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A Systematic Study on the Recommender Systems in the E-Commerce

PEGAH MALEKPOUR ALAMDARI[1], NIMA JAFARI NAVIMIPOUR[2], MEHDI HOSSEINZADEH[3,4], ALI ASGHAR SAFAEI[5], AND ASO DARWESH[6]

[1]Department of Computer Engineering, Qeshm Branch, Islamic Azad University, Qeshm 7953163135, Iran
[2]Future Technology Research Center, National Yunlin University of Science and Technology, Douliu 64002, Taiwan
[3]Institute of Research and Development, Duy Tan University, Da Nang 550000, Vietnam
[4]Health Management and Economics Research Center, Iran University of Medical Sciences, Tehran 1449614535, Iran
[5]Department of Biomedical Informatics, Faculty of Medical Sciences, Tarbiat Modares University, Tehran 14115-111, Iran
[6]Department of Information Technology, University of Human Development, Sulaimaniyah 0778-6, Iraq

Corresponding author: Mehdi Hosseinzadeh (hosseinzadeh.m@iums.ac.ir)

ABSTRACT Electronic commerce or e-commerce includes the service and good exchange through electronic support like the Internet. It plays a crucial role in today's business and users' experience. Also, e-commerce platforms produce a vast amount of information. So, Recommender Systems (RSs) are a solution to overcome the information overload problem. They provide personalized recommendations to improve user satisfaction. The present article illustrates a comprehensive and Systematic Literature Review (SLR) regarding the papers published in the field of e-commerce recommender systems. We reviewed the selected papers to identify the gaps and significant issues of the RSs' traditional methods, which guide the researchers to do future work. So, we provided the traditional techniques, challenges, and open issues concerning traditional methods of the field of review based on the selected papers. This review includes five categories of the RSs' algorithms, including Content-Based Filtering (CBF), Collaborative Filtering (CF), Demographic-Based Filtering (DBF), hybrid filtering, and Knowledge-Based Filtering (KBF). Also, the salient points of each selected paper are briefly reported. The publication time of the selected papers ranged from 2008 to 2019. Also, we provided a comparison table of important issues of the selected papers as well as the tables of advantages and disadvantages. Moreover, we provided a comparative table of metrics and review issues for the selected papers. And finally, the conclusions can, to a great extent, provide valuable guidelines for future studies.

INDEX TERMS Recommendation systems, electronic commerce, personalization, review.

I. INTRODUCTION

Electronic commerce (e-commerce) is concerned with such diverse activities as marketing, servicing, developing, delivering, selling, and expending for services and products by using online platforms [1], [2]. Today, e-commerce is an inseparable part of the business for a variety of reasons, including the ease of use, universal accessibility, wide variety, and manageable compassion of products from different vendors, trusted payment ways [3], and the convenience of home shopping with the least waste of time. These facilities of e-commerce applications improved the lives of users to a highlevel of quality, particularly with the technological development of mobile devices [4] and the Internet in every time and every place. Some services, such as payment, selling and buying digital goods and physical products, ticket and hotel reservations, online registration, e-learning [5], electronic customer relationship management [6], and many others are widely available with these applications. E-commerce websites, such as eBay, Alibaba, Amazon, and Netflix, provide great opportunities for their users. These e-commerce platforms tend to utilize the social network features [7], expert cloud technology [8]–[12], big data [13], and using mobile devices to provide user satisfaction for their users.

The Recommender Systems (RSs) learn the experiences and opinions from their customers' behaviors and recommend the items or products that they will find the most relevant among the possible results. Also, they provide the facilities to enhance the adaption of applications to each user [14]. Recommender systems have been utilized

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in many fields, like e-commerce [15], health [16], social networks [17], [18], industry [19], e-learning [20], music [21], Internet of Things (IoT) [22], [23], food and nutritional information system [24], and marketing [25]. They produce automation of personalization in the e-commerce environment by employing traditional and modern techniques [26] like machine learning techniques [27]. The recommender systems in e-commerce increase the turnover by providing the relevant products for each customer, suggesting additional goods and products to boost cross-sell and improving client loyalty [28]. The considerable importance of Internet marketing activities, especially e-commerce resulting in the personalized recommendation techniques, is only one of the features that RSs provide to e-commerce platforms. The main problem is the elevation of the accuracy of the RSs results. The vast amount of information that is generated in e-commerce websites makes numerous difficulties for their users to decide which products they would buy. Employing RSs can greatly address the problem [29], [30].

The paper has intended to review recently published papers in RSs that concentrate on e-commerce and show the developing opinions of these systems, particularly their types, methods, algorithms, and implementations in detail. We studied some fundamental algorithms, like Collaborative Filtering (CF) and knowledge-based, demographic-based, hybrid, and content-based filtering. Therefore, we gathered and analyzed various recent papers of RSs used in e-commerce via a structured methodology [31], [32]. The fundamental goals of this survey are as follows:

- Reviewing the pros and cons of traditional techniques that are used in the selected papers.
- Expressing some of the main challenges of the selected papers and viewing the relevant solutions.
- Pointing out some aspects of RSs to improve their accuracy and functionality for future studies.

The remainder of the present article is as below: Section 2 expounds on the relevant work. In Section 3, we briefly describe RSs in e-commerce, its characteristics, and the relevant metrics. Section 4 discusses the relevant studies in RSs used in the e-commerce field in a Systematic Literature Review (SLR) approach. Section 5 expresses the traditional methods of RSs in the selected papers. Also, Sections 6 and 7 include the evaluation plan and open issues based on the review, respectively. In the end, Section 8 concludes the article.

II. RELATED WORK

Many kinds of research on RSs in e-commerce fields have been performed. The present section explains review articles, which discuss the utilization of RS in e-commerce applications and summarizes their main advantages and disadvantages.

Xiao and Benbasat [33] studied e-commerce product recommendation agents and considered empirical papers on e-commerce product offering agents issued from 2007 to 2012. They selected 34 papers to review such highlighted topics as recommendation agent type, preference-elicitation, explanation, and the social aspects of recommendation agents. Also, they covered the operative features of social recommendation agents, variables for user perception such as pleasure, comprehended recommendation quality, comprehended trade-off issue, and comprehended social presence, and modifying factors, including gender, regulatory focus, reactance level, temporal distance, and decision context. They presented the refreshed conceptual model of the recommendation agent to conduct further research. However, the study mostly focused on some issues, such as social presence, perceived usefulness, trust, satisfaction, and perceived ease of use as the user's evaluation factors of recommendation agents. Using the conceptual model is a significant point in their research.

Lu *et al.* [34] reviewed the papers published between 2013 and 2015 in the application developments of RSs in eight basic rankings, including e-government, e-business, e-commerce/e-shopping, e-library, e-learning, e-tourism, e-resource services, and e-group activities [35]. They examined RS's techniques systematically in some perspectives, such as recommendation methods, RS software, real-world application domains, and application platforms. Also, they used multiple databases for searching papers, such as Science Direct, ACM Digital Library, IEEE Xplore, and SpringerLink. Their review is significantly valuable in both describing the content and categorizing the methods.

Furthermore, Karimova [36] reviewed the papers on e-commerce recommender system techniques published between 2014 and 2016 in journals and conference proceedings. He examined the developments of e-commerce recommender systems from the viewpoint of e-commerce providers or e-vendors. He searched the journal databases like ACM Digital Library, IEEE Xplore, Science Direct, and SpringerLink. The paper included such critical results as the dominant role of traditional RS techniques in e-commerce, especially collaborative filtering and hybrid methods, improving the personalized recommendation with high accuracy, and the researchers' efforts to overcome problems, for example, decreasing computational complexity and improving recommendation accuracy. The author employed the SLR strategy for the review process.

Li and Karahanna [37] reviewed 40 empirical investigations of the recommendation system published from 1990 through 2013. Indeed, they classified the selected papers in three major fields, including understanding consumers, delivering recommendations, and the impacts of recommendation systems. Furthermore, some significant terms like customization, interactive decision aid system, personalization, recommendation system, and recommendation agent proposed in the review. The study included some tables with valuable summarized information in addition to reviewing the selected papers, and also it refers to a set of theories that RSs used.

Adomavicius and Tuzhilin [38] reviewed three main recommendation technique categories, containing content-based filtering, hybrid, and collaborative filtering. They provided constraints and limitations of these methods and possible solutions to improve the recommendation performance [39].

Sezgin and Özkan [40] selected eight papers in the Health Recommender System (HRS) domain and provided an SLR study. They have concluded that HRS is a promising development for healthcare services. Also, their review provides a set of challenges and opportunities in HRS. Khan *et al.* [41] have conducted an SLR of 94 shortlisted studies on the field of Cross-domain recommender systems (CDRS). They have expressed conventional recommender system problems and issues in four categories in their selected studies as follows:

- Mature: Accuracy and Sparsity.
- Current research focus: UI modeling, Confidence, Cold-start, and Diversity.
- Gaining popularity: Trust and Utility.
- Open research issues: Privacy, Novelty, Serendipity, Risk, and Adaptivity.

Çano and Morisio [42] have presented an SLR on the state of the art in hybrid recommender systems. Based on their review, a high amount of selected investigations has combined collaborative filtering with a different method frequently in a weighted manner. Additionally, they have concluded that top problems were cold-start and data sparsity. Also, movie datasets were widely used by researches to do the hybrid approaches RS.

However, this study aims to review and analyze the selected papers based on the following issues:

- Proposing a systematic review and a summary of five traditional mechanisms in recommender systems in e-commerce for emphasizing on the pros and cons in each ranking for the selected paper.
- Introducing the challenges of recommender systems mechanisms in e-commerce.
- Pointing significant issues for future study.

III. BACKGROUND

The present section introduces the main notions and associated terminologies regarding e-commerce and recommender systems.

A. E-COMMERCE CONCEPTS AND BENEFITS

E-commerce supports commerce transactions in the most uncomplicated approach on the Internet. Although people consider e-commerce to be online selling and purchasing, the e-commerce world includes other activity sorts. Thus, any business activity form that is transferred electronically is called e-commerce. Some instances for e-commerce are electronic payments, online shopping, Internet banking, online ticketing, and online auctions. E-commerce may be categorized depending on the member type in the transaction in some categories like Business to Consumer (B2C), Consumer to Consumer (C2C), and Business to Business (B2B) [43]. The basic e-commerce advantages result because it omits the geographical distance and time restrictions. Figure 1 shows some benefits of doing business online by using e-commerce websites, including Personalized Recommendation Systems (PRSs) advantages, loyalty, saving the earth, faster delivery, increase income, easy setup, time-saving, cost-effective, cost-effective, convenience shopping, and flexibility.

FIGURE 1. The benefits of online business based on an e-commerce platform.

B. RECOMMENDATION SYSTEMS CONCEPTS RELATED TO E-COMMERCE

The recommender systems help handle user interaction and sales by assisting users to find products and services that they may never find by themselves. In traditional commerce and business, people have been notified and encouraged about purchasing products and services through their friends, news, and marketers [44]. By growing the use of e-commerce and the advancement of its related technologies, the use of RS has great importance due to its benefits. The recommender systems usually provide items like products, movies, events, warnings, and articles to the users, such as customers, visitors, system administrators, and content. Thus, the approach increases the conversion rate and improves the customer's loyalty and makes satisfaction. Also, based on practical and reported evidence, RSs can help businesses to improve their vital e-commerce metrics [45]. For example, in a real shop, a good salesman knows the personal preferences of buyers, and her/his high-quality recommendations make clients' satisfaction to increase earnings. Some researchers utilize social resources to get more accuracy in resulted recommendations. For example, Li *et al.* [46] have incorporated the recommendation trust, social relation analyses, and preference similarity to provide product offerings in e-commerce. They have shown that their proposed method could outperform better performance and provide more accuracy than other traditional collaborative filtering based on experimental results.

Also, some studies provided methods to preserves customers' privacy. For instance, Rosaci and Sarné [47] have presented a fully decentralized trust-based B2C recommender system framework for generating more useful recommendations. Their approach utilizes recommender methods of CF and CB for supporting the traders of the B2C by evaluating the reputation of the products, clients' orientations, and the trustworthiness of traders. They have provided a distributed architecture to increase the computation efficiency of trust measures and recommendations. Thus, the method guarantees scalability and privacy. Also, Jiang *et al.* [48] have suggested a slope one algorithm depending on the integration of user similarity and trusted data to perform more precisely compared to other customary slope-one methods using the Amazon dataset. Selecting trusted data, calculating the similarity between users, and adding the resemblance to the weight factor of the developed slope one algorithm are three critical phases of the method to produce the recommendations.

The recommender system makes better results when it knows more about the properties of users and items [49]. Also, the system gathers more data from available resources to feed the algorithms and produces more relevant content for users. Various evaluation metrics are applied to the systems to improve the quality of recommendations. The evaluation of recommendations on impact, interaction, and conversion for a particular period are well-known parameters for examining the effectiveness of system output, especially in e-commerce platforms [34]. There are some metrics for evaluating RSs, like MAE (Mean Absolute Error) [50], MSE (Mean Squared Error) [51], RMSE (Root Mean Squared Error) [52], evaluating lists of recommendation (based on relevancy levels) [53], recall [54], MAP (Mean Average Precision) [55], nDCG (normalized Discounted Cumulative Gain) [56], diversity (intra-list similarity) [57], implicit feedback, diversity of Lathia *et al.* [58], and MPR (Mean Percentage Ranking).

C. METRICS DEFINITIONS

The current study illustrates an RSs technique comparison with the utilization of such measures of performance like security, response time, scalability, accuracy, operation cost, diversity, novelty, serendipity [59], type of data sources (implicit/explicit), and evaluation method. Also, we comprised and evaluated the selected papers in section 6 by considering these metrics. Consequently, this section contributes to a brief discussion of them.

1) ACCURACY

Accuracy is known as a part of the true recommendations from the whole feasible recommendations. In other words, the better quality of the output recommendations leads to having a higher accuracy of the system and fewer errors. In e-commerce, the quality of recommendations led to increase sales and improve customer loyalty. Since the measurement accuracy is complicated, the authors consider the content of the selected papers.

2) DIVERSITY/NOVELTY/SERENDIPITY

RSs use a diversity of items in the recommended list to improve user satisfaction. In other words, when there is a higher versatility of intra-list, users have the willingness to attain more satisfaction with recommendations [60]. Therefore, diversity is essential for improving customer loyalty. Serendipity is a measure that the RS has been able to surprise the user by producing and presenting serendipitous items [61]. Thus, for example, in e-commerce, the system can also include one or more attractive items for the user in his/her suggestion list. In this case, the recommendations will not be bored.

On the other hand, the common investigation is that a system might desire to attempt to assess the possibilities, which a user will identify an item [62]. Novelty is the dimension for measuring the recommendation's non-obviousness. A serendipitous recommendation assists the user in detecting a surprisingly exciting item that she/he may not discover.

3) INDEPENDENCE

Since the operation of the software is embedded in the current software application, the approach of using the agent can be valuable in many applications. Therefore, the metric is called independence, which specifies the proposed method as a part of the current e-commerce software, or it can work independently or as the agent.

4) OPERATION COST

Operating costs are expenses associated with running, maintenance, and administration of a recommender system in this paper based on computational resources such as CPU consumption, memory usage, and network traffic. In other words, this metric indicates whether the method needs to be optimized or not. Some authors emphasized that their methodologies must be optimized for real word usages.

5) RESPONSE TIME

When the online user demands a recommendation, she/he anticipates to get the response abruptly, therefore, measuring the response time that the user tolerates is very important to evaluate RSs [63].

6) SCALABILITY

A scalable system is a system that is capable of meeting the growing demands of work or process and is capable of integrating growth [64]. For example, when we call a recommender system technique scalable, it can be applied to large-scale input data without compromising on the efficiency of the technique or forcing any considerable overhead on the system.

7) SECURITY

RSs collect more and more such personal information as login time, location, and social network profiles and data [65] to provide better recommendation services, so they make high privacy concerns to the public. On the other hand, RSs have to protect themselves from attacks begun by malicious users who want to influence the recommendations [66]. So, it is essential to consider the security issues in the RSs.

8) TYPE OF THE DATA SOURCES (IMPLICIT/EXPLICIT)

The input data of the algorithms used in the recommender systems affect the quality of the resulted recommendations. Some of these algorithms require the use of explicit data, such as user rating matrix, users' profiles, and items' catalogs. However, others work with implicit data only like user behavior. Moreover, some methods use both types. The use of implicit data requires some particular processes and methods, such as the use of data mining and machine learning techniques [67]. Therefore, in this research, this metric is used to classify these types of algorithms.

IV. RESEARCH METHOD

To present a clear image of the techniques in recommender systems in e-commerce, we provided a Systematic Literature Review (SLR) along with a concentration on the relevant and recent studies. Thus, we used the applied review protocol based on the guidelines of Kitchenham and Charters [68] and considered the implementation of an exhaustive and thorough abstract of the present literature related to the field of the study as one of the SLR purposes [32], [69], [70]. For reducing the researcher's bias, the use of review protocol is inevitable. As such, we focused on a set of Research Questions (RQs) that serve as the object of this literature and originate from the ideas that initiated this review. We completed this study by conducting three processes, including question formalization, searching papers, and applying the desired limitations to select the relevant papers to review. Consequently, we outlined the research aims as RQs in Section 4.1, searching papers process from resource libraries in section 4.2, and finally, the classification and inclusion/exclusion criteria are applied in Section 4.3.

A. QUESTION FORMALIZATION

The objective of the existing research is to collect all of the credible and influential studies that investigated the recommender systems in e-commerce in recent years. In particular, exploring the techniques, open issues, and critical points of the selected papers are the main aims of this paper. To achieve these goals, we defined the Research Questions (RQs) as follows:

- **RQ 1**: What are the recommender systems in e-commerce and their important and applied techniques? Which types of research methods are useful? What categories are important?
  Section 5 conducts the response to the mentioned question.
- **RQ 2**: What are the open issues?
  Section 6 explains these matters.
- **RQ 3**: How are the search procedure of paper and the selection of it for assessing?
  The answer is provided in Section 4.
- **RQ 4**: How researchers conducted the study?
  In section 6, we directed the relevant answer.
- **RQ 5**: What parameters are necessary for this research, and what are their assessments from the viewpoint of the researchers in this study?
  The second part includes a response to it.

B. PAPER SELECTION PROCESS

To identify the relevant papers for completing the review plan, in the first step, we used the Google Scholar service to do the searching phase. Thus, we searched the papers for various combinations of the relevant keywords, including recommender system(s), recommendation system(s), e-commerce, and electronic commerce. We also applied the "allintitle" filter of the Google Scholar service to find the most relevant studies.

We did our search on April 20, 2019, and considered the range of publishing from 2008 to 2019. It is important to note that the titles of some research directly point to the recommender systems in the e-commerce environment, while some titles are related implicitly. Therefore, we considered research whose title was directly related to the subject of the study. Table 1 shows the number of papers found according to the search terms. The total number of detected items was 289 papers by eliminating the patents and citations types.

TABLE 1. Results from google scholar service related to search keys using the "allintitle" phrase.

Search keys	Result# (any time)	Result# (2008 - 2019)
recommendation system e-commerce	137	123
recommendation systems e-commerce	24	15
recommender system e-commerce	84	70
recommender systems e-commerce	86	65
recommendation system electronic commerce	11	8
recommendation systems electronic commerce	6	3
recommender system electronic commerce	5	4
recommender systems electronic commerce	5	1
Total	358	289

After the searching phase, we applied our selection strategy based on some crucial issues, such as the year of publication, the language of the papers, and their title. We limited our study to English papers. Also, recently published papers were of greater importance for selection, and we consider the reputation and validity of the journals. Figure 2 shows the distribution of the papers obtained by publication year from 2008 until 2019. In 2014, the published papers had the highest rank.

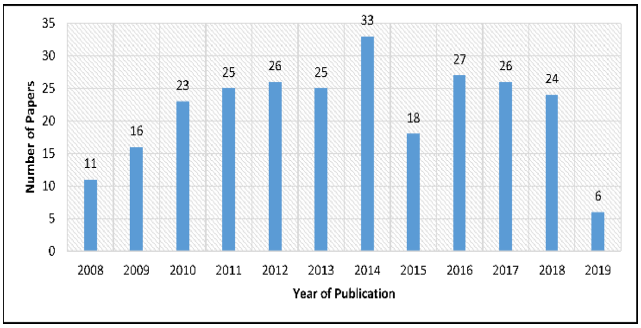

FIGURE 2. The number of papers published from 2008 to 2019 in the subject of the study area.

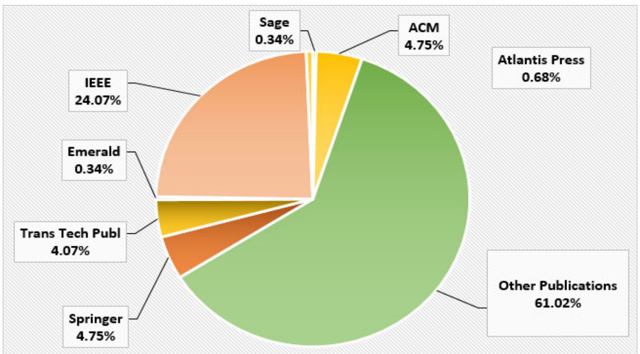

FIGURE 3. A pie chart of the percentage of the papers based on selected publishers (Step 1).

Then, we excluded some types of studies, such as thesis, reports, work articles, commentaries, editorial notes, books, and books' sections. Additionally, we did not consider non-English papers. To select the most relevant papers, we reviewed the chosen papers considering the year of the publication, subject, and journal category as the primary critical points for the final selection step. For example, we considered some issues related to journal filtering, such as having high-quality factors in journal publications, the validity of retrieved items, novelty, and most relevant results as well as the critical points found in the conclusion sections.

Figure 3 illustrates the paper ranking by various publishers. We considered all the studies which are published by famous publishers and removed the rest from our field of study. After purifying the items, we selected 33 papers to review and examine them.

Finally, the categorization of the articles chosen depending on the basic recommender system methods in e-commerce is described. Table 2 demonstrates the categorization of the related investigations in all the groups. 11 papers out of 33 papers are based on the CF method. Also, six papers are related to DBF, three papers are in the CBF category, and for KBF and hybrid, we selected five and eight papers, respectively.

Additionally, Figure 4 illustrates the paper classification among seven publishers. IEEE publishes 54% of the articles, and Springer publishes 17% are on the top of other publications.

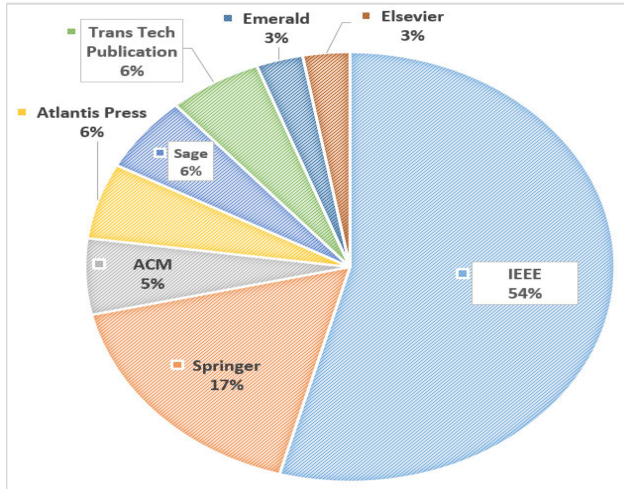

FIGURE 4. A pie chart of classification of selected papers among publishers.

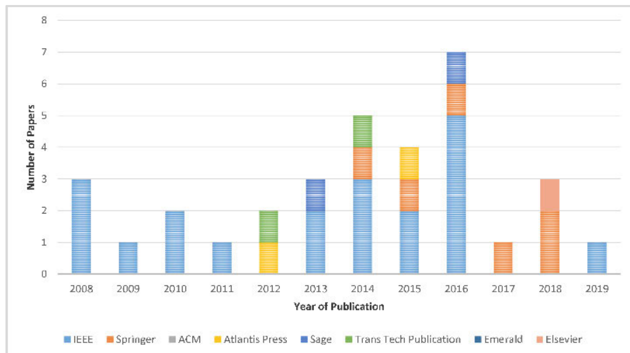

FIGURE 5. Distributions of selected papers over time infamous publications for reviewing.

Figure 5 shows the distributions of selected papers over time infamous publications to review. In the 2016 portion, it shows the highest rank.

V. REVIEW OF SELECTED PAPERS

In addition to solving the information overload problem, the RSs help users to find products related to their preferences by providing personalized services [38]. We want to review the basic models of recommendation techniques to examine recommender systems in e-commerce. The user-item interactions, like ratings or purchasing behavior, and the information for quality regarding the items and users like related keywords or textual profiles are two fundamental kinds of input data to feed basic models of RSs. CF methods use the user-item interactions [101], and CBF approaches employ the features of users and items [102]. Explicitly specify the outward knowledge foundations, user requirements, and restrictions that are essential information for KBF methods [103]. Demographic RSs use demographic information regarding the user for constructing the recommendations based on special mapping demographics for ratings or purchasing tendencies [104]. Hybrid systems are able to integrate the power of different RSs kinds for creating systems that may operate powerfully

TABLE 2. Selected papers distinguished by categories and publishers to review.

Main Categories	Publisher	Year	Author	Journal/ Conferences
Collaborative filtering	IEEE	2008	Wu, et al. [71]	Multimedia and Information Technology
	IEEE	2014	Choi and Kim [72]	Big Data and Smart Computing (BIGCOMP)
	IEEE	2014	Sivapalan et al. [107]	World Automation Congress (WAC)
	IEEE	2014	Sun, et al. [73]	Computing, Communication and Networking Technologies (ICCCNT)
	IEEE	2015	Lin and Wenzheng [74]	Intelligent Transportation, Big Data and Smart City (ICITBS)
	IEEE	2016	Aditya, et al. [75]	Advanced Computer Science and Information Systems (ICACSIS)
	Springer	2015	Cao, et al. [76]	National Conference on Embedded System Technology
	Trans Tech Publication	2012	Kuang [77]	Advanced Engineering Forum
	Elsevier	2018	Hwangbo, et al. [78]	Electronic Commerce Research and Applications
	Springer	2018	Jiang, et al. [79]	Journal of Ambient Intelligence and Humanized Computing
	Springer	2018	Gaikwad, et al. [80]	Information and Communication Technology for Sustainable Development
Demographic Based	IEEE	2008	Cho and Ryu [81]	Management of Innovation and Technology
	IEEE	2008	Fan, et al. [82]	Electronic Commerce and Security
	IEEE	2011	Souali, et al. [83]	Multimedia Computing and Systems (ICMCS)
Knowledge-based	IEEE	2010	Ya [84]	Digital Content, Multimedia Technology and its Applications (IDC)
	IEEE	2009	Martín-Vicente, et al. [85]	Semantic Media Adaptation and Personalization
	Springer	2014	Ku, et al. [86]	International Conference on HCI in Business
	Atlantis Press	2012	Luo [87]	International Conference on Computer Application and System Modeling
	Atlantis Press	2015	Xiaosen [88]	International Conference on Social Science and Technology Education
	Sage	2016	Huseynov, et al. [89]	Information Development
Content-based	IEEE	2013	Gatchalee, et al. [90]	Computer science and engineering conference (icsec)
	IEEE	2016	Gao, et al. [91]	Consumer Electronics-Taiwan (ICCE-TW)
	IEEE	2016	Chen, et al. [92]	Computer and Information Technology (CIT)
	Sage	2013	Palopoli, et al. [93]	Concurrent Engineering
	Trans Tech Publication	2014	Miao [94]	Advanced Materials Research
Hybrid	IEEE	2010	Qiu, et al. [95]	Intelligent Information Technology and Security Informatics (IITSI)
	IEEE	2013	Dong, et al. [96]	Systems, Man, and Cybernetics (SMC)
	IEEE	2015	Xue, et al. [97]	Industrial Engineering and Engineering Management (IEEM)
	IEEE	2016	Aprilianti, et al. [39]	Advanced Computer Science and Information Systems (ICACSIS)
	IEEE	2016	Jiao, et al. [98]	Control and Decision Conference (CCDC)
	Springer	2016	Zakharov and Philippov [99]	International Conference on Data Analytics and Management
	Springer	2017	Saini, et al. [100]	IFIP International Conference on Computer Information Systems and Industrial Management

in an extended diversity of settings [105]. Also, Bajpai and Yadav [106] provided an improved dynamic e-commerce RS by using web usage mining and content mining. They examined the proposed method and concluded the accuracy of the system in terms of precision, recall, and memory consumption in comparison with other traditional models. Also, based on the definition of the selected metrics that are expressed in section 3.3, we evaluated the selected papers.

In this section, we examine the selected papers in basic categories of RSs. Also, we review their methods, differences, benefits, and challenges.

A. COLLABORATIVE FILTERING MECHANISM

In this section, first, CF mechanisms and their fundamental aspects have been described in Section 5.1.1. Afterward, the selected papers are reviewed in Section 5.1.2. Ultimately, in Section 5.1.3 provides and compares their problems, advantages, and disadvantages.

1) OVERVIEW OF COLLABORATIVE FILTERING MECHANISM

CF, one of the most popular and widely implemented methods in RSs, is a technique utilized for linking the data of an applier with the data of other alike appliers depending on buying patterns to produce directions for the user for prospective shopping [71], [75], [85], [107]–[114]. Amazon uses CF techniques for making its recommendations depending on a client's previous buying and buying of those that bought the same products. E-commerce platforms use this technique to create market segmentation depending on client behavior compared to the psychographics and demographics metrics. Creating a database of user preferences and processing it optimally for the preparation of recommendations is the primary performance of this method [115]. Scalability and accuracy are two different critical issues associated with the CF technique. The problems of scalability and efficiency on a global scale require modern processing space and speed optimization to support customer satisfaction. Thus, CF is the most popular and successful technique that utilizes client ratings, details, and reviews gathered from the total clients to construct recommendations [116]. Several studies presented the proper framework [117]–[122].

There have been two principal modes of implementing collaborative filtering: a) memory-based approach, b) model-based approach [123]. The memory-based approach computes the resemblance among the appliers by computing the similarity function like cosine formula. The model-based approach uses some sophisticated methods like machine learning techniques to find patterns in the dataset and learn from them to employ the new data [124] and also some approaches like matrix factorization [125].

2) REVIEWING SELECTED COLLABORATIVE FILTERING MECHANISMS

Sivapalan *et al.* [116] showed the significant challenges of CF methods such as sparsity, scalability, and synonymy and expressed high personalization for users enabled by using RSs. The CF method uses the user ratings, reviews, and details gathered from the total appliers to produce recommendations by analyzing the active user with the same characteristics and preferences of the present applier. Moreover, the CF approach applies some resemblance measures, containing cosine metric, personalized data, and Jaccard coefficient. They concluded that due to data sparsity, sales volumes on large e-commerce sites are decreasing. Therefore, they suggested that the developers of the RSs stop using the nearest neighboring algorithms in implementing the RSs for large e-commerce websites. Because they make low accuracy in recommendations, and also the coverage metric reduces. Also, the similarity measurement of product or users is the essential neighborhood-based CF procedure component. Some measures like Pearson's Correlation, Cosine, and Adjusted Cosine often used for the CF method [126]. Some studies expressed new similarity measurement techniques for specific criteria in CF. For example, Patra *et al.* [127] showed a new one for sparse data.

Aditya *et al.* [75] examined the memory-based and model-based CF performance as two implementation plans using a data sample of an e-commerce case study. They evaluated each method by using offline and user-based testing and indicated that the model-based RS performs better compared to memory-based RS in the precision, the calculation time, and of recommendation relevance. They concluded that model-based CF is better compared to memory-based ones concerning calculational velocity in products of recommending. Also, they resulted in the model-based CF is better compared to memory-based ones in producing the recommendations depending on the mean number of related products comprehended by the applier. The study did not concern with some other features of RS performance, like variety, serendipity, coverage, and newness. Also, they implemented model-based and memory-based CF by using developed Naïve Bayes and Nearest Neighbor techniques.

Wu *et al.* [71] studied an improved CF-based recommender system for mobile e-commerce to provide personalized recommendations. The method comprises three primary operations: recommendation method module, output functions module, and input function module. Also, they stated that some problems like the attainment of data depended on the clear assessment by the user, insufficiency in spontaneously attaining obvious data of the user, and rarity of the information in system progress systems. Thus, they designed the Item Rating Prediction-based CF method to firstly prognosticating the client rankings for items unrated by the calculation of the resemblance among items and then determine the closest neighbors by attainment of a novel resemblance measuring procedure. Furthermore, they studied the item rating prediction-based CF to solve the specific sparsity of the user data problem in mobile electronic business. Finally, they suggested some issues required for ongoing progress and completeness in pragmatic utilization for future studies.

Cao *et al.* [76] designed and implemented a distributed SVD++ algorithm for enhancing the recommendation quality of the personalized items in an e-commerce platform. The SVD++ algorithm can use implicit and explicit feedback data of the client at the same time. Thus, they decided to evaluate the distributed calculation of the SVD++ algorithm. Also, they made use of the algorithm implemented in the real exam in the products recommended. They concluded that their proposed algorithm solves the problem of mass data processing with the data size up to TB level or scalability problem, and the difficulty of the sparse matrix to a determined limit, and notably improve the personalized product recommendation quality. Although this method has some significant advantages, it requires high processing costs. It also has a particular complexity due to the use of big data technology and distributed data platforms.

Lin and Wenzheng [74] designed and implemented a personalized recommender system in e-commerce depending on the web mining approach. As the web data such as content and structure have high complexity, the use of data mining or other technologies for providing them as the input data for use in e-commerce recommender systems has a certain complexity. The system considered the main functionality of any e-commerce project, such as user, commodity, and order management to provide the appropriate recommendations.

However, the performance of the proposed method is related to computing resources such as CPU power. Thus, the optimization and development of performance are necessary for further studies to apply the method for implementing RSs.

Sun *et al.* [73] proposed a big-data based retail RS based on CF by using the corresponding distributed computing algorithm on MapReduce. The method used cosine resemblance and Pearson resemblance correlations in the Item-CF algorithm. The importance of this research is that customers do not rate any items in real stores. Hence, the authors of the article examined the use of RSs for marketing activities such as selecting the most relevant store-product pairs and deploying product advertising. They concluded that, in addition to the effectiveness of the system on retail sales regarding goods and shops, it could deal with large-scale datasets and get further scalability and a new mean of accuracy marketing assistance. Because of the requirement to use the concept of big-data technology, this method has high computational cost and complexity.

Choi and Kim [72] proposed a recommendation mechanism using the iteration purchase number for goods for each client as the repurchase ratio measurement against a one-time purchase as the recommendation criteria and explored the repetitive purchase pattern. The repurchase ratio is one of the critical metrics of customer loyalty in business. The method offered three product groups by making use of a user-based CF method, item-based CF procedure, and by discovering Associate Products, which customers often buy them simultaneously. Thus, they used the user-based CF and item-based CF method to recommend the associate items analyzed by Association Rules. Also, they examined the sales data belonging to a firm for almost one and a half years to obtain the efficiency of the proposed method.

Also, Kuang [77] proposed the recommender systems in e-commerce, depending on the CF mechanism. Furthermore, due to a large number of users in real-world applications of e-commerce, the researchers should optimize algorithms in such a way to minimize the time it takes to respond to each user request and time spent. Despite the conventional algorithms, the effectiveness and reasonability of the proposed method in the accuracy of prediction of interest degree verified via the experimental datasets. He used the prognostication and real amounts of the Mean Absolute Error (MAE) as a standard measure for algorithm precision. Also, running the CF algorithms in e-commerce websites with a significant amount of data related to the products' and users' profiles have a high amount of the computational resources requirements to process in the RSs algorithms.

Hwangbo *et al.* [78] offered a procedure to suggest fashion goods for clients by enhancing the existing CF procedure to consider the features of fashion products. They also assessed offline and online modes of buying those products in their approach. Also, they recognized that the product that the client wants to buy is considered as a product that substitutes or completes the product that the consumer favored earlier. They employed the system to a real online shopping mall to prove the performance of it. They showed that the stated system produces further efficiency compared to the conventional collaborative filtering system regarding buying and customer. Also, the replacing suggestions are always better compared to supplementary offerings for buying and customers.

Jiang *et al.* [79] proposed a slope one algorithm depending on the integration of user resemblance and valid data. Their method uses three procedures: trusted data selecting, calculating the similarity between users, and including the resemblance to the factor of weight of the elevated slope one algorithm. Also, they used the Amazon dataset to show the more accurate performance of the proposed method than the customary slope one algorithm.

Gaikwad *et al.* [80] proposed a model-based CF recommender system depending on the eventual model with the utilization of developed Naive Bayes algorithm. They used query time, search query, and click time as the aspects of the model of the Naive Bayes algorithm. They resulted that their approach produces more precision than a basic Naive Bayes model.

3) COMPARISON AND SUMMARY OF THE MECHANISMS REVIEWED

In the previous section, we analyzed eight selected papers in CF mechanisms and their pros and cons. We found that some issues, such as the cold-start problem, low security, low trust, and high response time, are the main problems in the CF methods.

Table 3 illustrates the proposed methods and the comparison of the most significant pros and cons of each article. The problems with Low Scalability, Data Sparsity problem, Data acquisition problem, and high computational time are unsolved entirely in this mechanism. The method has advantages like better relevance, recommendation quality result, and considering the user experiences. Although efforts made by researchers to find solutions for these problems, this method still requires further development.

B. DEMOGRAPHIC-BASED FILTERING MECHANISMS

In the current part, first, DBF mechanisms and their fundamental aspects are explained in Section 5.2.1. Afterward, the selected papers are reviewed in Section 5.2.2. Ultimately, their problems and pros and cons are compared and considered in Section 5.2.3.

1) OVERVIEW OF DEMOGRAPHIC-BASED MECHANISMS

The DBF algorithms apply the users' demographic profile such as location, language, age, religions, and some useful parameters to accomplish the items' recommenders to the users. This technique makes the recommendations to be more relevant to the user realities [128]. Thus, it is widely used by e-commerce companies as an effective solution to respond to their user interests. Some RSs are based on the demographics of customers [28], [129], and it is necessary for e-commerce environments.

TABLE 3. Comparing the most significant pros and cons of the CF mechanisms of selected papers in recommender systems in e-commerce.

Paper	Method	Advantages	Disadvantages
Sivapalan, et al. [116]	• association rules • CF • CBF • hybrid filtering	• Widely used • Decreasing dimensional	• Low Scalability • Data Sparsity problem • Synonymy problem • Reduced coverage in the large-scale platform
Aditya, et al. [75]	• Memory-based CF • Model-based CF	• Improving relevance	• Low accuracy • High Computation time
Wu, et al. [71]	• Improving Personalized CF for Mobile e-Commerce	• Enhancing the recommendation quality	• Scarcity in development and application • Data acquisition problem
Cao, et al. [76]	• Distributed SVD++ Algorithm	• High Scalability • Enhancing the recommendation quality • Solving Data Sparsity problem	• Without considering security issues
Lin and Wenzheng [74]	• Web Mining	• Low response time • Considering the user's explicit data and behaviors	• High operation cost • Synonymy problem
Sun, et al. [73]	• Big data	• High scalability	• Without considering security issues
Choi and Kim [72]	• repetitively purchasing items	• Low operation cost	• Without considering user's behaviors without purchasing
Kuang [77]	• CF method	• Enhancing the recommendation quality • Widely used	• Low scalability • High computational time

2) REVIEWING SELECTED DEMOGRAPHIC-BASED MECHANISMS

Cho and Ryu [81] proposed an applied e-commerce personalized RS making use of the RFM method and the demographic data. RFM analysis involves the use of three key customer behavior metrics, including Recency, Frequency, and Monetary. Recency is the number of days since the last purchase of the customer. Frequency is measured as the number of orders placed within a specified period, and Monetary is the total amount of money spent by a customer in a specified time. On the other hand, they used several data groups ranked by demographic variables, including gender, age, customer's propensity, and vocation for the user's personal information. Also, they showed the procedure of the proposed system and given some technical concerns about its performance by using the implicit data without causing trouble for the user. Also, the system contains three agents: 1) analytical agent, 2) the recommending agent, and 3) the learning agent. They implemented for prototyping of the internet shopping mall that works for the cosmetics professionally [76]. The authors solved the new user or new item challenges using the clustering purchase data approach. Finally, the method has recommended the item with a high probability of purchasing and has increased the accuracy of recommendations experimentally.

Fan *et al.* [82] used the customer registration information or demographic characteristics of users as an essential source of data mining algorithms for implementing RSs in e-commerce websites. They proposed the workflow of a personalized recommender system in e-commerce that consists of four phases: 1) Acquire information explicitly and implicitly, 2) Preprocessing of the information, 3) Recommendations of the form, and 4) Indicating recommendation outcomes to clients. Plus, they employed a data diversity in e-commerce such as server log data, online market data, query data, hyperlinks inside web pages, web pages, and client registration data. Finally, the authors concluded that the proposed method improves the quality of recommendation efficiently. However, although the authors of the article presented the proposed approach concerning the great theoretical and practical significance and some advantages such as providing real-time recommendations and enhancing the recommendation quality, they did not show consideration about the privacy and the security.

Souali *et al.* [83] introduced an ethical-based RS using the data related to behaviors and customs with no intervention by the user. The method used the information written by clients within their registration level and depending on a catalog of the ethics. They expressed that they want to develop an enhanced RS that automatically supports ethics without the user intervention to examine the efficiency, accuracy, and some potential challenges. The significant problem with the use of DBF recommendation methods is that some individuals with similar demographic features may different interests. The detection of these differences is not possible by this method. Therefore, the researchers recommended using the DBF method in the hybrid approach. However, despite the high level of accuracy offered by the recommendation

TABLE 4. Comparing the most significant pros and cons of the DBF mechanisms of selected papers in recommender systems in e-commerce.

Paper	Method	Advantages	Disadvantages
Cho and Ryu [81]	• Personalized demographic -based RS and RFM method	• Solving new user problem • High accuracy	• Low efficiency • Low scalability
Fan, et al. [82]	• Data mining	• Real-time recommendation • Enhancing the recommendation quality	• Without considering security issues
Souali, et al. [83]	• Automatic ethical-based RS	• High accuracy	• New habit problem

results, it works poorly for new users because of the lack of demographic information.

3) COMPARISON AND SUMMARY OF THE MECHANISMS REVIEWED

In the prior part, we analyzed six selected papers in DBF mechanisms and their pros and cons. The selected papers mentioned that the main problem in the DBF method is data collecting about demographics. We need to do some preprocessing algorithms to achieve the related data.

Table 4 shows the proposed methods and the comparison conducted between the most significant pros and cons of the articles. One of the optimal choices is to use this method to solve problems such as over-specialization problem and new user problem. This technique has unique flexibility for use in different domains and increases cross-sell. With all of these benefits, issues such as the lack of attention to significant ethical challenges, the problem of user new habit and security, are still not entirely solved in this approach.

C. KNOWLEDGE-BASED MECHANISMS

In the present part, first, the mechanisms of the KBF in RSs and their fundamental aspects are explained in Section 5.3.1. Afterward, the selected papers are reviewed in Section 5.3.2. Ultimately, their problems and pros and cons are compared and explained in Section 5.3.3.

1) OVERVIEW OF KNOWLEDGE-BASED MECHANISMS

KBF recommender approach is depended on explicit knowledge about the criteria of the recommendation, item classification, and user preferences. In KBF RSs, a measure of distance or similarity utility like Euclidean distance and cosine similarity judges how much the recommendation match with user needs. Although solving the cold start problem is one of the strengths of this approach, the difficulty of understanding the need to define recommendation knowledge explicitly is its weaknesses.

2) REVIEW OF SELECTED KNOWLEDGE-BASED MECHANISMS

Ya [84] proposed using the expert system technology for implementing the personalized recommender system in e-commerce. The proposed method solved the complex e-commerce personalized recommendation problem, but high operation costs and highly complex systems are two significant disadvantages. The author suggested using a heuristic search and artificial intelligence (expert system) implementation method for future research for this domain.

Chun and Hong [130] presented a KBF product recommendation and implemented the proposed system using JESS (Java Expert System Shell) and Java servlet and examine it on a sample internet shopping mall that sells cellular phones. Also, the architecture of the proposed system consists of four sections: an inference engine, a user interface module, a client database, and a knowledge base of the product field. Given that the system was designed for the phone store, it stores and processes related data for this domain, namely score, picture, model, Service Company, manufacture, and price, so that it can generate related proposals. Information gathering fed on questioning the user and the system find the products that meet the user's requirements best. The product domain, inference engine, and user interface module are required parts of knowledge based on the system. Since the use of hybrid methods compared to the single plan is a better result, the authors of the paper suggested the implementation of the hybrid method, including CF and KBF, using JESS in the future studies.

Knowledge-based methods require the creation of a database containing information related to the goods or items in the area of use. For example, in a car shop, features like type, size, and color are stored in the database, and offers based on these features are provided to users. On the other hand, the combination of the method with CF usually provides better recommendations. Therefore, Tran [131] introduced a hybrid RS architecture that uses the integrating of KBF and CF techniques. Although using the KBF method does not depend on the user ratings of items, it is essential to know the features of the relevant field, so the weaknesses of the approach are the necessity of knowledge engineering, which is a difficulty.

Also, to solve the fake neighborhoods in e-commerce RSs, Martín-Vicente *et al.* [85] suggested a method depending on applying semantic logic for the CF mechanism. They decreased the size of the user interests' vector greatly to reduce the computational cost of the process. Also, the authors showed the improvement of the quality of recommendations. Two primary disadvantages of the proposed method are high data sparsity problem and low scalability.

Using the lab experiment, Ku *et al.* [86] outlined the significant attributes of e-commerce product RS as the important hints for designing RS. They chose and examined six significant attributes of RS concerning users' attitudes and preferences toward an RS interface. These features are description, rating, associated products, offered product number, client's review, and a comment of the review. They found that the feature "Explanation for Recommendation" is significant for all participants. "Rating" is essential for the particular members, and "Comment" looks to contain less important for all of them. They adopted a conjoint analysis for examining the differences in the clients' preferences for the quality integration of the interface of the RS. Also, they measured the significance ranking of RS's properties in various parts when RS appliers have been looking around the offered contents. Despite the valuable advantages of the method, like enhancing the satisfaction of the client and producing user trust, it does not solve the scalability problem. The RAs track online user action or collect data from the customer explicitly to provide high-quality recommendations about the services that the client may like them.

Huseynov *et al.* [89] assessed the influence of KBF Recommender Agents (RAs) on the online-client decision-making procedure, where the RAs track. they considered the length of the shopping, buying the necessary item, and the attempt to look for the essential products. They showed that KBF RAs enhance the client decision-making method by decreasing the length of the shopping and power used in looking for proper products. Furthermore, they concluded that the technique improves the quality of the decision, and increases the customer number who buy the items they want. Although the proposed method facilitates the decision-making process for users to purchase, authors of the article tested and evaluated it in a limited environment by university students, and to ensure results, and the system must be in a real situation with regular e-commerce users.

Luo [87] proposed a framework of Web mining based on the data clustering analysis, including content, web usage, and structure, to provide a high-quality recommendation for recommender systems in e-commerce. Moreover, He used pattern analysis in web mining to store knowledge rules on proper media and support the recommender engine. Finally, the author concluded that the proposed method could deal with large data volume, improving scalability, and response speed considerably. On the other hand, the system integrates all the results from web usage, content, and structure mining. It provides the quality personalized RSs in the cases where there is fewer usage data or frequent change of website content. With significant advantages such as improving the accuracy of resulted recommendations, the system still has some disadvantages, such as complexity and high computing cost. Plus, collecting various web data, such as structural, content, and usage data are challenging, complicated, and expensive.

Xiaosen [88] has analyzed and designed the requirements and function of personalized RS for e-commerce. He has tested respectively on mainly model of the front and back systems using a series of test data, and the results of experts recommended the decision algorithm model to validate the feasibility of the proposed model. Additionally, the method has examined in four levels: data collection, user modeling, the algorithm of recommendation, and recommend output. The proposed plan keeps the user model up to date in RSs by collecting and analyzing the user information regularly to build the user model and then rebuild the model after examining the feedback. The proposed model overcomes the new- user challenges because it will suggest the best-selling merchandise for new users. Also, for registered users, it uses the user characteristics resulted from some user-related data like age, occupation, interests, and hobbies.

3) COMPARISON AND SUMMARY OF THE MECHANISMS REVIEWED

In the prior part, we analyzed six selected papers in the mechanisms of the KBF and their pros and cons.

Table 5 illustrates the proposed methods and the comparison of the most significant pros and cons of the articles. Some problems like a cold-start problem, early-rater problem, and fake neighborhoods are solved using this method. Although they bring customer satisfaction and, in some cases, boost sales and enhance the recommendation quality, the problems such as low scalability and high operation cost still show up.

D. CONTENT-BASED FILTERING MECHANISMS

In this section, first, the CBF mechanisms in RSs and their fundamental properties are explained in Section 5.4.1. Afterward, the chosen papers have been reviewed in Section 5.4.2. In the end, in Section 5.4.3, their problems and pros and cons have been considered and compared.

1) OVERVIEW OF CONTENT-BASED FILTERING MECHANISMS

The RSs use the customer preferences and description of the items to filter the query resulting data and suggest the proper items to the user. Fundamentally, the CBF techniques recommend items or products which are similar to the items that user liked priorly or is looking for nowadays [84], [90]. In this case, items have been grouped by how closely they match the user attribute profile, and the best ones are offered. On the other hand, the CBF algorithms recommend the items that are like those the user liked priorly, but the CF methods recommend the items that similar users liked.

2) REVIEW OF SELECTED CONTENT-BASED FILTERING MECHANISMS

Gatchalee *et al.* [90] described an ontology development for small and Medium-Sized Businesses (SMEs) e-commerce website depended on the analysis method of the content for acquiring knowledge for developing RS based on this ontology. The proposed system consists of three main tasks: 1) content analysis, 2) Ontology development, and 3) Recommendation system for SME e-commerce websites.

TABLE 5. Comparing the most significant pros and cons of the KBF mechanisms of selected papers in recommender systems in e-commerce.

Paper	Method	Advantages	Disadvantages
Ya [84]	• Expert system	• Solving the complex e-commerce personalized recommendation problem	• High operation cost • High complex system
Martín-Vicente, et al. [85]	• Semantic reasoning techniques	• Avoiding Fake Neighborhoods • Improving the recommendation quality • Low operation cost	• High Data Sparsity problem • Low Scalability
Ku, et al. [86]	• Feature comparison for RS	• Increasing user satisfaction • Building user trust	• Low Scalability
Huseynov, et al. [89]	• KBF RA	• Enhancing the customer decision-making process • Increasing sales	• Low quality of evaluation method
Xiaosen [88]	• Personalized RS	• Realization of RS • High accuracy	• Low scalability
Luo [87]	• Web mining	• High accuracy	• High operation cost

The authors suggested that content analysis plays the primary role in developing ontologies of any domain for improving RSs. They defined the ontology domain as the SME e-commerce website in Thailand with the significant concepts of the ontology. The proposed method recommends sample websites with considerable relevance to meet user requirement rules. However, since SME e-commerce sites operate independently and different structures, collecting their essential information and analyzing them with changes over time may be problematic to provide the online recommendation.

The CBF techniques use structured and unstructured text documents, multimedia such as images, photos, songs, and other file formats to extract features. Recently, some studies introduced a sentiment analysis of contents and different machine learning algorithms to gather some useful inputs for recommendation components. Gao *et al.* [91] expressed that the limited resource is the primary challenge of the CBF approach and challenges of new users as well as other methods. Moreover, limited information or tags reduces the quality of recommendations.

Because of problems such as sparse and missing in the use of explicit information, the researchers try to use implicit information to explore user activities such as purchase, click, collection, and cart. Chen *et al.* [92] combined some types of user actions and timestamps to get better recommendation results. They introduced the At-BPR method to overcome the restriction of one kind of action in Bayesian Personalized Ranking (BPR) and other extensions to explore user preferences and got better-ranking performances experimentally. They used a global score function on the proposed method to assess the preferences of the user over various items. On the other hand, the authors employed two different sampling strategies in the experiments as an alternative to consistent sampling like BPR adoption. They suggested exploring another area like movie or music suggestion concerning a distinct life scene and novel time decay factor for future work.

Palopoli *et al.* [93] proposed a distributed architecture of RS depending on a system of the multi-tiered agent to generate more useful recommendations and reduce the operation cost. This plan overcomes the calculational difficulty on the gadget that the local agents operate, and the existence of determined agents enhances the clients' knowledge depiction. They conducted practical operations to assess the system performance concerning benefit by executing specific software. Also, the method has significant advantages concerning openness, privacy, and security. The authors suggested the principal issues, such as considering the various moral models of a B2C procedure and producing behaviors, examining other related features in a distributed environment like dependability, protection, and reliability.

Miao [94] has proposed the effective mobile recommender systems in e-commerce method. The method combines CBF technology with CF technology to get high accuracy in recommendations. Additionally, the author has introduced a weighted combination filtering RS that mainly consists of three modules: the input function module to collect required information about customer's personal and community groups, the core function module of RS to generate recommendations, and the output function module to provide the content for users. Meanwhile, the latest module uses the results of two sub-sections: the suggestion component and the prediction component.

3) COMPARISON AND SUMMARY OF THE MECHANISMS REVIEWED

In the prior part, we analyzed six chosen papers in CBF mechanisms and their pros and cons. Table 6 illustrates the comparing procedure of the significant pros and cons of the selected mechanisms. As the table shows, the author could

TABLE 6. Comparing the most significant pros and cons of the CBF mechanisms of selected papers in recommender systems in e-commerce.

Paper	Method	Advantages	Disadvantages
Gatchalee, et al. [90]	• Content analysis	• High scalability	• High operation cost • High response time
Gao, et al. [91]	• The limited resource table method • Considering users' location and time to solve the cold start problem	• Solving problem	• Without considering more complex parameter
Chen, et al. [92]	• User actions and timestamp -based Personalized RS	• Enhance the recommendation quality • High performance	• Required to consider more parameters
Palopoli, et al. [93]	• distributed RS based on multi-agent system	• Enhance the recommendation quality • High performance • High security	• High network traffic
Miao [94]	• Hybrid based on CBF and CF	• Enhance the recommendation quality	• High operation cost

consider some more complex parameters to get better results in their methods. Also, this point needs to be worked on the optimization of the proposed algorithms. Although this method solves the problems like cold-start and the complex e-commerce personalized recommendation, it improves the quality of resulted recommendations compared to other methods. However, it still has problems such as increased processing resources. On the other hand, to enhance the accuracy of this method, we need to consider more parameters, which increases the response time and the need for storage and processing resources.

E. HYBRID MECHANISMS

In the current part, first, the hybrid mechanisms in RSs and their fundamental aspects have been explained in Section 5.5.1. Afterward, the selected papers are reviewed in Section 5.5.2. Ultimately, their problems and pros and cons have been compared and considered in Section 5.5.3.

1) OVERVIEW OF HYBRID MECHANISMS

We use hybrid RS to create a more robust RS by joining various algorithms and methods. Hybrid RS provides all the benefits of algorithms and reduces their disadvantages effects. For example, by linking CF methods, where it breaks in un-rating new items, with content-based models, anyplace that aspect info on the items is available, novel items may be offered more accurately and more efficiently [39], [96].

2) REVIEWING CHOSEN HYBRID MECHANISMS

Dong *et al.* [96] proposed a personalized hybrid RS to address the challenges that traditional algorithms face in the growth of the number of products and users of the e-commerce platforms, such as improving accuracy in user's interests modeling, providing high diversity, and supporting large-scale expansion. Also, the method can support massive dataset. However, they designed and implemented the technique using MapReduce to speed up the execution process of RS algorithms and cloud technology, highlight the system performance, and solve the scalability challenge. The authors employed several RS algorithms to use in various web pages of real e-commerce applications to meet various necessities of the user. They tested the method on a real platform and showed an increase in system performance. They suggested the improvement of parallel processing optimization for future studies.

The hybrid approach in RSs is the use of several different algorithms for collecting and processing information of the users or the items that improve the quality of recommendations. Zakharov and Philippov [99] proposed a hybrid method for data preparation for recommender systems in e-commerce. They solved the cold-start problem using the Item-Item CF algorithm and User-User CF. Explicit and implicit user data clustering is the base of both algorithms. They concluded that their proposed method could raise the number of resulting products in fewer clicks than the plans that do not make utilization of the implicit data. The system produces a simple environment and empowers the visitors' fidelity toward the online resources that, in the medium term, may result in increasing the returning observations and the production of the pool of loyal clients, who certify constant yield enhancement of the online shop.

Also, Xue *et al.* [97] advanced hybrid RS using the Bipartite Network Recommendation model depending on the allotment of the resource and developed the CF model to optimize the accuracy and coverage of the recommendation results. They employed a graphing approach to abstract items and users as its nodes and mined purchase information and user click behavior to get user preference ratings. Moreover, the conclusion has shown the improvement of recommendation accuracy and customer satisfaction. Furthermore, because of the shortcomings mentioned in the research, such as the limitation of the experimental use of e-commerce transaction data and lacking demography and other commodities features, they suggested some open issues for future researches.

These issues are considering the feeling mining to assess the client's preferences, and examining the environmental factors to conduct the more proper personalized suggestion.

Qiu *et al.* [95] studied the complex e-commerce architecture, which can collect multiple data types, use a difference of recommendation methods for meeting the requirements of various recommendation service sorts. They schemed a multi-mode recommender system in e-commerce to improve accuracy and comprehensively of recommendations. On the other hand, the approach collects a wide range of user's information, combines with a variety of recommendation methods that can learn from each other, and finally comprehensively consolidates all results into an overall conclusion to provide the users' goods of service recommendations. Moreover, the proposed system solved data sparsity and cold-start problems and has advanced high efficiency with low response time. Ultimately, although this method solves the above problems, it has a high operating cost, and some optimizations are needed.

Aprilianti, *et al.* [39] proposed and implemented a weighted parallel hybrid method for recommender systems in e-commerce in Indonesia, which is a combination of the CF and CBF approaches. Additionally, the proposed plan can overcome the weaknesses of those two methods, such as the item diversity shortage to be offered to the client in CBF, and the cold-start issue in CF [132], [133]. However, the disadvantages of the system are the impossibility of providing the recommendation for new users and the inability of recommending the new products to users. Furthermore, the authors of the paper also suggested issues such as considering more details of products like categories, price, description for use in CBF algorithms, and other hybridization like monolithic hybrid and pipelined hybrid for future studies.

Saini *et al.* [100] proposed an approach to detect the sequences coming after clients while buying products to develop the RS effectiveness. Since the purchase of some products frequently takes place step by step, the idea of using sequence pattern mining provided by the study. Contrary to other methods that consider customer profile and product description, the authors not taken into account the users who not made any purchases, which is one of the weaknesses of this approach. The proposed method improved the RSs by suggesting various items that are carried one by one after some months. Also, they evaluated the accuracy of the system with testing data and showed a big advantage. However, they proposed the future work to discover sequences for the particular client or the same client by employing a similar approach and include the sequences that come after the client in many years.

As most e-commerce platforms and search engines do not contain sentiment and semantic offering features, Shaikh, *et al.* [134] proposed a system that considers semantic factor and sentiment in RS to get an improvement in their recommendations, and they proved their opinion. They applied the graph algorithm, and the tags attached product images with the assistance of overlap formula to complete their approach. Also, they compared the well-known e-commerce websites like Amazon, eBay, FlipKart, Snapdeal, and Paytm in the article. In the approach, they stored better modeling of the item and client information in the database and considered some abundant information like feedback, and multi-criteria ratings in RSs. The authors proved that the proposed method could successfully integrate recommendations and semantics to improve products or services recommendation results.

Jiao *et al.* [98] presented the fuzzy theory to cope with the clients' data of the behavior and classify the result of quantitative semantic analysis of the trade comment text data. They built the personalized recommendation model and improved its accuracy using the applied evaluation and optimization function with the case study. As both users' data and items' data have similar data analyzing and processing, they recommended the optimization of the situation. On the other hand, they defined their proposed model in five levels, including purchase database, customer shopping website, data format, customer shopping personalized recommendation, and the customer level. The authors showed the growth of user satisfaction using the radar chart and considered the user's experiences by providing high accuracy.

3) COMPARISON AND SUMMARY OF THE MECHANISMS REVIEWED

In the prior part, we made an analysis of eight chosen papers in hybrid mechanisms and their pros and cons.

Table 7 illustrates the proposed methods and the comparison of the most significant pros and cons of the articles. This method works better than the previous ones. In other words, in this method, given the combination of several methods, the results are more accurate. However, it requires more processing times and higher computational costs.

VI. RESULTS AND COMPARISON

We categorized and mentioned some of the RS methods in the previous section. We reviewed five basic techniques, including CBF, CF, DBF, KBF, and hybrid, with expressing the advantages and disadvantages for each model. Also, we compared the selected paper for such challenges and issues as cold start, scalability, response time, data sparsity, accuracy, performance, and security.

Table 8 demonstrates an overview of the analyzed techniques of the RS and their fundamental challenges and issues like answer time, protection, precision, scalability, diversity/novelty/serendipity, operation cost, implicit/explicit data source, and independence. These features obtained from selected papers and scored by a checkmark (✓), cross (×), and minus (-) sings. The minus and checkmark signs indicate the least and the most incidents of these aspects, respectively. Moreover, Checkmark sign shows that the authors expressed the metric as the advantage of the proposed method. On the other hand, the cross sign represents the disadvantage of the feature. The minus sign explains that the authors not considered the issue in the selected paper. A number of

TABLE 7. Comparing the most significant pros and cons of the hybrid mechanisms of selected papers in recommender systems in e-commerce.

Paper	Method	Advantages	Disadvantages
Aprilianti, et al. [39]	• Weighted parallel hybrid RS	• High accuracy • High scalability	• High response time • High operation cost
Dong, et al. [96]	• Personalized Hybrid RS (with considering mass data in the cloud)	• High scalability • Low response time • High accuracy	• High operation cost • Without considering optimization issues
Zakharov and Philippov [99]	• Clustering real implicit data	• Improving the efficiency of the recommendation • Solving cold start problem • Considered both implicit and explicit user data	• High operation cost • Without considering security issues
Xue, et al. [97]	• Intelligent mining on purchase information	• High accuracy • Solving data sparsity problem • Improving coverage of the recommendation	• Without considering the user's experience
Qiu, et al. [95]	• Multi-mode recommender system in e-commerce	• Solving data sparsity problem • Solving cold start problem • High accuracy • Low response time	• High operation cost
Saini, et al. [100]	• Sequential purchase RS	• Improving the efficiency of the recommendation • Low response time	• Without considering the users without any purchases
Shaikh, et al. [134]	• Graph-based	• Improving the efficiency of the recommendation	• High operation cost
Jiao, et al. [98]	• Customer trade behavior	• High accuracy • Considering the user's experience	• High operation cost

the mentioned aspects are stated implicitly. Accordingly, the investigators determined the implicit aspects by content analysis of the chosen papers and scored them.

In the Diversity/Novelty/Serendipity column, the letters "D," "N," and "S" are used instead of diversity, novelty, and serendipity, respectively. If the method does not any of these features, a minus sign is used. In the next column, the letter "I" indicates the implicitness of the data, and the letter "E" indicates the explicit type of data used for the proposed method. If we show the "IE"; it means that both data types are used by the method. Finally, in the last column, the letter "I" shows the independence of the implementation, like RA; otherwise, the letter "D" means that it should be used in the current e-commerce platform. Both letters "DI" are for the proposed method that can be used in both cases.

It is important to note that the results obtained in this review study were conducted only by comparing selected articles and cannot be generalized to all methods of recommender systems. For example, an article may have been intended to increase scalability and ignore security issues. However, in general, each method may consider several metrics we studied and ignore others due to the nature of the research. We suggest that researchers set their goal to balance the essential metrics in their innovative methods because the efficiency of new methods is measured based on the results of various metrics. Also, our selected metrics may be useful in all systems and do not specialize in recommender systems. For example, accuracy is the most critical metric for any information environment, especially in recommender systems.

The results of the given comparison in Table 8 pointed out that the authors of the selected papers have focused on accuracy, response time, and scalability. Since many articles did not meet our search criteria, we do not recommend to generalize the conclusion. For instance, security is a vital metric in many systems, but we resulted in many of the selected papers have ignored it.

Figure 6 shows a stacked column diagram of the metrics we reviewed in the selected papers.

Figure 7 shows a bar chart of the distribution of diversity, novelty, and serendipity of recommended items in e-commerce methods in the selected papers. According to

TABLE 8. An overview of the discussed RSS techniques and their main features.

Main Categories	Paper	Security	Response time	Scalability	Accuracy	Operation cost	Diversity Novelty Serendipity	Implicit Explicit Data Source	Independence
Collaborative filtering	Sivapalan, et al. [116]	×	×	-	✓	×	-	IE	D
	Aditya, et al. [75]	×	-	×	-	-	-	E	D
	Wu, et al. [71]	×	×	×	✓	-	-	E	D
	Cao, et al. [76]	-	×	✓	✓	×	D	I	I
	Lin and Wenzheng [74]	×	-	×	✓	-	D	I	I
	Sun, et al. [73]	×	✓	✓	×	×	DN	I	I
	Choi and Kim [72]	×	✓	×	×	-	D	I	D
	Kuang [77]	×	×	×	✓	×	-	E	D
	Hwangbo, et al. [78]	×	×	×	✓	-	-	E	D
	Jiang, et al. [79]	×	✓	×	×	-	D	I	D
	Gaikwad, et al. [80]	×	×	-	✓	×	-	IE	D
Demographic Based	Cho and Ryu [81]	×	×	✓	✓	×	DN	I	D
	Fan, et al. [82]	-	✓	×	✓	×	DNS	I	D
	Souali, et al. [83]	×	×	×	✓	×	DN	I	D
Knowledge-based	Ya [84]	×	×	×	✓	-	DN	I	I
	Martín-Vicente, et al. [85]	✓	×	-	✓	✓	DN	I	I
	Ku, et al. [86]	✓	✓	-	×	×	D	I	D
	Huseynov, et al. [89]	-	✓	×	✓	-	-	IE	I
	Xiaosen [88]	×	×	-	✓	×	DN	IE	I
	Luo [87]	×	-	✓	✓	×	DN	I	D
Content-based	Gatchalee, et al. [90]	×	-	✓	×	-	DN	I	I
	Gao, et al. [91]	×	×	✓	×	×	DNS	IE	DI
	Chen, et al. [92]	×	✓	×	✓	-	-	I	D
	Palopoli, et al. [93]	✓	-	✓	✓	✓	-	IE	I
	Miao [94]	×	✓	×	✓	✓	D	IE	I
Hybrid	Aprilianti, et al. [39]	×	-	✓	✓	-	DN	IE	D
	Dong, et al. [96]	×	✓	✓	✓	-	D	I	D
	Zakharov and Philippov [99]	×	✓	×	✓	-	D	I	D
	Xue, et al. [97]	×	×	-	✓	×	DN	IE	D
	Qiu, et al. [95]	×	✓	×	✓	-	DN	IE	DI
	Saini, et al. [100]	×	✓	×	✓	×	-	I	D
	Shaikh, et al. [134]	×	×	×	✓	-	D	I	D
	Jiao, et al. [98]	×	✓	×	✓	-	-	I	D

Figure 7, diversity/novelty is the most considerable approach to the selected papers' authors.

Figure 8 shows a bar chart of the distribution of implicit/explicit/both data sources for using e-commerce algorithms in the selected papers. Because of using these factors by recommender systems in e-commerce, the user's fatigue disappears from repetitive and known recommendations in the system. Also, it can be valuable in improving the

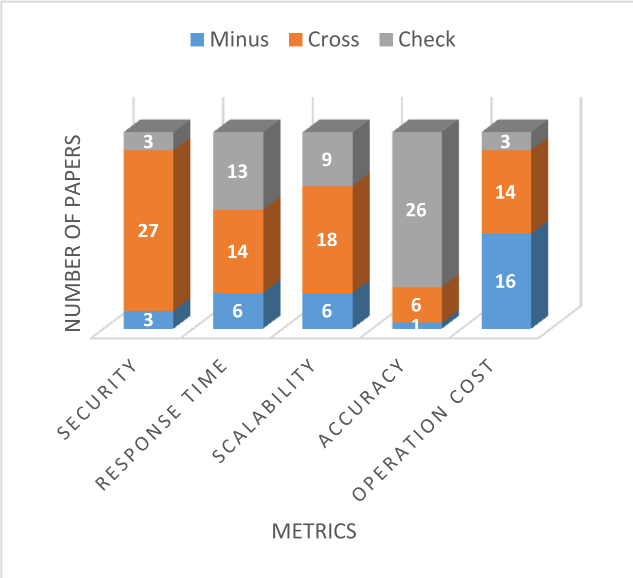

FIGURE 6. The stacked column diagram of the metrics based on comparative analysis.

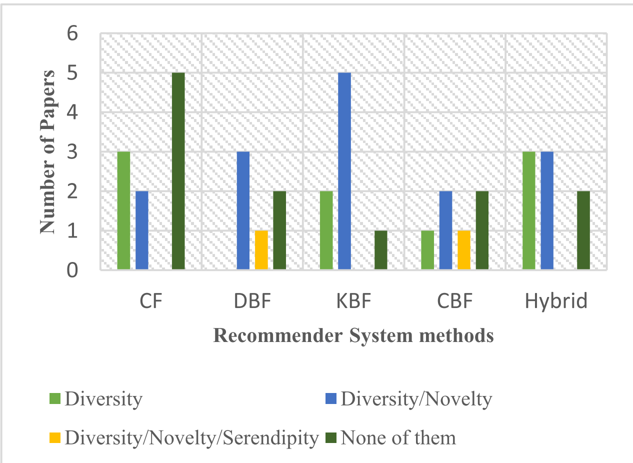

FIGURE 7. The bar chart of the distribution of using the diversity/ novelty/ serendipity in the reviewed papers.

level of customer loyalty. We propose these essential topics for future studies.

Figure 9 shows a bar chart of the distribution of the independence feature of selected papers. According to Figure 9, dependence is the most considerable approach to the selected papers' authors. In other words, most papers studied methods that are independent of the current e-commerce system and connect the system to operate. Thus, the independence property of the RS method needs to research in future studies, especially in DBF and Hybrid methods, when issues such as network overhead and information security are also of paramount importance at the same time.

VII. OPEN ISSUES

As far as RSs are concerned, many vital issues are outside the scope of the current research. This section covers the

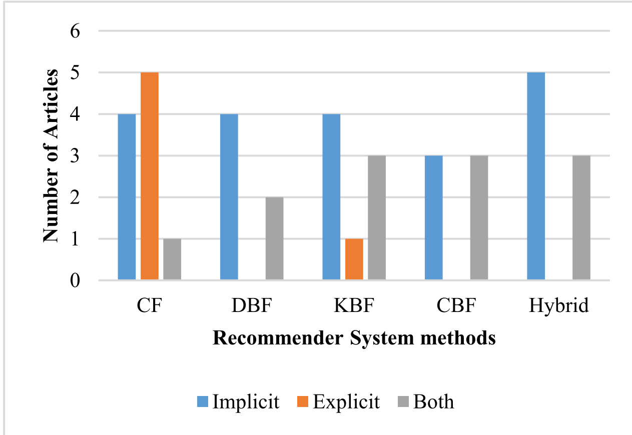

FIGURE 8. The bar chart of the distribution of using implicit or explicit data in the reviewed papers.

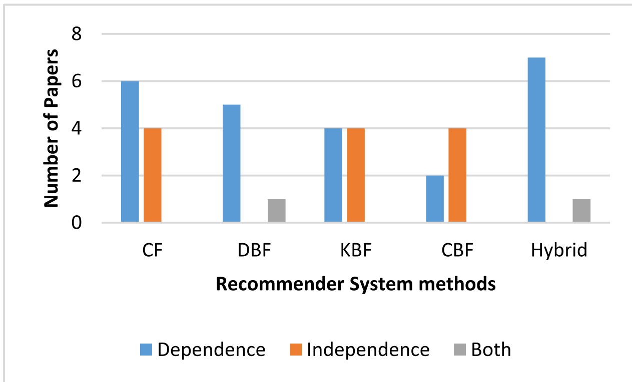

FIGURE 9. The bar chart of the distribution of Independent feature in the reviewed papers.

open problems of the matters discussed for future studies. It is undeniable that no technique includes all issues relating to recommender systems in e-commerce. For example, some methods provide scalability or response time, while some ignore these concerns. Also, some algorithms used the computer simulation plan while some others use evaluation frameworks. Such methods can be examined in a real-world e-commerce platform to offer efficient results. Furthermore, the authors of selected papers addressed some significant ideas of the discussed algorithms to be investigated in future studies. The personalized and context-sensitive recommendations to mobile users are very interesting for future research because of the complexity of mobile data, data distribution in some fast-changing of the environment related to the e-commerce platform, data sparsity problems, big data era, and numerous dimensions of data [34].

To enhance the quality of recommendation in recommender systems in e-commerce, many researchers suggested various algorithms, especially for CF mechanisms. The CF methods face some challenges such as sparsity, scalability, and cold-start problem. Thus, even though e-commerce websites widely use recommendation techniques to improve their business, Sivapalan *et al.* [116] expressed that they still face some research and practical challenges, including scalability, rich data, consumer-centered recommendations, anonymous users, and connecting recommenders to markets.

Suitable data types for use in recommender systems in e-commerce include on-site user activity (clicks, searches, page, and item views), and off-site user activity (tracking clicks in the email and mobile applications), particular items or user profiles data [135], and contextual data (the device used, current user location, and referral URL). On the other hand, the RSs requires sufficient data to run their algorithms more carefully and provide the relevant recommendations. Big data makes this possible [136]. However, its significant problem is the high consumption of CPU and memory. To solve the problem, the researchers proposed some solutions such as using Hadoop and Mahout or some tools such as PredictionIO. The traditional methods for processing this large volume of data are not suitable at high speed. Therefore, the researchers should develop new strategies for using e-commerce data generated, especially on globally-developed Web sites.

On the other hand, some studies do not consider all mentioned metrics in section 6 to improve the proposed systems. For example, many researchers focused on their methods, and they did not mention security. So security gets the minimum focused against all other evaluation metrics in the selected papers. In the real-word, the performance of the recommender systems in e-commerce depends on multi-criteria. For instance, Aznoli and Navimipour [32] pointed to some limitations of all RSs, such as the lack of data and a large amount of data, changing data, changing users' preferences, unpredictable items, and complexity.

In content-centric techniques, problems like overspecialization, limited-content analysis problems, and new user problems may occur.

Thus, in summary, the most important challenges in RSs in e-commerce are the limitations related to big-data problems or scalability challenges [121], Internet of things and personalized RSs, shared clients or devices, unknown user problem, and multilingual and contextual processing matters. Based on the previous section results, we found some open issues such as operation cost, optimization, and security in the field of RSs in e-commerce [137].

Nevertheless, despite extensive and useful research in the field of recommender systems in e-commerce, there are still some issues that need to be considered for future researches. Accordingly, the research is required to consider the following RSs limitations in the field of research and propose relevant solutions:

Both a lack of data and a significant amount of data cause problems in recommender systems in e-commerce. There are reasons to suggest that RSs result in useful recommendations through the consideration of the adequacy of data. On the other hand, a vast amount of data consumes more computational resources and increases the response time for the user. Therefore, future researches need to consider both issues.

Considering data changes and users' preference changes in such systems is essential. Changes in the level of consciousness in the community cause a change in the user's temperament, so the recommender system should consider these changes to process the results following the user's desire.

Getting a complete picture of the user is so challenging because it needs to use and analyzing more data resources about the user. Therefore, it is necessary to make more relevant recommendations by joining different data sources and possibly using user activities on other websites or social networks. It is also necessary that the results do not fatigue the user, so it is vital to consider diversity, novelty, and serendipity in the recommendations for each user.

The technical issues associated with algorithms used in RSs, such as complexity and optimization, distributed methods, and creative approaches, are also suggested as future studies.

VIII. CONCLUSION AND LIMITATION

In this paper, the researchers exposed the systematic literature review of the latest issues in recommender systems in e-commerce. According to the performed SLR in recommender systems in e-commerce mechanisms from 2008 to 2019, the number of published papers are discovered very high in 2016. Additionally, famous publishers published most of the selected papers. We classify 33 preferred studies in five categories that 11 of them are CF techniques, three of them are DBF techniques, six of them are KBF, five of them are CBF, and eight of them are Hybrid techniques. We summarized the selected papers and showed the comparison and evaluation of each proposed mechanism with significant advantages and disadvantages to point out the essential issues for future researches.

Furthermore, all selected mechanisms are compared based on some crucial metrics such as security, response time, scalability, accuracy, operation cost, diversity/novelty/serendipity, implicit/explicit data source, and independence. The results confirmed that most of the studies work to improve the accuracy of recommendations, but security, response time, novelty, diversity, serendipity are not considered in many papers. In this study, we found that collaborating filtering techniques were used more than all other methods. However, the latest papers focused on new approaches such as data and web mining algorithms, neural network-based methods, and genetic algorithms. We expressed the most critical open issues related to recommender systems in e-commerce.

Research limitations generally result from the choice of papers, the selection method of relevant issues, used techniques of analysis, and interpretation of review. We attempted to perform the systematic study of RSs used in e-commerce carefully, but it might some limitations. In this regard, future studies must take into account the limitations of the current research as follows:

- **Research Scope:** Although the subject reviewed and documented in many scientific documents, such as academic publications, technical reports, editorial notes, and web pages, books, and papers, we limited just academic leading international journals to obtain the best qualification. We excluded the papers published in national journals and conferences.
- **Study and publication bias:** We decided Google scholar as a reliable source for our search. However, there are all restrictions on Google Scholar in the present study. So, we do not claim that we found and reviewed all of the related items.
- **Study queries:** We preferred some keywords to select the relevant papers and search those in the title of papers. There may be research in which the research title does not include the different combinations of our selected keywords, but the article is entirely relevant to the subject. Therefore, we did not recognize such items.
- **Classification:** We ranked the selected papers in some categories, but it can be arranged creatively, too.

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PEGAH MALEKPOUR ALAMDARI received the B.S. degree in computer and software engineering from Islamic Azad University International Jolfa Branch, Jolfa, Iran, in 2010, and the M.Sc. degree in computer science from Tabriz University, Tabriz, Iran, in 2013. She is currently pursuing the Ph.D. degree with the Department of Computer Engineering, Qeshm Branch, Islamic Azad University, Qeshm, Iran. Her research interests include recommender systems, E-commerce, machine learning, data mining, and programming.

NIMA JAFARI NAVIMIPOUR received the B.S. degree in computer and software engineering and the M.S. degree in computer engineering and computer architecture from Islamic Azad University at Tabriz Branch, Tabriz, Iran, in 2007 and 2009, respectively, and the Ph.D. degree in computer engineering and computer architecture from Islamic Azad University Science and Research Branch, Tehran, Iran, in 2014. His research interests include QCA, cloud computing, grid systems, computational intelligence, evolutionary computing, and wireless networks.

MEHDI HOSSEINZADEH received the B.E. degree in computer hardware engineering from Islamic Azad University (IAU) at Dezful Branch, Iran, in 2003, and the M.Sc. and Ph.D. degrees in computer system architecture from IAU Science and Research Branch, Tehran, Iran, in 2005 and 2008, respectively. He is currently an Associate Professor with the Iran University of Medical Sciences (IUMS), Tehran. His research interests include SDN, information technology, data mining, big data analytics, E-commerce, E-marketing, and social networks.

ALI ASGHAR SAFAEI received the B.Sc. degree in computer software engineering from Shahid Sattari Air University, Tehran, Iran, in 2001, the M.Sc. degree in computer software engineering from Ferdowsi University, Mashhad, Iran, in 2004, and the Ph.D. degree in computer software engineering from the Iran University of Science and Technology, Tehran, in 2011. He is currently an Assistant Professor of the Department of Computer Engineering, Tarbiat Modares University, Tehran. His research interests include medical software design, nursing informatics, free/open-source software (FOSS) development, advanced databases, advanced software engineering, and distributed systems.

ASO DARWESH received the B.Sc. degree in mathematics from the University of Sulaimani, Iraq, in 2001, the M.Sc. degree in computer science from the University of Rene Descartes, in 2007, France, and the Ph.D. degree in computer science from the University of Pierre and Mari Curie, France, in 2010. He is currently an Associate Professor with the Department of Computer Science, University of Human Development, Iraq. His research interests include serious games, adaptive learning, and cognitive diagnosis in E-learning.