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RESEARCH ARTICLE

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Social networks data analytical approaches for trust-based recommender systems: A systematic literature review

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Summary

With the explosive growth of information on the web and the quick provision of novel web services, recommendation systems have emerged as efficient mechanism for providing advice regarding items in which users might be potentially interested. However, a traditional recommender system, which solely mines the user's previous behavior and item descriptions for recommendations, has some drawbacks. To overcome these limitations, a new solution that has recently garnered significant attention is using trust data. This approach, however, presents challenges in utilizing suitable trust data according to recommender systems applications, underlying social network structures, and user needs. In addition, in a selective decision-making system, trust, as a kind of social network data, plays a significant role and needs an appropriate approach for making inferences. This article provides a systematic literature review of the current trust-based social recommender systems. It also presents a detailed categorization of the trust type utilized and inferred from the existing trust-related social networks data analytical approaches. Furthermore, it addresses the main properties and challenges of the most popular trust-based social recommendation systems. Finally, it presents our findings and discusses open issues that provide researchers with insight to develop more enhanced recommender systems.

KEYWORDS

social network data analytical approaches, systematic literature review, trust-based social recommender systems

1 | INTRODUCTION

Because of the expansion and inundation of information existing on the web in addition to the fast presentation of novel web services, information overburden has turned into a great challenge encountered by users, and providing a means of aiding users to find information they are interested in has attracted considerable attention in both application and research areas. For this purpose, recommendation systems have appeared as an efficient technique presenting advice on items (e.g., friends, services, movies, and so on) in which users might potentially be interested. In recent years, recommender systems have demonstrated that they are a valuable means for solving the mentioned above information overload problem.[1] Furthermore, they are mostly pertained to machine learning, data mining, information retrieval and other research areas outside the scope of this study. Recommendation systems are generally classified into four main categories: demographic filtering systems, content-based methods, collaborative filtering methods and hybrid approaches.

Though recommendation systems have been extensively investigated in both the industry and academia, the following major problems still persist: the sparsity problem which defines the conditions that a small fraction of the existing items is rated by users; the cold-start problem which defines users with no or few ratings or defines items with few provided ratings by users; and trustworthiness problem that represents the inability to distinguish users' credentials and ratings.

Hence, a traditional recommender system, which solely mines the user's previous behavior and item descriptions does not have the capability of providing accurate and reliable suggestions. Significant research has been carried out to address the abovementioned issues and novel results have been accordingly presented. Among the presented techniques, a type of creation that has attracted a great deal of interest is integration of social networks information as a supplementary information to the traditional recommender systems data.[2,3]

Analyzing social networks has been an important scope of investigation for sociologists for many years. Lately, the evolution of Web 2.0 has received substantial attention in addition to the vast growth of social networking-based applications' utilization, blogs, and user review websites. Such media provides unique features to the Web such as an inherent link between users, the tags provided by users and high update rate. These specifications could be utilized for mining needed information toward the dynamics of user interactions. One popular kind of analysis is specifying users' groups which have similar preferences. Another type of analysis is specifying the content which might potentially be interesting to users, be it a posted tweet, a product or a blog. It has been proven that utilizing social network information improves the recommendation process.[4] Moreover, among the various types of social information used, one which has attracted much attention and has played a significant role in enhancing recommender systems is the trust factor. However, in spite of their widespread utilization, recommender systems that use this factor still need further improvement in various aspects such as identification of important contextual information for the trust factor, creating appropriate solutions for inferring trust information from different social networks data, identifying the limitations and shortcomings of common algorithms, social data usage, the use of appropriate social data, and probable special conditions of each environment. For instance, in relation to the matrix factorization method, which is a commonly used method in trust-based recommender systems, setting the initial value for it is effective in the final result. Therefore, finding a solution to set the appropriate initial value can help to further enhance the system. In addition, when the purpose of the trust-based recommendation system is to suggest an interesting event, there is the limitation of not having feedback from the users. Therefore, in this situation, it will be useful to adopt the appropriate solution and use other complementary social data in addition to the trust information. Time and bias of trust value are two main contextual information that should be considered when utilizing trust factor. Hence, the identification of other contextual information will further enhance the trust-based recommendation results.

However, to the best of our knowledge, despite the usefulness of trust-related social networks data for recommender systems and the aforementioned issues, no precise and comprehensive systematic review of its analytical approaches exist. Reviews of the challenges of recommendation systems, location-based recommendation systems, link prediction recommendation, the cold start problem of new users in recommendation systems, mobile-based recommendation systems and personalization of recommender systems have been carried out. However, none of these reviews are related to trust-based social recommender systems, which demonstrates the novelty of the present research topic. So, the aim of this research was to investigate the existing approaches for trust-based social recommender systems. For this purpose, it was determined that social networks data analysis approaches for trust-based social recommendation systems can be investigated from two categories: trust of items-based category and trust of relationships-based category. Trust of items-based category investigates the recommender systems with main focus being on determining the more trustworthy products by utilizing the underlying network attributes in order to compute their trust degree. However, trust of relationships-based category considers the recommender systems, which use explicit or implicit friendship strength between users for utilizing their opinions for recommendations. In addition, the trust-based social recommender systems were surveyed, social networks data utilized in the current trust-based approaches for recommendation was presented, the differences between applied techniques for utilizing these data was compared, the types of challenges that could be addressed were outlined, the evaluation parameters for investigating the improvements achieved with social networks data utilization were presented and the opinions on some important weaknesses of these trust-based recommendation systems were provided. Furthermore, nine questions were formalized in order to explore the most significant studies (current trust-based social recommender systems) by answering each of these questions. In summary, the present paper's contributions to existing knowledge are as follows:

- Analysis of trust-related social networks for recommendation systems approaches based on evaluation goal, metrics, measures, datasets, benchmarks, and case studies
- Investigating the upcoming challenges for recommendation systems and the functionality that trust-related social networks data can have
- Presenting key finding of current social trust-based recommendation systems from different perspectives using a systematic review
- Defining key areas that future research can enhance the trust-related social networks data's utilization for recommendation systems

The results of this paper present a detailed categorization of the trust types utilized and inferred from existing trust-related social network data analytical approaches. We also identify the growing significance of trust-related social network data with increasing usage of recommendation systems.

Furthermore, we analyze the main properties of the most popular trust-based social recommendation systems. This analysis encompasses their main ideas, techniques, utilized trust-related social network data, their improvements, weaknesses, and the challenges they face. Additionally, we delve into the evaluation properties of these recommender systems, focusing on the metrics that have received more attention for improvement, the measures employed to enhance these metrics, and the datasets used for evaluation.

We also identify more effective trust-related data in improving trust-based recommender systems and address the most being recommended data. Lastly, we present our findings and highlight open issues, providing valuable insights for researchers seeking to develop more advanced recommender systems.

The present article is organized as follows: The main concepts and associated terminologies are discussed in Section 2. Section 3 depicts the research methodology. Section 4 explains recommender systems techniques utilizing trust-based social networks data and categorizes them based on its analytical approaches. Section 5 describes the results. Discussion of the findings are provided in Section 6. Open research issues are discussed in Section 7. Finally, Section 8 presents the concluding remarks.

2 | MAIN CONCEPTS AND ASSOCIATED TERMINOLOGIES

This section presents the main concepts and associated terminology widely used in the trust-based social recommender systems. These main concepts and associated terminologies describe the recommender systems, metrics, measures and real datasets used in the primary studies.

2.1 | Recommender systems

Recommender systems: Recommender systems are an effective mechanism capable of filtering a humongous amount of information available on the World-Wide-Web and returning those most likely to be of interest to users by providing a more dynamic and personalized services.[5]

Content-based recommender systems: These recommender systems provide recommendation by making a comparison between the content of an item with the features of the user's favorite content.[6]

Collaborative filtering recommender systems: These recommendation systems provide recommendation by utilizing the items-related judgment of similar users to the target user. In fact, given the provided-ratings by similar users for a particular item, a collaborative filtering method can predict the possible rating of the target user for that particular item. Collaborative recommendation systems are divided into two categories: memory-based collaborative recommendation systems that are also called neighborhood collaborative recommendation systems and model-based collaborative recommendation systems. The memory-based recommendation system differentiates a set of similar users to the target user, and then determines the target user's opinion about items by aggregating the opinions of similar users. A model-based recommendation system is a method of latent factor models that demonstrates the items and users in low-dimensional space; the recent demonstration of items and user are calculated by minimizing the regularized squared error.[6]

Demographic recommender systems: These recommendation systems provide the recommendation established on the utilization of the user's personal features (gender, location, age, income and so on).

Hybrid recommender systems: These recommendation systems incorporate two or more kinds of recommendation systems into one model; they usually have superior results to simple recommender techniques, but are much more complex in design.[7,8]

Social networks-based recommender systems: Social recommendation systems can extract heterogeneous information from social networks for improving the classical recommendation approaches and present novel kinds of recommendations. For instance, they can suggest not only items but also movies, users, events, locations, groups, and services to users, using particular algorithms.[9] Figure 1 presents an illustrative instance of these recommender systems.[9]

Trust-based social recommendation systems: The main utilized social networks information of these systems is the trust factor related information such as trust explicit statements between users and implicit trust calculated from other social networks data for further improving recommendation results.[10]

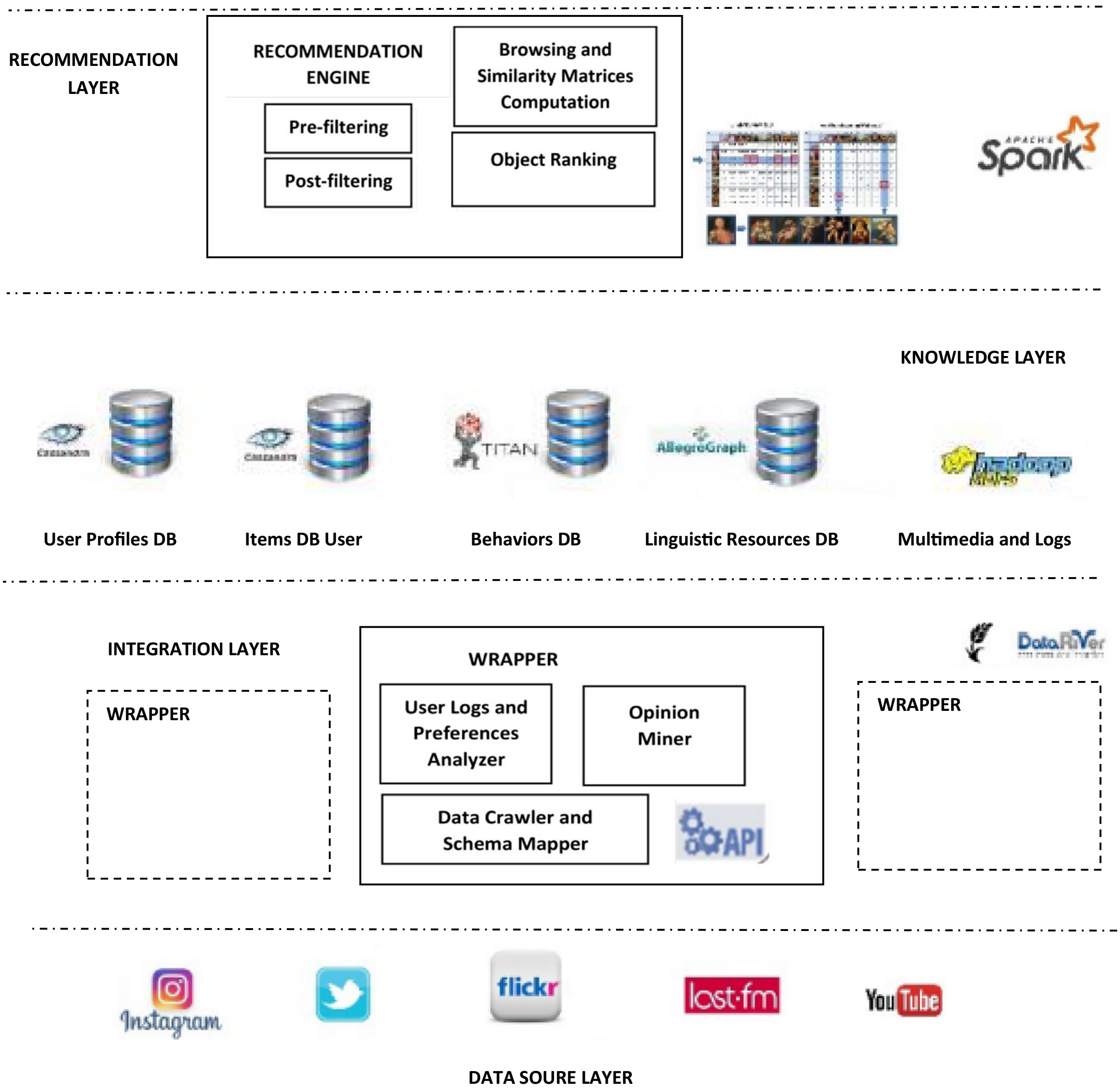


FIGURE 1 An illustrative instance of recommender system in social networks.

2.2 | Evaluation goals and metrics

Because of the ever-increasing volume of information content available on the web, locating appropriate items to meet a specific necessity, becomes extremely difficult for users. Recommender systems target decreasing the information overload by predicting appropriate items of interest to users. Therefore, evaluation experiments of the recommender systems are undertaken to distinguish how well it matches the determined requirements. These requirements therefore result in evaluating the goals such as performance, efficiency, or the metrics to be measured by the experiments. In the following section, the used metrics for amelioration evaluation in the primary studies and some other important metrics for recommender systems are discussed.

Accuracy: This determines the quality of closeness to the truthfulness or the true value obtained by a system, which includes prediction accuracy.

> *Prediction accuracy:* This measures the recommended accuracy. There are four broad categories of prediction accuracy metrics used in the reviewed studies: ratings predictions metric, usage predictions metric, rankings of items metric and time prediction metric.
> *Rating prediction accuracy:* This measures the closeness degree of the predicted ratings of recommender system to the actual rating provided by users.
> *Ranking prediction accuracy:* This metric represents the closeness of the correct arrangement of the appropriate recommended items in the suggestion list to how the user would arrange the same items.
> *Interesting items (classification) prediction accuracy:* This metric determines the capability of a recommendation algorithm to suggest the items the user might be interested in.
> *Time prediction accuracy:* This measure determines how the recommender system's predicted information diffusion time is close to the true time that information was diffused.

Coverage: This measures the portion of existent information for which recommendation can be provided and usually indicates the catalog coverage, prediction coverage or cold-start coverage.

> *Catalog coverage:* This metric represents the percent of items of training set the recommendation system can suggest on a test set.
> *Prediction coverage:* It measures the percentage of users for whom the recommender system can provide recommendations.[11,12]
> *Cold Start:* This metric measures system performance in confronting new items and new users.

Prediction speed: It measures the execution time or achieved response time of a recommendation system for providing suggestions.[13]

User satisfaction: It measures usability of the system.

Task support: It determines achieved helpfulness or amount of guidance presented by the recommendation system.

Trust: It represents the degree of user's trust to the suggestions provided by system.[12]

Novelty: It determines success rate of a recommender system in predicting the novel or unseen items.[11,12]

Diversity: It is user's perceived diversity (opposite of similarity) of the recommendations.[12]

Serendipity: It measures the succeeded extent of a recommendation system in recommending appealing yet beneficial suggestions.

User preference: This measure is related to the users' perception of that system.[11,12]

Utility: It measures the amount of value which is achieved of each recommended item for the target user or system.[14]

Risk: It determines the extent of user risk in choosing each recommendation.

Robustness: It measures tolerance amount of a recommendation system to bias and incorrect information under extreme conditions.

Learning rate: This metric describes how quick a system is in incorporation of novel information for updating its suggestions list.

Confidence: It determines confidence amount of a recommendation system in its recommendations.[11]

Welfare: It determines how different probabilities of recommending items, if successful, lead novel welfare to the system.[15]

Content spread: It indicates how well the system disseminates the information in social networks with a proper recommendation.[16]

Congestion: It determines how many distinct items are recommended to multiple users.[1]

Usability: It represents how usable the recommendation system is and prepare some degree of satisfaction for the target user.

Privacy: It represents the level of users related information leakage protection.[17]

Scalability: It measures the compatibility of a system with changing the users' number, the amount of data and performance of the algorithm.

Stability: It measures the consistency of suggestions over a specific duration of time.

Computational complexity: It measures the amount of work an algorithm must do in order to perform its operation on a set of data.[14]

2.3 | Evaluation measures

In this subsection, the measures used to present volume of the effects on the metrics used for evaluation of the recommender systems are explained.

Ranking score: This measure determines how closer the more relevant items are to the top of the provided recommendation list.[1] In fact, this measure is the ordinal number of the project in the recommendation list divided by the number of the items that are not graded.[18]

Coverage: This measure computes the ration of the number of different items which are recommended for all users by the recommendation system to the whole number of items existing in the system.[1,19] Accordingly, this measure determines the proportion of items that the system can suggest to users.

Precision: This measure determines the proportion of the really relevant items for a user to the whole number of recommended items and is related to classification prediction accuracy.[1]

Recall: Recall determines the portion of appropriate recommended items to the total amount of appropriate items which exist in the system for a target user and shows the classification prediction accuracy.[20]

F-measure: This measure shows the integration of precision and recall as a harmonic average.[21]

Mean average precision (MAP): This measure is utilized to show the ranking prediction accuracy and represents the average precision of K recommended positions. Accordingly, it determines the mean of calculated precision at the position of every appropriate item in a ranked arrangement.[21,22]

Root mean square error (RMSE): This measure determines the closeness of the rating that is predicted by the recommendation system to the true rating that is provided by user by computing the root mean squared difference between the true rating and the predicted rating of an item for the N number of tested ratings.[3,19]

Mean absolute error (MAE): This measure determines the closeness of the rating which is predicted by the recommender system to the true rating that is provided by user by calculating the average of difference between the true rating and the predicted rating of an item for the N number of recommended items.[3,23,24]

Hit rate (HR): This measure describes the ratio of users for whom the true predicted answer exists in the suggestion list and the percentage of items that appears in the suggestion list.[25,26]

Normalized discounted cumulative gain (NDCG): This describes the average of the similarity proportion of the predicted rating and real rating of K items in the ranked list of recommendation so that it gives a higher weight to the similarity of predicted rating and the real rating of the items that have higher position in the ranked listed of these K recommended items for N users.[26,27]

System security engineering (SSE): This measure represents the amount of perturbation on the original data indicating the privacy maintenance.[17]

Mean reciprocal rank (MRR): This measure computes the rank of the first founded relevant items in the related recommendation list for each user. Then, it performs an overall average for them.[22]

Data utility: This measure calculates the intersection of the clustered noisy community and the actual community divided by actual community.[14]

Accuracy: This measure calculates the ratio of the number of rightly recommended cases in the test set to the number of rightly recommended cases within all test cases.[28]

Area under the curve (AUC): This measure plots the relevant recommended item rate against the not relevant recommended item rate.[29]

G-measure: This is a geometric mean of precision and recall that normalizes right positives to the geometric mean of predicted positives and real positives by calculating the square root of the multiplication of precision and recall.[30]

Average reciprocal hit-rank (ARHR): This measure presents a weighted version of the hit rate measure and indicates the strength of proper recommended items in a suggestion list such that the strength of a proper recommended data item refers to its position in the list.[25]

Per-rating HR (rHR): This measure represents the hit rate of items having a specified rating. Accordingly, it expresses the capability of a recommendation system to suggest the items which have a certain rating value.[25]

Cumulative HR (cHR): This measure represents the hit rate of items having a rating that is greater than a specified threshold rating value. Accordingly, it expresses the capability of a recommendation system to suggest the items which have a certain rating value.[25]

2.4 | Evaluation datasets

This subsection presents the real datasets utilized for the trust-based recommender systems evaluation.

Amazon website: This dataset is related to the metadata of products and the review information provided by users about various products.[31]

Epinions: This dataset contains the product review information where users provide the ratings for items and present their own review. Moreover, social network of trust is established based on specifying the trusted people by each user.[26,32]

Advogato: This dataset is an online community for software developers. In this dataset, each user can admit the other users under four measures including observer, apprentice, journeyer and master.[33]

Wikipedi vote network: This dataset is a social network website with connection that is constructed through a voting process. For example, a directed edge from user X to user Y implies that X voted Y to become an admin.[4]

Enron email: This is an email dataset that is formed by sending and receiving emails.[34]

Flixster: In this dataset users provide their ratings for movies besides adding some users as their friends for creating a social network.[19]

MovieLens: This dataset is a relatively small dataset containing user ratings of movies and some demographic information for the users.[35,36]

Baidu: This dataset contains users' ratings for different movies, users' relationships and movie tags.[24,37]

Facebook: This dataset is one of the well-known social network websites in which users can keep in touch with family and friends and share information.[29,38]

Sina Weibo: This dataset is a microblogging site including follower/following relationships.[18,21]

Tencent Weibo: This dataset is one of the largest microblogging websites that connects all users together.[22,39]

Youku: This dataset is a large video sharing website, where for each video a list of tags is provided by users which contain different short sentences explaining the videos' content.[39]

Slashdot: This dataset is a technology-related news website where users are connected through friend and foe relationships.[40]

Renren: This dataset is Chinese social networking service similar to Facebook in which the users are allowed to connect and communicate with each other, share information and access mobile live streaming.[41]

INFOCOM: This dataset contains users' connection via their contacts and attributes.[42]

Douban: This data set is a social networking website in which registered users can record information such as ratings related to recent events, books, music and activities and share the review to their friends. Additionally, Douban's mechanism is exactly like twitter.[26]

Ciao: This dataset includes records of movie ratings given by users and statements of trust issued by users.[26]

Meetup: This data set is an event driven social networking site where event developers announce their events. Moreover, users are allowed to participate in an event and to join groups related to their own personal interests.[43]

FilmTrust: This dataset includes the users' ratings on items and the users' trust statement to other users.[44]

Foursquare: This dataset is a location-based social networking site which includes user profiles, trust relationships between users, check-in activities and points of interest.[45] In more detail, each check-in visit contains location id, user id, location category, date and time, longitude and latitude and tagged users in these visits. Friendships are achieved utilizing tagged information in these visits so that users tagged in the same visit are considered friends with each other.[13]

Gowalla: This dataset is a location-based social network site where the provided information by users called checking-ins enables sharing of their visited locations.[45]

Geolife: This dataset is related to the users' trajectory over a specified period of time, containing not only their daily routines but also their hobbies and sports activities.[14]

T-Drive: This dataset includes the GPS trajectories of a number of taxis during the specific period of time within Beijing.[14]

Last.fm: This dataset is a music and track recommendation social networking website. It also includes friendship relationships between users and the music tracks and the artists which are tagged by these users.[46]

Delicious: This dataset is a social bookmarking web service for storing, sharing, tagging and discovering web bookmarks. Also, there are mutual fan relationships between users that form a social networking website.[46]

Hi5: http://www.hi5.com.[29]

Brightkite: This dataset is a location-based social network site that users share their locations of interest by checking-in. Furthermore, this dataset contains users' friendship activities.[47]

2.5 | Trust of relationships' properties

In this subsection, several important factors are described from different perspectives that were perceived by further investigation of the trust-based social recommendation systems.

Trust: In signed networks, edges that have positive weights represent friendship between users.

Distrust: In signed networks, edges that have negative weights represent enmity between users.[29]

Explicit trust: This means that trust information is explicitly collected from users' statements. In explicitly collected trust, a user expresses their degree of trust in another user whom they have interaction with.

Implicit trust: This means that trust information is implicitly inferred from users' behaviors.

Local trust: Local trust is demonstrating the trust-related past interactions between the trustor and trustee.

Global trust: Global trust demonstrates the reputation level of the trustee in the community. Calculation of global trust is based on the combination of the trusted level of a particular user which is provided by others in the network (namely in-degree of a user node).

Direct trust: This implies that in social trust networks where trust relationships between users is not symmetrical, the resulting network has direct trust relationships.

Indirect trust: This implies that in the social trust networks where trust relationships between users is symmetrical, the resulting network has indirect trust relationships.

Binary trust: The binary trust is a binary representative of the degree of each social trust connections existing between social network users.

Numerical trust: The numerical trust represents the strength of each trust relationship between social network users in a numerical value.

Trust propagation: Transitivity is an obvious property of local trust. Local trust publishes from user-to-user in the social trust networks so that it provides a more accurate assessment of users by finding implicit relationships.[3]

Trust aggregation: In a social network constructed from trust relationships between users, all trustee path entered in a trustor node are aggregated to represent the overall effect.[3]

Trust contextualization: Trust inference between social network users is based on considering some contextual factors so trust evaluation between users is according to contextual information. Also, the context itself can be any information that describe the state of an existence.[34]

Trust temporalization: Incorporates element of time in trust inference process between users because of having the time sensitivity feature of the trust factor.[4]

Trust privacy-preservation: Considers privacy leaks and protection approaches regarding the trust information between users of social networks because it potentially uncovers information on an individual's friendships and social circles.[42]

3 | RESEARCH STRATEGY

To present the authors' perception of recommender systems, this section was based on the systematic literature review's guideline which is provided by[48–51] with a particular focus on available research connected to trust-related social networks data for recommender systems improvement. A systematic literature review presents a specific investigation procedure and should provide adequate characteristics to be a template for other investigators.[49] into confirm the necessity of trust-related social networks data for recommender systems, nine questions were proposed for investigation of the main aspects of trust-based social recommender systems in the present research. The mentioned questions were formalized as per below section.

3.1 | Question formalization

This section presents the most relevant issues and challenges of trust-based social recommender systems, its current approaches, utilized social networks data and possible recommender systems techniques. The present research thus attempted to answer the below questions:

RQ1. What is the significance of trust-related social networks data with increasing use of recommendation systems? The dominant purpose of this question was to determine the total sum of trust-based social recommendation systems studies published in a certain period of time, to underline the importance of trust-related social networks data in addition to increasing recommender systems usage.

RQ2. Which problems and solutions have been identified in trust-based social recommender systems for future directions? This question aimed at understanding the recommender systems using trust-related social networks data, recognizing its challenges and techniques utilized to ensure improved objectives using the data.

RQ3. How much are the recommender systems improved by utilizing the trust-related social networks information according to the main metrics of recommender systems? This question aimed to evaluate current recommender system techniques using a trust-related social network data based on primary recommender systems metrics including evaluation goals, metrics, measures, datasets or benchmarks and case study.

RQ4. Which social networks data analytical approaches for trust-based recommender systems are covered? This question aimed at providing a categorization of social networks analytical approaches for trust-based recommender systems. Furthermore, it showed how frequently these approaches were studied.

RQ5. What are the available primary study publication statistics for the trust-based literature? The answer to this question enabled identification of distributions among popular publishers in the field.

RQ6. To what extent are the recommender systems improved by utilizing the trust-related social networks information according to the main recommender systems metrics? This question aimed at obtaining comprehensive information on ameliorated metrics in the trust-based analytical approaches.

RQ7. Which datasets in existing trust-based social recommender systems are used? This question aimed at determining the datasets that are used for evaluation in existing trust-based social recommender systems and which ones are utilized to a greater degree.

RQ8. Which available data is more recommended by trust-based social recommender systems? The aim of this question was to present data more recommended by trust-based social recommender systems and to identify data that is required more.

RQ9. Which available trust-related data in social networks are more effective for recommendation? The purpose of this question was to present source data namely ratings, tags, and social contacts for trust-based recommender system techniques to exploit.

This process can provide detailed answers within the domain of this article. After determining the necessity of research, the research questions of a review protocol were formulated for the current study. The development of this protocol involved several steps including search query, source and criteria selection, and data extraction.

3.2 | Search query

Appropriate search strings were applied on the educational databases in addition to the definition of exclusion/inclusion criteria by selecting appropriate keywords. Search string were described by determining synonyms and alternate spelling for each component of the question and connecting them through using the Boolean *OR* and Boolean *AND*.[49,51] An appropriate search string was described by choosing the most appropriate keyword for presenting the subject. Therefore, two keywords were chosen: ((“recommender systems”) *AND* (“social networks”)). After various phases and using the primary analyses results as a pilot for investigation, the query string was described. In other words, the query for appending further keywords were refined and finally the main keywords were selected as: ((“recommender systems” *OR* “recommendation”) *AND* (“social networks” *OR* “social networks-based” *OR* “social networking”)). In order to obtain the most relevant and important articles, the search string was applied to their titles. Then, the resultant studies were inspected to discover studies that contained “trust” in their title, abstract or full body. In addition, one more search string for detecting regular surveys and systematic literature reviews related to the study topic was created. For this purpose, a search string such as ((“recommender systems” *OR* “recommendation”) *AND* (“social networks” *OR* “social networks-based” *OR* “social networking”) *AND* (“survey” *OR* “challenges” *OR* “study” *OR* “view” *OR* “overview” or “state-of-the-art” *OR* “systematic literature review” *OR* “*SLR*”)) was created listed in Table 1. The search was carried out in March 2023 in a defined time range from 2012 to 2023.

3.3 | Sources selection

Primary journal articles related to both the present study specific topic and proposed *RQ* were chosen from the results of the search process. Publishers were then categorized and explored for extracting the relevant outcomes. Therefore, the search process included articles available in four scientifically and technically peer-reviewed ISI-indexed databases: *ACM Digital Library*, *Elsevier, Springer Link* and *IEEE Xplore* among others. These database sources are illustrated in Table 2.

3.4 | Selection criteria

Be eligible for inclusion in this overview, a quality assessment checklist according to[49] was provided to distinguish only papers which were published in peer-reviewed journals with the publication date from 2012 to March 2023. The mentioned checklist contained the following questions: (*a*) Is the investigation methodology distinctly specified in the present research article? (*b*) Is the investigation methodology suitable for the investigated problem? (*c*) Is the analysis of study correctly carried out? If the appropriateness of each study was discerned with the distinguishing criteria, then it was filled with ‘yes’. The inclusion–exclusion criteria used for the article selection is summarized in Table 3.

3.5 | Quality assessment and data extraction

The data withdrawal phase determines the data of selected studies suitable to be further analyzed. First, by noting the title of articles and their publisher, they were selected based on their relevance to the study topic. Thus, inadequate articles were omitted and the initial primary studies were obtained. Then, for the initial primary studies, except the regular survey studies where the relevant categories of analytical approaches for recommender systems were listed, the full text of these studies were read to omit those not relevant to the topic of trust-based social recommender systems. Excluded primary studies were those that did not have the word trust in their title, abstract, keywords or text. After filter of these studies based on inclusion/exclusion criteria and quality assessment criteria, 47 articles were determined as a primary study, 0 articles as a trust-based regular survey study and 0 as a trust-based systematic literature review study.

TABLE 1 Existing regular surveys on social networks-based recommender systems.

#	Reference	Publisher	Journal/encyclopedia	Subject
1	Muhlenbach, Largeron et AL, 2017[52]	Springer	Encyclopedia of Social Network Analysis and mining	Presenting a survey on the challenges of recommendation systems in social networking website
2	Stan, Muhlenbach et AL, 2014[53]	Springer	Encyclopedia of Social Network Analysis and mining	Presenting a survey on the challenges of social network-based recommendation systems
3	Zhou, Xu et AL, 2012[54]	Springer	Artificial Intelligence Review	Providing an overview in social network-based personalized recommendation systems
4	Bao, Zheng et AL, 2015[55]	Springer	GeoInformatica	Presenting an overview on location-based recommendations in social networking sites
5	Eirinaki, Gao et AL, 2018[56]	Elsevier	Future Generation Computer systems	Presenting an overview of challenges and solutions of recommendation systems for large-scale social networks
6	Li, Fang et AL, 2017[57]	ACM	ACM Transactions on Management Information Systems	Providing a survey of link recommendation for social networks
7	Camacho and Alves-Souza, 2018[58]	Elsevier	Information Processing and Management	Providing a systematic review of cold-start problems alleviation in recommendation system utilizing social networks data
8	Campana and Delmastro, 2017[59]	Elsevier	Online Social Networks and Media	Presenting an overview of recommendation systems for mobile-based social networking sites

TABLE 2 Database sources for finding articles.

Source	URl
ACM	http://www.sciencedirect.com
Elsevier	http://link.springer.com
Springer	http://dl.acm.org
IEEE Xplore	http://ieeexplore.ieee.org

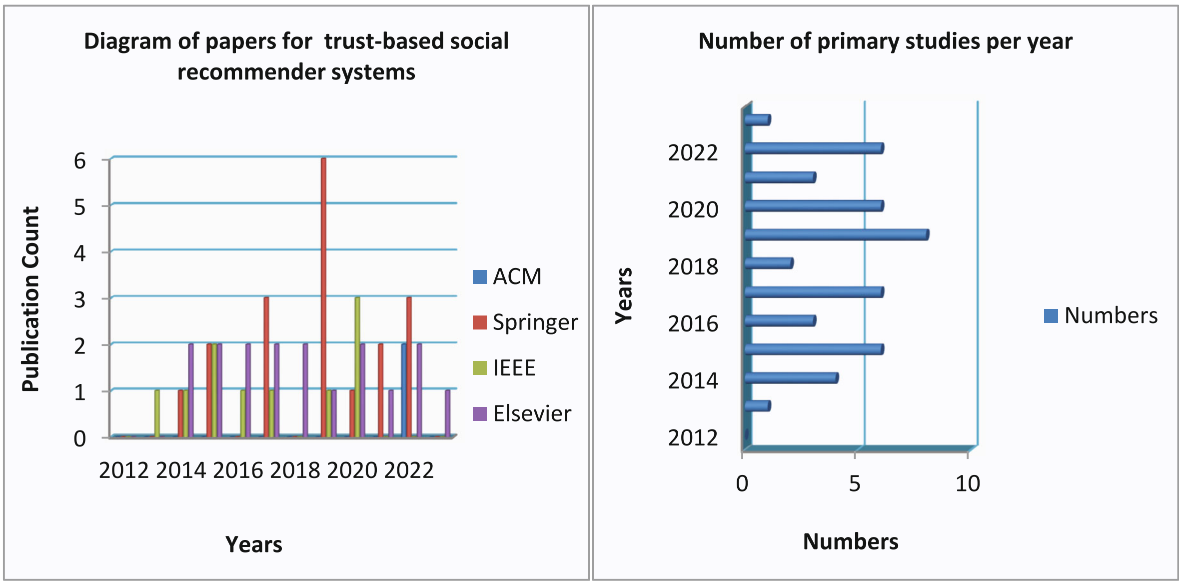
Figure 2 illustrates the selected articles' distribution over publication time. It is obvious that the number of articles in the field of trust-based social recommendation systems has increased in recent years. Pertinent to issues introduced in the first formalization question (*RQ1*), the importance of trust-based social recommendation systems and the necessity of novel and improved trust-based recommender system techniques in addition to the increase in the use of trust-related social networks data is significantly outlined.

4 | PRIMARY STUDIES' CATEGORIZATION SCHEMES

The chosen primary studies were wholly investigated and it was found that the existing recommender systems utilizing trust-related social networks data can be investigated from two broad categories. These two broad categories were classified based on their types of analytical approaches of trust-related social networks data used in recommender systems and thus named trust of items-based recommender systems and trust of relationships-based recommender systems. Trust of items-based recommender systems were those with analytical approaches based on calculation of the trust degree of products. More precisely, in these recommender systems, the utilized social networks data were trust-related data such as sale rank of the products and sale frequency of the products. Furthermore, in trust of relationships-based recommender systems, the type of analytical approaches used were based on achieving the trust degree of relationships between users. These recommender systems were adapted for trust-aware applications or the utilized social networks data were trust-related data such as trust relationships value between users explicitly expressed by them, trust

TABLE 3 Inclusion-exclusion criteria for article selection.

Criteria	Rational
Inclusion 1	An article describing analysis of social networks data for trust-based social recommendation systems and the role of social networks in trust-based recommender systems
Inclusion 2	An article that addresses the challenges of recommender systems which uses trust-related social networks data
Inclusion 3	An article that is written in English
Inclusion 4	An article that is published in a journal
Exclusion 1	An article that is a conference paper, master and doctoral dissertation, textbook, editorial notes, workshop report, non-peer-reviewed and unpublished working paper
Exclusion 2	An article that is published before 2012
Exclusion 3	An article that does not focus on trust-based recommender systems utilizing social networks data
Exclusion 4	An article that does not have experimental evaluation
Exclusion 5	An article that is a survey on social networks-based recommender systems



(A) (B)

FIGURE 2 (A) Annual distribution of primary selected studies from 2012 to march 2023, (B) numbers of primary selected studies per year.

relationships value between users achieved implicitly from some factors like friendships strength. In the following section, trust-based social recommender systems are discussed in greater detail.

4.1 | Trust-based social recommender systems

The classical recommender systems' development is fully developed, but they all assume users as independent entities. In fact, friendships exist among users and their feelings, behaviors or opinions are influenced by their friends, which is called social influence. Moreover, it is likely that some users who have no knowledge of products might prefer to select products based on their reputation and purchase frequency. Based on the mentioned statement, many researchers have focused on trust-based social recommender systems which incorporate the social trust information for greater improvement of classical ones.[60] Moreover, the initial primary studies of trust-based social recommender systems were further investigated and it was revealed that these recommendation systems based on the type of focused social trust can be categorized as trust-of-item-based recommender systems and trust-of-relationship-based recommender systems. Different studies that belong to these categories are investigated in Sections 4.1.1 to 4.1.2. Figure 3 illustrates this subject and Table 4 represents the number of primary studies in each approach.

4.1.1 | Trust-of-item-based social recommender systems

In this subsection, the trust-of-item-based recommender systems is defined with their main properties. Then, primary studies related to trust-of-item-based recommender systems are explained. Finally, observations of these recommender systems' properties and evaluations are shown in Tables 5 and 6. These analysis tables contain author names and years of publication, the name of publishers, techniques used in the articles, main ideas, utilized trust-related social networks data, improvements, weaknesses, evaluation goals, metrics, as well as used measures and datasets in the studies.

Trust-of-item-based recommender systems consider the attributes of such items as (for products) their purchase frequency, reputation, sale rank, ratings and other attributes to distinguish between trustworthy items and malicious items for improvement of the recommendation results and mitigation of deviation from the real demand of users. Below, several important trust-of-item-based recommender systems are reviewed.

A personality-based recommendation method utilizing the trust factor was proposed by Vatani et al.[31] First, more trusty similar users to the target user were determined based on their personality-based purchasing records. The similarity value of these reliable similar users also varied according to different categories. Then, according to the reliable similar users' opinions and correlation relationships among the products, the probabilistic matrix of product recommendation was constructed. Furthermore, the compatibility degree of the content aspect of the products with the personality-based purchases records of the target users was considered to overcome the cold start of new items problem. Finally, more trusty similar users' opinions and correlation among the products, calculated products' trust and products content closeness with the target user's purchasing behaviors were combined to form the recommendation algorithm. Results from the conducted experiments demonstrated that the provided recommendation algorithm's components improved the recommendation results and had higher accuracy value to the baseline algorithms. However, the coverage improvement of the presented algorithm was not evaluated through comprehensive experiments and the textual opinions provided by users were not utilized for further improving the recommendation results.

A trust–aware probability-based recommendation method for product recommendation in social networks was proposed by Wang et al.[20] They considered two recommendation attributes, frequency and reputation, for deriving similarity users. Then, using purchasing records of the target users and similar users to them and considering correlation relationship of products, they specified the probabilistic method based on transmission probability of the target users.

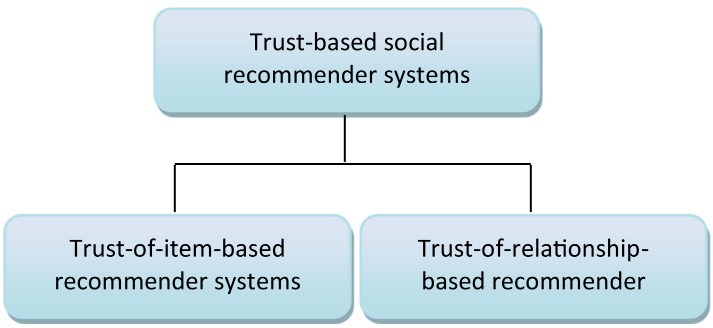


FIGURE 3 Initial primary studies categorization based on trust-related social networks data analytical approaches for recommender systems.

TABLE 4 A categorization of primary studies.

#	Category	Number of studies
1	Trust-of-item-based social recommender systems	9
2	Trust-of-relationship-based social recommender systems	38
Total		47

TABLE 5 Popular trust-of-item-based social recommender systems and their properties.

#	Reference	Publisher/journal	Technique	Main idea
1	Vatani, Rahmani et AL, 2022[31]	Springer/Applied Intelligence journal	A product recommendation method established on the personality of users and the trust factor	Using a hybrid recommendation algorithm utilizing trust factor of both the products and the users' relationships for providing personality-based recommendation in social networks
2	Wang, Yin et AL, 2015[20]	Elsevier/Journal of Network and computer Applications	A probabilistic recommendation method using trust factor for items in social networks	Using collaborative recommendation algorithm based on a probabilistic method which uses the trust factor for recommending the items
3	Wu, Chen et AL, 2015[21]	Springer/World Wide Web	A recommendation model utilizing trust factor for items in heterogeneous social networks	Using subscription relationship between users to media for warm-start users clustering and assigning cold-start users to existing clusters for media recommendation
4	Noh, Oh et AL, 2015[61]	IEEE/Journal of Communications and Networks	Designing trustworthy recommender systems	Using link analysis and user/item influence function for designing trustworthy item recommender system
5	Li, Liu et AL, 2016[15]	IEEE/IEEE Access	A similarity-based recommendation method recommending unknown items in social networks	Using A trust-based recommendation model utilizing similarity among users and stores, among shops, among items and among users in social networks for product recommendation
6	Lingam, Rou et AL, 2018[40]	Elsevier/Computers and Electrical Engineering	A trust-aware and automata-based learning model for user recommendations in online social networks	Utilizing a learning automata-based recommendation trust pathway selection algorithm to recommend service provider (trustworthy service) in social networks
7	Cui, Sun et AL, 2017[33]	Springer/Journal of Signal Processing Systems	Investigating a trust-aware video recommendation approach in social networks	A recommendation approach utilizing trust factor according to the user detection model and a video detection model for recommending interesting videos in social networks
8	Wei, Lin et AL, 2019[14]	Elsevier/Parallel and Distributed Computing	A trajectory community recommendation considering privacy preserving	Using a semantic expectation-based location shift algorithm and a geographical distance-based trajectory making algorithm in a novel differential privacy-based trajectory community recommendation schema
9	Seo, Kim et AL, 2017[27]	Elsevier/Expert Systems with Applications	Personalized friendship strength-based topic recommendation system in social networks	Using a collaborative filtering utilizing a friendship strength-based personalized recommendation system based on interaction similarity, personal similarity and group similarity for topic recommendation in social networks

TABLE 5 (Continued)

#	Social networks data	Improvements	Weaknesses
1	• Product metadata such as products' price, products' brand, categories, sales rank, purchased frequency and links • Products review such as social ratings of users on purchased items and users' id • Social network sites' user profiles	• Improved classification prediction accuracy • Improved solving the cold start problem of new users and products • Improved personalization of recommendation results	• Not evaluating the coverage improvement of the algorithm for cold start items • Not considering the provided textual opinions by user for items to further improve the results
2	• Social network sites' user profiles • Products review such as social ratings of users on purchased items and users' id • Product metadata such as sales rank and purchase frequency	• Improved classification prediction accuracy • Improved solving the cold start problem of new users	• Not considering trust relationships between users • Not considering any factor to personalize the recommendation
3	• Terms inside the tweets (Micropost) • Subscription relationships between users to media derived from retweet or comment on the tweets posted by media	• Improved classification prediction accuracy • Improved ranking prediction accuracy • Improved users' trust • Improved the diversity of recommendation • Improved solving the cold start problem of new users and data sparseness issue	• Not considering any contextual information for recommendation • Not considering the time factor while inference of trust degree of product
4	• Social ratings of users on items • Items' features	• Reducing the impact of Sybil attacks while maintaining a high prediction accuracy	• Not considering bias of rating • Not considering any context information in recommendation process
5	• Social network sites' user profile • Products review such as social ratings of users on purchased items and users' id • Product metadata such as sales rank and purchase frequency	• Improved classification prediction accuracy • Improved solving the problems of over-matured, cold start of new users and items • Improved the welfare of the system	• Not considering trust relationships between users • Not considering any factor to personalize the recommendation
6	• User to service preferences • Trust relationships' value between users • Friendship relationships between users	• Improved the utility value obtained from the recommendation result • Reduction of computational time	• Not considering any kind of privacy preservation of users • Not considering distrust information as a supplementary factor
7	• Video tags • Friendship relationships • Watched videos list • Trust of videos derived from posted statistics, commented statistics, forwarded statistics, praised statistics and collected statistics of watched videos	• Improved classification prediction accuracy	• Not considering the cold start problem of new items • Not considering the communication bottleneck

TABLE 5 (Continued)

#	Social networks data	Improvements	Weaknesses
8	• Feature locations • Users' activities • Users' movements	• Improved rating prediction accuracy • Improved the execution time of the algorithm • Providing privacy-preservation issue for users • Improved the utility value obtained from the recommendation result	• Not providing any explanation for the recommendation reasons • Not considering personal information during the recommendation process
9	• Friendship relationships • Social ratings of users on items • Tweet content (Micropost) such as words for determining interesting topics (movie, book, etc.) for users and related items to these topics • Tweet statistics and posting time • Retweets and mentions statistics between users	• Improved the classification prediction accuracy • Improved the rating prediction accuracy • Personalized recommendation in a multi-domain environment	• Not considering any context information for recommendation • Not considering optimization of computation time

TABLE 6 Popular trust-of-item-based social recommender systems and their evaluation properties.

#	Reference	Evaluation goals	Metrics	Measures	Datasets
1	Vatani, Rahman et AL, 2022[31]	• Performance	• Accuracy	• Precision • Recall • F-measure	• Amazon
2	Wang, Yin et AL, 2015[20]	• Performance • Effectiveness	• Accuracy	• Precision • Recall • F-measure	• Amazon
3	Wu, Chen et AL, 2015[21]	• Performance • Effectiveness	• Trust • Accuracy • Diversity	• Precision • Recall • F-Measure • MAP	• Sina Weibo
4	Noh, Oh et AL, 2015[61]	• Performance	• Accuracy • Robustness	• RMSE • PS	• MovieLense
5	Li, Liu et AL, 2016[15]	• Performance • Effectiveness • Efficiency	• Accuracy • Welfare	• Precision • Recall • F-Measure • Theoretical welfare analysis	• Amazon
6	Lingam, Rou et AL, 2018[40]	• Efficacy	• Utility • Prediction speed	• Computational time analysis • Utility value analysis	• Slashdot • Epinions
7	Cui, Sun et AL, 2017[33]	• Performance • Effectiveness • Efficiency	• Accuracy	• Precision • Recall • F-Measure	• Sina Weibo • Youku
8	Wei, Lin et AL, 2019[14]	• Performance • Efficiency • Effectiveness	• Accuracy • Privacy • Prediction speed • Utility	• Precision • Recall • F-measure • Data utility • Security analysis • Execution time	• Geolife • T-Drive
9	Seo, Kim et AL, 2017[27]	• Performance	• Accuracy	• Precision • Recall • F-Measure • MAE • NDCG	• Twitter

Moreover, trust level of products was achieved according to their reputations and purchase frequencies. To control the cold start of new users' problem, they considered hidden features of the target users for finding their hidden similar users. Finally, to establish the recommendation method, they combined the mean transmission probability, products' trust and hidden features of new users. The results of the conducted experiments demonstrated that their recommender method had improved in term of accuracy. However, we believe they did not consider trust of relationships between users' factor for achieving more trusted similar users. Moreover, we think that it would have been better if they paid attention to personalizing the recommendation results unique to the individual preferences.

Wu et al[21] presented a novel framework including a two-phase process for providing trust-aware and accurate media recommendation in heterogeneous social networks to effectively deal with the problems related to the cold start of new users and data sparseness. In the first phase, they classified the user nodes to warm-start set and cold-start set by using the subscription relationship evaluation between the user nodes and the media nodes in users' interest graph. Then, motivated by the current graph summarization techniques, they presented a clustering algorithm for clustering the warm-start user set according to these users' interest graph. In the second phase, by using the global clustering algorithm, the user nodes related to the cold-start set were clustered to the warm-start cluster. This global clustering was based on normalized Goggle distance similarity measure calculation between content vectors constructed from the posted tweets of cold-start user nodes and warm-start clusters. Finally, using the Slope One algorithm, ultimate media recommendation was provided according to the result of the global clustering. Experimental results demonstrated the improvement of their algorithm. However, they should have thought about the time of the retweet or comment of the tweets posted by media while obtaining trust of product because of the time sensitivity property of the trust. In addition, it would have been better if they had considered some contextual information for their recommendation process.

Noh et al[61] presented a new approach established on analyzing weighted link and influence degree for recommender systems resisting Sybil attacks. For this purpose, they used link analysis and repetitive upgrading by transmuting a recommendation matrix in a bipartite graph. Item and user influence degree upgrading function based on dissemination of the influence degrees from the user side to the item side (or vice versa) were presented for verifying Sybil users utilizing the bipartite graph. Then, they eliminated low influential users and made prediction utilizing a matrix factorization method. The conducted simulations' results of a wide range of attacks validated their approach, and it was determined that it performed better than the baseline recommendation methods in terms of robustness and accuracy. However, they did not make note of the bias of rating when using social ratings of the items for recommendation and it would have been better if they had considered some contextual information (such as geographical distance) for their recommendation process.

In 2016, a probabilistic recommendation model using the trust factor with the capability of providing small recommendation probability for unknown items to alleviate the cold start problem was introduced by Li et al[15] for social networks. In this model, the items' recommendation values were primarily obtained of the probabilities computed by an equivalent mature recommender system within the initiation phase of the recommendation system. Under the condition of entering the term of maturation, the recommender system mainly applied the probability values of recommendation computed by the self-system. However, current recommender systems have the problem of exceedingly mature suggestions that lead to losing the chance of suggesting the more optimized items. Therefore, this model recommends not only the items with higher probability value of recommendation but also items with lower probability value which presents greater advantages to the recommender systems. Experimental analysis showed the effectiveness and efficiency of their model. However, they did not consider trust of relationships factor between users for achieving more trusted similar users. Moreover, it would have been better if they had focused on personalizing the recommendation results unique to the individual preferences.

Lingam et al[40] designed a trustworthy user recommendation (as service provider for trustworthy service recommendation) network architecture by integrating trust factor's information, relevance level and recommended influence value in online social networks. They presented a social trust related model in order to evaluate a suggested trust pathway. The provided model evaluated utility values with related weights according to Shannon's entropy information gain. Furthermore, proposing a learning automata-based recommended trust pathway selection algorithm, they identified several trust pathways to identify aggregated pathway to select the best recommended trust pathway. The experimental results illustrated the efficacy of their provided algorithm. However, they did not observe the privacy issue of the trust value revealing some information about users. They should have included the distrust information as a supplementary factor for trust inference in their algorithm.

Utilizing trust information, Cui et al[33] proposed a recommendation approach according to a user detection model and a video detection model for recommending interesting videos to users. In order to detect the users that had a greater influence on the target user, they categorized the users into two groups: users who had direct influence and users who had indirect influence. They estimated the trust value between the target user and each of their more influential users taking into consideration some factors such as the user similarity factor derived from number of common type video tags among users, the friendship factor derived from following/follower relationships and the interaction factor derived from the number of reposted, commented and praised watched videos. In the video detection model, they calculated the trust level of the video according to the rating of the video and the activity concerning the video. Through incorporating the user detection and video detection models, they presented their trust-aware video recommendation algorithm in social networks. They also performed some experiments, the results of which demonstrated the improvement of their algorithm in terms of accuracy. However, it would have been better if they had designed a decentralized algorithm for their video recommendation systems dealing with big social data because including a centralized service provider could cause single-point failure and communication bottleneck problems. They should have also concentrated more on the cold start problem of new items.

Wei et al[14] proposed a social location-based recommendation schema for recommending a community to a user. The trajectories in this recommended community were also alike to the target user's trajectory according to their movements model. Moreover, their schema protected the privacy of the trajectory by the user with the aid of their proposed differential privacy-based recommendation feature. For this purpose, according to private semantic expectation method that certifies the semantic similarity between the real locations and noisy locations, their schema shifted the real trajectory's location into the noisy attribute locations. Then, their schema utilized a private geographical distance method to make a noisy trajectory with a minimum geographical distance to the real trajectory. Lastly, their schema utilized a semantic-geographical distance model for clustering a community that had great similarity with the built noisy trajectory. Their experimental results showed their schema improved in term of data utility factor. However, had they provided some explanation for the recommendation reasons to obtain greater users' trust in the results would have been an advantage. Moreover, they should have considered some personality information during the community recommendation process because it is one of the main factors influencing human behaviors.

In 2017, a personalized friendship degree-based recommendation system using trust factor for items was proposed by Seo et al.[27] Their proposed friendship degree was based on three kinds of similarity including personal, group and interaction. For computation of personal similarity, they considered the similarity of user's preferences of items and the similarity of user's topics distribution as trust of item, and affinity of topic according to user-provided contents. The interaction similarity was calculated based on different types of communication between users including mention, retweet and review. In order to calculate group similarity, they used not only direct connections between users but also indirect connections based on Jaccard similarity measure. Finally, utilizing friendship degree between users which was established based on collaborative filtering algorithm, they provided recommendations for users. The conducted experimental results demonstrated that the proposed friendship strength-based system's performance was better than that of the baseline in all metrics they used. However, they should have considered some contextual information for inferring the trust degree of items because of the existence probability of malicious data. Moreover, they should have optimized the time of the recommendation process to efficiently deal with the vast amount of data created in social networks.

4.1.2 | Trust-of-relationship-based social recommender systems

The initial selected primary studies relevant to trust-of-relationship-based recommender systems were thoroughly reviewed and it was discovered that these systems can be further investigated according to several important factors from different perspectives besides their overall properties and evaluations.

Below, the trust-of-relationship-based recommender systems and their basic properties are first described. Then, the primary studies related to trust-of-relationship-based recommender systems are discussed. Finally, observations of these recommender systems' properties and evaluations are presented in Tables 7 and 8 and according to the authors' views, these recommender systems' detailed properties are described in Table 9. These analysis tables contain author names and years of publication, the name of publishers, techniques used in the articles, their main ideas, utilized trust-related social networks data, improvements, weaknesses, evaluation goals, metrics, as well as used measures and datasets in the studies, trust sign, trust type, trust notation, trust relation, trust value, trust propagation, trust aggregation, trust conceptualization, trust temporalization and trust privacy-preservation.

Trust-of-relationship-based recommender systems considers friendship strength between users to improve recommendation results. These recommender systems are based on the fact that there is a social networking relationship among users and people oftentimes refer to friends for some suggestions concerning music, locations or other topics, and their friends' viewpoints have a considerable influence on people's decisions. Figure 4 illustrates a trust-based social recommender system.[2] Several trust-of-relationship-based recommender systems and their main features are discussed in the following section.

Wan et al[19] provided a trust-aware matrix factorization recommendation method utilizing deep learning. Moreover, utilizing deep learning technique combined with the trust factor, their method addressed the problem related to matrix initialization of items and users. For this purpose, first, they provided a linear deep matrix factorization and a non-linear matrix factorization for feature extraction from provided rating of items by users. Moreover, they utilized trust of relationships among users in their model according to the similarity of users' preference and users' derivation of items. Second, utilizing deep marginalized denoising autoencoder, they achieved latent description of the trust relationship matrix for estimating the user factor matrix from the user rating matrix. Finally, they provided a joint optimization function which included a community regularization for considering the neighbors' effects. The outcome of deep matrix factorization was also used for deep marginalized denoising autoencoder's updating variables to improve the results. Experimental evaluation on the real datasets demonstrated the effectiveness of their method. However, they should have considered some factors for inferring the trust degree of items because of existence probability of malicious data. Moreover, they should have used the trusted collaborative neighbors' rating in trust degree inference process.

A trust-based neural network model named adjustable attention neural network for item recommendation in social networks was proposed by Li et al.[26] The motivation of their proposed neural network model was to investigate the

TABLE 7 Popular trust-of-relationship-based recommender systems and their properties.

#	Reference	Publisher/journal	Technique	Main idea
2	Li, Tei et AL, 2020[26]	IEEE/IEEE Access	A deep recommendation model based on an attention neural network algorithm for social network-based item recommendation	Designing a co-attention neural network model extended by using the network embedding in order to learn the degree of different friends' influences for item recommendation
3	Liao, Huang et AL, 2019[43]	IEEE/IEEE Access	A group event-based recommender system considering unexperienced events in social networks	Providing a group event recommendation model utilizing trust relationships among users based on the users who have participated in an event or users who join a group in order to recommend unexperienced events
4	Ahmed, Saleem et AL, 2020[23]	IEEE/IEEE Access	A time sensitive trust-based recommendation model in social networks	Using a matrix factorization technique utilized trust relevancy computed from time sensitive trustworthiness weight of neighbors in multi domains for item recommendation in social networks
5	Kashani and Hamidzadeh, 2020[17]	Springer/Soft computing	A privacy-preserving recommendation according to mutual trust and collaborative filtering	Using privacy-preserving-based chaos function and clustering algorithm to maintain privacy of users and to reduce error rate in product recommendation process in social networks
6	Liang and Qin, 2019[18]	Springer/Cluster Computing	An inspection of the social factors that influence online shopping decision making	Inspecting the factors which influence users' decision making in online shopping process for improving products recommendation
7	Shokeen and Rana, 2021[44]	Springer/Ambient Intelligence and Humanized Computing	A social network-based recommendation utilizing trust and semantic factors	Using a matrix factorization algorithm that capture the explicit and implicit relations between network members according to trust relationships and sematic friendships between users to recommend items in social networks
8	Cheng, Zhang et AL, 2019[47]	Springer/Machine Learning and Cybernetics	Fusing information based on multi-sources in social networks for friend recommendation	Using a fusion recommendation algorithm embedded in a D-S evidence-based theory framework for friend recommendation in social networks
9	Chen, Chang et AL, 2020[35]	Springer/Multimedia Tools and Applications	A matrix factorization model based on social network according to user interactions	Using an improved social network-based matrix factorization model utilizing various social interactions between users for item recommendation
10	Zhu, Wang et AL, 2019[45]	Springer/Wireless Communications and Networking	A location-based recommendation using trust factor for recommending friends and points of interest	Using co-clustering approach in the collaborative filtering process utilizing trust and distrust values for friend recommendation, and a fused framework for recommending appropriate point of interest
11	Teoman and Karagoz, 2022[13]	ACM/Symposium on Applied Computing	A group-based recommendation according to the trust factor and the location features	Using random walk with restart algorithm utilizing trust factor for location recommendation to a group of users for social networks
12	Ahmadian, Ahmadia et AL, 2022[46]	Elsevier/Applied Soft Computing	A tag- and trust-based recommendation utilizing deep learning	Using deep neural network for achieving latent features related to the matrices of trust and tag in order to obtain lower computational complexity of users' similarity calculation in item recommendation process

TABLE 7 (Continued)

#	Reference	Publisher/journal	Technique	Main idea
13	Xu, Lin et AL, 2022[37]	Springer/Cognitive Computation	A social cognitive learning-based item recommendation through group-enhanced ranking model	Using matrix factorization technique based on cognitive-knowledge-based recommendation through group-enhanced learning to rank model
14	Meo, Fotia et AL, 2018[62]	Elsevier/Information Systems	An integration of local and global reputation for item recommendation	Using collaborative filtering recommendation approach using an integration of local and global reputation for recommending items in social networks
15	Deng, Huang et AL, 2014[32]	Elsevier/Expert System with Applications	A service recommendation algorithm using trust information in social networks	Using matrix factorization and an improved random walk algorithm utilizing trust relevancy composed of trustworthiness weight of neighbors and similarity of these neighbors in social networks for service recommendation
16	Lee and Ma, 2016[3]	Elsevier/Knowledge-Based Systems	An optimized collaborative recommendation by incorporating users' liking and propagation of trust-distrust value in social networks	Using hybrid recommendation consisting of matrix factorization and k-nearest neighbors collaborative recommendation utilizing social trust-distrust propagation for item recommendation
17	Eirinaki, Louta et AL, 2013[4]	IEEE/IEEE Transactions on Systems, Man, and Cybernetics: Systems	A trust-based and personalized user recommendation algorithm in social networks	Using a reputation management model that captures the implicit and explicit connections between the network members and analyzes the semantic and dynamic of these connections for friend/enemy recommendation (friend/enemy)
18	Gua, Zhang et AL, 2014[42]	IEEE/IEEE Transactions on Dependable and Secure Computing	A trust-aware privacy-preserving recommendation technique for friend suggestion in online social networks	Using an establishment of social relationships with strangers via a multi-hop trust chain for privacy-preserving friend recommendation
19	Wang, Li et AL, 2015[34]	Springer/World Wide Web	A context-aware trust degree inference for service providers recommendation in social networks	Using a probabilistic approach for trust inference utilizing social contextual information including preferences, expertise in domain, social intimacy, trust and interaction context between users for service recommendation
20	Deng, Huang et AL, 2016[2]	IEEE/IEEE Transactions on Neural Networks and Learning Systems	Deep learning utilizing trust factor for recommendation for online social networks	Using matrix factorization approach based on deep learning considering the preferences of trusted friends and the impact of community on recommendations
21	Xu, Zhong et AL, 2017[41]	Springer/Wuhan University Journal of Natural Sciences	Service recommendation utilizing both the trust factor and the context information for mobile social networks	Using a collaborative filtering algorithm utilizing the user context and the trust network for service recommendation in mobile social networks
22	Zhang, Xu et AL, 2017[63]	Springer/Applied Intelligence	Personalized recommendation according to extensive trust for social networks	Using a collaborative filtering recommendation algorithm utilizing a probability matrix factorization model and comprehensive trust evaluation for item recommendation in social networks
23	Ma, Ma et AL, 2018[38]	Elsevier/Future Generation Computer systems	Privacy-preserving based friend recommendation utilizing trust factor in a decentralized framework in online social networks	Using a trust-aware privacy-preserving framework utilizing trust relationships and users' social attributes for recommending friend in a decentralized way in social networks

TABLE 7 (Continued)

#	Reference	Publisher/journal	Technique	Main idea
24	Xiong, Qiao et AL, 2020[28]	Elsevier/Neurocomputing	A recommendation framework based on trust/distrust inference for point of interest suggestion in heterogeneous social networks	Employing a Latent probabilistic recommendation model established on the latent Dirichlet allocation algorithm for sentiment-based analysis of user-generated comments for location recommendation in heterogenous social networks
25	Zhang, li et AL, 2019[64]	Springer/Journal of Ambient Intelligence and Humanized Computing	An item recommendation algorithm utilizing trust information according to stochastic gradient matrix decomposition for social networks	Using matrix factorization approach based on stochastic gradient descent to calculate decomposed matrices utilizing trust information for item recommendation in social networks
26	Zhang, Shi et AL, 2020[65]	Elsevier/Neurocomputing	Integrating Markov chains and social network-based embedding using trust factor for cold-start user recommendation	Using the Markov chain model based on network embedding information using the trust factor in order to make recommendations to new users
27	Weng, Zhang et AL, 2021[66]	Elsevier/Expert systems with applications	Gray relational analysis using trust information for item recommendation in heterogenous social networks	Using matrix factorization technique incorporated in gray relational analysis to extract implicit relationships between users for item recommendation in heterogenous social networks
28	Hao, Li et AL, 2015[67]	IEEE/IEEE Transactions on Service Computing	Providing location-based recommendation for ad-hoc social networks	Using aggregation measure of similarity achieved from user-item similarity according to provided ratings of users on items, user-user similarity according to friendship relationships, and user-location similarity according to geographic distances between users and items for location recommendation
29	Symeonidis and Tiakas, 2014[29]	Springer/World Wide Web	Link recommending in signed social networks	Using trust information while considering network structure features for friend recommendation in signed social networks
30	Carullo, Castiglione et AL, 2015[30]	Springer/World Wide Web	Trust factor utilization based on triadic closure and homophily for friend recommendation in social networks	Employing Hubs and Authorities algorithm to use triadic closure with similarity measure to consider homophily for friend recommendation in social networks
31	Dou, Guo et AL, 2019[24]	Springer/Multimedia Tools and Applications	A privacy preserving-based method established on weighted noise injection while using trust factor for multimedia recommendation in social networks	Using collaborative filtering algorithm according to noise injection technique based on social trust factor for multimedia recommendation
32	Feng, Sharma et AL, 2016[25]	Elsevier/Engineering Application of Artificial Intelligence	A regularized sparse linear model for item recommendation in social networks	Using the integration of user- and item-based regularized sparse linear model using users' trust relationships and users provided social rating in the process of user weight matrix learning for item recommendation in social networks
33	Li, Song et AL, 2014[36]	Elsevier/The Journal of China Universities of Posts and Telecommunications	Incorporating users' preferences for item recommendation in social networks	Using a probabilistic matrix factorization technique employing explicit social relationships between users, users' implicit preferences of items, and user-provided ratings of items for item recommendation

TABLE 7 (Continued)

#	Reference	Publisher/journal	Technique	Main idea
34	Choudhary, Minz et AL, 2021[68]	Springer/Soft Computing	Generating social circles in social networks based on trust information for item recommendation	Using social trust information to construct a circle of users for item recommendation to group members
35	Canturk, Karagoz et AL, 2023[47]	Elsevier/Expert Systems with Applications	Trust-based recommendation according to network structure in location based social networking websites	Incorporating trust information with random walk algorithm for location recommendation in social networks
36	Suhail and Berri., 2022[69]	Elsevier/Journal of King Saud University-Computer and Information Science	Personalized tweet recommendation according to various factors to calculate the similarity of users in social networks	Using user-based collaborative filtering algorithm utilizing trust factor for tweet recommendation in social networks
37	Chen and Zhu., 2022[70]	Springer/International Journal of Machine Learning and Cybernetics	Tree-way community recommendation method for a user in social networks	Using the Logistic Regression algorithm to create a three-way recommender system in social networks
38	Li, Wang et AL, 2022[71]	ACM/ACM Transactions on Knowledge Discovery from Data	Unbiased rating prediction in recommendation systems in social networks	Using two perspectives including inherent information and social networks factor for de-biasing rating predictions in social recommender systems

TABLE 7 (Continued)

#	Social networks data	Improvements	Weaknesses
2	• Trust relationships' values between users • Social ratings of items by users	• Improved classification prediction accuracy • Improved ranking prediction accuracy • Improved solution for data sparseness problem	• Not considering the trust factor for items • Not considering the trust value decay over time
3	• Users' participations in the events as trust information • Users' memberships in the groups as trust information	• Improved rating prediction accuracy • Improved classification prediction accuracy	• Not providing any explanation for the recommendation reasons • Not considering any limitation information on events in the recommendation process
4	• Trust relationships' value between users • Social ratings of users on items	• Improved rating prediction accuracy • Improved classification prediction accuracy • Improved coverage • Improved solution for data sparseness and cold start of new users problems	• Not considering the trust factor for items • Not considering bias on the trust degree during trust inference
5	• The value of trust relationships between users • Social ratings of items by users	• Providing privacy-preserving issue of users • Improved rating prediction accuracy	• Not considering any contextual information for recommendation • Not considering the problems related to data sparseness and cold start of new users

TABLE 7 (Continued)

#	Social networks data	Improvements	Weaknesses
6	• The value of trust relationships between users • Social ratings of items by users	• Improved rating prediction accuracy • Improved ranking prediction accuracy	• Not considering the trust factor for items • Not considering the trust value decay over time
7	• The value of trust relationships between users • Social ratings of items by users • Semantic friendships relationships-based on the follower/following relationships	• Improved rating prediction accuracy • Improved ranking prediction accuracy • Improved solving the problem of cold start of new users	• Not providing any explanation for the recommendation reasons • Not considering the trust value decay over time
8	• Social network sites' user attributes (demographic information and location) • Users' interactions such as review, thumb up, and retweet • Follower/following relationships	• Improved rating prediction accuracy • Improved ranking prediction accuracy	• Not considering the problems of cold start of new users • Not considering the trust factor for items (users' trustworthiness)
9	• Friendship relationships between users • Social ratings of items by users	• Improved rating prediction accuracy • Improved ranking prediction accuracy • Improved computational complexity • Improved solution to the data sparseness issue and cold start problem of new items	• Not considering any contextual information for recommendation • Not considering the trust factor for items (users' trustworthiness)
10	• Trust and relationships' values between users • Check-in activities • User profiles	• Improved rating prediction accuracy • Improved solution to the problems of data sparseness • Improved running time of the algorithm	• Not considering the problems of cold start of new users • Not considering the trust factor for items (users' trustworthiness)
11	• Friendship relationships • User' s check-ins • Social ratings of users on locations	• Improved classification prediction accuracy • Improved running time of the algorithm	• Not considering any context information for recommendation • Not considering more sufficient trust factors
12	• Friendship relationships • Social ratings of items by users • Tags of items by users	• Improved classification prediction accuracy • Improved running time of the algorithm • Improved solution to the problem of data sparseness	• Not considering any context information for users' similarity calculation in recommendation process • Not considering trust value for items
13	• Trust relationships' value between users • Social ratings of items by users	• Improved ranking prediction accuracy	• Not considering propagation feature of the trust factor while inferencing the trust value • Not considering distrust information while inferencing the trust value
14	• The value of trust relationships between users • Social ratings of items by users	• Improved classification prediction accuracy	• Not considering the problems of cold start of new users • Not considering any context information for trust value inference process

TABLE 7 (Continued)

#	Social networks data	Improvements	Weaknesses
15	• The value of trust relationships between users • Social ratings of services by users • Services' features	• Improved rating prediction accuracy • Improved speed of algorithms • Improved coverage • Improved solution to the data sparseness issue and cold start problem of new users • Improved scalability	• Not considering any contextual information for recommendation • Not considering trust factor for items
16	• Trust and distrust relationships' values between users • Social ratings of items by users • Item features	• Improved rating prediction accuracy	• Not considering the problems of cold start of new users • Not considering some bias for the explicit trust stated by users
17	• Trust and distrust relationships' values between users • Social rating of users to another users' published articles for deriving implicit trust relationships between users	• Improved rating prediction accuracy • Improved classification prediction accuracy	• Not providing any explanation for the recommendation reasons • Not considering privacy preserving issue of users
18	• Trust relationships' values between users • Social network sites' (SNSs) users' social attributes • Friendship relationships	• Improved reachability • Improved contact duration time • Suitable computational cost • Improved user privacy preservation • Improved scalability	• Not providing any explanation for the recommendation reasons • Not considering any factors to personalize the recommendation
19	• Trust relationships' values between users • Social intimacy degree, role impact factors and interaction context obtained from subjects and contents of emails • Social network sites' (SNSs) user profiles for obtaining users' preferences	• Improved trustworthy results • Efficient execution time • Improved scalability	• Not providing any explanation for the recommendation reasons • Not considering the decay of the trust value during its propagation
20	• Explicit trust relationships' values between users • Item features (and trust values) for deriving implicit values of trust relationships between users • Social ratings of users on items	• Improved classification prediction accuracy • Improved coverage • Improved solution to the data sparseness issue, cold start problem of new users, and trustworthiness	• Not considering the decay of the trust value during its propagation • Not considering any contextual information in the trust inference process
21	• Social ratings of users on items • Friendship relationships • Social network sites' user personal information including contextual information such as current time and location • Messages between users	• Improved classification prediction accuracy • Improved personalization	• Not considering the problems of cold start of new users and items • Not considering the distrust value as a supplementary feature
22	• Trust relationships' values between users • Social ratings of items by users • Item features	• Improved rating prediction accuracy • Improved personalization	• Not considering the aggregation feature of the trust factor • Not considering the decay of the trust value during its propagation

TABLE 7 (Continued)

#	Social networks data	Improvements	Weaknesses
23	• Trust relationships' values between users • Social network sites' (SNSs) users' social attributes • Friendship relationships • Role impact factor and social intimacy degree between users derived from their social attributes	• Improved reachability between users • Improved computational cost • Improved user privacy protection • Improved scalability • Providing a decentralized method	• Not considering decay of the trust value during its propagation in the social network • Not providing any explanation for the recommendation reasons
24	• Trust and distrust relationships between users obtained from friendship relationships and user comments • Sentiments extracted from comments and words • Check-in activities • Provided comments on points of interest • Provided reviews for points of interest	• Improved classification prediction accuracy • Improved computational cost	• Not considering real-time preference representation for recommendation • Not considering global trust to utilize experience of experts
25	• Social rating of items by users • Trust relationships between users	• Improved rating prediction accuracy	• Not considering decay of the trust value during its propagation in the social network • Not considering bias on the user-provided rating of items
26	• Social rating of items by users • Trust relationships between users	• Improved classification prediction accuracy • Improved ranking prediction accuracy • Improved solution to the cold start problem of new users	• Not considering any contextual information for users' similarity calculation • Not providing any explanation for the recommendation reasons
27	• Social rating of items by users • User relationships including following/follower, trust relationships and friendship relationships • Users' personal profiles • Item features	• Improved classification prediction accuracy • Improved rating prediction accuracy • Improved computational cost	• Not considering trust factor for items • Not considering propagation feature of friendships relationships
28	• Trust relationships' value between users • Social ratings of items by users • Social network sites' user attributes (demographic information such as zip codes) • Item features (spatial features such as location)	• Improved rating prediction accuracy • Improved classification prediction accuracy • Better consideration of users' preferences	• Not considering the problems of cold start of new users • Not considering the temporal information for trust factor
29	• Friendship relationships • The value of trust and distrust relationships between users	• Improved classification prediction accuracy • Improved solution to the problem of data sparseness • Improved computational cost (time and space) • Improved scalability	• Not considering any content information for calculation of the similarities between users • Not considering the trust value decay over time
30	• Trust relationships' values between users	• Improved classification prediction accuracy	• Not considering any content information for calculation of the similarities between users • Not considering the problems of cold start of new users

TABLE 7 (Continued)

#	Social networks data	Improvements	Weaknesses
31	• Social ratings of movies by users • Trust relationships' values between users derived from friendship relationships	• Maintaining good rating prediction accuracy, while protecting user privacy information • Improved computational cost (time and space)	• Not considering the cold start problem of new items • Not considering any contextual information in the user preference modeling process
32	• Trust relationships' values between users • Social rating of items by users • Friendship relationships	• Improved ranking prediction accuracy • Improved classification prediction accuracy • Improved computational cost • Improved scalability • Improved learning speed	• Not considering any trust factor items • Not providing any explanation for the recommendation reasons
33	• Trust relationships' values between users • Item features • Social ratings of items by users	• Improved rating prediction accuracy • Improved scalability in terms of computational complexity • Improved solution to the problem of data sparseness	• Not considering the distrust value as a supplementary feature • Not considering bias on the user-provided rating of items
34	• Trust relationships' values between users • Social ratings of items by users • Users' personal profiles	• Improved classification prediction accuracy • Improved rating prediction accuracy • Improved user satisfaction • Improved ranking prediction accuracy	• Not considering privacy preserving issue of users • Not considering scalability issue of system
35	• Social ratings of items by users to calculate users' trustworthiness value • Check-in activities • Friendships relationships	• Improved classification prediction accuracy	• Not considering group recommendation alongside individual recommendation • Not providing any explanation of the reasons for the recommendation
36	• Tweets • Social ratings of tweets by users extracted from their actions • Users' relationships including following/follower relationships • Users' personal profiles	• Improved classification prediction accuracy • Improved ranking prediction accuracy • Improved solution to the problem of data sparseness	• Not considering any contextual information for recommendation • Not considering the cold start problem of new users
37	• Users' personal profiles • Friendships relationships as trust relationships	• Improved classification prediction accuracy	• Not considering any temporal information in the recommendation process • Not providing any explanation for the reason of provided recommendation
38	• Social rating of items by users • Friendships relationships	• Improved classification prediction accuracy • Improved rating prediction accuracy	• Not considering any semantic-aware method in their system • Not considering and evaluating user satisfaction

TABLE 8 Popular trust-of-relationship-based recommender systems and their evaluation properties.

#	Reference	Evaluation goals	Metrics	Measures	Datasets
1	Wan, Xia et AL, 2020[19]	• Performance • Effectiveness • Efficiency	• Accuracy • Coverage	• Coverage • F-measure • RMSE	• Epinions • Flixter
2	Li, Tei et AL, 2020[26]	• Performance • Effectiveness	• Accuracy	• HR • NDCG	• Epinions • Douban • Ciao
3	Liao, Huang et AL, 2019[43]	• Performance • Effectiveness	• Accuracy	• Precision • Recall • F-measure NDCG	• Meetup
4	Ahmed, Saleem et AL, 2020[23]	• Performance	• Accuracy • Coverage	• Precision • Recall • Coverage • F-measure • RMSE • MAE	• Epinions • Ciao
5	Kashani and Hamidzadeh, 2020[17]	• Performance	• Accuracy • Privacy	• RMSE • SSE	• Epinions
6	Liang and Qin, 2019[18]	• Performance • Efficiency • Effectiveness	• Accuracy	• MAE • Ranking score	• Epinions • Sina Weibo
7	Shokeen and Rana, 2021[44]	• Performance • Effectiveness	• Accuracy	• RMSE • MAE • NDCG	• FilmTrust
8	Cheng, Zhang et AL, 2019[47]	• Performance • Effectiveness	• Accuracy	• • MAR • NDCG • MRR	• Tencent Weibo
9	Chen, Chang et AL, 2020[35]	• Performance • Efficiency • Effectiveness	• Accuracy • Prediction speed	• MAE • RMSE • Complexity analysis	• Movielens • Epinions
10	Zhu, Wang et AL, 2019[45]	• Performance • Efficiency • Effectiveness	• Accuracy • Prediction speed	• Precision • Recall • Running time	• Foursquare • Gowalla
11	Teoman and Karagoz, 2022[13]	• Performance	• Accuracy • Prediction speed	• Precision • F-measure • Hit rate • Running time	• Foursquare
12	Ahmadian, Ahmadian et AL, 2022[46]	• Performance • Efficiency • Effectiveness	• Accuracy • Prediction speed	• Precision • Recall • NDCG • Running time	• Last.fm • Delicious
13	Xu, Lin et AL, 2022[37]	• Performance • Effectiveness	• Accuracy	• NDCG	• Epinions • Baidu
14	Meo, Fotia et AL, 2018[62]	• Performance • Effectiveness	• Accuracy	• Precision • Recall • RMSE • MAE	• Ciao

TABLE 8 (Continued)

#	Reference	Evaluation goals	Metrics	Measures	Datasets
15	Deng, Huang et AL, 2014[32]	• Performance • Efficiency	• Accuracy • Coverage • Prediction speed • Scalability	• Coverage • Precision • F-measure • RMSE • Time cost of recommendation	• Epinions
16	Lee and Ma, 2016[3]	• Performance • Effectiveness	• Accuracy	• RMSE • MAE	• Epinions
17	Eirinaki, Louta et AL, 2013[4]	• Performance	• Accuracy	• Precision • Recall • F-measure • MAE	• Epinions • Advogato • Wikipedia vote network
18	Guo, Zhang et AL, 2014[42]	• Performance • Efficiency • Feasibility • Security	• Privacy • Prediction speed • Scalability	• Reachability between users • Contact duration time • Security analysis	• Facebook • INFOCOM
19	Wang, Li et AL, 2015[34]	• Performance • Effectiveness • Efficiency	• Trust • Prediction speed • Scalability	• Trust inference results • Execution time	• Enron email
20	Deng, Huang et AL, 2016[2]	• Performance • Effectiveness	• Accuracy • Coverage	• Precision • RMSE • F-measure • Coverage	• Epinions • Flixster
21	Xu, Zhong et AL, 2017[41]	• Performance • Effectiveness	• Accuracy	• Precision • Recall • F-Measure • MAE	• Renren
22	Zhang, Xu et AL, 2017[63]	• Performance • Effectiveness • Feasibility	• Accuracy	• RMSE	• Epinions • Flixster
23	Ma, Ma et AL, 2018[38]	• Performance • Effectiveness • Efficiency • Security	• Accuracy • Reachability • Prediction speed • Scalability • Privacy	• Precision • Recall • AUC • Reachability between users • Computational cost analysis • Privacy preservation analysis	• Facebook
24	Xiong, Qiao et AL, 2020[28]	• Performance • Efficiency • Effectiveness	• Accuracy • Computational complexity	• Accuracy • Training time	• Foursquare • Twitter • Facebook
25	Zhang, li et AL, 2019[64]	• Performance • Effectiveness	• Accuracy	• RMSE	• Epinions • Flixster
26	Zhang, Shi et AL, 2020[65]	• Performance • Effectiveness	• Accuracy • Coverage	• Precision • NDCG	• Epinions • Ciao • Last.fm

(Continues)

TABLE 8 (Continued)

#	Reference	Evaluation goals	Metrics	Measures	Datasets
27	Weng, Zhang et al, 2021[66]	• Performance • Effectiveness • Efficiency	• Accuracy • Computational complexity	• Precision • Recall • F-Measure • MAE • RMSE • Computational cost analysis	• MovieLens
28	Hao, Li et AL, 2015[67]	• Performance • Effectiveness • Feasibility • Usability	• Accuracy • User preference	• Precision • Recall • Property (properties between item and location, including energy and traveling time)	• MovieLens • Epinions
29	Symeonidis and Tiakas, 2014[29]	• Performance • Efficiency • Effectiveness	• Accuracy • Prediction speed • Scalability	• Precision • Recall • AUC	• Epinions • Facebook • Hi5 • Synthetic datasets
30	Carullo, Castiglione et AL, 2015[30]	• Performance • Effectiveness	• Accuracy	• Precision • Recall • F-Measure • G-Measure	• Twitter
31	Dou, Guo et AL, 2019[24]	• Performance • Efficiency • Security	• Accuracy • Privacy • Prediction speed • Scalability • Utility • Robustness	• MAE • RMSE • Computational time analysis	• Baidu
32	Feng, Sharma et AL, 2016[25]	• Performance • Efficiency	• Accuracy • Prediction speed • Scalability	• HR • ARHR • rHR • cHR • Computational cost analysis	• Epinions • Flixster
33	Li, Song et AL, 2014[36]	• Performance • Efficiency • Effectiveness	• Accuracy • Scalability	• MAE • RMSE • Complexity analysis	• MovieLens • Epinions
34	Choudhary, Minz et AL, 2021[68]	• Performance • Effectiveness	• Accuracy • User satisfaction	• Precision • Recall • F-measure • MAE • NDCG • Satisfaction value	• Epinions
35	Canturk, Karagoz et AL, 2023[47]	• Performance	• Accuracy	• Precision • Recall • F-measure	• Brightkite • Gowalla • Foursquare • Wee places

TABLE 8 (Continued)

#	Reference	Evaluation goals	Metrics	Measures	Datasets
36	Suhail and Berri., 2022[69]	• Performance • Effectiveness	• Accuracy	• Precision • Recall • F-measure • MAP	• Twitter
37	Chen and Zhu., 2022[70]	• Performance • Feasibility • Rationality	• Accuracy	• Precision • Recall • F-measure • Accuracy	• Brightkite • Karate club network • Football network • Dolphin social network • Email
38	Li, Wang et AL, 2022[71]	• Performance	• Accuracy	• Precision • Recall • MAE • RMSE	• Epinions • Ciao • MovieLens

interrelationship between the target user and their social friends in addition to the impact of the user's likings. Using the co-attention method, they obtained the user's distinct attention to some aspects of their social friends and specified the adjustable impact of individual friends on the user. In addition, their model provides various attention weights to the active user and his social friends according to user interaction with various items. Using network embedding for learning greater features of users and incorporating these features into the adaptive attention neural network of the social recommendation model, they improved their method recommendation results. However, they did not consider decay of the trust value during its propagation in the social network. They also did not take into account some factors for inferring the trust degree of items because of existence probability of the malicious data.

Liao et al[43] presented a model which is established on a two-phase and trust-aware recommendation to recommend interesting and unexperienced events to a group of members. To this end, they mined implicit friendship between users and simulated both the consultation procedure between users and their out-group friends as well as the negotiation procedure among group members. They first presented a global trust network among users according to some information such as users' social behaviors, event participation of users and the topological structure of the event-based social network. Then, they employed the random walk algorithm in their built trust network for obtaining the predicted interest of user in the uncontemplated events. Experimental evaluation on the real datasets revealed the effectiveness of their model. However, they did not provide any explanation for the recommendation reasons to obtain greater users trust in the results. Moreover, they should have considered some limitation features for the events (such as the co-occurrence of events) in the recommendation process.

Ahmed et al[23] presented a recommendation model established on a cross-domain scenario that recommends items to source users from target domain. Additionally, based on their generated user attributes and item attributes, they applied a matrix factorization technique to reduce dimensions in user-rating information. Moreover, they utilized users' trusted neighbor preferences by computing the time-aware trust degree between the users at the source domain and target domain. For this, they used cosine similarity formula and ant colony optimization technique. Experimental evaluation showed that their approach performed satisfactorily in cold start problem solving and rating prediction accuracy. Nevertheless, their model has some drawbacks. First, they did not show any concern for trust degree of products because of the existence probability of malicious data. Second, they did not take into consideration bias on the explicit trust value stated by users during trust inference.

A privacy-preventing of users and reducing error rate recommendation method was provided by Kashani et al.[17] First, they used anonymity method on the primary data to provide secondary data which did not include any user identification information. Then, they used the confidence-based trust estimation algorithm to gain a trust coefficient according to user confidence. This was followed by utilizing perturbation-based disturbance function to gain confidential data of user. Finally, they used a fuzzy c-order-means and swarm optimization algorithm to cluster the data. Experimental results demonstrated that their method had the ability of preserving privacy, maintaining amount of the error

TABLE 9 Popular trust-of-relationship-based social recommender systems and their relationships properties.

		Trust sign		Trust type		Trust notation		Trust relation	
#	Reference	Trust	Distrust	Direct	Indirect	Explicit	Implicit	Local	Global
1	Wan, Xia et AL, 2020[19]	•		•		•	•	•	
2	Li, Tei et AL, 2020[26]	•		•		•		•	
3	Liao, Huang et AL, 2019[43]	•			•		•	•	•
4	Ahmeed, Saleem et AL, 2020[23]	•			•		•	•	
5	Kashani and Hamidzadeh, 2020[17]	•		•			•	•	
6	Liang and Qin, 2019[18]	•		•		•		•	
7	Shokeen and Rana, 2021[44]	•		•	•	•	•	•	
8	Cheng, Zhang et AL, 2019[47]	•		•		•	•	•	
9	Chen, Chang et AL, 2020[35]	•		•		•	•	•	
10	Zhu, Wang et AL, 2019[45]	•	•		•	•	•	•	
11	Teoman and Karagoz, 2022[13]	•		•	•		•	•	
12	Ahmadian, Ahmadian et AL, 2022[46]	•			•	•			
13	Xu, Lin et AL, 2022[37]	•		•		•		•	
14	Meo, Fotia et AL, 2018[62]	•			•	•	•	•	•
15	Deng, huang et AL, 2014[32]	•		•		•	•	•	•
16	Lee and Ma, 2016[3]	•	•	•		•	•	•	•
17	Eirinaki, Louta et AL, 2013[4]	•	•	•		•	•	•	•
18	Guo, Zhang et AL, 2014[42]	•			•	•	•	•	
19	Wang, Li et AL, 2015[34]	•		•		•	•	•	•
20	Deng, Huang et AL, 2016[2]	•			•	•	•	•	•
21	Xu, Zhong et AL, 2017[41]	•		•			•	•	•
22	Zhang, Xu et AL, 2017[63]	•		•		•	•	•	
23	Ma, Ma et AL, 2018[38]	•			•	•	•	•	
24	Xiong, Qia et AL, 2020[28]	•	•		•		•	•	
25	Zhang, li et AL, 2019[64]	•		•	•	•		•	
26	Zhang, Shi et AL, 2020[65]	•		•		•	•	•	
27	Weng, Zhang et AL, 2021[66]	•		•		•		•	
28	Hao, Li et AL, 2015[67]	•		•		•		•	
29	Symeonidis, Tiakas, 2014[29]	•	•	•	•	•	•	•	•
30	Carulla, Castiglione et AL, 2015[30]	•		•			•	•	•

TABLE 9 (Continued)

#	Reference	Trust sign		Trust type		Trust notation		Trust relation	
		Trust	Distrust	Direct	Indirect	Explicit	Implicit	Local	Global
31	Dou, Gui et AL, 2019[24]	•		•		•	•	•	
32	Feng, Sharma et AL, 2016[25]	•		•	•	•	•	•	
33	Li, Song et AL, 2014[36]	•		•		•	•	•	
34	Choudhary, Minz., 2021[68]	•		•		•		•	•
35	Canturk, Karagoz et AL, 2023[47]	•			•		•		•
36	Suhail and Berri., 2022[69]	•		•			•	•	
37	Chen and Zhu., 2022[70]	•			•		•	•	
38	Li, Wang et AL, 2022[71]	•		•	•	•		•	

TABLE 9 (Continued)

#	Trust value		Trust propagation	Trust aggregation	Trust contextualization	Trust temporalization	Trust privacy preservation
	Binary	Numeric					
1		•	•				
2		•			•		
3		•	•	•	•		
4		•	•			•	
5		•	•				•
6		•	•	•			
7		•	•		•		
8		•	•			•	
9		•	•			•	
10		•	•				
11		•					
12	•						
13		•		•			
14		•	•	•			
15		•	•	•			
16		•	•	•			
17		•	•	•		•	
18		•	•		•	•	•

TABLE 9 (Continued)

#	Trust value		Trust propagation	Trust aggregation	Trust contextualization	Trust temporalization	Trust privacy preservation
	Binary	Numeric					
19		•	•	•	•	•	
20		•	•	•			
21		•	•	•	•	•	
22		•	•			•	
23		•	•				•
24	•		•				
25		•	•				
26		•					
27		•					
28		•	•				
29		•	•	•			
30		•	•	•			
31		•	•				•
32		•	•				
33		•					
34	•			•			
35	•						
36	•					•	
37	•						
38	•						

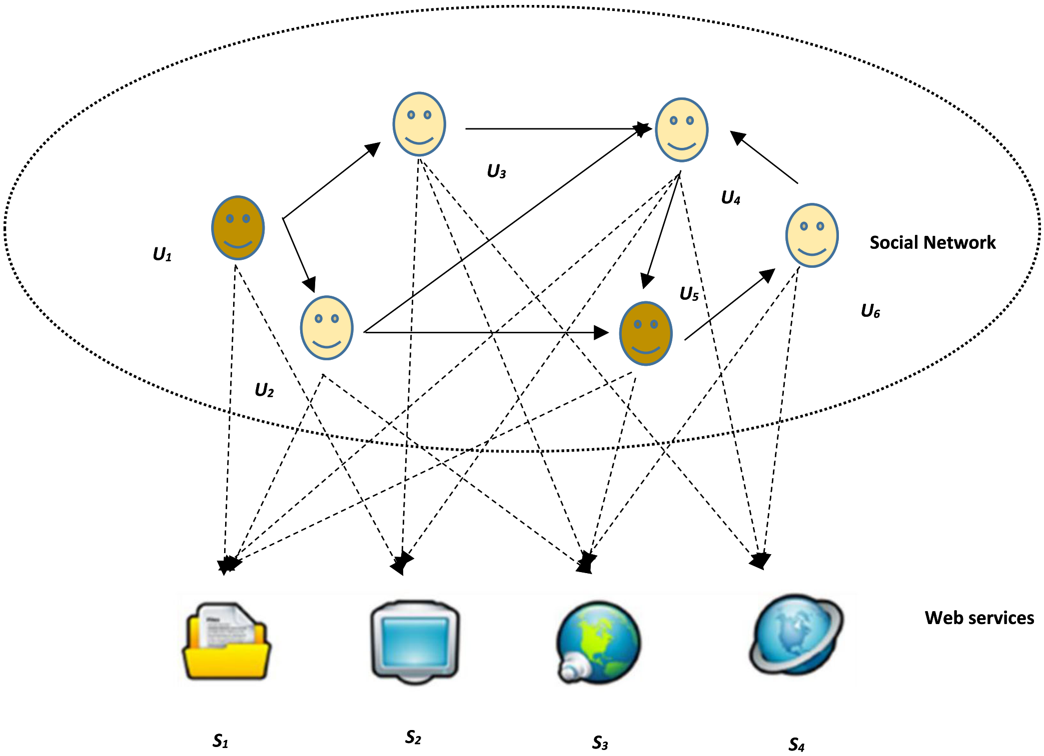


FIGURE 4 An example of trust-enhanced service recommendation.

to an acceptable degree and could confront attacks. They did not, however, consider some contextual information for their recommendation process. Their system also had problems related to the cold start for new users and data sparseness.

Liang et al[18] attempted to inspect social network factors affecting users' decisions during the online shopping process. To this end, they investigated the impact of some factors such as the cognitive ability of users, social relationship intensity between users and the interaction between users on the decision of online shopping process. Moreover, the factors mentioned above were established based on the trust network of users to enhance their recommendation results. Through experimental evaluation, they showed the improved performance of the presented method. One of the disadvantages of this method was not considering any factors for determining the trust value of products in order to avoid recommending malicious items to users. It would have been better if they had considered the trust value decay because of the time sensitivity of the trust factor.

A recommendation approach which utilizes trust relationships between users and semantic friends with different levels of influence was proposed by Shokeen et al.[44] For this purpose, their trust relationships were based on the explicit trust statements provided by users and their semantic friends according to the following friends of users. Moreover, they applied matrix factorization technique in their recommendation process. Experimental results illustrated that their proposed approach improved performance in term of accuracy. However, it would have been better if they had provided explanation for the recommendation reasons to obtain more users' trust in the results. They should have considered the trust value decay because of the time sensitivity of the trust factor.

A social network-based friend recommendation framework was proposed by Cheng et al[22] which integrates various sources according to belief function evidence theory. To this end, they integrated three classes of features including network structure features, personal features and social features. The network structure features information was used to achieve the structure relevancy between users. In addition, the personal features which was attained from user profiles were applied for user similarity computation. Moreover, social features information related to the user's position within the network was utilized for calculation of the trust degree between users. Finally, they integrated all the mentioned above features based on an improved belief function evidence theory for their recommendation. The experiments showed that their approach was improved the accuracy metric. However, their approach has some weaknesses. First, their recommendation approach has the problems of cold-start of new users. Second, their approach did not take into account any factors for determining users' trustworthiness for recommending trusty friends to users.

Chen et al[35] presented a friend recommendation approach in social networks. For this purpose, they integrated three social factors into a matrix factorization model. These three factors included interest similarity between users, trust relationships and item similarity. Moreover, they introduced social interaction in order to improve achieved trust value during propagation between users. Experimental results showed that their presented approach improved performance of their comparative algorithms. However, they did not consider contextual influence for achieving trusted users for recommendation and it would have been better if they had paid attention to the trustworthiness factor of users, namely expert users, for utilizing their influence on another user.

A location-based recommendation utilizing trust factor to recommend friends and point of interest to the target user was proposed by Zhu et al.[45] They first presented a trust value estimation method according to their proposed trust cluster identifier algorithm. Then, they fused achieved trust value and computed similarity among users for recommending friends. In regards their point of interest recommendation, they proposed a framework that merged trust relationships, user preference, and geographical influence for recommendation. The experimental results demonstrated that their approach was improved in terms of accuracy. However, their system has the problems of cold-start of new users. Moreover, they should have considered some factors for achieving the credibility of the user to deal with users' dishonesty and malicious attacks.

Teoman et al[13] provided a location-based recommendation approach using a trust factor that recommends interesting locations to a group of users. To this end, they used random walk with restart algorithm according to the present location of experts, group members and trustworthy users. Initially, according to individual preferences, they aggregated recommended locations for each member which were produced with the random walk algorithm. Next, they blended the individual preferences and the category type of location to apply random walk algorithm again. They also conducted a series of experiments which demonstrated an enhancement of performance in their approach. However, they should have considered some more features for their trust inference method. Moreover, they did not consider any contextual information for their recommendation process.

In 2022, a social recommendation method utilizing trust factors and tag information was proposed by Ahmadian et al.[46] This method used deep neural networks for constructing a model according to trust connections between users and tag information provided by users. For this purpose, they utilized a deep sparse auto encoder to achieve hidden attributes of trust connections and tag information. Finally, they used the obtained latent features for computing users' similarity values for constructing the neighbors of the target user and to make predictions. Experimental evaluations showed the outperformance of their method over the baseline algorithms. However, they disregarded all contextual information for their users' similarity calculations (such as users' ages and users' genders) in the process of providing recommendation results. It would have been better if they had taken into consideration some factors for determining the trust value of items in order to avoid recommending malicious items for users.

Xu et al[37] introduced a social cognitive learning-based model through group-enhancement ranking for improving user preferences model for recommending items. To this end, utilizing matrix factorization technique, they provided a group-enhanced ranking method. They first calculated the trust weights according to trust relationships between users. Then, they integrated a matrix of trust relationships between users to the cost function with a punishment term which diminished the priority vectors' distances related to trustworthy users. Finally, they conducted a series of experiments which revealed improvement of their method. However, they did not include the distrust information as a supplementary feature for trust value inference in their algorithm which would have been a greater improvement. In addition, it would have been better if they had not only considered the incoming edge and outgoing edge of a node as trust relationships in the graph for deriving the trust value as aggregation of these trust relationships from all paths might have led to better results.

De Meo et al[62] provided a recommendation model which incorporated local reputation into global reputation obtained from trust factor in social networks. Their local reputation was according to the explicit trust relationships between users in the social graph whereas their global reputation was related to the collected feedback which was provided by users about the user. Finally, they performed a sequence of experiments, results of which demonstrated an improvement of their method in term of precision. The disadvantages of their method were not considering some contextual information for their trust value inference process which would have led to greater improvement in their approach, and not focusing on the cold start of new users in their recommendation process.

A trust-enhanced recommender system for recommending social network-based services was introduced by Deng et al.[32] To obtain a weighted trust network, they proposed the concept of trust relevancy based on both the existing trust relationships between social network users and the similarities between these users. Calculating user similarity in their method was carried out through matrix factorization method and cosine similarity measure. Next, they proposed an extended random walk algorithm applied in the constructed trust network to obtain recommendation results. The experimental results confirmed an improvement of the quality of recommendation and speed. However, one drawback of their method was not taking into account any factors for determining the trust value of items in order to avoid recommending malicious items for users. They should have also considered some contextual information (such as geographical distance) for their recommendation process.

Lee et al[3] provided a hybrid recommendation approach composed of neighborhood-based collaborative filtering and matrix factorization method to get the benefits of both user rating and social trust information by linear combination of prediction rating obtained from them. Matrix factorization uses the information derived from co-rating similarity between users, while collaborative recommendation utilizes the rating provided by users and the social trust. Additionally, the utilized social trust in their method included both the local and global trust which were combined in linear combinations for choosing neighbors and rating prediction. Local trust is based on past interactions between the trustor and the trustee while global trust is based on the reputation in the community. For local trust, not only is the positive degree of trust considered but also the negative degree of trust which is called distrust are considered in addition to their propagation effects. The results demonstrated that their developed approach improved rating prediction and effectively enhanced the recommendation performance. However, the bias was not considered for the explicit trust stated by users in the trust inference process. Their system also has problems related to the cold start of new users and data sparseness.

To provide a personalized user recommendation for social networks, Eirinaki et al[4] presented a trust-aware system established on a collaborative reputation mechanism. Following processing of the information published on the network, not only positive but negative relationships named trust were formed. Then, for estimating of members' reputation ratings, their presented mechanism obtains and measures the quantity of the connections among users in addition to utilizing propagation feature of the trust factor and the dynamic of the social network. Utilizing these reputation ratings, the recommendation system provided novel trust/distrust relationships for members of the social network. However, it would have been an improvement if they had provided some explanations for the recommendation reasons to attain more users' trust in the results.

Another technique based on utilization of trust information in social networks was proposed by Guo et al,[42] which is a friend recommendation system while maintaining the privacy of users. To develop their friend recommendation technique, they utilized users' social features and trust relationships in a progressive manner while protecting the privacy related to users' identities and features. For privacy concerns, they used users' close friends (1-hop trust relationship) to establish an anonymous communication channel. Then, using the available1-hop trust relationship, they extended the existing friendship to multi-hop trust chains while preserving the privacy of recommenders' identities. In addition, their trust degree derivation technique enabled strangers to obtain an objective trust degree on a particular trust chain. Through experimental evaluation, they demonstrated the efficiency, feasibility and security of the presented technique. However, they should have provided some explanations for the recommendation reasons to attain greater users' trust in the results. Greater attention should have been paid to personalizing the recommendation results unique to individual preferences.

Another solution was a service provider recommendation in social networks established on the context driven trust inference process introduced by Wang et al.[34] First, they presented a context-aware social network model which considered both personal features of the participant including expertise in domain and preference, and mutual relations including social intimacy, trust and the context of interaction between two participants. Moreover, they introduced a new probabilistic approach that infers the value of trust by considering the context in social networks. Demonstrated result of this approach was particularly significant in evaluation of the trust from an original participant to a terminal recommender who suggests a target service or service provider through the sub-network containing mediator recommenders/participants between them and related contextual information. Furthermore, they presented algorithms which took into account the cycles and updates of information in social networks. The experimental results demonstrated an improvement in delivering more reasonable and trustworthy results in an efficient manner. However, they did not take into account the trust value decay during propagation of the trust in the social network. Moreover, it would have been better if they had provided some explanations for the recommendation reasons to achieve greater users' trust in the results.

As another technique for utilizing social trust factor, Deng et al[2] applied deep learning in a matrix factorization technique. For addressing the problems related to the cold start of new users and data sparseness, they investigated the matrix factorization methods' initialization importance. Thus, for appropriate initialization of their proposed learning model's parameters, they used a deep autoencoder which pretrained the initial values. For the trustworthiness problem such as trustworthiness of user ratings and fake ratings of spam users, they presented a learning model based on both the trusted friends' opinions and the community effect. Moreover, for utilizing the community effect, they presented a community detection algorithm which had the capability of forming the community in a trust network. For evaluating the algorithm, they conducted some experiments according to real datasets. The results showed improvements in terms of recommendation accuracy. However, they should have considered decay of the trust value during its propagation in the social network and some contextual information for their recommendation process.

Utilizing the trust factor, Xu et al[41] presented a recommendation algorithm for appropriate services recommendation in mobile social networks. In their algorithm, the more trustworthy neighbors of the target users were determined according to the users' similarity degree and the friends' familiarity level. The users' similarity degree of their algorithm was based on the contextual information and the number of items which were co-rated while the friend familiarity level was calculated based on the graph-based method, which was inspired by the theory of six degrees of space. They also conducted a series of simulations for evaluating their algorithm's accuracy. The results demonstrated that utilizing the friend familiarity level factor helped to a greater degree than the users' similarity degree factor, both of which improved recommendation performance. However, their system had the problem of cold start of new users' and data sparseness and they should have considered the distrust factor as a supplementary feature for the trust value inference process.

In 2017, a personalized recommendation model utilizing the trust factor in social networks was provided by Zhang et al.[63] The model considers several factors including explicit and implicit trust among users, a method for calculating the trust value resulting from its propagation among users and the user similarity. This model integrated the trust relationships and the similarities among users into a factorization of a probability matrix. Moreover, it analyzed hidden factors between the likings of selected trusted users and target user. Their conducted experimental results empirically verified the improvement of their model in the prediction accuracy in two actual datasets. However, the main drawback of their system is the consideration of only the shortest path for deriving the trust value through its propagation in the network whereas aggregation of these trust values from all paths in addition to considering the trust value decay according to the length of its path might lead to better results. Furthermore, another major disadvantage of their system is related to lack of consideration of the trust value decay during its propagation in the network.

Utilizing the social attributes of users and the trust relationships, Ma et al[38] provided a decentralized framework for recommending friends while maintaining user privacy. Their framework was based on a light-weight privacy preserving protocol for utility aggregation of multi-hop trust chains and security calculation of recommendation results. They also analyzed their framework's efficiency theoretically and demonstrated privacy-preservation of the online social network users. Finally, they performed a sequence of experiments for evaluation of their framework and the results showed that this framework has the capability of preserving users' privacy while recommending friends effectively and efficiently to users. However, they should have considered decay of the trust value during its propagation in the social network. Moreover, it would have been better if they had provided some explanations for the recommendation reasons to attain greater user trust in the results.

Another technique established on the use of trust information in social networks was proposed by Xiong et al[28] for the purpose of location recommendation in heterogenous social networks. To develop their recommendation technique, they utilized several factors including geographical information of locations, users' interactions, words within the comments and social communities. They also introduced a point of interest recommendation framework incorporating geographic clustering taking into account the locations and popularity of points of interest simultaneously. Moreover, they conducted a series of experiments for evaluating their framework. The results verified the superiority of the effectiveness and efficiency of their framework. However, their system does not take into account any temporal information in addition to other social network features in displaying user preferences to provide a real-time recommendation and this is problematic. In addition, it is better to use the experience of experts in the location recommendation who can be determined by, for instance, using global trust information.

Zhang et al[64] presented a recommendation algorithm according to trust factor in social networks. For this purpose, they used the trust factor as supplementary information and provided a matrix factorization based on the recommendation method, which provides the objective function design of matrix factorization with social network-based information regularization. They created a matrix with user-provided rating matrix and social relationships and provided a stochastic gradient descent algorithm for matrix factorization. To evaluate the algorithm, they conducted some experiments using real datasets. The results showed improvement in terms of recommendation accuracy. However, they did not consider decay of the trust value during its propagation in the social network which would have led to enhancement of their approach. Furthermore, it would have been better if they had employed some bias on the user-provided ratings on items while utilizing them in their algorithm.

Using trust information, Zhang et al[65] proposed an integrated model established on the personalized Markov Chains structure to allocate the user cold-start problem for item recommendation system in social networks. To this end, they first employed user embedding information to determine network neighbors for new coming users with few or insufficient relationships. Then, they developed a two-level model according to Markov chains not only at the user level but also at the user group level to dynamically model user preferences. Finally, they performed a sequence of experiments for evaluation of their model, and the results showed that it outperformed their baseline models. However, their system has the problem of not taking into account any contextual information that leads to a more accurate representation of users' preferences (such as information embedded in their personal profile) in the process of calculating similarities between users. In addition, it would have been a greater improvement if they had presented some explanations of the reasons for the provided recommendations.

In 2021, a recommendation approach on different types of social relationships including trust relationships, following/follower relationships, and friendship relationships was proposed by Weng et al.[66] They first established a heterogenous social network via such information as user -provided ratings on items and explicit relationships between users and users' attributes. Then, they used gray relational analysis to determine implicit relationships between users, which were then integrated to their matrix factorization model. Finally, they conducted some experiments, the results of which showed the improvement of their recommendation approach against some baseline methods. However, the drawbacks of their method is not considering any factors for determining the trust value of items in order to avoid recommending malicious items for users and it would have been better if they had considered propagation of friendship relationships as this connection has the characteristic of expanding in the network.

Using trust information, Hao et al[67] provided a location-based recommendation approach in ad-hoc social networking sites. They proposed an approach which integrated multiple similarity matrices including user-item rating matrix, user-user social relationship matrix, and user-location distance matrix. Based on the integrated similarity measure, they predicted ratings of locations for recommendation to users. Their conducted experimental results empirically verified the effectiveness of their approach while considering the preferences of users. However, the main weakness of their approach is the cold start problem of new users. Furthermore, because of the time sensitivity of relationships between users, it is better to consider the time information of user relationships such as trust relationships.

Symeonidis et al[29] provided a method that considers the local and global characteristics of the social network for friend recommendations according to trust information. They introduced a local similarity measure which calculated the proximity between users in the network. Moreover, they took advantage of the global network characteristics by providing transitive node similarity using the weights of the paths that connect two users in the network. They performed some experiments to compare their method with other baseline methods. The results demonstrated an improvement of their method in term of efficiency and accuracy. However, they should have used deeper characteristics of social networks with a combination of the semantic content information with users' connections for their friends' recommendation process. Moreover, they should have considered the trust value decay because of the time sensitivity of the trust factor.

Another technique that uses trust information to recommend friends in online social networks was proposed by Carullo et al,[30] consisting of three steps. The first step included hubs and authorities algorithm to identify the more trustable neighbor users as candidate recommendations. Using the Tversky index, the second step involved the calculation of the similarity degree between the target user and their determined more trusty neighbor users to refine the previous step's results. Finally, the last step integrated the results of the two previous steps to ultimately rank each user within the network. For evaluating the algorithm, they conducted some experiments using real datasets. The results showed improvement in terms of recommendation accuracy. However, their approach is problematic as it did not take into account any content information (such as tagging videos, photos, etc.) in the process of calculating similarities between users to achieve a more accurate representation of users' preferences. Another drawback of their approach is not considering the cold-start problem of users.

As another technique using trust information, Dou et al[24] proposed a privacy-preserving multimedia recommendation system according to weighted noise injection. For this purpose, they first identified key users who were the best representative of the features compared with all users to extract their provided ratings and the trust relationships' value. Then, according to the value of the trust relationship between these key users and the target user, they injected a different weight of Laplace noise into the provided ratings of key users. Finally, they used the perturbed rating matrix established on a mix collaborative filtering technique for multimedia recommendation. To evaluate this method, they conducted some experiments, results of which illustrated improved accuracy while preserving the privacy of users' personal information. However, the main disadvantage of their system is not focusing attention on the cold start problem of new items. They should have considered some contextual information including his/her demographic information and user's current condition their multimedia recommendation system.

Feng et al[25] proposed a recommendation method based on integrating social relationships between users including trust relationships into a social regularized sparse linear model. First, their model learned the coefficient vector of every user with respect to the matrix of ratings provided by users about the items and matrix of social relationships between users at once. Then, using the learned weight matrix, it recovered the user-provided rating matrix as a prediction matrix for the suggestion. The prediction was afterwards incorporated with the prediction induced by the presented distance regularized sparse linear model based on the advanced sparse linear model. Through experimental evaluation, they demonstrated the improvement of performance and efficiency of the proposed method. However, it would have been better if they had considered some factors for inferring the trust degree of items because of the existence probability of malicious data. Moreover, they should have provided some explanations for the recommendation reasons to obtain greater user trust in the results.

In 2014, a social recommendation method established on probability matrix factorization was proposed by Li et al.[36] Their method integrated various social information including user-provided ratings on items, explicit relationships between users, and implicit preferences of users of items. Explicit relationships were derived from expressed trust relationships between users and implicit preferences were achieved from similarity computation between users according to user-provided ratings of items. In addition, their conducted experimental results demonstrated improvement in terms of accuracy, scalability, and computational complexity. However, it would have been better if they had considered the distrust factor as a supplementary feature for the trust value inference process. In addition, taking into account some biases in the ratings provided by users of the items in their algorithm could have provided better results.

As another technique utilizing trust information, Choudhary et al[68] proposed a recommendation system generating suggestions for groups of users by determining circles in a social network. Accordingly, they first used genetic algorithm to create circles of users in the network. For creating a social circle of users, they used various social characteristics including the degree of similarity of users' personal profiles, trust relationships between users, and tie strength. Moreover, a genetic algorithm k-means clustering framework was used to divide the entire network. Then, the status degree of every user was calculated to achieve their influence in the overlapping circles. Finally, based on the group members' selection and nearest neighbors calculation, they provided a suggestion for a specific group. In addition, they conducted a series of experiments for evaluating their algorithm's accuracy. The results demonstrated the prominence of their algorithm with respect to the baselines algorithms. However, the main drawback of their system was not considering the privacy issue of users to maintain their privacy of personal information. It would have been better if they had considered the scalability issue for their systems.

Canturk et al[47] provided a location recommendation method using trust information as an important factor to improve their recommendation results. In their method, they calculated the trust value of users to recommend interesting locations according to users' check-ins activities, social relationships between users, and users' calculated trust value. In their proposed method, the trust value was calculated according to users' check-ins data. In addition to trust information, the current location of users was also another information utilized in their method. Finally, by performing random walk algorithm, they provided the location suggestions to users. For evaluating the algorithm, they conducted some experiments based on real datasets. The results showed improvement in terms of recommendation accuracy. However, if they had taken into account group recommendations with individual ones, better results would have been achieved since group recommendation is developed to support users to interact with people who share similar preferences and provide suggestions for common activities such as going to a museum with friends. Moreover, it would have been better if they had provided some explanations for the recommendation reasons to obtain greater user trust in the results.

Utilizing the social relationships of users and the trust factor, Suhaim et al[69] provided a personalized recommendation method for recommending ranked tweets in social networks. For developing their method, they first determined all kinds of target user relationships in social networks to identify the trusted relationships. Then, they extracted all the tweets produced by the target user, by his/her followings, and by any users which had social relationships with the target user. It is noteworthy that these tweets included likes, replies, retweets, and quote tweets generated by the users who had social relationships with the target user. Next, according to the type of user interaction with tweets, their provided ratings on tweets were calculated. Finally, employing a collaborative recommendation algorithm based on the calculation of users' similarity, contents suggestions were provided. To evaluate the algorithm, they conducted some experiments using real datasets. The results showed improvements in terms of recommendation accuracy. However, the major disadvantages of their method are not considering any contextual information for the recommendation and not taking into account the new users' cold-start problem.

In 2022, a three-way recommender system utilizing trust information for community recommendation was proposed by Chen et al.[70] For this purpose, they first divided the network into the information table of features and network structure, and analyzed various forces which might impact relationships between users and communities. For this purpose, they first divided the network into a table of attributes and network structure, and analyzed various forces which might affect connections between users and communities. In the table of features, they defined the initial force according to equivalence relation and conditional probability. They also used two-bounded rough set model of a pair of nodes on the user community pairs for defining other forces. In order to create the three-way recommendation system, they used the logistic regression algorithm to calculate the force weights and the evaluation function. In the next step, they proposed a supervised algorithm motivated by the threshold calculation algorithm according to maximum weighted entropy. Through an experimental evaluation, they demonstrated the improvement of their method. However, it would have been better if they had taken into account temporal information in their recommendation process because of the possibility of change in users' interests over time. In addition, providing explanations for the reasons of the presented suggestions would have yielded greater user trust in the system.

Li et al[71] presented a method to overcome the problem of confounding bias in rating prediction for recommender systems in social networks. For developing their method, they not only used inherent information such as latent factor of users/items, but also social networks characteristics such as relationships between users including trust via confounding correction which arises from social networks. Furthermore, for evaluating the algorithm, they conducted some experiments based on real datasets. The results affirmed improvement in terms of recommendation accuracy. However, they did not consider a semantic-aware method in their system to be able to reflect user preferences more correctly. They should have also considered and evaluated the user satisfaction to more precisely demonstrate their system's improvement.

5 | RESULTS

This section provides the answers to the research question related to trust-based social recommender systems.

RQ1, Annual distribution: Figure 2 represents the publication trend of the selected article over a specified period of time. It is obvious that there was an increase of papers related to the domain of trust-based social recommender systems from 2012 to March 2023. It clearly reveals the value of trust-based social recommender systems and the need for novel and improved recommender system techniques in addition to the increase in the use of trust-related social networks data.

RQ2, Main properties: The selected articles were reviewed in detail and the most often addressed trust-based social recommender systems identified. As previously mentioned, these recommender systems are based on their focus on type of social trust (trust of items or trust of relationships) categorized as trust-of-item-based and trust-of-relationship-based. The main properties of the most frequently addressed trust-based social recommender systems including their publisher, journal, main idea, technique, utilized trust-related social networks data, improvements and weaknesses are provided in Tables 5 and 7.

RQ3, Evaluation properties: Tables 6 and 8 are to be referred to for presentation of the improvements of the recommender systems using the trust-related social networks data. These tables provide the required information for evaluation of the most popular trust-based social recommender systems including evaluation goal, metrics, measures, datasets or benchmarks and case study.

RQ4, Analytical approaches: 47 articles were found after thoroughly reviewing the primary resulted articles from searching in the database sources shown in Table 2. These resulted articles were classified into two categories based on the type of their focused social trust (trust of items or trust of relationships) shown in Figure 3 and Table 4. This table illustrates that 9 out of 47 articles were focused on item-based trust analytical approaches and 38 articles were focused on relationship-based trust analytical approaches. Figure 5 shows the percentage of each category in the primary articles on the corresponding slice of the pie chart. It was observed that 19% of the primary articles were related to trust-of-item-based analytical approach and 81% related to trust-of-relationship-based analytical approach.

RQ5, Publishers: Regarding the number of primary articles per publisher, refer to Figure 6. This diagram provides an illustration for the article frequency in the corresponding rectangle of the bar chart. In Figure 6, it can be observed that

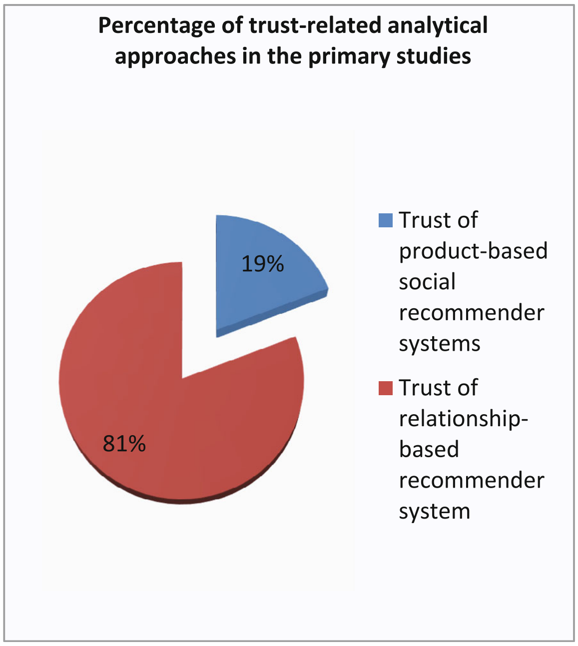


FIGURE 5 Percentage of trust-related analytical approaches in primary studies.

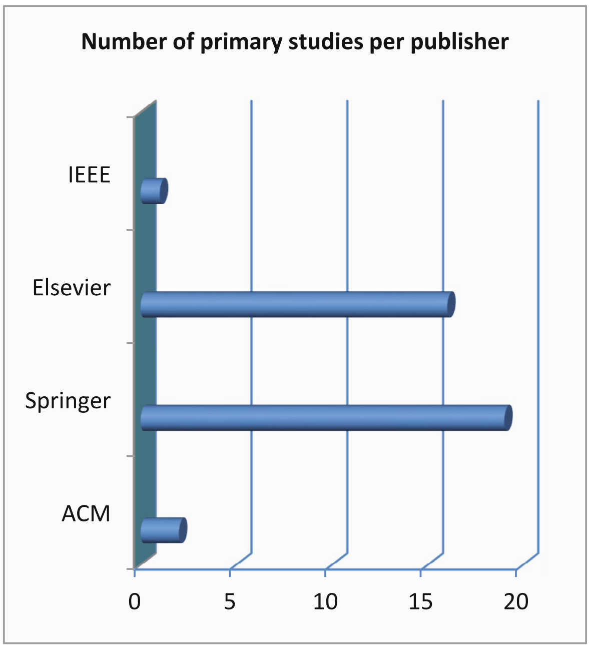


FIGURE 6 Number of primary studies per publisher.

most of the articles were published by *Springer*; of the 47 articles, 19 were published by *Springer*, 16 by *Elsevier*, 2 by *ACM* and 1 by *IEEE*.

RQ6, Evaluation metrics: For answering *RQ6*, refer to Figure 7. Figure 7A demonstrates the percentage of ameliorated metrics in the primary studies. Figure 7B illustrates the number of ameliorated metrics in the primary studies. In the present study, *accuracy* (50%) and *prediction speed* (15%) metrics had the highest number of primary studies ameliorated. Only few studies ameliorated the other metrics.

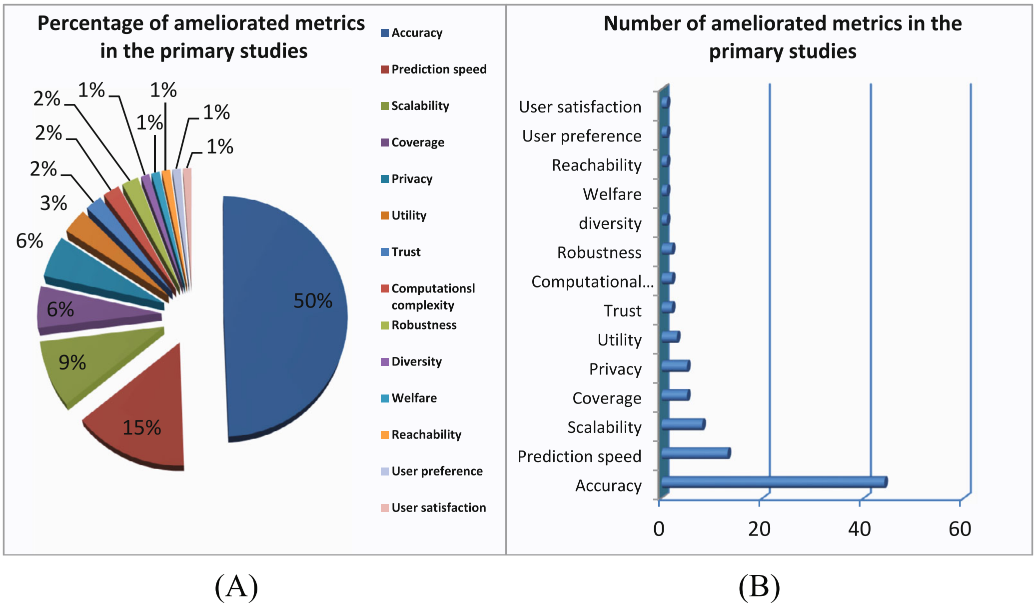


FIGURE 7 (A) Percentage of ameliorated metrics in the primary studies. (B) Number of ameliorated metrics in the primary studies.

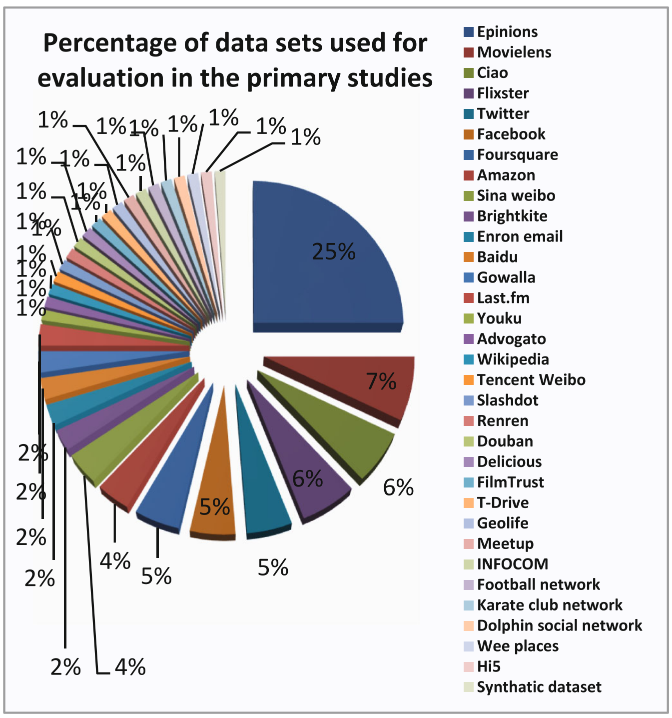


FIGURE 8 Percentage of data sets used for evaluation in the primary studies.

RQ7, Data sets: To address the utilized datasets in the primary studies, the required information from Tables 6 and 8 were extracted. These data sets and their statistics are illustrated in Figure 8, from which it can be inferred that the highest percentage of usage can be seen in the *Epinions* (25%) dataset.

RQ8, Recommended data: The recommended data is the information needed for the recommender systems to provide for the target user. This data extracted from Tables 5 and 7 are shown in Figure 9. This figure reveals the comprehensive view of the recommended data based on their frequency of occurrence in the trust-based social recommender systems reviewed literature. By not considering the not specified recommended data namely items, the highest

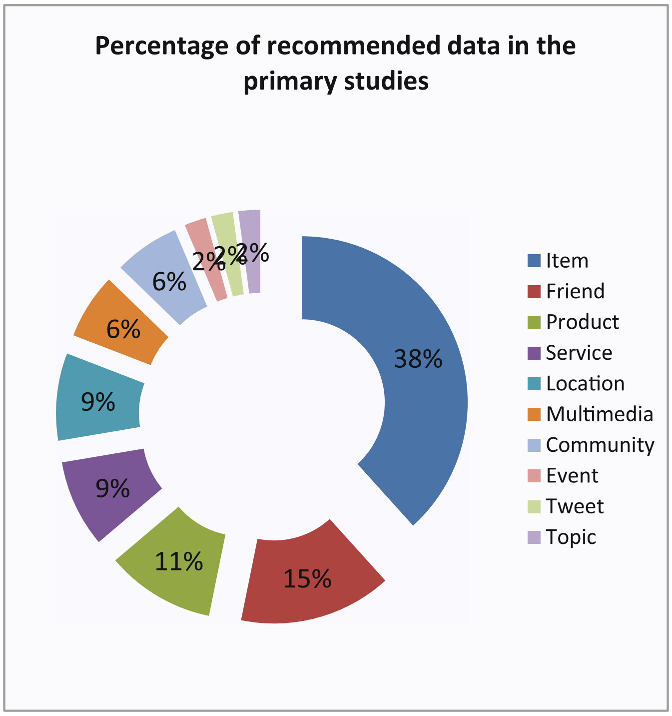


FIGURE 9 Percentage of recommended data in the primary studies.

percentages of the recommended data was related to friend (15%) and the lowest percentages of the recommended data was related to event, tweet and topic (2%).

RQ9, Social networks data: For definition of the exploited social networks data in the studied articles, refer to Tables 5 and 7. These social networks data were provided after a comprehensive review of the trust-related social network data analytical approaches in recommender systems. It can be observed that social ratings of items by users, trust relationships' values between users, friendship relationships between users, social networks sites' users' personal profiles, and item features were the primary social data used in trust-based social recommender systems.

6 | DISCUSSION

Recommendation accuracy in trust of relationship-based recommender systems using collaborative filtering algorithms depends on the similarity function's efficiency, and many primary studies were focused on enhancing similarity function by integrating supplementary information in addition to co-rating information. One supplementary information used in the majority of studies was the trust relationship between users. However, because of some limitations such as social networking sites in which the users do not have the possibility of explicitly expressing the trust degree with each other, it was often difficult to gather explicit trust level between users' relationships. Accordingly, implicit trust information was used to improve this function without relying on explicit trust information.

In regards to providing recommendations in social networks containing explicitly stated trust value, there was an increasing attempt in using the trust propagation feature in calculating the trust degree between two users who were not directly connected and were connected to each other by multiple links from different paths. Therefore, a solution would be to utilize all these paths by aggregating them to calculate the degree of trust. Since there might be many different trust paths, the issue of scalability issue in terms of computational time must be considered. To solve this problem, focusing on taking advantage of the trust propagation feature only using the shortest possible trust path would be appropriate in reducing processing of massive data. Otherwise, the random walk algorithm, which allows determination of the importance of a node in the network according to the network structure can be employed to make use of fewer data.

It is noteworthy that recently there has been a growing interest in implicitly inferring trust relationships between users. Therefore, one solution was to use social relationships including friendship relationships, follow/follower relationships between users, which can represent trust, the value of which can be computed in different ways. Furthermore, borrowing from Hubs and Authorities algorithm, friends of the trusted user of the target user can be accepted as people who can implicitly have a trust relationship with the target user. As another alternative, calculated degree of similarity between users based on various social information such as user-provided tags can be employed as the trust relationships' value between users. Otherwise, exploiting the reputation mechanism, which is evaluated by weighting the feedback provided by other users, can be used as an implicit trust value for a particular user.

The social information and techniques used in determining the trustworthiness of items to be recommendation candidates were explored which can improve the accuracy and performance of the trust of product-based recommender systems. The investigation revealed that the reputation-based approach which uses feedback value (such as rating) based on different factors including user creditability and selecting a dense subset of user-item ratings information can represent other users' perceptions of items. In addition, weighted link analysis and determination of users' influence degree based on the interpretation of user social feedback such as user-provided ratings on items to identify sybils can determine the trust level of items for being recommended or not recommended. As another alternative, machine learning algorithms based on maximum utility value can recommend the best trust path aggregation to recommend a trusted item/service. In addition, other solutions were more focused on the use of various social network information such as the social activities of the items and their review information, so that the types of these side information can be different depending on the recommendation environment. For instance, considering a video as a recommendation item, some statistical data of watched videos such as the number of posts, the number of comments, the number of submissions, and the number of collections can be referred to as their social activity. However, by considering a product as a data item for recommendation, another side information such as the ratings provided by the user, their reputation and the frequency of their purchase as review information can determine their trustworthy degree for the recommendation.

To mitigate data sparsity issue in recommendation systems focusing on this challenge, in addition to the trust factor, co-rating items and other social data, and co-clustering can be leveraged in collaborative filtering to increase the density of the social networks' graphs, thereby expanding the range of the target user's neighbors. Moreover, by employing deep learning techniques such as deep neural networks, more latent features can be obtained from users' connections such as trust relationships and tag information on users or items to alleviate the data sparsity problem. Graph summarization techniques have been utilized in sparse social networking websites since they are effective in finding beneficial patterns which are latent in the underlying data. Otherwise, improved matrix factorization technique including matrix factorization based on deep learning and probabilistic matrix factorization can remarkably predict the unknown items' ratings and thus achieve superior performance.

Another challenge that has received a great deal of attention in the investigated studies was the cold start coverage of new users which were solved by using various techniques in addition to social network data including trust. To help the cold-start problem of users, graph summarization technique and content-based filtering can be used. In this solution, graph summarization creates a two-level cluster including local and global clusters, then content similarity method assigns each new coming user to the local clusters utilizing content data such as user posts. Moreover, by using social network sites' user personal profiles, their demographic information can be captured to execute content-based filtering when only a few feedback of users such as their provided ratings are available. Furthermore, matrix factorization including matrix factorization utilizing cross domain information by integrating the latent factor model and neighborhood model to find the user interest, deep learning applied to matrix factorization based on collaborative filtering to extract hidden features, and representation of social graphs such as trust relationships graph to derive user preferences have been used to help relieve the cold start problem. Network embedding method can also find a group of users who are the representative of the new coming user's preference when there is not any explicit feedback of him.

One of the main objectives of the present research was to determine the most effective type of supplementary information for exploitation by recommendation systems. Therefore, studies that address RQ9 demonstrate that, in most cases, user-provided ratings on items, trust relationships, friendship relationships, as well as features of items and user profiles are used by the system to improve recommendation results.

The measures used to determine the outcome of the main ameliorated metrics of recommender systems were also investigated. The query demonstrated that measures such as precision, recall and F-measure are common in evaluating the classification prediction accuracy of recommendation systems. Measures such MA and RMSE are also related to rating prediction accuracy, while for evaluation of the ranking prediction accuracy of recommendation results, the measures NDCG and MAP are more commonly used. In addition, most of the improved metrics are calculated based on the standard measures, while other metrics including, welfare, and prediction speed, use theocratical analysis for evaluation.

7 | OPEN RESEARCH ISSUES AND FUTURE DIRECTIONS

This section presents the main trust-based social recommender systems issues that have not yet been comprehensively addressed as bases for future research direction.

1. By discussing and analyzing the mentioned state of the art approaches, it was observed that in none of these approaches improvements in terms of risk, serendipity, stability, task support, usability, confidence and learning rate were considered. These improvement issues for trust-based social recommender systems are also important and will increase the current analytical approaches' popularity, performance and effectiveness. Therefore, a future point of study would be to consider the not addressed enhancement issues.

2. Another unobserved factor in the investigated studies was lack of explanation for recommendation results. Explanations provide the reasons for occurrence of the items in the recommended list, absence of which would greatly reduce efficiency of the recommender systems. In many cases, the suggested items are in perfect accordance with the interests of user, but most users are idle and refuse to click on the links to view the strange items in detail, which will make them miss out on useful items. Therefore, new techniques which enable trust-based social recommender systems to present rich explanation of 'how the system works and the reasons for recommending suggested items not only presents the items users actually need, but also help users understand the recommended items are extremely promising.

3. Another important trust-based social recommender systems' improvement factor for future research which has received little attention in the existing trust-related social networks data analytical approaches is user satisfaction. The ultimate measure of a recommendation system should be user satisfaction since recommendation results are provided for target users and the ultimate goal of recommender systems is target user satisfaction. However, if recommender systems achieved improvement in terms of other factors, they would not necessarily be beneficial for the users. One of the most important issues other than improvement factors is the inability to obtain user satisfaction in the available recommendation systems. Therefore, research with a focus on evaluating user satisfaction from various aspects would be desirable. To this end, receiving feedback from users with different types of social networks data such as textual comments and tagging would be a good solution in addition to the usual social rating utilized in the majority of the current trust-based social recommender systems; to investigate user satisfaction as well as other factors such as accuracy and diversity would be another solution. By integration of different types of data according to underlying network structure for the purpose of general inference and tracking the temporal dynamics of users' feedback, adjustment would be made to the recommendation evaluated by users and thus achieve a personalized recommendation which is the main intention of recommender systems.

4. None of the review studies considered trust value biases. Potential bias that might exist in explicit trust stated by user for the other users refers to the user's inherent tendency in providing higher or lower rating than the average. By taking into account user and trust notation biases while recommendation process and results enhancement can be achieved since it can show the inherent difference between users and between trust notations. Therefore, future research studies should consider this issue by employing social networks data such as textual comments to which it is possible to associate a specific sentiment in addition to the explicit trust stated by users to infer a more accurate trust value for improving performance of the recommender systems.

5. Finally, the reviewed trust-related social networks data analysis approaches have some drawbacks. One drawback is that only a few approaches utilized a decentralized cloud-based approach scalable enough to handle large volumes of geographically distributed data and deal with the storage of these large-scale data. Another disadvantage is absence of sufficient consideration of the necessity of applications which are simple to use offering a light workload in the user terminal because mobile devices provide significant constrains related to screen size, processing capacity, battery lifetime or network connection. This statement implies there is a need for optimizing the architecture and improving the implementation of recommender systems. Therefore, there is a necessity for designing a recommender system with great adaption to each kind of terminal and user and using a cloud-based scenario in future research.

8 | SUMMARY AND CONCLUSION

This investigation, provides a systematic review of trust-related social networks data analytical approaches for recommender systems improvement. Additionally, it reviews various state-of-the-art trust-based social recommendation systems while explaining open issues through a comprehensive analysis of 47 primary articles extracted from a search query.

The answers generated from nine exploratory investigation questions confirm the increasing use of trust-related social network data as an emerging approach, introducing a novel paradigm to enhance trust-based social recommender system results across various aspects.

After an in-depth study of trust-based social recommender systems, the studies were classified into trust-of-relationship-based and trust-of-item-based recommender systems. We discussed the improvements achieved by utilizing trust-related social network data with social recommender systems and examined the challenges faced by recommender systems. This discussion aims to pave the way for more effective and efficient trust-related social network data analytical approaches in the future.

In a broader perspective, future trends in trust-related social network data analytical approaches for recommender systems still require enhancements to ensure user satisfaction. These improvements should encompass several key aspects, including:

i) Providing explanations for recommendation results; ii) Inference of the best trust value between users; iii) Adapting to mobile applications; iv) Employing decentralized methods to address geographical scalability issues; v) Implementing effective risk management; vi) Enhancing the usability of the system; vii) Utilizing suitable trust data tailored to specific recommender system applications and user needs; viii) Establishing an appropriate trust inference process; x) Investigating user satisfaction factor in recommendation.

The data collected in the present investigation facilitates the familiarization of the researchers with the state-of-the-art trust-based social recommender systems scope. It summarizes key aspects, including main target, existing challenges, open issues, techniques, and methods within the field.

Our hope is that this investigation's outcomes will provide valuable insights to researchers, allowing them to establish new research foundations and contribute to the ongoing improvement of trust-based social recommender systems.

DATA AVAILABILITY STATEMENT

Data sharing not applicable to this article as no datasets were generated or analysed during the current study.

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