 2018	Event- partner	Bipartite graphs based embedding model	Multidimensional	cold-start	Douban.
[87], 2015	locations	Markov chain	Multidimensional		Foursquare, Gowalla, and Brightkite.
[88], 2016	POI	PageRank model	Multidimensional	sparsity	Weeplaces and Gowalla dataset.
[114], 2016	Friend	Random walk	Location-based		Brightkite, Gowalla and Foursquare.

a collaborative phase on the target user to discover closest neighbors while uses a modified Bayesian probability scheme to generate recommendations. The work in [85] presents an approach based on ontologies to recommend advertisements to users in social networks. The proposed framework uses a shared ontological model to represent user interests and advertisements as vectors of concepts. The recommendation is based on the similarity found between these profile vectors. Another approach proposed in [115] and implemented as an application for the Facebook social network is primarily designed to recommend media content published by user's friends. The authors are interested in discovering similar interests in fine-grain categories that are not standard and are yet to be discovered. Hence, all content published by a user's friend is re-categorized into more specific categories. Then sentiment analysis is performed to the text content to detect the sentiment of the publisher about the posted content. Finally, based on an interest score calculated using the previous information and the user's profile, the system decides on the content to recommend to the user. A hybrid system presented in [37] defines the content-based similarity of users and contextual similarity of places through the use of user-based CF, item-based CF, CB, and contextual recommendation systems that process information from users' visits history and their contextual information and place-related information. Furthermore, modeling location-based user behaviors in location-based social media network services through a context-aware regression mixture model is presented in [33]. The input to this system is a query entered by the user and the corresponding querying spatial-temporal context. Simultaneously, the output is a top-k recommendation extracted from combining the discovered interest of the querying user, the local preference of the querying location, and the context-aware influence factor. Exploring rich context in EBSNs has been studied in the literature, including content, social, and geographical information. The objective of these algorithms is to utilize content information and explore LDA to capture events that match users' interests through topic relatedness between users and events. The main idea focuses on the local popularity and interest concepts where the former measures the similarity between an event and a user's interest, and the latter takes all events in the user's neighborhood into consideration. Finally, these algorithms rank the recommendations using a pairwise learning technique as the user-event participation relationship can be represented in a binary format [40]. Additionally, the user-item rating matrix expands using the CB approach by predicting on the matrix containing all users' ratings. The CF approach processes the outcome matrix to identify neighbors [24]. In contrast, the technique presented in [61] enhances, through LDA, the recommendations by using a collaborative user-item regression model that utilizes the rich context and infers various contexts from different sources in a social-based recommender system.

Authors in [92] recommend POIs to users by a sentimental-spatial context-based recommendation model. The proposed method mined the POIs that have a density of social media data and similar sentimental attributes by using sentiment analysis and a global positioning system. Their recommendation method incorporated the factor of sentiment similarity between POIs and the factor of geographical distance between user's multiactivity centers into the probabilistic matrix factorization model for POI recommendation.

Alternatively, the work proposed in [34] uses a kernel density estimation technique and a random-walk technique to model spatial influence and sequence of geographical influence of location, respectively. The kernel density estimation generates a different distribution for each user, while a random-walk integrates the user's preference, social impact, and sequence properties of geographical influence. Another model is presented in [86] for ranking events in a personalized recommendation system based on a combination of social, location, and temporal signals. A multi-relational factorization and Bayesian personalized ranking are used to exploit group memberships for social signals. A kernel-based estimation technique is used for the user's geographical preferences for location signals. Finally, the user's time preferences help in obtaining temporal signals. Moreover, recommending events using personalized weighted geographical, categorical, social, and temporal influences through a multi-criteria decision-making technique has been presented in [89]. The framework uses an adaptive kernel density estimation (KDE) technique to model the personalized two-dimensional geographical influence on a user and uses the TF-IDF technique to model the categorical preference. Additionally, the framework models the social impact as the group of relevance to a user and uses the KDE technique to model the temporal influence. The system proposed by Zhang *et al.* [39] uses collaborative filtering to provide recommendations for time-social network topic features by exploiting social relations and time-sequenced topics using the LDA and the similarity between users according to their interest similarity of each historical period. The system presented by Katarya and Verma [79] predicts cultural items while captures user's preferences through applying collaborative filtering and a graph-based depth-first-search algorithm, respectively. The graph-based depth-first-search algorithm traverses the whole graph through the paths in different contexts. The algorithm presented in [102] analyzes social networks to obtain relevant information about users and their activities, represented as a model of user's interests stored in a graph database. The outcome is personal itineraries recommendation based on the user's profile and the physical and social contexts. Pradhan and Pal [81] proposed CNAVER, an academic venue recommender system to help researchers choose the suitable venue for publishing their research. CNAVER constructs two networks: paper-paper peer network and venue-venue peer network. The first network represents the similarities between papers based on the abstract and the title of each paper by applying LDA to the abstract and Doc2Vec to the title. The second network is constructed based on paper attributes. To recommend the top venues, CNAVER applies rank-based fusion employing both paper-paper and venue-venue peer models, allowing for selecting the best recommendations out of the fusion of the two models.

A prior work proposed in [41] evaluates candidate researchers for recommendation using a contextual trust analysis technique that amalgamates three aspects of researchers and companies' context. The authors in [47] propose developing of a recommender system for tourists planning to visit some destination. The system recommends personalized attractions based on user interests, including trust, reputation, social relationships, and social communities. The novelty of the approach is the use of trust and reputation in the recommendation process, which are calculated based on ratings and reviews of users using CF and CB approaches that can be tailored to the type of stage. Another work presented in [56] aims to predict the user's next click behavior by analyzing the user click events within-session and news contextual features using the learning to rank method. The model uses CNN and RNN techniques to learn article contextual properties and sequential temporal patterns in streams of clicks, respectively. The framework presented in [93] uses the large-scale information network embedding algorithm to combine attention and network embedding in three phases. Firstly, it produces semantic topics and forms static attribute features by utilizing the LDA algorithm. Secondly, it obtains latent deep structural feature representation from the dynamic behaviors through the CNN network. Finally, it extracts features on the attribute information using attention. The concept of "attention" has obtained popularity in training neural networks as it permits models to learn alignments between different modes. Table 7 presents a synthesis of systems using the hybrid approach.

VI. DISCUSSION

Context-aware recommender systems are complex systems that use various algorithms to process, analyze and recommend results based on contextual information to suit user needs. These systems deal with different forms of data related to the user, item, context, and rating. Each specific record is analyzed to what degree a user likes a given item, as well as the contextual information that has to do with the user, upon which circumstance the item is evaluated.

The scope of this study is quite focused; it is driven by the following criteria: i) it is dedicated to the field of context-aware recommender systems that exploit context in online social networks for recommending various types of information to users; ii) it is restricted to research published during the period from 2015 to 2020, where 85 primary studies were methodically selected, studied, and analyzed; iii) it is focused on analyzing two main research questions (RQ1 and RQ2, see Introduction Section) revolving around context factors, approaches and techniques for CARSs.

A. CARSs' CHALLENGES

Various challenges and problems resulting from this review hinder research in CARSs. These are classified into three categories (Fig. 7). The first category is related to the recommendation process itself, the second is about identifying the context before and during its integration in the recommendation process, and the third category includes problems outside the recommendation process boundaries.

CARSs in social networks suffer from two significant problems, namely cold-start and data sparsity. Hybrid and CF approaches attempt to solve these two problems by using techniques such as MF and NN to model the contextual information, as shown in Table 3. Hybrid approach mines the historical behavior data of items from users, the content data of items and user profiles, interaction behaviors among users, the user's context information such as trust relationships between users and integrate multiple recommendation techniques. CF approach combines model-based and memory-based techniques with context information. Nevertheless, hybrid and CF approaches face the dimensionality challenge, which is an inherent problem in CARS. Factorization methods, principal component analysis, latent semantic

TABLE 7. Context aware recommender systems using hybrid approach.

Ref. ,Year	Application field	Recommendation technique	Contextual factor	Problems handled	Data set
[24], 2016	Event	User-Based Nearest Neighbor algorithm	Multidimensional	sparsity cold-start	Dataset stored in a MySQL database which connected to a RESTful web service
[31],2021	POI	Tensor factorization and weighted distance kernel density estimation	Content	sparsity	Foursquare
[33], 2016	Location	Regression mixture model	Location	sparsity	Dianping and Foursquare.
[34], 2017	Location	Kernel density estimation	Location	sparsity	Brightkite and Gowalla.
[37], 2018	Venue	User similarities, venue similarities, and distance from the venue to the user center	Temporal	sparsity	Twitter, Foursquare, and Weather Underground.
[38], 2015	Articles	Decision tree	Temporal		Plista online web news portals.
[39], 2017	Friends to follow	Matrix factorization model and similarity calculation	Temporal		Sina Weibo.
[40], 2015	Event	Features aggregation	Social	cold-start	Meetup
[41], 2017	Candidate researchers	Trust analysis model	Social		ScholarMate.
[47], 2020	Tourist attractions	Similarity in graph model	Social		Real dataset of an international travel agency in Asia.
[51], 2017	Link recommendations on Twitter	Similarity scores	Social		Twitter and DBpedia.
[56], 2018	News	Deep neural networks	Social	sparsity cold-start	Adressa website And Last.fm
[61], 2016	News and local event	User-item regression model	Content	cold-start	Medium.com, Meetup.com users datasets. And Twitter.
[63], 2018	POI	Similarity scores	Content	sparsity	Yelp and Foursquare.
[74], 2020	Items (movie, restaurant)	Real-coded Genetic Algorithm and similarity measures	Multidimensional	sparsity	LDOS-CoMoDa dataset, UCI Machine Learning Repository
[76], 2020	Items	kernel functions, Bidirectional RNN	Multidimensional		XING and UserBehavior
[79], 2018	Music	Depth-first-search	Multidimensional		Last.fm
[80], 2019	Bookmark	Nearest neighbors and Bayesian probability	Multidimensional		Diigo.
[81], 2020	Academic venues	Random walk with restart incorporated into networks models	Multidimensional	sparsity cold-start	DBLP.
[85], 2020	Advertisements	Ontology model	Multidimensional	sparsity cold-start	15 users.
[86], 2015	Event	Feature-based	Multidimensional	sparsity cold-start	Meetup.com.
[89], 2018	Event	objective distance-based method	Multidimensional	cold-start	Meetup.com.
[92], 2020	POI	Probabilistic matrix factorization	Multidimensional		Sina Weibo
[93], 2019	Friend	Deep neural network with network embedding	Multidimensional	sparsity	Weibo
[96], 2019	Event	Latent topic model	Multidimensional	cold-start	Douban Event.
[102], 2019	Points of cultural interest	Heterogeneous social graph with semantic similarity	Multidimensional		Facebook and linked open data (DBpedia, Europeana).
[115], 2020	Media content (music, videos, and online clips)	Similarity evaluation of fine-grained interest profiles	Multidimensional		Facebook.

indexing, and LDA are the most common techniques used in CARS to reduce dimensionality. Despite this, there is a need to balance dimensionality with necessary information. In order to make the recommendation more intelligent, genetic algorithms can be used with CF to handle the level of importance of all contextual dimensions.

The unbalanced use of contextual factors remains also a challenge because of the ease of extracting some of them,

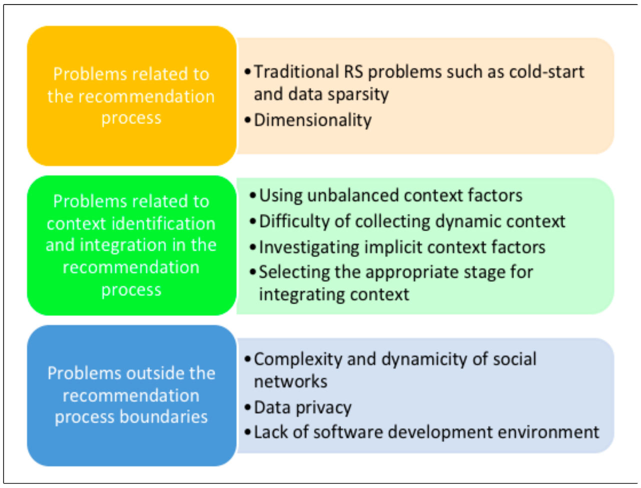

FIGURE 7. **Categories of problems in recommender systems.**

such as location, and the difficulty in extracting others like emotion. There are very few works that have been able to integrate users' emotional states [57], [58]. This is also due to the fact that very few studies have considered using daily life activities to improve the data collected and used in CARSs. However, it is possible to automatically infer the users' activities in real-time through data from mobile phone sensors like time, noise, location, etc. Nonetheless, identifying the correct technique for any specific type of application domain for which RSs are built remains a challenge for application developers.

Dynamic contextual factors particularly the environment and the user, help improve the recommender methods especially the CF approach as it reduces the dimensions when the user is represented, particularly the users' likes and continuous interactions change which are difficult to collect. Usually, special techniques such as tensor decomposition are used to aid these factors and reduce the dimensions. However, this affects the recommender accuracy negatively, as it increases the sparsity. The new data mining techniques tried to overcome this challenge as they utilize deep learning by representing user interaction with the items (i.e., movie, product, and tweet) on a continuous basis. These studies [31], [109] enhance the recommender system by making full use of latent factors that affect user's activities which can help in improving the rating and the performance of CARSs.

In addition, there has been much more research investigating implicit contextual factors that use the CB approach to recommend suitable content to user. The proposed systems in these researches use conceptual representations of text to match user models with the best content. Most of these systems focus on exploiting the bag-of-words model that considers word frequency and neglects word orders and sentence structure. However, there is a more efficient way to represent the user model based on NN that allows capturing text semantic meaning and utilizes text conceptual representation built using the knowledge available in the social network.

With the emergence of context in RS, many researchers focused on improving the classical existing recommendation algorithms by incorporating contextual modeling approach in the recommendation process which, in many cases, has been proved to be more effective than pre-filtering and post-filtering approaches. The state-of-the-art algorithms in CARSs are derived primarily from traditional recommendation algorithms, although they are gradually evolving over time and can be implemented across different application domains. We illustrated the integration of the main traditional approaches of RS with machine learning and data mining techniques that take into consideration different types of contexts.

Social network systems are continuously growing making these systems dynamic and difficult to manage. New reliable real time solutions to such problem should be developed. Another relevant challenge arising is the need to assure data privacy which is an important aspect to develop as confidence is vital for personalization in CARSs. Moreover, there is a lack of software development environments that can help developers in their tedious task to implement CARSs and be able to test, compare and validate different solutions.

B. RESEARCH OPPORTUNITIES

This study revealed various research opportunities. First, although CARSs field has been investigated intensively, there is still a potential for a new research, specifically those dedicated to investigate implicit context factors. This tendency is clear in very recent research [52], [82], [113], where systems strive to discover the key context information for efficient and quality recommendation. Second, there are many opportunities for researchers to develop novel techniques for the recommendation that efficiently deal with the growing complexity and dynamicity of social networks, to personalize and adapt recommendations to users. The trend is to combine different techniques and integrate them into an original fresh approach [77], [99]. Visibly, this tendency is desirable and has noticeably improved results compared to single techniques. Third, although recommendation approaches are quite limited to only four major approaches, namely CF, CB, GB, and Hybrid, there is an opportunity to design and develop a conceptual framework that offers an integrated approach that identifies and includes the common concepts, approaches and techniques for use by researchers in the field. Some attempts have been proposed by authors, such as [1] for link prediction in social networks, but these were generally destined to handle a specific problem for a particular setting. Fourth, the development of available datasets can advance noticeable research and development in this field. It relieves researchers from the tedious task of collecting data that is not always available and offers standard data and benchmarks for fair system evaluation. Finally, the Internet of Things (IoT) and wearable computing are recent technologies that can collaborate with recommendation systems. Using IoT algorithms to get the user context either explicit or implicit from heterogeneous sources will enhance the recommendation process.

IoT has the ability to combine data from different sources and share that data with other systems. On the other hand, there are many characteristics in wearable computing that can explain the development of CARSs. For instance, wearable sensors can be easily connected to people's smartphones. Configuring the wearable sensors is needed to handle and protect personal information by defining specific mechanisms that allow people to manage their permission to access and control their information and share it.

VII. EVALUATION

Evaluating SLR research is a challenging task that needs to address mainly two aspects: selecting the primary studies and the accuracy of the results obtained. The first aspect relates to the search and selection process of primary studies and questions about the validity of the selected studies. The second aspect examines the study results and how far it provides accurate results and classification of the studies. In order to have an objective evaluation, we developed a search and selection protocol, a measurable template for data extraction, and metrics that allowed us to assess the quality of review results. These evaluation tools made our work methodical and systematic and have eased the validation of the SLR results. Most of these tools have been designed for SLR and can easily be reused for replicating the work and promoting reproducibility for research reviews in general.

A. PRIMARY STUDIES SELECTION

The selection of the primary studies for SLR needs to be conducted with care and should be accurate and complete. The selection is accurate if the selected studies are relevant to the field of study. It is complete if the search is able to find all the relevant studies. If the search was done in a closed database, accuracy and completeness could easily be measured by precision and recall, which are two measures commonly used in information retrieval [116]. In general, the selection of primary research studies is made in open databases, which grow continuously. These databases are owned by different organizations having different resource classification standards. This led us to define our own protocol and metric to ensure that our search process strengthens accuracy and completeness.

The search protocol is the method adopted to conduct the search and selection of primary studies. In order to ensure completeness in the selection process, the following measures were followed: First, we used a database portal that offers access to major scientific databases in the computing field (see Section III). Second, the search has been done in four cycles, as shown in Table 8, which means that the selection set was growing incrementally allowing several fine inspections of any addition to the set of primary studies. Third, we used two types of search: automatic search using Saudi Digital Library and manual search using Google scholar (see Section III).

The following measures enforce the search results' accuracy: first, both researchers were involved in the search in an alternative way in the four search cycles. Accordingly, in the first cycle, the first researcher performs the search and checks for duplicates, then the second researcher performs the same tasks in the second cycle taking into account the findings of the first cycle and so on. Conducting the search in an alternative manner allows cross-checking of the selected studies in the current cycle with the primary studies selected in the previous cycles. This method fosters discussion between researchers about their findings and allows them to refine the search queries and the selection criteria. Second, we set a rigorous procedure to select studies based on title and abstract. In order to minimize subjective judgment, the paper is selected or rejected according to the following procedure: the two researchers read the title and abstract and decide whether to accept or reject the paper. In case there is no agreement, both researchers read the paper and discuss its relevance. If at this stage both decisions still diverge, then the paper is rejected.

In order to measure the validity of the selection process, we defined the saturation metric S, which denotes the stability of the primary studies set. Given a threshold σ, S indicates how far the search process is productive at some search cycle. The metric calculates the ratio between the number of selected studies at some cycle p_n over the total number of selected studies in the previous n search cycles. Note that p_i considers only query search results and excludes the results of the backward search.

$$S_n = {p_n}/{\sum_{i=1}^{n} p_i} \tag{4}$$

When the search result at some cycle is unproductive ($p_n = 0$) this means that no more relevant studies are found, hence, $S_n = 0$ indicating that the search is complete and accurate. We used the following algorithm (Fig. 8) to calculate S_n during the search cycles with the threshold σ set to 0.2.

Table 8 shows the results of the study's selection using the search controller algorithm shown in Fig. 8. The search stopped in the fourth cycle where S_n equals 0.17.

TABLE 8. Four cycles search and selection of primary studies.

Search Cycle #	Type of Search	Papers Found	Excluding duplicates	Excluding Same authors	Selection based on Title & Abstract	Excluding papers not related to RQ	Total of papers found	S_n
1st	Query Search	75	48	46	37	26	26	1.0
2nd	Query Search	67	35	31	28	21	47	0.45
3rd	Query Search	71	33	32	24	15	62	0.24
	Backward Search	8	5	5	5	5	67	
4th	Query Search	47	25	21	17	13	80	**0.17**
	Backward Search	6	5	5	5	5	85	
Total		**274**	**151**	**140**	**116**	**85**		

input p;	*P: initial papers selected in cycle 1*
σ = 0.2;	*Set the threshold σ to 0.2*
S = 0;	
sum = p;	
cycle = 1;	
while (S > σ) do {	*The loop terminates if S<=σ*
input p;	
sum = sum + p;	
S = p/sum;	*Calculate S with equation (4)*
cycle = cycle +1;}	*Variable cycle is incremented*
output S, cycle;	

FIGURE 8. The search controller algorithm.

The above protocol allowed us to set a clear work setting monitored by the stability metric S. The entire set of selected primary studies at the end of the fourth cycle is 85.

B. ACCURACY OF THE RESULTS

Evaluation of the results obtained from any review study is challenging as it relies on many factors for which no clear method or measure exists. Objectivity and validity are two factors that are identified as relevant to be evaluated in our study. Objectivity is about using objective measurements to measure the quality of extracted data and avoids bias that can be introduced via personal judgments of researchers who use their domain expertise and knowledge to interpret the concepts, the results and more generally the text of research papers. Validity relates to the correctness of data extracted from the primary studies. Data sought in the research papers is not obvious to find and sometimes it is incomplete, requiring more reading, and investigation in other knowledge sources. Therefore, it is important to define a clear measure to reduce the dependence on subjective judgments and ensure the correctness of extracted data.

In order to measure objectivity and validity, we developed a template that is filled by researchers of this study for each read paper. The template includes a set of fields to fill out when extracting data. The following fields (Fi) were set to help us compare and evaluate the appropriateness of the primary studies for our review:

F1. Is the data collection process well clarified?

F2. Does the paper use a data analysis approach appropriately?

F3. Is the research methodology well described and explained comprehensively?

F4. Is the system implemented and results are provided?

F5. Is there an evaluation done and comparison with other systems?

For fields requiring an assessment or decision by the researcher, a confidence score is associated with the field. The confidence score represents the estimation of trust in the correctness of data or researcher judgment. For instance, the assignment of a class to the paper according to the classification in Figure 8 is part of the objectivity score, while the metric used or accuracy of the experimentation results are part of the validity score. Confidence scores are then aggregated to calculate the objectivity and validity scores for the paper. Data filled in the template is accepted if the aggregation of scores is above a threshold. In case the threshold is not met, the investigators discuss the paper evaluation template, and a decision is taken about refilling the template by the second researcher or using multiple sources, specifically other related works by the same paper authors, to interpret unclear data.

C. NOTES ON VALIDATION

SLR is becoming a popular methodology used in many fields to review a research topic systematically. SLR has inherent limitations and threats, which have been discussed by other researchers [116]–[119]. We are aware that this research has potential limitations, which we tried to reduce in many ways. Although we used a portal that includes major databases in the field and worked as a team cross-checking each other's findings, it is possible that some research papers have been missed. We also used our personal judgment in interpreting data extracted from primary studies. Efforts spent in developing the evaluation tools have certainly contributed to improve the quality of the present SLR results. Indeed, they allowed us to conduct a relatively systematic evaluation by objectively measuring some validation aspects related to the search and selection process and the data extraction from primary studies. We believe that these tools contribute to making SLR methodical and measurable and facilitate reproducibility of this type of research.

VIII. CONCLUSION AND FUTURE CHALLENGES

This paper provides a review of the literature related to CARSs for social networks. The research relies on a systematic literature review methodology which sets research questions and defines a comprehensive plan to carry on the research. Eighty-five scientific research papers related to CARSs for social networks published between 2015 and 2020 were reviewed, analyzed, and discussed in this review. The objective was to review approaches and techniques used in the development of context-aware recommender systems for social networks and identify the gaps, challenges, and opportunities of research in this field. We were also interested in identifying the principal contextual factors used to adapt recommendations for users. Moreover, evaluating the research results led us to develop evaluation tools that contributed to making this research methodical and measurable.

Recent research in CARSs is mainly directed by developing novel techniques or adapting and combining existing ones that can efficiently deal with the growing complexity and dynamicity of social networks. The development of efficient and quality CARSs for social networks concentrates on investigating implicit context factors that allow personalizing recommendations to users and adapt them to their ever-changing interests. Many challenges are still to be solved in this research field. Context-aware recommender systems have to be able to rationally and independently manage the entire context information dynamically at runtime. The main challenge is to deal with the dynamic nature of context and ensure data consistency as recommendations need to be done generally in real-time. Collecting context information from heterogeneous sources from both the environment and user activities represents another challenge that necessitates synchronization of information sources and the definition of the tradeoff between data correctness and timeliness, and system efficiency. The last challenge is related to the persistent problems associated with recommender systems. Although we have focused on cold-start and sparsity of the input data in this study, other problems such as scalability, novelty, and trust may be a real challenge in some application domains necessitating a substantial overhead on the development of recommender systems, as highlighted in many studies.

ACKNOWLEDGMENT

This work was supported by the Research Center of College of Computer and Information Sciences, King Saud University. The authors are grateful for this support.

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