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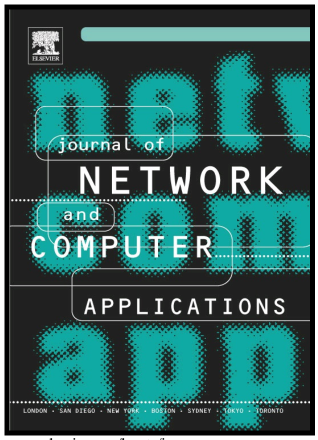


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# Cloud services recommendation: Reviewing the recent advances and suggesting the future research directions

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## Abstract
Cloud computing systems provide a vast amount of various services, therefore it is difficult for a user to choose a suitable service. Cloud recommender systems are intelligent engines that suggest the best item for users in a cloud environment. Due to the importance of the recommender systems in the cloud environments, this study aimed to systematically investigate the articles and important mechanisms in recommender systems. In this regard, a systematic review of the recommender system's mechanisms which have been used in cloud computing was conducted. We classified the cloud recommender system's mechanisms into four main categories: collaborative filtering, demographic-based, knowledge-based and hybrid. Moreover, this study represented a systematic review and comparison of the above-mentioned techniques in terms of scalability, availability, accuracy, and trust attributes. The results of the present review revealed that previous studies contributed scalability and accuracy to the recommender system, but the contribution of the trust and security improvement has not been considerable well.

**Keywords**: cloud computing, recommender system, systematic literature review, demographic filtering, knowledge filtering, collaborative filtering.



## 1. Introduction
Recently, the fast extension of the IT-based and distribution systems (Navimipour & Soltani, 2016; Zareie & Navimipour, 2016), such as social networks (Aghdam & Navimipour, 2016; Sharif, Mahmazi, Navimipour, & Aghdam, 2013), grid computing (Khanli, Razavi, & Navimipour, 2008; Navimipour & Khanli, 2008; Navin, Navimipour, Rahmani, & Hosseinzadeh, 2014; Souri & Navimipour, 2014), cloud computing (Asghari & Navimipour, 2016; Chiregi & Navimipour, 2016; Navimipour, 2015b; Navimipour & Milani, 2015), Peer-to-Peer computing (Ashouraie & Jafari Navimipour, 2015), and wireless networks (Abdollahzadeh & Navimipour, 2016; Jafari & Es-Hagi, 2011; Navimipour, 2011; Navimipour & Rahmani, 2009; Navimipour, Shabestari, & Samaei, 2012) facilitate the data transfer and resource sharing. Among the mentioned studies, cloud computing, a new concept representing the cooperation between multiple computers and services via a network, provides several powerful on-demand services to the users (A. S. Milani & N. J. Navimipour, 2016). In other words, cloud computing as a new and completely web-based approach offers a great accessible, scalable, and adaptable computing system for different applications (Navimipour, Rahmani, Navin, & Hosseinzadeh, 2015; Xiao, Hu, & Zhang, 2013). Cloud computing consists of different virtualized resources scattered over many networks and locations. Four types of such virtualized resources are known as Software as a Service (SaaS), Infrastructure as a Service (IaaS), Platform as a Service (PaaS) (Jafari Navimipour, Rahmani, Habibizad Navin, & Hosseinzadeh, 2015; Navimipour & Zareie, 2015), and Expert as a Service (EaaS) (Ashouraie & Jafari Navimipour, 2015; B. A. Milani & N. J. Navimipour, 2016; Navimipour, 2015a). SaaS

allows customers to have access to applications through the Internet without difficulties and costs (Wu, Garg, & Buyya, 2012). IaaS provides different services like hosting, hardware, provisioning, and basic required to run a cloud (Manvi & Shyam, 2014). PaaS refers to a high-level incorporated environment that custom applications are constructed, tested, and deployed in(Foster, Zhao, Raicu, & Lu, 2008). EaaS provides expert as service with special knowledge and skills to the user. Implementation of the cloud computing based applications are highly developed and applied in real systems which lead to the complex relations between services, service providers, and service requesters. We can find the trace of cloud computing by studying the development of several technologies like internet technologies, web services, hardware virtualization, multi-core chips, distributed computing, and systems management (Voorsluys, Broberg, & Buyya, 2011). Therefore, finding a suitable service in cloud computing is the key problem to be solved (Buyya, Yeo, & Venugopal, 2008).

A recommendation system is one of the best methods which can suggest necessary and proper items from a large number of resources in a cloud environment (Chengwen Zhang, 2014). An intelligent system like recommender solves the information overload problem on the internet by offering choices that take into account users' needs or interests (C. Zhang, Bian, Cheng, & Li, 2013). The role of recommender systems is not negligible in multiple high-level websites such as Amazon, YouTube, Netflix, Yahoo, etc. (Koren, Bell, & Volinsky, 2009). Recently, many researchers discussed the Web 3.0 (Berners-Lee, Hendler, & Lassila, 2001; Stuckenschmidt, 2012) where all information are kept as data which are semantically related to each other. Web 3.0 or Semantic Web has employed knowledge of linked open data cloud, specifically domain-specific and cross domain interrelated datasets, to change its conventional way of related approaches. (Kushwaha & Vyas, 2014). Also, with the advent of wireless technologies (E. Ahmed, Gani, Khan, Buyya, & Khan, 2015) mobile devices bring about the paradigm shift in e-application paradigm (E. Ahmed, Gani, Sookhak, Ab Hamid, & Xia, 2015) and mobile cloud computing offers innovative services and facilities, mobile users use these services at their disposal to take full advantages of cloud computing (Dinh, Lee, Niyato, & Wang, 2013). There is a great potential of offering a wide range of applications by the Mobile Edge Computing (A. Ahmed & Ahmed). In this regard, mobile users have a tendency to use similar applications on the resource-constrained mobile device to those of a stationary resource-rich system (E. Ahmed, Akhunzada, et al., 2015).

However, despite the importance of recommender systems and their use in various domains in cloud environments; there is a gap in literature to systematically analyze its important techniques. Therefore, this paper aims to survey and analyze existing gap in terms of:

- Offering a systematic review and analysis of the four techniques in recommender systems to highlight the advantages and disadvantages in each domain.
- Checking out some of the main challenges in the field of recommender systems and providing instructions to the current challenges.
- Describing the key areas where future studies could improve the function of the recommender system techniques.

The rest of this paper is structured as follows. Section 2 classifies the important articles in cloud recommender systems field systematically. Section 3 discusses cloud recommender system mechanisms taxonomy and categorizes them. Section 4 reflects the results and comparison of the reviewing techniques. Section 5 maps out some open issues. Secession 6 notes the limitations of this study. Finally, the obtained results are presented in Section 7.

## 2. Systematic literature review

In order to have a clear picture of the recommender systems in cloud environments, this section provides a systematic literature review (SLR) of recommender systems with a specific focus on researches related to cloud computing. According to Cook, Greengold, Ellrodt, and Weingarten (1997), a systematic review was distinguished from a traditional one in the case of the replicable, scientific, and transparent process. As a research method, SLR is inspired from the field of medicine (Kitchenham, 2004) which provides a repeated research method and should supply sufficient details to be replicated by other researchers (Charband & Navimipour, 2016; Kupiainen, Mäntylä, & Itkonen, 2015; Navimipour & Charband, 2016). Particularly, the number of studies on recommender systems has been increasing dramatically, therefore in this section, in order to conduct a comprehensive study of the important mechanisms of the recommender system in the cloud environment, the required data was culled from the existing SLR of 2009. In order to have valid data, the SLR selection procedure was evaluated and outlined in the following section.

### 2.1. Article Selection Process

The article selection strategy consists of three main stages:
Stage 1: Automated search based on the keywords;
Stage 2: Selection based on the title of the papers, the publication year and papers language;
Stage 3: Selection based on the reputation and validity of the journals

In stage 1, keywords (recommender systems, service recommender systems in cloud computing, supplier recommender systems in cloud computing, and resource recommender system in cloud computing) have been searched to find relevant articles. The result of the search was 940 articles from journals, conference papers, books, chapters, notes and any articles in which a part of these keywords were mentioned.

Stage 2 was conducted by considering some criteria to ensure that only high-quality publications were included in the study. Therefore we focused on the articles retrieved from journal publications and IEEE conferences published by Elsevier[1], Springer[2], IEEE[3], DOAJ[4], and ACM[5]. In this regard, the invalid conference articles, reports, working papers, editorial notes, erratum, commentaries, and book review articles were excluded. The articles were selected based on their titles related to cloud recommender systems and related concepts.

In stage 3, full texts and abstracts of the selected articles were reviewed by authors to verify the relevance of these articles. Based on this relevance to the subject matter, publication year, and journal rank, each article was either included or excluded. The cited information, abstracts, and keywords of all articles were exported to an Excel spreadsheet for further analysis. The selected articles were refined through three steps. After applying filters, we chose 5 famous publishers and studies that were related to cloud computing, therefore, 895 articles were excluded. Those articles written in the English language were included, moreover, opinion-driven reports (editorials, commentaries, and letters) and books were excluded. Finally, 43 articles were obtained and analyzed.

### 2.2. Articles Classification

In this section, the classification of the papers based on their relevance to the cloud recommender system is described. Among the four categories of cloud recommender systems, 14 articles out of 43 (32.55%) were related to collaborative filtering (Table 1); 9 articles out of 43 (20.93%) referred to demographic filtering (Table 2); 8 articles of the 43 (18.60%) were on knowledge-based filtering (Table

[1] - www.elsevier.com
[2] - www.link.springer.com
[3] - www.ieeexplore.ieee.org
[4] - www.doaj.org
[5] - www.dl.acm.org

3); and 12 out of the 43 (27.90%) were about hybrid filtering (Table 4). Also, the classification of the papers based on the year of publication that opted from 2009-2015 is shown in Fig.1. In 2014, the number of published articles was maximum. Also, Fig 2 shows the classification of the papers over time in each category including Elsevier, Springer, IEEE, DOAJ, and ACM. Fig. 3 shows the classification of the articles among 5 publishers, where 46 % of the total article of journals belong to Springer, 34% of the articles are related to the IEEE, 11% of the articles are related to Elsevier, 7% of the articles are related to the ACM, and, the remaining 2% of the articles are related to the DOAJ.

TABLE1. DISTRIBUTION OF COLLABORATIVE-BASED RECOMMENDER SYSTEM ARTICLES BY JOURNAL AND CONFERENCE NAMES

| Publisher | Year | Author | Journal/Conferences name |
|---|---|---|---|
| Elsevier | 2013 | J.-H. Chang, Lai, Wang, and Wu (2013) | Computers and Electrical Engineering |
| IEEE | 2011 | Yaming Zhang, Liu, and Li (2011) | Artificial Intelligence, Management Science and Electronic Commerce |
| | 2012 | Kong and Zhai (2012) | 2012 International Conference on Cloud and Service Computing (CSC), |
| | 2012 | Jiang, Pang, Deng, He, and Gu (2012) | International Joint Conference on Service Sciences |
| | 2013 | Jung, Sharma, Goetz, and Mukherjee (2013) | International Conference on Cloud Computing |
| | 2014 | Zain, Aslam, Imran, and Martinez-Enriquez (2014) | 11th International Conference on Electrical Engineering |
| Springer | 2011 | Lai, Chang, Hu, Huang, and Chao (2011) | Verlag Berlin Heidelberg |
| | 2011 | S. Wang, Xie, and Fang (2011) | Natural Sciences |
| | 2014 | Shrestha, Kudo, Gautam, and Shrestha (2014) | International Publishing Switzerland |
| | 2015 | Fan, Yang, Perros, and Pei (2015) | International Journal of Automation and Computing |
| | 2015 | Kumar and Pandey (2015) | Intelligent Systems and Computing |
| | 2015 | Hu, Lin, Hassan, Alamri, and Alelaiwi (2015) | Science Business Media New York |
| | 2015 | Carullo, Castiglione, De Santis, and Palmieri (2015) | Science+Business Media New York |
| ACM | 2014 | Boutet, Frey, Guerraoui, Kermarrec, and Patra (2014) | MIDDLEWARE |

TABLE2. DISTRIBUTION OF DEMOGRAPHIC-BASED RECOMMENDER SYSTEM ARTICLES BY JOURNAL AND CONFERENCE NAMES

| Publisher | Year | Author | Journal/Conferences name |
|---|---|---|---|
| IEEE | 2013 | Krishna, Misra, Joshi, and Obaidat (2013) | Computer, Information and Telecommunication Systems |
| | 2013 | Jung, Mukherjee, et al. (2013) | Ninth World Congress on Services |
| | 2014 | Mo, Chen, Xie, Luo, and Yang (2014) | IEEE SYSTEMS JOURNAL |
| | 2011 | Lee et al. (2011) | MulGraB |
| Springer | 2012 | Yoon, Zheng, Xie, and Woo (2012) | Pers Ubiquit Comput |
| | 2012 | M. Zhang, Ranjan, Nepal, Menzel, and Haller (2012) | the series Lecture Notes in Computer Science |
| | 2013 | Ying, Lu, Shi, and Tseng (2013) | 13th international conference on Advances in Spatial and Temporal Databases |
| | 2014 | Y.-C. Chang, Peng, Chang, and Hermanto (2014) | International Publishing Switzerland |
| DOAJ | 2014 | Chengwen Zhang (2014) | Applied Sciences, Engineering and Technology |



TABLE3. DISTRIBUTION OF KNOWLEDGE-BASED RECOMMENDER SYSTEM ARTICLES BY JOURNAL AND CONFERENCE NAMES

| Publisher | Year | Author | Journal/Conferences name |
|---|---|---|---|
| Elsevier | 2014 | Vera-del-Campo, Pegueroles, Hernández-Serrano, and Soriano (2014) | Information Sciences |
| | 2011 | Chen, Yang, Shih, Lee, and Lo (2011) | Procedia Engineering |
| | 2014 | Soltani, Martin, and Elgazzar (2014) | International Conference on Cloud and Autonomic Computing |
| IEEE | 2014 | Im, Sohn, Jeong, and Lee (2014) | Eighth International Conference on Innovative Mobile and Internet Services in Ubiquitous Computing |
| | 2009 | Han, Hassan, Yoon, and Huh (2009) | Verlag Berlin Heidelberg |
| Springer | 2015 | Amin et al. (2015) | Electrical Engineering |
| | 2014 | D. Wang, Liu, He, and Fan (2014) | International Publishing Switzerland |
| ACM | 2014 | Patiniotakis, Verginadis, and Mentzas (2014) | CrossCloud Brokers |

TABLE4. DISTRIBUTION OF HYBRID RECOMMENDER SYSTEM ARTICLES BY JOURNAL AND CONFERENCE NAMES

| Publisher | Year | Author | Journal/Conferences name |
|---|---|---|---|
| Elsevier | 2014 | Fülöp, Avornicului, and Bresfelean (2014) | Procedia Economics and Finance |
| | 2014 | Umanets, Ferreira, and Leite (2014) | Procedia Technology |
| | 2011 | Park et al. (2011) | MultiMedia, IEEE |
| | 2012 | Yan, Chen, Zhao, and Lee (2012) | Network and service management (cnsm), 2012 8th international conference |
| | 2014 | Yan et al. (2012) | 33rd Chinese Control Conference |
| IEEE | 2015 | Kung and Wang (2015) | International Conference on Industrial Engineering and Operations Management |
| | 2014 | Ke, Chang, Jen, and Liao (2014) | Springer Berlin Heidelberg |
| | 2014 | Amato, Mazzeo, Moscato, and Picariello (2014) | 7th International Symposium on Intelligent Distributed Computing |
| Springer | 2014 | Yin Zhang, Zhang, Hassan, Alamri, and Peng (2014) | Science+ Business Media New York |
| | 2014 | J.-H. Chang, Lai, and Wang (2014) | Science+ Business Media New York |
| | 2014 | Afify, Moawad, Badr, and Tolba (2014) | Springer International Publishing Switzerland |
| ACM | 2014 | Kushwaha and Vyas (2014) | 7th ACM India Computing Conference |

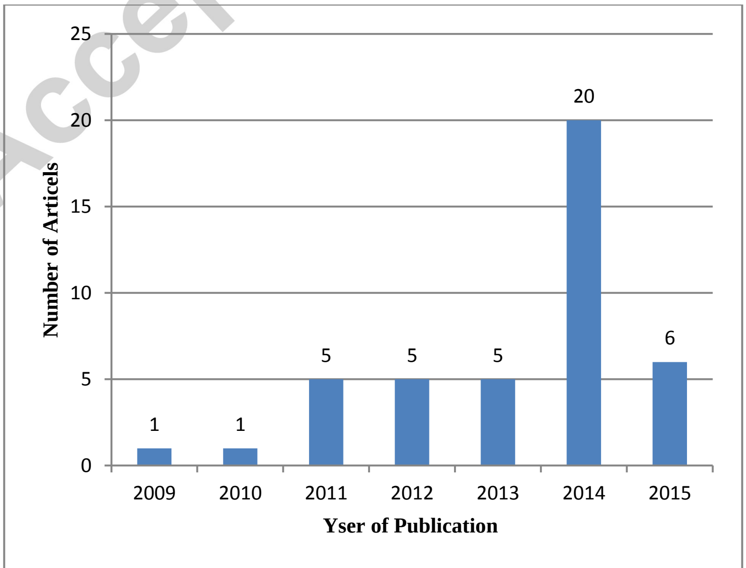


Fig.1. Distribution of articles by year of publication

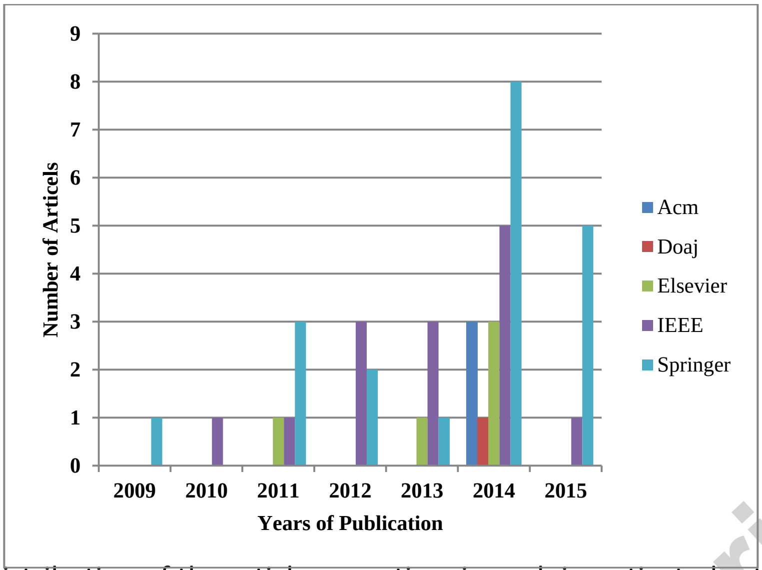


Fig.2. Distribution of the articles over time in each investigated categories

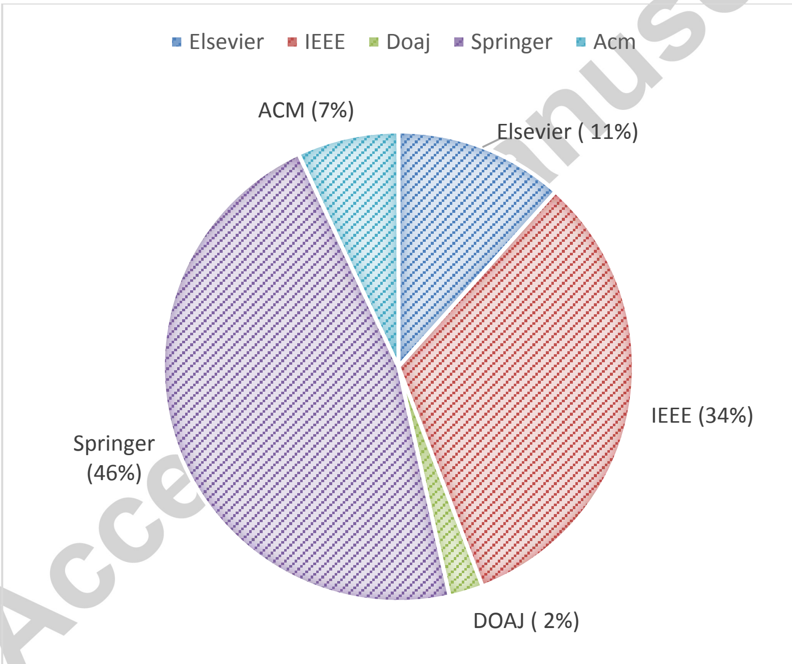


Fig.3. A pie chart of the percentage of the cloud recommender system articles based on different publishers

## 3. Cloud recommender system mechanisms

Recently, recommender system has become a growing research area in IT technology. Researchers proposed various types of recommendation algorithms such as Bayesian networks (Friedman, Geiger, & Goldszmidt, 1997), cluster algorithms (Dempster, Laird, & Rubin, 1977), association rules (Anderson et al., 2003), hosting based on graph-theoretic (Aggarwal, Wolf, Wu, & Yu, 1999), and collaborative filtering recommendation algorithm to ameliorate accuracy and reduce complexity. The purpose of this section is to present an understandable trend of cloud recommender system by examining all 43 selected articles. This section is divided into five categories: knowledge-based, demographic-based, collaborating filtering, community-based and hybrid cloud recommender systems. In addition, their method, differences, advantages and disadvantage of them will be discussed and described as well.

### 3.1. Overview of collaborative filtering

In this section at first, we will describe the collaborative filtering then summarize the presented 14 articles in collaborative filtering mechanism. Finally, in Section 3.1.2 the discussed mechanisms will be compared.

Collaborative filtering offers items to the user that other users with same orientation preferred in the past. In this regard, the similarity in the rating history of the users was considered as a touchstone to find out about their similarities (Schafer, Frankowski, Herlocker, & Sen, 2007). This is the reason why Schafer, Konstan, and Riedl (2001) refers to collaborative filtering as "people-to-people correlation" (P. 12). Collaborative filtering is also, one of the most common and extensively implemented techniques in RS (Kantor, Rokach, Ricci, & Shapira, 2011).

#### 3.1.1. Collaborative filtering mechanisms

Taking into account various concepts like cloud computing and a map-reduce framework, with a map-reduce version of k-means, and the k-nearest neighbor (KNN) algorithm, Lai, Chang, Huang, and Chao (2011) have presented an architecture for a TV program recommendation system. In order to qualify large-scale data processing in the system, the presented architecture offered a measurable and powerful back-end. The main contribution of the back-end of the recommendation server was to use and consequently extend the power of cloud computing into sets of computers to examine large numbers of users' records in a short time span without considering cold start problem in the system.

S. Wang et al. (2011) have introduced the cloud model and combined it with the item-based collaborative filtering recommendation algorithms. This combination has offered a computation model to examine the similarity between items considering the statistical characteristic of items. The findings indicated that this method can enhance the performance and solve sparsity of data. However, it did not consider the operation cost and cold start problem in collaborative filtering method.

In another research, Yaming Zhang et al. (2011) have designed a recommender system and an algorithm for mobile commerce, and also to solve its related problems like high-dimensional sparse data, centralized management, poor scalability, and robust. They provided this algorithm based on cloud computing in order that approach mentioned problems by broadening development space and making an accurate decision that could resolve the real time problems. However, the research on cloud computing is still a sign of the insufficiency in a clear framework for the system and try to solve cold start problem in future.

Jiang et al. (2012) have presented a new blog recommender system based on cloud computing infrastructure. This system used Hadoop distributed file system to cache blog data and executed the distributed processing of blog crawl and index creation phase for adopting the user collaborative filtering recommendation algorithm in blog search. At first, user priority from the blog search results was recorded by the blog recommender engine of the system; then, considering user's possible preference satisfaction, it applied collaborative filtering algorithm in order to make unique and high-quality blog recommendation with high measurability and reliability. Findings of this study showed that the blog recommendation can fulfill the user's desires, but they need to support web clustering and improve the system availability.

Kong and Zhai (2012) have proposed a Trust-based Recommendation System in service-oriented cloud computing (TRSC). They initially presented an architecture of TRSC needed to evaluate cloud services based on the trust of these services. In TRSC, a trust value can be accounted as the combination of direct and recommendation trust. They reported that direct trust of a cloud service user A on a cloud service C is computed based on the direct interaction of A with C. Also, the measuring method for calculating recommendation trust was based on the interaction of cloud service user B with C where B was the user who was trusted by A, correlative with A or authorities of the field

(P. 176). The results indicated that the discussed approach can get better recommendation accuracy than traditional collaborative filtering but the response time was high.

Jung, Sharma, et al. (2013) have described a cloud recommender system which offers an accurate-based optimal cloud configuration. This system provided the capability vector that shows scores of resource kinds (e.g., CPU, memory, and disk) in relative performance. These scores have been estimated to take account of user workload using benchmarks. Consequently, considering the collected capability vectors, a search algorithm has developed in order to identify an optimal cloud configuration. Results showed that this approach precisely evaluates the performance capability (less than 10% error). Moreover, it is scalable enough to apply for a large-scale workload deployment but did not have any solution for data sparsity.

Moreover, J.-H. Chang et al. (2013) have described a program recommendation system for digital TV programs based on the cloud computing technology, which was used to enhance processing performance Hadoop fair scheduler, as well. The required data were culled from watched TV program by means of an electronic program guide. K-means clustering, term frequency/inverse document frequency, and k-nearest neighbor algorithms were utilized to attain groups of audiences and to find each group's favorite TV programs. Findings indicated that the proposed system can analyze a large amount of user's data in real time and can easily be increased but users' preferences from a psychological perspective and system's complexity go highly unnoticed.

In order to allow users to specify their perception of quality criteria in service selection, Zain et al. (2014) have focused on cloud service selection method. An unsupervised learning technique like data mining technique clustering was used in this approach. Based on the developed algorithm and quality properties, cloud services have been classified and ranked into different groups. The main focus of this study was to offer the users with an option to choose a cloud service without any financial requirements. Validation of the approach has been tested in the system by utilizing cloud vendors like Google, Microsoft, and Amazon. The analysis was based on the user's feedback and it would be dynamically updated with the inclusion of latest feedback in it which increased the system's performance but did not consider trust in the system.

Boutet et al. (2014) have presented HyRec for user-based collaborative filtering personalization. HyRec can be defined as an online economical and scalable system which assigns recommendation tasks to the users' web browsers while coordinating the process and managing the relationships between users' profiles has been done by a server. Researchers used HyRec to evaluate some workloads that have been adopted from MovieLens and Digg. In order to make the operation cost-effective to nearly 50% which would be beneficial to the content providers and to have a 100-fold improvement in scalability regarding a centralized/cloud-based recommended approach while keeping the quality of personalization, researchers have extended the ability of HyRec. Moreover, researchers stated that HyRec was virtually transparent to users and it induced only 3% of the bandwidth consumption of a P2P solution but it had a high response time because of generation and update user profile at first.

In order to provide users with a service usage pattern in the system , Shrestha et al. (2014) have described a recommendation method based on mining. The recommendation algorithm was derived from the mining result of Time Weight Sequence Mining Algorithm (TWSMA). By considering sequences of service usage template, TWSMA took an innovative approach to characterize each set of sequences based on multidimensional properties like user ID, time series, and usage frequencies. Researchers showed that the use of recommendation in cloud system (Huynh, Denoeux, Tran, Le, & Pham, 2013) offered a user with services based on the log of service used by the other users. The results indicated that this approach improved the response time and accuracy; meanwhile, it had a low level of scalability and didn't consider cold start problem.

As another research, Kumar and Pandey (2015) have discussed a recommender system based on the collaborative filtering which enabled the use of Mahout environment as well. First, the dataset loaded into Hadoop; then, user-based CF has been performed to take rating matrix. In the second step, after loading the dataset into Hadoop, item-based CF has been performed to collect past information and preference of users. In the third step, the result of user-based and item-based CF have been combined on Hadoop. The great performance of the presented approach improves speedup, efficiency, and high throughput but it does not handle real-time data randomly.

Hu et al. (2015) have proposed the large-scale e-Commerce recommendation using Smoothing and Fusion (CFSF) for e-commerce providers. Two phases of the CFSF were distinguished as online and offline. In the offline phase of CFSF, a global item similarity (GIS) matrix and user clusters have been created. It is worth to note that user's ratings within each cluster were smoothed. In the online phase, where a recommendation was required, CFSF used the top M similar items from GIS and top K like-minded users from user clusters to dynamically construct a locally-reduced item-user matrix for the active user. The findings indicated that CFSF outperformed existing collaborative filtering approaches in terms of recommendation accuracy and scalability, but it sounds better if the gray sheep users have been separated before clustering.

Taking into account Evidential Reasoning (ER) approach, Fan et al. (2015) have projected a multi-dimensional trust-aware cloud service selection mechanism. Evidential Reasoning (ER) approach combined perception-based (direct) trust value and reputation based (indirect) trust value to identify trustworthy services. In this technique, based on the historical users_ feedback ratings, the multi-dimensional trust evidence which reflected the trustworthiness of cloud services from different aspects has been elicited. Then, in order to obtain the real-time trust value and select the most trustworthy cloud service of a certain type for the active users, the ER approach was used to accumulate the multi-dimensional trust ratings. Finally, the fresh feedback from the active users has updated the trust evidence for other service users in the future.

In online social networks, extending the relationships between users' friends is gaining considerable attention and according to the fact that, nowadays, most of the users connect to the different social networks via their mobile, Carullo et al. (2015) designed a new scheme based on mobile-cloud which deals with the findings of right trade-offs between the utilization of the already existing relationships and the common interest between users. To achieve the mentioned purposes in a cloud scenario, this scheme used inherently parallel hubs (which controls triadic relationships) and authority's algorithm (which considers homophile) together with similarity measures. This scheme has been supported by Twitter where the extensive performance analyses were publicly available. Findings of this study indicated that this system used different performance metrics such as precision, recall, F-measure, and G-measure effectively which led to the provision of more accurate recommendations but did not consider the trust between users.

### 3.1.2. Summary of collaborative filtering mechanisms

In the previous section, researchers have analyzed 14 selected collaborative filtering mechanisms, as well as their advantages and disadvantages. Table 6 shows the comparison of the most important advantages and disadvantages of each article.

TABLE6. A COMPARISON OF THE MOST IMPORTANT ADVANTAGES AND DISADVANTAGES OF COLLABORATIVE FILTERING MECHANISMS IN CLOUD RECOMMENDER SYSTEMS.

| Paper | Advantages | Disadvantages |
|---|---|---|
| Lai et al. (2011) | • High scalability | • High response time<br>• Cold start problem |
| S. Wang et al. (2011) | • High scalability<br>• High accuracy | • Low security<br>• Cold start problem<br>• Didn't considered the operation cost |
| Yaming Zhang et al. (2011) | • High scalability<br>• High accuracy<br>• Decrease dimensional | • Didn't have clear framework<br>• Cold start problem |
| Jiang et al. (2012) | • High QoS<br>• High scalability<br>• High accuracy | • High response time<br>• High operation cost |
| Kong and Zhai (2012) | • High scalability<br>• High accuracy | • High response time |
| Jung, Sharma, et al. (2013) | • Low response time<br>• High scalability | • Low accuracy<br>• Didn't considered user's preferences<br>• Data sparsity problem |
| J.-H. Chang et al. (2013) | • Low operation cost<br>• High QoS | • Didn't used user feedback<br>• Data sparsity problem<br>• Gray sheep problem |
| Zain et al. (2014) | • Trustable<br>• High accuracy<br>• High QoS | • Low availability<br>• Didn't used user feedback |
| Boutet et al. (2014) | • High QoS<br>• High scalability<br>• Low operation cost | • High response time<br>• Low trust |
| Shrestha et al. (2014) | • High QoS<br>• Low response time | • High operation cost<br>• Cold start problem |
| Kumar and Pandey (2015) | • Low response time<br>• High scalability<br>• High Accuracy | • Didn't handle real-time data<br>• Cold start problem |
| Hu et al. (2015) | • High QoS<br>• High scalability<br>• High accuracy | • Low security<br>• Low availability |
| Fan et al. (2015) | • Trustable<br>• High correctness | • Data sparsity |
| Carullo et al. (2015) | • High accuracy | • Low QoS<br>• Low scalability |

### 3.2. Overview of demographic-based mechanisms

In this section, we initially described the demographic-based mechanism. Then, the 9 selected articles were discussed in demographic-based mechanisms. Finally, the described mechanisms were compared and summarized in Section 3.2.2. The demographic-based mechanism uses the demographic profile of the user to recommend items. The presumption is that various recommendations should be created for various demographic niches. Demographics is used by many Web sites to offer simple and effective solutions in accordance with user demands. For example, users are sent to particular Web sites based on their country, language or age. While these approaches are quite popular in the marketing literature, there has been relatively few RS types of research in demographic systems (Kantor et al., 2011).

#### 3.2.1. Demographic-based mechanisms

The first article is about music recommender. Lee et al. (2011) have proposed the intelligent music recommender system based on cloud computing. Recently, a growing interest in media contents gives rise to the introduction of various smart devices without the need to load music. After a total of 12 musical features extractions on the cloud, it was acknowledged that user selected music showed similar tendency by the algorithm of music kind classification. This system was classified using Thayer’s model (Thayer, 1996) of mood and music based on current weather conditions. The findings indicated that performance evaluation led to a system that could efficiently support weather condition and season information and haven’t cold start problem but they did not include user's environment. Also, this approach just works for music recommendation, not general use.

In order to provide a satisfying itinerary to users, Yoon et al. (2012) have presented a model regarding properties elicited from user generated Global Positioning System (GPS) trajectories. In order to find and rank itinerary candidates, a framework based on the social itinerary recommendation has been presented. A baseline algorithms with a large set of user-generated GPS trajectories collected from Beijing, China was employed to show the efficiency of the recommendation method. First, the required data to compare the recommendation performance at the algorithmic level were obtained from systematically generated user queries. Second, a study was carried out to show users’ attitude and satisfaction on the recommended itinerary. It is worth to note that the participants of the study were the current residents of Beijing. The third stage of this study has been projected by comparing mobile, especially Mobile+ Cloud architecture, for practical mobile recommender deployment. Finally, the discussion of different factors like personalization and adaptation in social itinerary recommendation has been presented. The system performance was great, but it could not compute the time in traveling and had low scalability.

M. Zhang et al. (2012) have offered a new declarative approach for selecting cloud-based infrastructure services. Within this approach, cloud recommender system automated mapping of user specified application requirements to configure cloud service. Cloud service configurations have been used in ontology and its implementation has been run on a structured data model which could be manipulated through regular expressions and SQL. This system exploited the power of a visual programming language (widgets) to enable simplified and sensorial cloud service selection. The design and the prototype implementation of cloud recommendations have been outlined and its effectiveness and scalability through a service configuration selection experiment in most of the today’s prominent cloud providers including Amazon, Azure, and GoGrid have been demonstrated. It was considered as the most cost-effective system with regard to data storage and transfer costs but it did not support the selection of more cloud service types such as PaaS services and it had latency in the recommendation.

Jung, Mukherjee, et al. (2013) have introduced Cloud Advisor system. By considering users’ preferences such as financial status, performance expectation, and energy saving for workload, it allowed users to find out several cloud configurations. Moreover, it offered cloud users a baseline to compare the presented price and performance with other clouds' offerings for the workload. Further comparisons showed that it can support cloud providers to develop a competitive pricing strategy such as price reduction driven by energy efficiency. In order to obtain a recommendation from a real data center and some external clouds, the mentioned platform has been applied. This platform offered a cost-efficient way to the user because it did not require users to deploy the target application itself into all possible cloud configurations to measure performances but it's possible to have synonymy problem because have many items with same feature and different names.

Krishna et al. (2013) based their recommendation system on learning automata and sentiment analysis. Learning automata were used to improve the recommendation score. The proposed system employed sentiment analysis to improve recommendation score. By the analysis of the feedback from the places, the proposed Learning Automata-Based Sentiment Analysis System (LASA) recommended the places nearby the current location of the users and consequently, calculated the score based on it. Findings indicated that through learning automata, the performance of the proposed system was improved, thus it helped users to find a specific location based on their needs.

By extending Personalized Trip Recommendation (PTR), Ying et al. (2013) have built a cloud-based travel recommendation system: Trip Cloud. This system was used to meet user's multiple constraints with efficient trip planning (Lu, Chen, & Tseng, 2012). TripCloud used several data mining mechanisms to rate how interesting each attraction is, meanwhile it employed cloud-based trip planning model to design an interesting trip. Moreover, by considering some of the user's characteristics, visualization interface have been provided to exhibit the recommended trips. Results showed that have high scalability and great performance but suffer from cold start problem.

In order to explore the hidden relationship between participants in the cloud computing environments, Chengwen Zhang (2014) have presented a cloud service which employed a format of the heterogeneous information network and automatic maintenance model. This system ranked and clustered heterogeneous service network based on the response time and operation cost but server reliability and cloud provider's rating have not been considered. It is worth to note that, this system employed high-level framework as well.

Y.-C. Chang et al. (2014) have presented a model for searching cloud server providers and used enterprise location (context aware method) in order to improve bandwidth and decrease latency problem by finding the cloud server providers which are near the enterprise and high Cloud Evaluation Value (CEV). Furthermore, the search model, recommendation system, and evaluation standard in the system have been implemented by considering users' requests and locations. Despite the reduction in response time, findings indicated that reliability and trust were neglected in the system.

Mo et al. (2014) have proposed a cloud-based mobile multimedia recommendation system which needs accurate classification rules to decrease network overhead, and accelerate recommendation process. In this regard, users were classified into various groups according to their context types and values. Hadoop platform was used to analyze the collected data (such as user contexts, user relationships and user profiles) from video-sharing websites to create multimedia recommendation rules. Extension and optimization of the rules to make a real-time recommendation would coincide with the arrival of a new user request. The results showed that the mentioned approach can offer services with high accuracy, high recall, and low response delay. In this system users' profiles have been obtained from comment information, but the misleading point in clustering was that users always made no comment on their interesting video or gives a positive comment for themselves video and negative for another one then cause shilling attacks . Also, this research didn't handle the data sparsity of user profiles but improved significant response time.

### 3.2.2. Summary of demographic-based mechanisms

In the previous section, we have analyzed 9 selected articles with the demographic-based mechanism. Besides, a summary of the mechanism, advantage, and disadvantage of each article have been presented. Table 7 shows the comparison of the most important advantages and disadvantages of each article.

TABLE7. A COMPARISON OF THE MOST IMPORTANT ADVANTAGES AND DISADVANTAGES OF THE DEMOGRAPHIC-BASED MECHANISMS IN CLOUD RECOMMENDER SYSTEMS.

| Paper | Advantages | Disadvantages |
|---|---|---|
| Lee et al. (2011) | • High accuracy<br>• Solved cold start problem | • Low availability<br>• Is not applicable to whole |
| Yoon et al. (2012) | • High performance in city scale<br>• Low response time | • Low scalability<br>• Low accuracy |
| M. Zhang et al. (2012) | • High scalability<br>• High accuracy | • High response time<br>• Just support IaaS services |
| Jung, Mukherjee, et al. (2013) | • Low operation cost<br>• High accuracy<br>• High QoS | • Just support PaaS services<br>• Synonymy problem |
| Krishna et al. (2013) | • High scalability<br>• Low response time<br>• High accuracy | • Low security<br>• It depends on user feedback |
| Ying et al. (2013) | • High scalability<br>• Low response time | • Cold start problem |
| Chengwen Zhang (2014) | • Low operation cost<br>• Low response time | • Low trust |
| Y.-C. Chang et al. (2014) | • High scalability<br>• Low response time | • Didn't consider cloud provider's rating<br>• Low trust<br>• Diversity and the long tail problem |
| Mo et al. (2014) | • High scalability<br>• Low response time<br>• High recall | • Didn't handle the data sparsity<br>• Gray sheep problem<br>• Shilling attacks |

### 3.3. Overview of knowledge-based mechanisms

In this section, the knowledge-based mechanism has been presented. Then, researchers have discussed presented articles in knowledge-based mechanisms. Finally, the discussed mechanisms were compared and summarized in Section 3.3.2.

Various criteria such as user's needs, preferences, and usefulness of the suggested item make the recommender system powerful. Knowledge-based systems recommend items based on the above-mentioned criteria. In these systems, a similarity function evaluates how much the recommendation (solutions of the problem) match with user needs (problem description). Here the similarity score can be directly translated as the utility of the recommendation for the user (Kantor et al., 2011).

#### **3.3.1**. **Knowledge-based mechanisms**

In order to provide users with different options in cloud service selection to meet their requirements, Han et al. (2009) have presented a framework in the cloud market that employed a recommender system. Cloud providers offered their services by taking into account different factors like network QoS and virtual machine platform and service rank that evaluated with user feedback, the cost of service and quality of virtualization. in this regard, the recommender system helped users to have the best service at their disposal. The experimental results revealed that this system combined cloud services to offer users an effective recommendation with low response time and high QoS, but the trust of recommendation was low and this system have shilling attacks problem because it used to evaluate the rank of services.

Chen et al. (2011) have proposed a cloud-based recommender system which provides a relevant recommendation for restaurants' introduction and commentaries. The summary of commentaries in cloud-based recommender system has taken place by employing a web content detection agent and multiple document summarization mechanisms. Further summarizations like multiple documents were required to provide delicacy recommendation services, for that reason, recommender system has been combined with the cloud computing. The system has used a simple algorithm and had low complexity but it did not have enough availability and it's provided just for restaurants.

Vera-del-Campo et al. (2014) have proposed DocCloud and defined it as "a recommender system that focused on the protection of all participants against legal attacks" (P.387). In order to test the existing security techniques in the system, the design of the DocCloud have been presented and the properties of plausible deniability and anonymity of the recommenders and intermediate nodes have been analyzed as well. The main role of the intermediate nodes was to recommend products to the customers. However, theses nodes denied any knowledge about the recommended product or their contribution in the recommendation process. The result showed that accuracy and security of the system were high but response time was not suitable because of creating a profile for each user and update clusters.

Based on case-based reasoning (CBR), Soltani et al. (2014) have offered a cloud infrastructure service recommender framework labeled QuRAMRecommender. QuRAMRecommender gave decision-making options that meet attributes such as the customer's preferences and feedback. With these attributes, the CBR engine has been queried by QuARAMRecommender to retrieve similar cases from the application case based. After retrieving the similar cases, the engine sent the retrieved and the specified cases to the adapter to meet the users' requirements. Findings indicated that the system used the case-based reasoning to suggest the best cloud services which fit the customer's requirements and increased the accuracy of recommendations to 71%. Among the three types of IaaS,SaaS, and PaaS services, this system has just supported the IaaS one.

Im et al. (2014) have proposed a query generation system employed automated keyword-based SPARQL. This system has an option which enables the users to gain information about linking open data cloud without having prior knowledge of web resources and structured query language. In other words, the users just need to type some keywords. In order to provide query recommendations for the users, researchers developed a pathfinding algorithm and an automated SPARQL query generation. In the experimental section, they have illustrated the efficiency of the system but it had high complexity and high response time.

Patiniotakis et al. (2014) have offered the preference-based cloud service recommendation in which the use of a holistic multi-criteria decision-making approach is necessary for providing optimization as brokerage service. In this study, the specification and implementation process of this system and the used background method have been discussed and summarized. According to the study, both method and brokerage service allow the multi-objective evaluation of cloud services in a federated way, taking into account precise and vague metrics and dealing with their fuzziness. The system had high accuracy and QoS whereas the response time was high. In addition, this system has not been evaluated in real life and heterogeneous hosting platforms.

D. Wang et al. (2014) have designed a new online workflow recommendation system which enables users to simply perform executable workflow applications by entering some keywords. It is worth to note that there is no need to a specific workflow modeling process in this system. The aim of this study was to prove the feasibility of system design. Researchers have conducted a case study on an online ordering business workflow but they did not use the users' experiences. Results showed that this system can be comprehensively evaluated and improved with general end-users and the user experiences, respectively.

In order to create an energy efficient recommendations in cloud infrastructures domains, Amin et al. (2015) have presented a software-based approach. In this study, an offline profiling of cloud nodes has been executed to create energy aware profiles. In a later stage,these profiles have been matched with runtime usage feed with the aim of achieving an energy efficient cloud platform. According to the real-time data, energy efficient profile is matched and provided for the provision of implementation. The system was evaluated in two cases in which recommendations generated to provision saved 24% and 22% power consumption by the cloud platform. So far, the system has only been evaluated over limited cloud nodes with a limited set of applications for profiling. On the other hand, it was not so scalable.

### 3.3.2. Summary of knowledge-based mechanisms

In this section, we have analyzed 8 selected knowledge-based articles and analyzed their advantages and disadvantages. Table 8 shows the comparison of the most important advantages and disadvantages of each article.

TABLE8. A COMPARISON OF THE MOST THE MOST IMPORTANT ADVANTAGES AND DISADVANTAGES OF THE KNOWLEDGE-BASED MECHANISMS IN CLOUD RECOMMENDER SYSTEMS.

| Paper | Advantages | Disadvantages |
|---|---|---|
| Han et al. (2009) | • High QoS<br>• Low response time<br>• High scalability | • Low availability<br>• Low trust<br>• Shilling attacks |
| Chen et al. (2011) | • High QoS<br>• High accuracy<br>• High scalability | • Low availability<br>• Didn't used user experience |
| Vera-del-Campo et al. (2014) | • High security<br>• Low response time | • Low availability<br>• High operation cost |
| Soltani et al. (2014) | • High QoS<br>• High accuracy | • High response time<br>• High operation cost |
| Im et al. (2014) | • High scalability<br>• High accuracy | • Didn't have user interface<br>• High response time |
| Patiniotakis et al. (2014) | • High accuracy<br>• High availability | • Low security<br>• High response time |

| | | |
|---|---|---|
| D. Wang et al. (2014) | • High availability<br>• Low operation cost | • low scalability<br>• Didn't used user experience |
| Amin et al. (2015) | • High accuracy<br>• Energy efficient | • Low scalability |

### 3.4. Overview of hybrid mechanisms

In this section, at first, the hybrid mechanisms have been explained. Then, the researchers discussed published articles in hybrid mechanisms. Finally, those mechanisms were compared and summarized in Section 3.5.2.

Achieving a high performance in recommender systems requires the combination of recommendation techniques. Due to the fact that most of the recommendation techniques have their own merits and demerits, in this regard, to come up with a perfect approach, researchers combined some techniques in different ways (Burke, 2002). For instance, one of the demerits of collaborative filtering methods is that it cannot recommend the new items which are not rated. On the other hand, content-based approaches did not suffer from new-item problems because this approach rates new items based on their accessible features. In order to create a new hybrid system, we can combine two or more recommender systems techniques in several ways (Kantor et al., 2011).

#### 3.4.1. Hybrid mechanisms

Park et al. (2011) have offered a hybrid approach. This approach had a simple and powerful framework which used content-based and collaborative filtering in an additive fashion and the specifications unique to solve online videos recommendation problem. The main difference between this approach and existing hybrids lays on their data basis. In other words, this approach considered users' view transaction data and thus, offered an automatic collection of tag clouds for users over time whereas other methods used obvious rating data. This approach found the similarity between users by means of the collected tag clouds. Particularly, it computed the similarity between users even though they have not viewed similar videos up to now. In contrast to the pure content-based and collaborative filtering systems, this approach exploited richer data for computing user similarity. As a result, it performed particularly well for the casual users with sparse data problem but the system accuracy was not so good.

Yan et al. (2012) have offered a leading systematic framework based on a hybrid cloud management platform. This system enables enterprises to recommend and select cloud services automatically. This selection and recommendation of cloud services have been done by considering business requirements, company policies and standards, and the characteristics of the cloud. Cloud infrastructure services can be built, packaged and provided for the internal users of enterprises by a multitenant self-service portal which has been offered by the hybrid system through a unified IaaS proxy service that is called Monsoon (Yan, Lee, & Singhal, 2010; Yan, Lee, Zhao, Ma, & Mohamed, 2011). According to Yan et al. (2012) "Monsoon has evolved to manage more generic cloud services from managing cloud infrastructure services only, and that makes it possible to build an enterprise cloud service catalog to allow the internal users consuming cloud services from various cloud providers across both private and public clouds" (P.430). The result showed that the system availability and scaling were acceptable; however, the accuracy was low.

H. Zhang, Ni, Zhao, Liu, and Yang (2014) have proposed a five modules approach that took the context of the user, rules of association between resources, and the structure of lessons into consideration. These five modules are: (1) Course model; (2) Association rules between resources; (3) Association rules between resources and lessons; (4) User dynamic profile, namely, user context which can be found in reasoning user dynamic profile module; and (5) Hybrid recommendation, which generates recommended lists in hybrid recommendation module. Finally, experiments implemented on a real dataset where the results indicating that hybrid method can outperform the general recommendation method. This approach has been tested on real data set when the number of recommendations changed from 1 to 40 and the results showed that the rate of recall and precision have been improved from 0.131 to 0.213 and 0 to 0.152, respectively; however, response time was high.

Kushwaha and Vyas (2014) aimed at exploring a hybrid recommender with two functions: 1. rating predictor, and 2. movie recommender of resource description framework datasets. Besides, researchers have presented a new model for recommender system. This system used DBpedia knowledge base and a preprocessing mechanism for sparsity removal to solve the existing problems in a recommender system. Researchers implemented and tested this system over another previous method to prove the correctness and accuracy of the model. Moreover, in storing and processing stages of this study researchers used different data structure. The system had high accuracy but did not consider complexity, scaling, and availability.

Fülöp et al. (2014) have presented a cloud computing system. It acts as efficient alternative methods to complete and characterize the included information. The companies that suffer from lack of investment funds and want to improve their IT infrastructure welcomes the offered solutions by this approach. In other words, many providers and especially potential customers have been attracted by various beneficial and highly computed features of this system like agility, collaboration, scaling, availability, and cost effectiveness. This system achieved a detailed analysis of "Comply or Explain" declaration in one year for the first Bucharest stock exchange category. The system examined how the listed entities complete this declaration in order to determine the degree of implementation of the corporate governance code issued by the stock exchange. This study has been conducted as a case-study and did not have availability.

Umanets et al. (2014) have addressed a tourist guide recommender system and its pertaining key features. GuideMe is a recommender system that its mobile and Web applications present consultation, publication, and recommendation of touristic places. It is obvious that before visiting touristic places, one may collect information about them, in this regard, a user may refer to places of touristic interest or get suggestions and recommendations from other users. These recommendations have been provided through the well-known Mahout Library. In contrast to previously tourist guide recommender systems, the distinguished features of GuideMe are its combination with social networks and suggestion of exclusive options. In order to evaluate the system and more specifically its recommendation engine, usability and load tests have been performed. The results showed the adequacy of the designed interfaces as well as good response times but low availability.

In order to improve software services searching effectively in an application market, Ke et al. (2014) have proposed an approach within which several advanced mechanisms have been applied. Determining key concepts and their hidden relationships in various software services have been done through information retrieval and rule mining technology. The relationships and discovered associations rules led to a semantic network. This network connected pertinent key concepts of software services. The candidates of software services should be ranked. In order to do this, first of all, software services have been configured, and then the multi-criteria decision analysis has been used. In sum, various criteria like key concepts of software services, discovered association rules, semantic network, and multi-criteria decision analysis have built a recommendation system which offered users the best software services among the ranking order. The results showed that this system had high

QoS; however, it suffered from low accuracy.

Previous users' experience and tourists' personal preferences were the building blocks of touristic context-aware recommendation system that have been offered by Amato et al. (2014) . The required data have been culled from various heterogeneous sources (sensors, web portals, repositories related to touristic events and locations). After collection of data, researchers used a cloud architecture to analyze and store it. It is worth to note that the mentioned cloud architecture is the most suitable system when the huge amount of data need to be processed and managed. Findings indicated that cloud computing infrastructure dealt with and ensured numerous user accesses and high performances, scalability, security in system respectively. However, the response time was high.

Y. Zhang et al. (2014) have proposed a novel cloud-assisted drug recommendation (CADRE). This system took into account symptoms to offer users top-N related medicines. In CADRE, at first, researchers have classified drugs based on their functional description information and used user collaborative filtering to design a basic personalized drug recommendation. Then, by considering the shortcomings of collaborative filtering algorithm such as computing costly, cold start, and data sparsity, researchers have presented a cloud-assisted approach to enrich end-user Quality of Experience (QoE) of drug recommendation. This approach modeled and represented the relationship of the user, symptom, and medicine via tensor decomposition. Finally, an experimental study was conducted to estimate this approach. Data were culled from a real data set available on the internet. The results showed that by considering customer's demand, CADRE can provide a valid, reliable, and effective drug recommendation, but low scaling was its disadvantage.

J.-H. Chang et al. (2014) have used cloud computing to generate a high-performance TV program recommendation. K-means and k-nearest neighbor algorithms were used in this approach to cluster users and to recommend programs, respectively. Also, frequency algorithm was used to find related popular programs. Most TV program recommendation systems focus on providing a personal recommendation system. The proposed system also considers user groups and the program watching preferences of the majority with high accuracy and high response time.

In the existing literature, there is a big gap about SaaS services. In this regard, Afify et al. (2014) have proposed the SaaS services from the business perspective. In order to advertise unified SaaS service, the authors have presented a semantic-based system. They, also, introduced a format and guide for the service registration model and a registration system. Moreover, they provided a semantic similarity model for services. Experimental results showed that by applying the fair scheduler architecture, processing performance and utilization of resources in the cloud environment have been improved and increased, respectively but it did not support PaaS or IaaS.

Kung and Wang (2015) have focused on cloud database, analytical module, and user interface to present a recommender system. Researchers have analyzed data according to the historical electricity data based on continuous Markov chain that analyzes the time series and multi-objective programming models; supports a long-term investment of renewable energy decision and can show the best combination of renewable energy. These modules were integrated to construct an enterprise-oriented cloud system. At the end, validation test was performed to ensure the effectiveness of the platform. Findings of this study showed that the recommender system can be applied to help the company in making the best investment of renewable energy and the best combination of energy consumption but the response time was high.



### 3.4.2. Summary of hybrid mechanisms

In the previous section, we have analyzed 12 selected hybrid mechanisms and analyzed their advantages and disadvantages. Table 9 shows the comparison of the most important advantages and disadvantages of each reviewed article.

TABLE9. A COMPARISON OF THE MOST IMPORTANT ADVANTAGES AND DISADVANTAGES OF THE HYBRID MECHANISMS IN CLOUD RECOMMENDER SYSTEMS.

| Paper | Advantages | Disadvantages |
|---|---|---|
| Park et al. (2011) | • Solved data sparsity problem<br>• High accuracy<br>• High scalability | • Cold start problem<br>• High response time |
| Yan et al. (2012) | • Low operation cost<br>• High security<br>• High QoS | • Didn't evaluate the effectiveness of system |
| H. Zhang et al. (2014) | • High scalability<br>• High accuracy<br>• High recall | • Low QoS<br>• High response time |
| Kushwaha and Vyas (2014) | • Solved data sparsity problem<br>• High accuracy | • High response time<br>• Low scalability |
| Fülöp et al. (2014) | • Low response time<br>• High scalability<br>• Low operation cost | • Didn't measure accuracy<br>• Is not applicable to the whole |
| Umanets et al. (2014) | • Low response time<br>• High scalability<br>• High availability | • Didn't used to user experience<br>• Low scalability |
| Ke et al. (2014) | • Low response time<br>• High QoS | • Didn't measure accuracy<br>• Shilling attacks problem |
| Amato et al. (2014) | • High QoS<br>• High accuracy<br>• High scalability<br>• High security | • Increase dimensional<br>• High response time |
| Y. Zhang et al. (2014) | • High scalability<br>• Solved cold start problem | • Low accuracy<br>• High response time |
| J.-H. Chang et al. (2014) | • Low response time<br>• High scalability | • It's tested with few nodes<br>• Cold start problem |
| Afify et al. (2014) | • High accuracy<br>• High security<br>• High scalability | • Just support SaaS services<br>• Didn't consider user's feedback |
| Kung and Wang (2015) | • High QoS<br>• High accuracy<br>• Low operation cost | • Low availability<br>• Low validation<br>• Didn't consider calibration |

## 4. RESULT AND COMPARISONS

In the previous section, some of the cloud recommendation techniques have been analyzed. The researchers focused on the most popular recommender systems techniques by considering four main categories including collaborative filtering, knowledge-based, demographic-based, and hybrid mechanisms. Generally, each category has some challenges that researchers must try to solve them. For example, collaborative filtering indeed its advantages, has some problems such as scalability, cold start, and data sparsity. According to the reviewed papers, researchers have been able to solve QoS, scalability and accuracy problems in collaborative filtering but it should be solved cold start, data sparsity and response time problems in future. Articles with demography-based techniques have been able to improve scalability, response time, and accuracy but most of the articles are not applicable to the whole and don't consider trust in the system. In the knowledge-based category, most of the articles increase accuracy and energy efficiently but have an average level of scalability and response time. Also, hybrid techniques have high-level accuracy and scalability and need to improve response time in future works.

During this review, the researchers found that cloud recommender system is an intelligent system to find a suitable supplier, resource, and services. The combination of recommender system and cloud computing can achieve large-scale data source, heterogeneous platforms, and ability to extend the breadth and depth of recommendation systems. Generally, the most important advantages of these techniques are that cloud recommender system can increase QoS, competition between suppliers and reduce the time to find the appropriate service and also offer update information and services to the users in the large-scale, and it makes the tasks to be done faster.

According to the performed SLR of recommender system mechanisms from 2009 to 2015, the researchers found that the number of published articles in 2014 and 2009 were the highest and lowest, respectively. In addition, the greatest number of articles was published by low-cited journals. Among the 43 selected articles, 46, 34, and 2 percent of the articles have been published by Springer, IEEE, DOAJ, respectively. In other words, the highest number of articles has been selected from Springer and IEEE's publishers.

The researchers compared and evaluated the factors that have any effect on recommender system (for each group) to find which factor is more important in each one. Furthermore, the researchers identified the most and least important factors that have any effect on the recommender system. Table 10 provides an overview of the discussed recommender system techniques and their main features like QoS, security, response time, availability, scalability, trust, accuracy and operation cost that the effect of these factors may be helpful or harmful. These features have been obtained from selected articles and scored by stars in which 1 star and 3 stars indicated the lowest and highest occurrences of these features, respectively. Features that have been expressed explicitly positive are considered as advantage were scored 3 stars as highest, the features that have been mentioned as disadvantages or have not been considered at all were scored 1 star as lowest, and the features that are slightly improved but still need to be strengthened scored with 2 stars. .On the other hand, some of the mentioned features are stated implicitly. In this regard, the researchers specified the implicit features by content analysis of the selected articles and scored them as well.

TABLE10. AN OVERVIEW OF THE DISCUSSED RECOMMENDER SYSTEMS TECHNIQUES AND THEIR MAIN FEATURES

| Main categories | Author Name | QoS | Security | Response time | Availability | Scalability | Trust | Accuracy | Operation cost |
|---|---|---|---|---|---|---|---|---|---|
| Collaborative filtering | Lai et al. (2011) | ** | * | * | ** | *** | * | ** | * |
| | S. Wang et al. (2011) | ** | * | * | ** | *** | * | *** | * |
| | Yaming Zhang et al. (2011) | * | * | * | ** | *** | * | *** | * |
| | Jiang et al. (2012) | *** | ** | * | * | *** | *** | *** | * |
| | Kong and Zhai (2012) | * | * | * | ** | *** | * | *** | * |
| | Jung, Sharma, et al. (2013) | ** | * | *** | * | ** | * | ** | * |
| | J.-H. Chang et al. (2013) | *** | * | * | * | ** | * | ** | *** |
| | Zain et al. (2014) | ** | ** | * | * | * | *** | *** | * |
| | Boutet et al. (2014) | *** | ** | * | *** | *** | * | ** | *** |
| | Shrestha et al. (2014) | *** | * | *** | * | * | * | ** | * |
| | Carullo et al. (2015) | ** | * | *** | ** | *** | * | ** | * |
| | Kumar and Pandey (2015) | ** | * | *** | ** | *** | * | *** | * |
| | Hu et al. (2015) | *** | * | * | * | *** | * | *** | * |
| Demographic-based | Lee et al. (2011) | *** | * | ** | * | ** | * | ** | * |
| | Yoon et al. (2012) | * | * | * | ** | *** | * | *** | * |
| | M. Zhang et al. (2012) | *** | * | * | ** | *** | * | *** | * |
| | Jung, Mukherjee, et al. (2013) | *** | * | * | ** | ** | * | *** | *** |
| | Krishna et al. (2013) | * | * | *** | ** | *** | * | *** | * |
| | Ying et al. (2013) | *** | * | *** | * | * | * | * | *** |
| | Chengwen Zhang (2014) | ** | * | *** | * | ** | * | * | *** |
| | Y.-C. Chang et al. (2014) | ** | * | * | * | *** | * | *** | * |
| | Mo et al. (2014) | ** | * | *** | * | *** | * | *** | * |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Knowledge-based | Han et al. (2009) | *** | * | *** | *** | *** | * | *** | ** |
| | Chen et al. (2011) | *** | * | ** | * | *** | * | *** | *** |
| | M. Zhang et al. (2012) | *** | * | * | *** | * | * | *** | *** |
| | Vera-del-Campo et al. (2014) | ** | *** | ** | * | ** | *** | *** | ** |
| | Soltani et al. (2014) | ** | * | *** | *** | * | * | *** | *** |
| | Im et al. (2014) | ** | * | * | ** | ** | * | *** | * |
| | Patiniotakis et al. (2014) | *** | * | * | *** | ** | * | *** | *** |
| | D. Wang et al. (2014) | ** | * | * | *** | * | * | *** | * |
| | Amin et al. (2015) | ** | * | ** | ** | ** | * | * | ** |
| Hybrid | Park et al. (2011) | ** | * | * | ** | ** | * | *** | ** |
| | Yan et al. (2012) | *** | ** | ** | ** | *** | * | ** | ** |
| | H. Zhang et al. (2014) | * | * | * | ** | ** | * | ** | * |
| | Mo et al. (2014) | ** | * | *** | *** | ** | * | *** | * |
| | Kushwaha and Vyas (2014) | ** | * | * | * | * | * | *** | ** |
| | Fülöp et al. (2014) | ** | * | *** | * | *** | * | ** | *** |
| | Umanets et al. (2014) | ** | * | *** | * | * | * | *** | ** |
| | Ke et al. (2014) | *** | *** | * | *** | ** | * | ** | ** |
| | Amato et al. (2014) | ** | *** | * | ** | *** | * | *** | *** |
| | Y. Zhang et al. (2014) | ** | ** | ** | *** | * | *** | *** | ** |
| | J.-H. Chang et al. (2014) | *** | ** | ** | *** | *** | * | *** | * |
| | Afify et al. (2014) | *** | *** | ** | *** | ** | * | *** | *** |
| | Kung and Wang (2015) | ** | * | * | *** | *** | * | *** | ** |



The results of the provided comparison in table 10 showed that scalability and accuracy are important in all four categories. The motivation of the end-users, functional and nonfunctional futures are important to create opportunities for recommender system and creativity. Preferences, response time and operation cost have a significant impact on quality of service of a recommender system that has not been considered in some articles. According to table 10, the highest and lowest score of each mechanism in all of the selected articles are obvious. It is interesting that all of the categories 'security and trust achieved the lowest score and highest score in accuracy and scalability. Finally, it can be seen that all factors are essential for effective recommender system but trust and security rarely are considered as a factor in articles. Also, some articles provide their mechanisms in academic or business environments that in forthcoming works the researchers can extend this mechanism to other communities.

## 5. OPEN ISSUE

There are some important issues in the development of cloud recommender systems that are out of the scope of present research direction. This section is about the discussion and analysis of the mentioned issues. It is incontrovertible that there is not any technique which includes all issues linked to cloud recommender systems. For example, some techniques provide trust or response time, while some totally ignore these issues. Also, some mechanisms have used the simulation scenario while some others use quatrains for evaluation. Such mechanisms can be tested in real-world scenarios to offer a very realistic result. In addition, some interesting points of modeling the discussed mechanisms can be investigated in future research. For example, in Y.-C. Chang et al. (2014), it's better to consider reliability and trust and find real cloud services to validate this recommended method and develop a prototype system for it.

Trust and credibility are the challenging research issues which have not been considered in cloud recommender systems' performance where they can enhance the security results. Nowadays, recommender system can be found virtually in many websites, social networks like Facebook or LinkedIn. The mentioned systems use recommender system to provide more useful services to their users. The recommendation information can be derived from user profiles and the communication among them. For this purpose, it's necessary to have two kinds of trust; trust to other users and trust to the systems' recommendations. Also, the bilateral trust of users can be exploited for upgrading the trust in the system.

In the other hand, some studies don't consider all quality criteria to improve system performance. Although the effectiveness of the reviewed systems depends on them, they may also be conflicting and it is important to distinguish between the criteria for evaluations. Then designing a powerful mechanism will become a challenge that convinces users to buy, read or listen to music. At first, it should be noted that system quality depends on the unique features of the selected items, likewise, on the recommendation algorithm. Also, some approaches limited to one type of cloud services; M. Zhang et al. (2012) may extend their systems to support the selection of more cloud service types such as PaaS services.

Many recommender systems use large amounts of data, especially in cloud environments, for example, the user-item matrix in collaborative filtering techniques can be very large and fragmented because this method is based on user previous selections, voting of new users and service information. It is clear that in many algorithms bringing data sparsity together with the growth of data collection is either slow or needs additional resources such as computing power or memory. One of the standard methods in computer science research is to evaluate the computational complexity of algorithms required in terms of time or space. Dimensionality is the other issue that should be addressed in studies because it refers to the dataset and its features that require more space in the system. Dimensionality reduction techniques can reduce system overhead and complexity. Another problem is the cold start that occurs in recommendation systems due to the lack of information on new users or items, and new system trouble. In such cases, it is very difficult to give the best recommendation to users. However, the content-based method can provide an appropriate recommendation to new users as they do not depend on previous information from other users and items. The last issue is scalability that happens with tens of millions of customers who suffer serious scalability problems where it can be solved with a hybrid approach and millions of traditional collaborating filtering algorithms items.

Future works need to be done to discard the existing obstacles of a recommender system, for example, how to increase system correctness and reduce response time. The second issue is about comments and likes that most of the users haven't propensity to take comments, then need to provide strong tendency on the post. Also, we have shilling attacks problem in likes and comments in the systems that use of user's likes to ranking. Researchers must require users to enter a valid account. The tendency may refer to users' vote or evaluation; also, it presents the state of users' emotions, interest or unwillingness. It's suggested to use such information for meet user requests. Meanwhile, we have shilling attacks problem in likes and comments in the systems that providers give a positive comment or like for themselves products. To prevent it, requiring users to enter a valid account suggested. Thirdly, the effect of user's emotions should be investigated in future studies. Moreover, taking into account reducing dimensionality to overcome high dimensionality space is critical for clustering and outlier detection. Furthermore, using the new heuristic and meta-heuristic algorithms likes artificial bee colony, artificial fish, and forest optimization algorithms for cloud service recommendation is very attractive to increase accuracy and correctness in the system. Finally, there may also be uncovered areas that are open to new improvements; meanwhile, there is still much interesting research to be done in the future.

Despite a great number of works that have been done in this domain, all of recommender systems have some limitations that must be considered in future researches. All of the recommender systems have five major limitations including:

I. Lack of data and large amounts of data; recommender systems need a lot of information to offer effective suggestions. An effective recommender system must have information about items or services, also, user's information and their preferences, therefore, a lot of users and data are required for the recommendations
II. Changing data; as an example in fashion recommender system, information change frequently and the system based on the user's trusted friend and families will give a suggestion
III. Changing users' preferences; users have various requests from suppliers, one day they want a romantic film and another day search about a gift
IV. Unpredictable items; some type of items are difficult to make recommendations on because the user reaction toward them tends to be diverse and unpredictable
V. Complexity; if algorithms supposed to consider more features to give an effective recommendation, they would be so complex.



## 6. Limitation

This study has attempted to conduct a systematic review as rigorously as possible but there may be some limitations as well. Hence, future studies should take into account the limitations of this study that have been outlined below.

Research scope: The recommender systems have been covered in various sources such as academic publications, editorial notes, technical reports and web pages, etc. Specifically, the researchers have omitted articles published in national journals and conferences. Also, the researchers have omitted the articles that were not about cloud environment. Hence, in the qualification of this review, it must be considered that this systematic review took into account studies published in the major international journals.

Study and publication bias: the researchers chose Google scholar as a reliable electronic database. Based on the existing statistics one can claim that this electronic database would offer the most relevant and credible studies. However, selection of all applicable studies could not be guaranteed. There is a possibility that some applicable studies were overlooked throughout the processes of article selection which have been mentioned in section 3. There could be various reasons that some applicable articles go unnoticed. These reasons can range from the searching of wrong keywords to the data extraction.

## 7. Conclusion

In this paper, the researchers presented a review concerning the past and state of the cloud recommender systems. According to the findings of a systematic literature review from 2009 to 2015, the number of published papers was very low in 2009, on the other hand, the number of published papers reached to its highest point in 2014. However, the greatest number of papers was published in low-cited journals. Among publishers, Springer and IEEE published the highest number of articles in journals and conferences with 46 and 34 percent, respectively. However, the least number of articles have been selected from DOAJ with 2%. 43 articles were classified into four main categories including collaborative filtering-based, demographic-based, knowledge-based, and hybrid. For each of those classes, the researchers reviewed and compared several features regarding cloud recommendation techniques and mechanisms. In this paper, the researchers, also, reviewed mechanisms comprehensively while comparing and highlighting some interesting lines for future studies. The results revealed that the cloud computing helps to increase the scalability, accuracy, and provide various update information using the data as a service to the recommender system. Cloud recommender systems in knowledge-based model increase energy efficient and fulfill supplier and customer's satisfaction. In addition, collaborative filtering increases scalability, accuracy, and QoS but it is essential to solving cold start and data sparsity in the system. Moreover, the demographic approach has a good response time, accuracy, and scalability in the system. Meanwhile, hybrid mechanisms improve the scalability and accuracy but had a high response time in most of the reviewed articles. It is an interesting area for further researches that will find a specific mechanism to supply all discussed issues and consider the trust and security in the recommender systems.



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## Highlights

- Offering a systematic overview of the existing techniques in cloud recommender systems.
- Highlighting the advantages and disadvantages in the each domain.
- Exploring some of the primary challenges in the field of the recommender system.
- Presenting the guidelines for the existing challenges.
- Outlining the key areas where future research can improve the function of recommender systems.