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Serendipity in Recommender Systems: A Systematic Literature Review

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Abstract A recommender system is employed to accurately recommend items, which are expected to attract the user's attention. The over-emphasis on the accuracy of the recommendations can cause information over-specialization and make recommendations boring and even predictable. Novelty and diversity are two partly useful solutions to these problems. However, novel and diverse recommendations cannot merely ensure that users are attracted since such recommendations may not be relevant to the user's interests. Hence, it is necessary to consider other criteria, such as unexpectedness and relevance. Serendipity is a criterion for making appealing and useful recommendations. The usefulness of serendipitous recommendations is the main superiority of this criterion over novelty and diversity. The bulk of studies of recommender systems have focused on serendipity in recent years. Thus, a systematic literature review is conducted in this paper on previous studies of serendipity-oriented recommender systems. Accordingly, this paper focuses on the contextual convergence of serendipity definitions, datasets, serendipitous recommendation methods, and their evaluation techniques. Finally, the trends and existing potentials of the serendipity-oriented recommender systems are discussed for future studies. The results of the systematic literature review present that the quality and the quantity of articles in the serendipity-oriented recommender systems are progressing.

Keywords systematic literature review, recommender system, serendipity, evaluation metric, evaluation method

1 Introduction

Recommender systems (RS) adopt different methods of data mining and machine learning to recommend items of interest. A recommender system predicts a target user's opinion on a set of items. There are mainly two methods for predicting user opinions: item-based and user-based [1]. The item-based method evaluates the features and similarities of existing items in user records compared with other items to find the most similar items [2]. The user-based method analyzes the similarity between a target user's tastes and those of other users to determine the target user's opinion on a specific item based on the most similar user who rated on that item [1].

A recommender system tries to reduce the information-overload by retrieving items based on the target user's preference [3]. Hence, a recommender system should be able to predict a user's opinion on the items and present a set of n preferable items to the target user. Indeed, with the expansion of social networks and online stores, recommender systems have entered a new era [4].

In a recommender system, it is assumed that the accuracy of recommendations leads to user satisfaction. However, other factors can also affect user satisfaction with a recommender system [5], for instance: users might be dissatisfied with an accurate recommendation if they have no trust in a recommender system, their privacy is not guaranteed, it takes them a long time to get a recommendation, or they find the user interface unfavorable [6]. On the other hand, taking accuracy criterion into account may lead to over-specialization of information and offer boring and even predictable recommendations. Therefore, researchers have concluded that the novelty and the unexpectedness should also be taken into account to prevent infor-

Survey

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mation over-specialization.

Novelty and diversity are two solutions for over-specialization problems. The novelty refers to the ability of a recommender system to make new and unprecedented recommendations. The diversity is defined as the criterion representing the difference between items. For instance, a film is diverse if it differs from other films in style. Castells *et al.* addressed the difference between novelty and diversity thoroughly [7].

Despite the previous work [7], novelty or diversity cannot merely guarantee that an item attracts users [8]. In other words, to make users more satisfied, we should consider unexpectedness and relevance in addition to novelty and diversity. Different definitions have been proposed for serendipity in the research literature, as discussed in Subsection 4.1.

The serendipity consists of other qualitative features such as relevance and unexpectedness. For instance, a serendipitous recommendation is not only unexpected but also relevant. Hence, it can increase the likelihood of user satisfaction in comparison with a recommendation, which is merely unexpected. As one of their advantages over novelty, serendipitous recommendations are more useful, which is not achieved if recommendations are randomly generated [9]. In fact, the usefulness of recommendations is the main advantage of serendipity over novelty and diversity, although the generation of serendipitous recommendations is not so simple as the generation of novel and diverse recommendations. For instance, novel recommendations can be generated by a random algorithm or a simple pre-filtering method to eliminate the items already encountered by the user.

Nowadays, serendipity has a major role in making appropriate and appealing recommendations in a recommender system [10]. As a result, researchers have paid close attention to this criterion. Subsection 4.3 presents a review of related studies.

The serendipity-oriented recommender systems have not been analyzed systematically, and only two surveys have been published so far [11, 12]. An empirical analysis was conducted by Kaminskas and Bridge in [12] to determine the criteria value for diversity, serendipity, novelty, and coverage in different methods of the recommender systems. Kotkov *et al.* intended to analyze the existing methods and identify research gaps [11]. It should be noted that our research differs from [11] by proposing following new materials:

• the study of serendipity concepts in recommender systems and identification of serendipity challenges, as discussed in Section 2;

• the study and analysis of convergence in the definitions of serendipity over the years, as discussed in Subsection 4.1;

• reviewing more recently-published papers and the quality assessment of them to identify the progress in serendipity-oriented researches, as discussed in Subsections 4.3 and 4.5, respectively;

• the complete study of the related datasets that are suitable for serendipitous recommender systems, as explained in Subsection 4.2;

• finally and most importantly, a systematic literature review (SLR) providing a roadmap for developing a serendipitous recommendation system in all aspects, from introducing a novel model to employing suitable datasets and the methods/metrics of evaluations.

This SLR evaluated articles published between 2013 and 2019 and classified them according to the research questions. It is expected that, with this SLR, researchers and practitioners can obtain more information about the serendipity in recommender systems field, and make better development or research decisions.

In what follows, Section 2 deals with the concept of serendipity along with the research background and relevant challenges. In Section 3, the systematic literature review process is presented. Section 4 includes the SLR results and the answers to the research questions. The future serendipity trends and directions are discussed in Section 5. Finally, Section 6 presents the research results and future work.

2 Concept of Serendipity

Serendipity is a complicated and interesting concept for research [13]. The main reason for the complexity and ambiguity of serendipity is an association with emotion. As a result, defining serendipity in recommender systems is a challenging problem. The concept of serendipity is not specific only to computer sciences. It is also used in management, psychology, computational science, etc., and, therefore, it is necessary to define the word serendipity. Then the concept of serendipity is discussed in recommender systems and other fields. Subsection 2.3 deals with serendipity challenges.

2.1 Context and History of Serendipity

For many years, the word serendipity has been used as an untranslated word. It was first used in a letter in 1754. The root of this word dates back to a Persian fairy tale, *The Three Princes of Serendip*, by Amir Khusrow Dehlavi. In this fairy tale, the three princes of Serendip embark on a journey to explore the world. They always made unexpected and intelligent discoveries of the things which they were not seeking. According to the Oxford English Dictionary, serendipity means "the occurrence and development of events by chance in a happy or beneficial way"①. Before taking a look at the concept of serendipity in recommender systems, a brief review of this concept in other fields is first presented.

The serendipity-related theories have long been present in different fields, especially psychology. One such case is the curiosity theory [14]. In psychology, the curiosity theory states that a user is not curious about what he/she knows or what he/she has no information about. Also, the prepared mind principle, presented by Louis Pasteur, is greatly similar to the curiosity theory ("chance favors only the prepared mind"). Cunha *et al.* investigated the impact of management on the discovery of serendipity in the Research and Development (R&D) unit [15]. In business, Sugiyama and Kan identified the factors affecting serendipity occurrence and modeling [16]. McCay-Peet *et al.* analyzed serendipity in a digital environment from a sociological perspective [17].

2.2 Serendipity in Recommender Systems

As discussed earlier, the negligence of novelty and unexpectedness of recommendations would make recommender systems boring and predictable. Iaquinta *et al.* pointed out the false belief that users are always interested in their previous purchases [18]. The proof mainly focuses on the fact that there are many unselected items that can attract the users' attention if shown to them.

Niu *et al.* pointed out that every serendipity item is novel, although every novel item is not considered as a serendipity item [19]. They emphasized that a serendipity item should be characterized by both novelty and diversity so that it could be unexpected and finally surprising. In a recommender system, diversity emphasizes the degree of difference between items. Increasing diversity decreases relevance, and striking a balance between diversity and accuracy is considered a challenge. Therefore, the mere consideration of novelty is not sufficient to make high-quality recommendations.

Yaqub analyzed a large number of discoveries made by chance to divide serendipity into four categories: Walpolian, Metronian, Bushian, and Stephanian [20]. Walpolian refers to the exploration of the items which the explorer has not been seeking. Metronian occurs when the explorer finds an unexpected solution to the problem. Bushian points out the serendipity exploration when an explorer seeks nothing and has no goals. Stephanian is a curiosity-based discovery. It can be defined as a solution to a problem that will be discovered later.

Since the challenges and definitions of accuracy, novelty, and diversity have been analyzed, it is now possible to discuss the necessity of serendipity in recommender systems. According to the curiosity theory and Pasteur's principle, a serendipity item includes a part of relevance. Therefore, the accuracy criterion experiences less damage compared with novelty and diversity, although serendipity is not aligned with accuracy due to unexpectedness. In the concept of serendipity, usefulness, and positive feedback are among the principles. Hence, a serendipity item is more likely to become popular than a novel and diverse item. Despite having accuracy to some extent, serendipity eliminates over-specialization [21,22], because serendipitous recommendations are also novel and unexpected.

2.3 Serendipity Challenges

In a serendipity-oriented recommender system, the major challenge arises due to the intrinsic feature of serendipity. In fact, serendipity is a vague concept and a complicated part of the information systems. According to Makri *et al.*, it is impossible to adopt a systematic and controllable method to deal with serendipity [22] However, we do not fully agree with the opinion of Makri *et al.* [22]. It may not be possible to achieve a 100% serendipity rate due to the emotional dimensions. Still, it is possible to progress, as different studies in the field of serendipitous recommendations demonstrate it.

2.3.1 *Ambiguity in the Definition of Serendipity*

Regarding serendipity, the real challenge is its definition. Iaquinta *et al.* referred to serendipity as an unexpected recommendation that can expand a user's preference [18]. According to [23, 24], the low accuracy of recommendations would indicate high serendipity. Zuva and Zuva showed that serendipity was still being analyzed along with the factors affecting it [25]. These

①https://en.oxforddictionaries.com/definition/serendipity, Dec. 2020.

definitions of serendipity indicate that there is no consensus on the definition of this criterion. Therefore, defining serendipity is the major challenge resulting in different evaluation methods.

2.3.2 Evaluation

McCay-Peet *et al.* proposed various methods for serendipity evaluations [26]; thus, it is difficult to compare them. The wide variety of evaluation methods is because there are different definitions of serendipity. At the same time, various components are contributing to serendipity.

2.3.3 Emotional Dimension

The difficulty of making serendipitous recommendations is partly due to their emotional aspect, which is always very subjective and ambiguous. It is hard to determine why a user selects one of two similar items. In addition, a user's opinion is influenced by contextual data and mental states. Thus, a serendipity item might not be considered as a serendipity item in different mind states [27].

Users may show contradictory behaviors known as the gray sheep, which is a challenge faced by a recommender system. The gray sheep emphasizes that some users have no particular priorities and can show interest in multiple items at the same time [28]. Hence, some papers identified such contradictory behaviors to reduce their effects [29, 30].

2.3.4 Uncommonness of Serendipitous Recommendations

A serendipity item indicates a recommendation which should be novel, unexpected, relevant, and hard to discover by the users. Items with these four features are very rare, making it hard to present serendipitous recommendations.

2.3.5 Lack of Public Datasets for Serendipity

The process of providing datasets is time-consuming and laborious. The presence of public datasets can speed up the research. Regarding recommender systems, various datasets such as MovieLens②, Last.fm③, OpenStreetMap④, and Jester⑤ have been used in different papers. However, for collecting serendipity datasets, users need to answer more specific questions in addition to rating items. We also know that most users have little interest in answering questions or even giving ratings. Lack of research on serendipity is another reason for the lack of serendipity datasets. Given the increasing number of papers related to serendipity in recent years, it is expected that more serendipity datasets will be published. Nevertheless, only one serendipity dataset was exclusively provided for the public in 2018 (MovieLens Serendipity 2018) [31]. This dataset has two problems, the first of which is the lack of demographic information, including age and gender. Such information influences the user preference. The second problem is the availability of only 2 150 serendipity opinions out of 10 million opinions in this dataset.

3 Research Methodology

The systematic literature review is getting more and more important in computer sciences. The SLR aims at performing the process of searching for answers to the research questions accurately and regularly. In this study, the SLR is based on the guidelines defined by Kitchenham and Charters [32]. Recently, several systematic literature review articles in recommender systems have been written based on [32], such as [33–35]. Every systematic literature review is started with a number of questions, although the mapping study is determined by the subject [36]. The results are mainly related to the extracted information, publication classification, categorizations, and publication frequency [37]. In Subsections 3.1 and 3.2, first, we discuss the research questions. Then, the developed SLR process for this study is presented.

3.1 Research Questions

The research motive is to provide interesting items that cannot be easily discovered by users. Based on the initial studies, three questions (Q1, Q2, and Q3) were formed. The in-depth analysis of different papers on serendipitous recommendations led to the main research question (Q4). Regarding each research question (Table 1), specific search fields (Table 2) were taken into account to analyze the research questions.

The definition of serendipity poses a significant challenge, as various definitions have been presented for this

②https://grouplens.org/datasets/movielens, Dec. 2020.
③http://millionsongdataset.com/lastfm, Dec. 2020.
④https://openstreetmap.org/export, Dec. 2020.
⑤https://goldberg.berkeley.edu/jester-data, Dec. 2020.

Table 1. Research Questions

No.	Question
Q1	Do the definitions of serendipity converge?
Q2	Which methods have been employed to make serendipitous recommendations?
Q3	How are serendipity evaluation criteria related?
Q4	Has there been any improvement in making serendipitous recommendations?

Table 2. Research Search Strings

	Search String	Question Number
S1	("Serendipity" OR "Serendipitous") AND ("Method" OR "Approach" OR "Technique") AND ("Recommender Systems" OR "Recommendations")	Q4, Q2
S2	("Serendipity" OR "Serendipitous") AND ("Recommender Systems" OR "Recommendations")	Q4, Q2
S3	("Serendipity" OR "Serendipitous") AND ("Definitions" OR "Meaning" OR "Concept")	Q1
S4	("Serendipity" OR "Serendipitous") AND ("Measure" OR "Measurement" OR "Evaluation" OR "Evaluating" OR "QoS")	Q3

concept. The uncertainty in this definition has made researchers regard their definitions of serendipity simply as personal opinions or research hypotheses. In some other cases like [23], researchers may also avoid giving an explicit definition. Thus, it will be very important to answer this question (Q1): do the definitions of serendipity converge?

Various methods have been employed to develop serendipity-oriented recommender systems, which leads to the second research question (Q2): which methods have been employed to make serendipitous recommendations?

Another challenge lies in the difference between evaluation methods, which are analyzed by answering the third research question (Q3): how are serendipity evaluation criteria related? Answering Q3 can help researchers select or propose a precise evaluation method.

Has there been any improvement in making serendipitous recommendations? This is the main research question (Q4), which has not been analyzed in recommender systems. Therefore, the answer to this question is very valuable because it determines whether the previous studies on serendipity-oriented recommender systems have been successful.

3.2 Systematic Literature Review Process

In this study, the systematic literature review process consists of five steps.

Step 1. Determining the research questions (Table 1), selecting the keywords for the research, and answering the questions.

Step 2. Different research fields are taken into account to search for papers (Table 2). The papers in this study have been selected from the reputable digital libraries such as Elsevier, Springer, Wiley, IEEE, ACM, IOS Press, Taylor & Francis, and Emeraldinsight.

Step 3. A superficial analysis is performed on the papers to ensure these papers are about serendipitous recommender systems. For this purpose, abstracts and introductions have been reviewed.

Step 4. In addition to the abstract, introduction, and conclusion of the selected papers in step 3, the entire articles have been quickly and briefly evaluated to identify whether they are related to the research questions. In this study, the related papers are the ones that have at least one answer to one of the research questions.

Step 5. The papers selected in step 4 are carefully reviewed, and seven following points are extracted:

- the definition of serendipity from the perspective of the authors;
- the method of providing serendipitous recommendations;
- the research dataset;
- the similarity measurement mechanism;
- the serendipity evaluation method;
- the research results;
- the research gap.

4 Results of Systematic Literature Review

This section presents the results and answers to the research questions (Table 1). Based on the research

search strings (Table 2), the papers of interest were collected. Fig.1 shows the number of collected papers from 2013 to 2019. In addition, Fig.2 shows the frequency of papers based on the publisher. These figures include only the papers meeting the conditions discussed in Subsection 3.2. Table 3 presents different definitions of serendipity sorted in different references and Table 4 shows the features of widely-used datasets in the serendipity-oriented recommender systems.

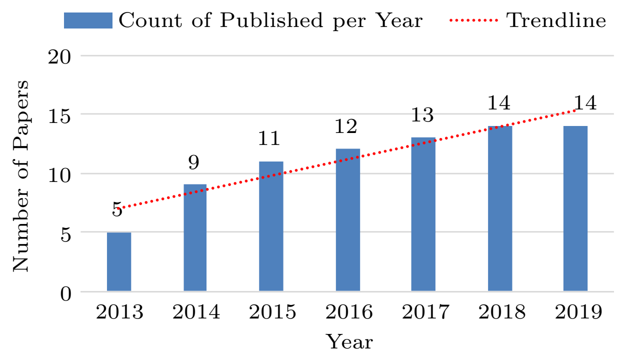

Fig.1. Number of published papers on serendipity in 2013–2019.

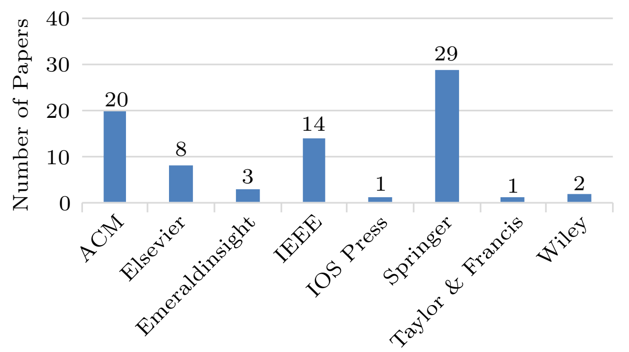

Fig.2. Number of published papers retrieved from each digital library.

Given the fact that 2019 articles were still being published during the systematic literature review, an increase is expected in the number of papers on serendipity. Looking at the trend in Fig.1, assuming the trend continues similarly in the future, the number of studies on serendipity recommender systems is expected to go up.

4.1 Convergence of Serendipity Definitions

In 1754, the word serendipity appeared in a letter written by Horace Walpole, who described it to Horace Mann [69]: "Serendipity is making discoveries, by accidents & sagacity, of things which they were not in quest of."

This definition marks a starting point for serendipity. As discussed earlier, the definition of serendipity is a daunting challenge in serendipity-oriented recommender systems and, therefore, various definitions have been proposed. To provide an answer to Q1, the definitions introduced in different papers from 2013 to 2019 were collected in Table 3. Then, serendipity components were extracted from definitions to be classified in the year and frequency of publication (Fig.3). In Fig.3, only five common components of serendipity definitions (novelty, relevance, unexpectedness, usefulness, and diversity) were classified separately, and the other components were categorized as others. The unexpected, unanticipated, and surprising components were regarded as unexpectedness, whereas the useful, interesting, and valuable components were regarded as usefulness. In Fig.3, every circle shows the frequency of a component in the definitions given in specific years.

Q1. *Do the Definitions of Serendipity Converge?*

According to Fig.3, unexpectedness and usefulness are the most widely-used components in the definitions of serendipity from 2013 to 2019. The relevance has been taken into account since 2014. Therefore, nearly most of the studies are in agreement on unexpectedness. However, no accurate comments can be made on other components.

In this study, we believe that it is necessary to focus on the definition and the nature of serendipity so that proper theories can be developed. According to Pasteur, "Without theory, practice is but routine born of habit." [70]. Nowadays, the majority of studies are based on trials and errors instead of strong theories, which leads to the divergence of serendipity definitions. Obviously, it is never expected that all definitions of serendipity should match word by word. This study emphasizes the conceptual similarity and convergence of definitions. It is predicted that a definition with the best output will be agreed upon by most researchers in the future. Such a definition can conceptually converge the other definitions of serendipity. We believe that serendipitous recommendation should include some level of novelty, unexpectedness, and relevance as given by the below equation:

$$\forall\ u \in U, I_{\text{Serendipity}} = I_{\text{unexpected}} \cap I_{\text{novel}} \cap I_{\text{relevant}}. \quad (1)$$

In (1), U indicates the set of users, and u is the target user. I also represents a set of items.

Table 3. Definitions of Serendipity Sorted in Publication Year

No.	Definition of Serendipity	Year	Reference
1	Serendipity is composed of six factors including unexpectedness, novelty, diversity, personalized content, visual cues and social collaboration	2013	[38]
2	Finding something good or useful that we were not looking for	2013	[39]
3	A serendipitous recommendation helps the user to discover the surprising or interesting items	2013	[40]
4	Serendipity is discovering the unexpected and useful items	2014	[41]
5	Items relatedness and surprisingness for the user	2014	[42]
6	An unexpected event	2014	[22]
7	Finding useful and unexpected recommendations	2015	[43]
8	An unexpected and useful event	2015	[5]
9	The surprisingness and success of a recommendation	2015	[44]
10	An unexpected, novel, and related recommendation	2016	[11]
11	Finding an unexpected and useful item for the target user	2016	[45]
12	Surprising and interesting items for users that are the result of unexpected recommendations	2016	[46]
13	Measurement of desirability and unexpectedness of the results	2016	[47]
14	Novel, unexpected, and related recommendations	2017	[48]
15	The quality to provide unexpected and useful recommendations	2017	[49]
16	An unexpected and valuable discovery	2017	[50]
17	Finding useful and unexpected items	2017	[23]
18	Recommendations based on the relatedness and unexpectedness	2018	[51]
19	Surprising and accurate recommendation at the same time to provide helpful suggestions to users	2018	[24]
20	Discovering interesting and valuable facts that we were not looking for	2018	[52]
21	Discovering surprisingly unexpected recommendations that enhance the discovery of information	2018	[53]
22	The unanticipated occurrence of happy events, such as the finding of valuable information	2019	[54]
23	The process consisting of: trigger, connection, follow-up, valuable outcome, and an unexpected thread	2019	[55]
24	An unexpected experience prompted by an individual's valuable interaction with ideas, information, objects, or phenomena	2019	[56]

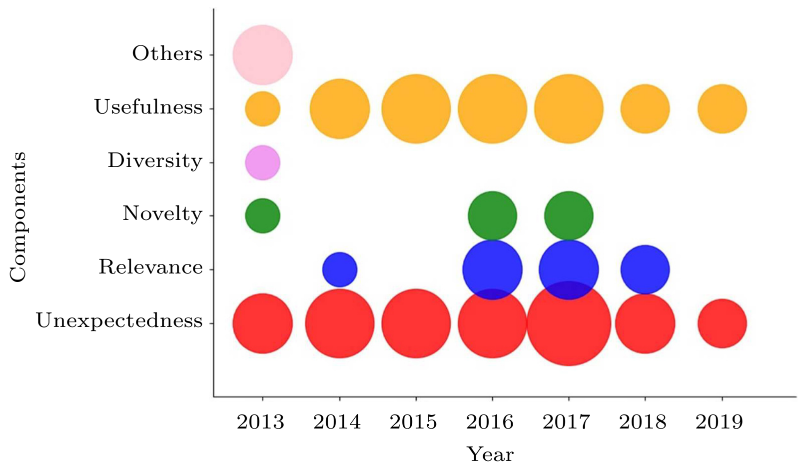

Fig.3. Dispersion diagram of components defining serendipity with respect to the publication year.

4.2 Datasets of Serendipity-Oriented Recommender Systems

As discussed earlier, a research challenge is the presence of public serendipity-specific datasets. The algorithms and studies on recommender systems need a particular dataset to analyze and evaluate the proposed method. A list of public datasets with specific features can be very useful for the researchers. Table 4 shows the datasets on which the studies of serendipity-oriented recommender systems are performed.

Subsection 4.4 analyzes the effect of dataset selection on evaluation methods. To put it in a nutshell, serendipity-oriented recommender systems benefiting from specific datasets will perform the evaluation more easily because they need to simply evaluate accuracy in the detection of serendipity items based on the la-

Table 4. Features of Widely-Used Datasets in the Serendipity-Oriented Recommender Systems

Dataset	Number of Users	Number of Items	Number of Ratings	Density	Rating Scale	Reference
MovieLens serendipity 2018	104 661	49 151	10 000 000	0.89%	[0.5–5]	[35, 57]
MovieLens 1 M	6 040	3 883	1 000 209	4.26%	[1–5]	[58–60]
MovieLens 10 M	69 878	10 681	10 000 054	1.33%	[0.5–5]	[41, 46, 51, 61, 62]
MovieLens 100 K	943	1 682	100 000	6.30%	[1–5]	[42]
Jester	124 113	150	5 865 235	31.50%	[–10, 10]	[59, 63]
Book-Crossing	92 107	271 379	1 031 175	0.004 1%	[1, 10]	[51, 59, 64]
Last.fm	1 892	17 632	92 834	0.28%	Play counts	[10, 65]
Wikipedia	5 583 724	4 936 761	417 996 366	0.001 5%	Interactions	[61, 66, 67]
Open Street Map	205 774	231	205 774	0.82%	Interactions	[24]
Netflix	480 189	17 770	100 000 000	1.18%	[1–5]	[60, 68]

beled dataset. However, serendipity methods employing other datasets will face certain challenges due to the absence of a specific method for serendipity evaluation.

As mentioned before, some of the serendipity articles benefit from general recommender system datasets [41, 51, 61]. Some of these articles generate a set of recommendations and evaluate their proposed serendipity approach based on user feedback [51, 58]. For example, Jain and Hasiga proposed an approach that asks its users to rate recommendations and determine if they are familiar with the recommended movie [58]. Others evaluate the serendipity of the recommendations based on mathematical relations [57, 62, 63]. For example, Wang *et al.* [10] evaluated its recommendations based on two mathematical equations. One refers to the interval of generating recommendation and the time it takes for the user to discover that item [10]. The other equation evaluates the distance between the user's previous favorite items and the new recommendations.

Public datasets lack the serendipity label. Therefore, papers with public databases often try to increase diversity and unexpectedness but make the slightest improvement in precision [25, 49, 51]. For this purpose, re-ranking and prefiltering are among the most conventional methods. However, if there is a serendipity dataset, features can be extracted from these recommendations. In this regard, five characteristics and their effects on serendipity and diversity have been analyzed by Nguyen *et al.* in [27]. Feature extraction can be employed to predict the labels of recommendations in public datasets.

4.3 Methods of Generating Serendipitous Recommendations

In order to answer Q2, this subsection reviews several important papers proposing new algorithms for generating serendipitous recommendations. This collection of articles has been chosen to maximize the coverage in various approaches to generate serendipitous recommendations. Through an extensive review of each paper, the advantages, disadvantages, and existing research gaps are identified and discussed.

4.3.1 Collaborative Filtering Approaches

Afridi made serendipitous recommendations in the e-learning field [51]. Instead of using an algorithm to make serendipitous recommendations, Afridi employed user controls, which enabled the user to contribute to the generation of recommendations. In the proposed method, collaborative filtering (CF) and accuracy are first utilized to make relevant recommendations. The relevance of the recommendations is based on user preferences and similarity measurement. In the next step, the re-ranking technique is applied to the set of generated recommendations. Re-ranking and the number of recommendations can be controlled by the user. The user controls can be combined with a heuristic algorithm to obtain better results. Afridi also wrote a book about serendipitous recommenders [71].

Khoshahval *et al.* employed the combination of association rule mining (ARM) and CF to generate a serendipity-oriented location-based recommender system [24]. They developed a mobile application to recommend serendipity locations based on user preferences. The proposed mobile application consists of two components: a serendipity-oriented recommender system and a user location registration module. The goal of employing ARM was to extract specific rules and relationships between the spots where the user was located. The proposed algorithm can be developed by expanding the user behavioral model. For instance, the user behavioral model can also include the duration of user presence in a location.

Niu and Abbas regarded curiosity as the factor in setting up serendipity [72]. The user-system engagement increases if the curiosity of a user is aroused. Therefore, they proposed an adaptive framework consisting of three models (value, surprise, and curiosity). The proposed framework was implemented and evaluated for the health news system. According to the results, more than half of the items were highly surprising. This method can be improved by getting user feedback and striking a balance among the three models.

Deng *et al.* proposed a deep collaborative filtering (DeepCF) framework [73]. DeepCF combines the strength of both representation learning based CF and matching function learning based CF methods. Employing vanilla Multi-Layer Perceptron (MLP), the authors developed a collaborative filtering network (CFNet) under the DeepCF framework to learn the complex matching function as well as low-rank relations between users and items. A similar framework has been proposed by He *et al.*, replacing the inner product used in the vanilla model with a neural architecture that can learn an arbitrary function from data [74]. Their proposed framework, NCF (Neural network-based Collaborative Filtering), ensembles MLP and MF (Matrix Factorization). This model combines the strength of the linearity of MF and non-linearity of MLP for modeling the user-item latent structures.

Wang *et al.* proposed innovator-based collaborative filtering (INVBCF) for recommending cold items [10]. Unlike the classic collaborative filtering, most similar users are not selected for generating candidate lists. Instead, INVBCF only selects innovator users who are identical at the very beginning and without the help of RS. Innovator users are those who can discover the cold item at the very beginning.

Yu *et al.* emphasized the higher importance of user satisfaction than accuracy [23]. They defined serendipity as an unexpected and high-quality item. Accordingly, they proposed a new serendipity evaluation formula and a strategy for striking a balance between accuracy and serendipity. The proposed strategy employed user records and feedback for the optimization of serendipity and accuracy so that these two criteria could be balanced. Given the contrast between accuracy and serendipity, the proposed strategy is very useful. Thus, this study can be developed on an online test and evaluation system.

4.3.2 Content-Based Approaches

Maccatrozzo *et al.* proposed a curiosity-based serendipitous recommendation named SIRUP (Serendipity In Recommendation via User Perception) [75]. SIRUP consists of two elements: 1) a novelty analyzer which compares the novelty of an item to those of other items existing in the user profile; 2) the evaluation of a user's ability to adapt to the novelty level of a candidate item. For this purpose, the cosine similarity is employed to determine the level of novelty because the novelty of an item is contradictory to its similarity in a user's records. Therefore, the lower the similarity, the higher the novelty of an item for the target user. SIRUP can be improved by getting direct feedback from users and conducting in-depth studies on the unexpectedness of recommendations.

Chang and Tang evaluated two music services (Spotify & KKBOX) with regard to serendipity [76]. The evaluation is performed in an online test by asking users a series of questions. The regression analysis is employed to analyze user responses. Since the study had access to the demographic information of the participants, it would have been better to consider such information in the behavioral analysis of users given the correlation between user preferences and demographic information.

Meng and Hatano proposed a new method by combining LDA (latent dirichlet allocation) and PCA (principal component analysis) to generate serendipity-oriented words [66]. LDA and PCA were employed to generate words and determine lexical relationships, respectively. Like many other papers on serendipity, a poor evaluation was presented in [66].

Kito *et al.* [43] proposed an algorithm for music serendipitous recommendations. According to the authors, serendipity is a combination of unexpectedness and usefulness [43]. Hence, the similarity between the metadata of music files and items the user usually listens to was used along with the acoustic similarity for the usefulness of recommendations. They employed Mel Frequency Cepstral Coefficients on 30 seconds of 1 000 music files to analyze the acoustic similarity. Focusing on the similarity of metadata indicates that the proposed algorithm was of the content-based filtering type. According to the algorithm results, there was no correlation between user preferences and acoustic similarity. Moreover, the singer similarity was more correlated with user preferences compared with the release year and the album year. The research results were very useful for music recommendation. This method can be generalized by regarding the similarity of lyrics as a parameter affecting the user preferences.

4.3.3 Context-Awareness Approaches

Karpus *et al.* intended to answer the question of whether contextual information could improve serendipity in addition to accuracy [49]. For this purpose, they employed two ontologies, used for a recommender system context, and for a user's profile context. In [47], the first challenge is the absence of a specific method for serendipity evaluation. The second challenge is the efficiency of the proposed method because the combination of two ontologies and a pre-filtering method will obviously be slow.

Koster *et al.* introduced a context-aware recommender system supporting serendipity [77]. This system receives certain signals from the user's mobile sensors to better analyze the potential behavior of users. The proposed method was introduced as a mobile application for finding a parking spot. This method needs to frequently receive the information from mobile sensors and preprocess the information locally. As a result, battery consumption increases.

Lambropoulos *et al.* collected and decomposed large and small data to identify latent factors in a serendipity event [87]. The secondary goal was to introduce evaluation techniques and tools. This study analyzed user behaviors in social networks to increase the chance of serendipity occurrence by scrutinizing the decision-making process of the human brain. For future studies, this work can be extended by analyzing other effective parameters. For instance, the textual comments of users can be analyzed to classify them as positive, negative, and neutral. The analysis of comments can provide researchers with more details on user behaviors. Lu and Chung proposed a serendipity video recommender system using machine learning to combine tags, which would finally make serendipitous recommendations [82]. The results indicate a significant decrease in accuracy and an increase in surprise recommendations. The disadvantage of this study is the lack of the balance between relevance and surprise levels.

De Gemmis *et al.* proposed a graph-based method by combining the random walk with restarts algorithm and knowledge infusion (RWR-KI) [61]. On average, 12.5% of the recommendations made by the RWR-KI algorithm are surprising and useful. However, 6.5% of the random recommendations are surprising on average.

4.3.4 Hybrid Approaches

Kotkov and Wang analyzed the effect of multiple data sources on accuracy and serendipity in the target domain [48]. Using collaborative filtering and content-based (CB) methods, a combination of three datasets was employed for simulation. According to the research results, serendipity increases in both CF and CB methods if datasets overlap at the system level. This study can be conducted on several datasets by utilizing data fusion techniques. Another study has been conducted by Kotkov *et al.* to generate serendipitous recommendation using cumulative link mixed-effect regression [31].

Menk *et al.* proposed a serendipitous recommendation system based on human curiosity for tourism [86]. They considered some users' information, such as the education level, curiosity, and other characteristics extracted from their Facebook profiles. Then, it provides a list of related recommendations and a list of unexpected recommendations. Sharing these two lists makes the serendipity items. However, the proposed algorithm is not evaluated based on the serendipity criterion.

Table 5 shows an overview of the methods used for generating serendipitous recommendations and similarity measurement mechanisms. It should be mentioned that [42] has simulated the proposed algorithm through CF, CB-CF, and CB separately. As a result, it appears in different rows in Table 5.

Fig.4 shows a roadmap for generating serendipitous recommendations that covers most of the available methods. Based on Fig.4, it should first be determined whether the goal is to improve accuracy-based algorithms to support serendipity or to consider a new approach to generate a candidate list of recommendations. In the next step, a pre-filter may be used. The purpose of pre-filtering is to remove items that are not novel. The next step is producing the candidate list or the final recommendation list. The candidate list is sorted by selecting the criteria to choose the top N recommendations. Finally, the selected recommendations are evaluated to determine the performance of the proposed method.

4.4 Serendipity Evaluation Methods

This subsection seeks an answer to Q3: How are serendipity evaluation criteria formulated? There have been many methods to evaluate serendipity. The methods of serendipity evaluation can be divided into three groups (Fig.5), the first of which includes the direct evaluation of serendipity or unserendipity value

Table 5. Methods of Generating Serendipitous Recommendations and Similarity Criteria

Recommendation Approach	Reference	Method	Similarity Measurement	Environment
Collaborative filtering	[3]	Shortest path finding	TF-IDF	Mobile App recommender
	[4]	Model-based	Cosine similarity	Research area
	[23]	Based on the user feedback	Cosine similarity	Movie
	[24]	K-furthest neighborhood	Cosine similarity and Pearson similarity	Location recommender
	[42]	Nearest neighbor	Pearson similarity	Movie
	[51]	Clustering re-ranking	Jacquard distance	E-learning
	[57]	Deep learning	Not mentioned	Movie
	[58]	Combined similarity and dissimilarity	Pearson similarity	Movie
	[72]	Model-based	Not mentioned	Medical news
	[78]	Theory-based	TF-IDF	Game-based application
	[79]	Greedy algorithm	Cosine similarity	Movie
	[80]	K-means	Cosine similarity	Movie
	[81]	Matrix factorization	Cosine similarity and Jaccard similarity	Movie
Content-based	[16]	Similarity-based	Pearson similarity	Paper recommender
	[40]	Bayesian information criterion	Other measure	Music
	[42]	Duine framework (InterestLMS)	Pearson similarity	Movie
	[43]	Similarity distance	Mel Frequency Cepstral Coefficients	Music
	[47]	Similarity-based	Cosine similarity	Video recommender
	[66]	Latent dirichlet allocation and principal component analysis	TF-IDF	Search
	[75]	Model-based	Cosine similarity	TV program
	[82]	Machine learning	Kullback-Liebler divergence	Video recommender
	[83]	Data fusion	Cosine similarity	Paper recommender
Context-awareness	[49]	Ontology, Pre-filtering, k-Nearest Neighbors (KNN)	Lack of similarity measure	Musical concert
	[52]	Graph-based	Other measure	Knowledge discovery
	[54]	Linear regression	Not mentioned	E-commerce
	[55]	Graph-based	Personalized PageRank and random walk based measure	Social network
	[61]	Random Walk with Knowledge Infusion	Cosine similarity	Movie
	[77]	Latent Dirichlet Allocation, deep learning	Based on probability	Location recommender
	[84]	Self-learning	TF-IDF	News
	[85]	Text mining	Not mentioned	Research area
Hybrid	[31]	Based on the user feedback	Cosine similarity	Movie
	[42]	Duine framework (InterestLMS), nearest neighbor	Pearson similarity	Movie
	[46]	Random Walk with Knowledge Infusion	Other measure	Movie
	[48]	Data fusion	Cosine similarity	Music
	[65]	Similarity-based	Cosine similarity	Music
	[86]	Theory-based (curiosity-based)	Self-defined	Social network

of recommendations through a formula. The second group includes evaluation through real user feedback. The third group includes the indirect determination of serendipity based on its components. For instance, the levels of unexpectedness and relevance can be evaluated instead of measuring serendipity directly.

The cosine similarity was employed by Zuva and Zuva to determine the mean similarity between the item and user records[25]:

$$\begin{aligned} & Unserendipity_u \\ & = \sum_{u\in U} \frac{1}{|U|\,|H_u|} \sum_{u\in H_u} \sum_{i\in R_{u,N}} \frac{\cos(i,h)}{N}. \end{aligned} \tag{2}$$

In (2), a lower value of $Unserendipity_u$ indicates a higher level of serendipity. In addition, i shows a new

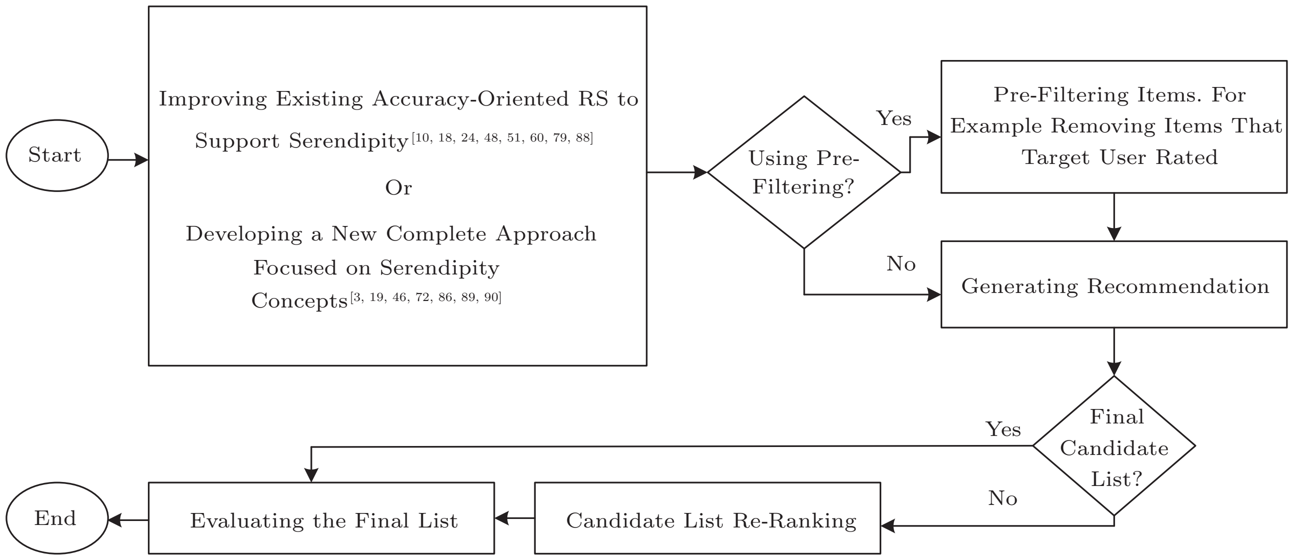

Fig.4. Roadmap of generating serendipitous recommendation.

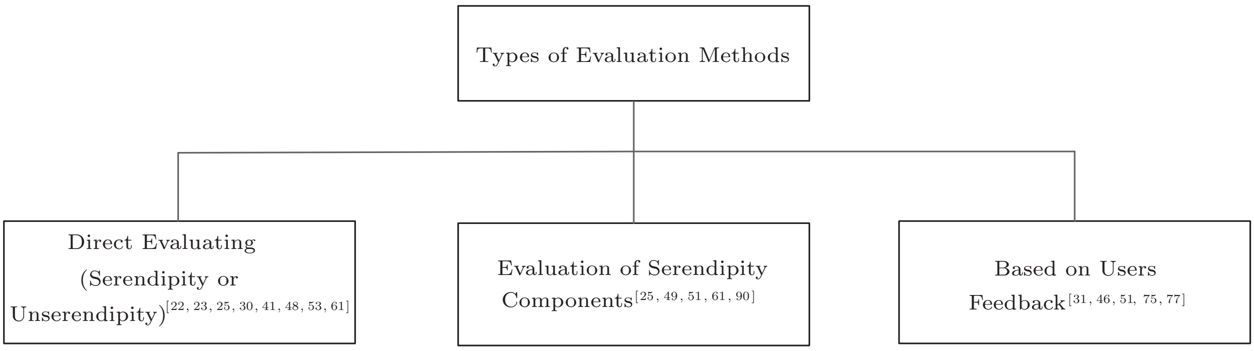

Fig.5. Serendipity evaluation methods.

recommendation, while H_u refers to a set of items existing in user records. The set of users is shown by U, and $R_{u,N}$ indicates N top recommendations. In [26], (3) is proposed for serendipity evaluation:

$$Ser_u = \frac{1}{N}\sum_{i\in N}\max(P_i(u) - P_i(all(u_s),0)) \times REL(u), \quad (3)$$

$$P_i = \frac{N - rank_i}{N-1}. \quad (4)$$

In (3), $REL(u)$ indicates the relevance of a recommendation to user u, and P_i is the probability obtained from (4). Moreover, $rank_i$ is the ranking of item i on the recommendation list, and N shows the number of recommendations.

(5) is used by Kotkov *et al.* to evaluate the serendipity criteria[48]. In this equation, U is the set of users, and $RS_u(N)$ indicates the top N items recommended to user u. Furthermore, PM refers to the set of recommendations generated by the recommender system, and E_u shows the set of items that are similar to the ones selected by the user. Finally, REL_u indicates a set of items which are relevant to the user's profile:

$$Ser@N = \frac{1}{\|U\|}\sum_{u\in U}\frac{\|(RS_u(N)\backslash PM\backslash E_u)\cap REL_u\|}{N}. \quad (5)$$

A simple formula is proposed by De Gemmis *et al.* for serendipity evaluation based on relevance and unexpectedness[61]:

$$Ser@N = \frac{\sum_{i\in L} S(i)}{N}, \quad (6)$$

$$S(i) = \begin{cases} 1, & \text{if recommendation is serendipitous,} \\ 0, & \text{otherwise.} \end{cases} \quad (7)$$

(6) introduces serendipity as the ratio of $S(i)$ to the size of a set L containing serendipitous recommendations. In other words, this formula indicates the ratio

of the number of serendipitous recommendations to the total number of recommendations every time a recommendation is made to a user. The same formula is used by Manca *et al.*[21]. In (7), $S(i)$ equals 1, if the item is serendipitous; otherwise, it equals 0.

Chantanurak *et al.* employed the ratio of the number of useful recommendations to the number of unexpected recommendations in order to evaluate a set of recommendations, as formulated by (8)[47]:

$$Ser@N = \frac{\#useful}{\#unexpected}. \tag{8}$$

In (8), $\#useful$ shows the number of useful recommendations. If the user's feedback is positive, then it is a useful recommendation. A new formula, (9), for serendipity evaluation was presented by Yu *et al.*[23]. (9) is based on the idea that a user's interest in an item decreases over time:

$$\begin{aligned} Ser_{u,j} = {} & \alpha \times \frac{\frac{1}{C}\sum_{c=1}^{C} R_{c,j}}{\frac{1}{N}\sum_{n=1}^{N} \frac{R_{u,n}}{R_{umax}}.Sim_{u,j}} + \\ & \beta \times \frac{1}{P_{u,j}(t)}. \end{aligned} \tag{9}$$

In (9), α and β are two positive values controlled by the system. In fact, α is zero for the item, which has already surprised a user. When the item is considered retrospectively, β is zero. Furthermore, C refers to the number of users voting for j, and N indicates the number of votes given by user u. Generally, (9) determines the serendipity level of item j for user u. $Sim_{u,j}$ is calculated using the cosine similarity formula. $P_{u,j}(t)$ shows the votes given by users at t. $R_{c,j}$ indicates the vote given by user c for item j. $R_{u,n}$ shows the votes given by user u for item n. R_{umax} is a maximum rate given by user u.

Another equation is proposed by Jain and Hasija to evaluate serendipity in making recommendations for serendipity movies[58]. (10) shows the Jaccard index used for measuring dissimilarity and distance:

$$Dist(i,j) = 1 - \frac{(G_i)\bigcap(G_j)}{(G_i)\bigcup(G_j)}. \tag{10}$$

$$S_{count}(i) = \min dist(i,j). \tag{11}$$

G_i is a set of genres that have been positively voted as serendipity, and G_j is a set of items that have been positively evaluated by collaborative filtering. In fact, (10) indicates the distance between the genres of the considered items, the minimum value of which for film i shows the level of surprise. (11) represents the minimum distance between i and j.

(12) evaluates serendipity using the ratio of the number of useful and unexpected recommendations to the total number of recommendations. This equation subtracts the product of expectedness by familiarity from 1 for an item to determine surprise:

$$\begin{aligned} surprise(d) &= 1 - (familiarity(d) \times \\ & \qquad expectation(d)), \qquad (12) \\ Ser(d) &= value(d) - abs(surprise(d) - \\ & \qquad surprise(\Theta', \delta')). \qquad (13) \end{aligned}$$

In (13), d indicates the value of a recommendation based on user preferences, and Θ', δ' are two surprise parameters given as inputs to the curiosity model proposed by Niu and Abbas to search for serendipity items[72].

(16) consists of (14) and (15). (14) results in high accuracy, whereas (15) increases serendipity[41]. Therefore, α is used in (16) to strike a balance between accuracy and serendipity. In fact, a higher value of α increases accuracy, whereas a lower value of α improves serendipity:

$$Confidence(A => B) = \frac{N(A\bigcap B)}{N(A)}. \tag{14}$$

$$\begin{aligned} d = {} & Confidence_{((A=R_t=>B=\text{Like}))} - \\ & Confidence_{((A=\sim R_t=>B=\text{Like}))}. \end{aligned} \tag{15}$$

$$Ser_B = \begin{cases} Confidence^{\alpha}_{(A=R_t=>B=\text{Like})} \times d, \\ \quad \text{if } d \geqslant 0, \\ Confidence^{\alpha}_{(A=R_t=>B=\text{Don'tLike})} \times d, \\ \quad \text{otherwise.} \end{cases} \tag{16}$$

In (14), $N(A\bigcap B)$ is the number of items meeting both conditions A and B at the same time, and $N(A)$ shows the number of items meeting condition A. In $(A => B)$, A is the condition, whereas B is the result. Confidence refers to the certainty at which B occurs when A is true. Moreover, R_t is the positive vote (Like) given by the target user, and $\sim R_t$ is the negative vote (Don't Like) given by the target user. Finally, d shows the difference between the target user's preference and those of other users.

Considering the challenge of measuring serendipity directly (as mentioned above), other studies measured its components (relevance, novelty, diversity, etc.).

Precision and recall are the two criteria used by Karpus *et al.* to evaluate serendipity through (17)[49]. The higher the precision, the more relevant the recommendations. The lower the expectedness, the higher the serendipity:

$$Expectedness = \frac{1}{N}\sum_{i=1}^{N} popularity(i). \quad (17)$$

The root mean square error (RMSE) criterion in (18) was used by Khoshahval *et al.* for determining the difference between predicted votes $\hat{r}_{u,i}$ for serendipity items and the real votes given by users $r_{u,i}$ [24]:

$$RMSE = \sqrt{\frac{\sum_{u,i}(r_{u,i} - \hat{r}_{u,i})^2}{N}}. \quad (18)$$

Maccatrozzo *et al.* benefited from the null hypothesis in addition to the user feedback to evaluate their proposed method [75]. They evaluated the p-value for relevance, unexpectedness, and interest.

De Gemmis *et al.* employed FaceReader to interpret the mental states of a user from the user's face at the time of receiving a recommendation [46]. Happiness and surprise were selected from Ekman's classification of emotions, showing that users have received serendipitous recommendations.

To complete the answer to Q3, it is necessary to emphasize that the formation of relationships for serendipity evaluation depends on the generated parameters of an algorithm. Therefore, if it is expected to select one of the above equations to evaluate the proposed algorithm, it is essential to ensure if the proposed algorithm is able to generate the required parameters. According to the results of Maccatrozzo *et al.* [75], Cunha *et al.* [15], and Kotkov *et al.* [31], the most accurate method to evaluate the performance of a recommender system to generate serendipitous recommendations is to benefit from the feedback given by the real users. However, this evaluation method increases the cost and the overhead of the system. For the offline evaluation, the MovieLens Serendipity dataset [31] can also be used, which contains a set of serendipity items based on the real feedback given by users. This dataset can be used to evaluate the performance of an algorithm to distinguish serendipity items from other items.

4.5 Quality Assessment

To answer Q4, all papers in Table 5 have been analyzed based on the following quality assessment questions (QAs) to identify and quantify the value of each paper in different aspects [90].

- *QA*1. Does the proposed approach have a strong technical/scientific background and own an appropriate mathematical model?
- *QA*2. Are the different steps of the proposed method discussed clearly?
- *QA*3. Does the proposed method have a proper and complete evaluation?
- *QA*4. Do the authors of the paper have experience and credentials in the recommender system?

We give a score for each QA as follows.

- *QA*1. Y (Yes): it has a strong technical/scientific background and owns an appropriate mathematical model. P (Partly): it has a strong technical/scientific background or owns an appropriate mathematical model. N (No): it is based on neither the technical/scientific background nor the mathematical model.
- *QA*2. Y (Yes): it has a clear workflow, different pseudocodes, and complete discussions of components. P (Partly): it is not clear and not repeatable in similar cases. N (No): the method is abstract.
- *QA*3. Y (Yes): it has been evaluated using mathematical relations or feedback from real users. P (Partly): it has not been evaluated using explicit serendipity factors. N (No): no evaluation has been carried out or has been postponed to future researches.
- *QA*4. Y (Yes): one of the authors has published more than five articles in recommender systems. P (Partly): one of the authors has published 3–5 articles in recommender systems. N (No): all authors have published less than three articles in recommender systems.

Now, we consider the score of Yes is 1, Partly is 0.5, and No is 0. Table 6 shows the scores for each paper.

Considering the results have been shown in Fig.6 and Table 6, it is obvious that serendipity-oriented researches have been progressed in recent years. Indeed, the research on serendipitous recommender systems has been steadily increasing since 2013; especially that in the last three years, it has revealed itself more. Although the systematic literature review was conducted before the end of 2019, the highest rate of progress is recorded in this year.

5 Discussions and Future Directions

In this section, we discuss the future directions and trends of serendipity-oriented recommender systems.

The accurate analysis of future trends on a research subject enables researchers to imagine the probable future paths more efficiently.

Table 6. Paper Quality Assessments Based on QAs

Year	Reference	QA1	QA2	QA3	QA4	Total Score	Average QA1–QA4 (for Each Year)
2013	[3]	N	Y	P	Y	2.5	0.56
	[39]	Y	Y	Y	Y	4.0	
	[40]	P	P	P	N	1.5	
	[91]	P	P	N	N	1.0	
2014	[42]	P	Y	Y	Y	3.5	0.53
	[65]	P	P	P	Y	2.5	
	[66]	P	P	N	N	1.0	
	[77]	P	P	N	P	1.5	
2015	[16]	P	Y	P	Y	3.0	0.69
	[43]	N	Y	N	P	1.5	
	[61]	Y	Y	Y	Y	4.0	
	[84]	P	P	P	Y	2.5	
2016	[45]	N	Y	Y	N	2.0	0.66
	[46]	P	Y	Y	Y	3.5	
	[47]	P	Y	Y	N	2.5	
	[48]	Y	Y	Y	Y	4.0	
	[58]	N	P	P	N	1.0	
	[82]	Y	Y	P	P	3.0	
	[92]	Y	P	N	Y	2.5	
2017	[23]	Y	Y	Y	P	3.5	0.65
	[72]	Y	Y	P	P	3.0	
	[75]	Y	Y	Y	Y	4.0	
	[78]	N	P	N	N	0.5	
	[86]	Y	Y	P	Y	3.5	
	[87]	P	P	N	N	1.0	
2018	[19]	Y	Y	Y	N	3.0	0.74
	[24]	P	Y	P	P	2.5	
	[25]	P	Y	Y	Y	3.5	
	[31]	Y	Y	Y	Y	4.0	
	[51]	N	P	N	Y	1.5	
	[52]	Y	P	P	N	2.0	
	[57]	Y	P	Y	Y	3.5	
	[79]	Y	Y	Y	Y	4.0	
	[80]	Y	Y	P	N	2.5	
	[81]	Y	Y	Y	P	3.5	
	[83]	P	P	P	Y	2.5	
2019	[10]	Y	P	P	Y	3.0	0.75
	[54]	P	P	Y	Y	3.0	
	[55]	P	P	P	Y	2.5	
	[88]	P	Y	Y	Y	3.5	
	[89]	P	Y	Y	N	2.5	
	[93]	Y	P	Y	Y	3.5	
	[94]	P	Y	Y	N	2.5	
	[95]	N	P	Y	Y	2.5	
	[96]	Y	Y	Y	N	3.0	

The bulk of studies of serendipity-oriented recommender systems indicate the probability of conducting more studies in the foreseeable future (Fig.1). Basically, the research on recommender systems has been increasing, given their vast applied domain in recent years, especially in relation to the use of data from social networks [97]. Considering the serious requirement of recommender systems to decrease repetitive and similar recommendations, one principle strategy is to generate serendipity-oriented recommendations. However, the usefulness of these recommendations is a new challenge faced by these systems. In this regard, machine learning can be an effective approach. Robustness is an important criterion for a serendipity-oriented recommender system benefiting from the data of social networks. This criterion can be very vulnerable to the common attacks on recommender systems, such as the shilling attack [98].

With the publication of a dataset of serendipitous recommendations [31], more model-based methods incorporating machine learning algorithms can be proposed. The challenges which machine learning algorithms face include the small number of samples existing in the dataset and the lack of demographic information. Considering different studies on various applications of recommender systems in music, films, business products, electronic education, etc., it can be expected that such studies can also be expanded based on the serendipitous recommendations.

A deep neural network, such as Convolutional Neural Network (CNN), can be employed to generate serendipitous recommendations. Deep neural networks will be useful for an efficient feature extraction layer since we know only a few factors and features that affect serendipity [99]. In this regard, future research can identify the characteristics that affect the serendipity criterion and assess the correlation between the serendipity's characteristics and the serendipitous recommendations.

However, the worst-case scenario may occur for serendipity-oriented recommender systems, which is the decrease in the number of relevant studies. The business applications of recommender systems can increase the possibility of such future trends because certain criteria, such as attracting user satisfaction, can replace serendipitous recommendations, although such criteria can make repetitive and boring recommendations. Considering the increased rate of studies and advances in serendipity, the probability of realizing the worst-case scenario for serendipity-oriented recommender systems will decrease.

The convergence of different definitions of serendipity can be an appropriate starting point leading to

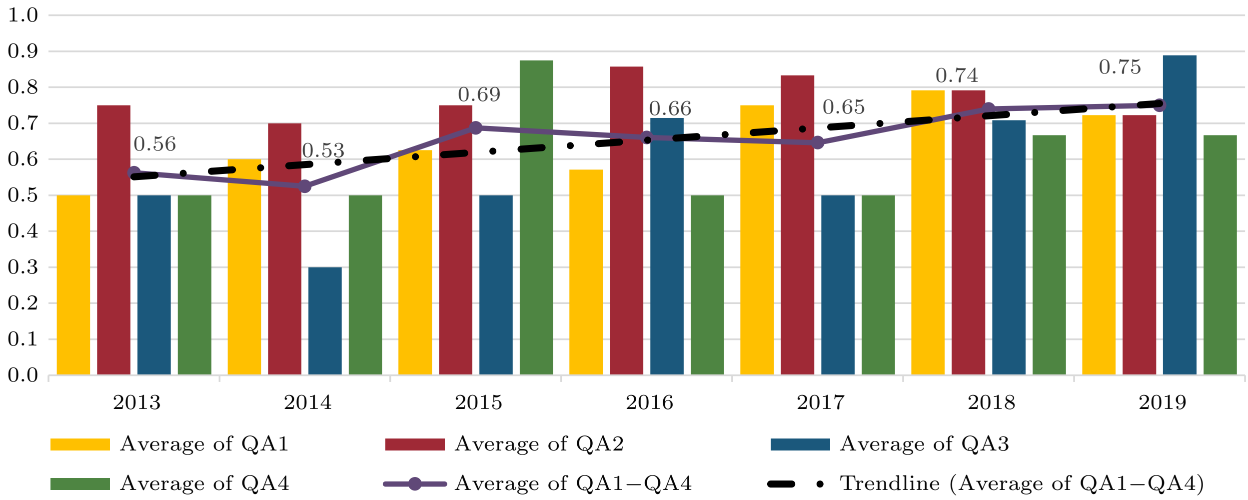

Fig.6. Progress in serendipity-oriented research.

future researches. Such a definition, having accurate and acceptable components, should be accepted by the majority of researchers. Then, presenting a comprehensive algorithm, most recommendations of which are serendipity, can lead to a preferable future, although there are huge challenges in the path towards both goals.

Unfortunately, serendipitous recommendations cannot include complete integrity and popularity, considering that the emotional aspect of users' behavior varies under different situations. In addition, it is believed that there is also a latent challenge in the studies conducted on serendipitous recommendations. Many of the studies did not evaluate their proposed methods very well. Some of them have postponed evaluation for future studies. Others have merely evaluated the serendipity components. Naturally, an extensive and acceptable method for the evaluation of serendipitous recommendation generation techniques can realize another aspect of future directions.

As discussed earlier, the only dataset of serendipitous recommendations was proposed by Kotkov *et al.*[31]. However, it has many constraints, either on the number of existing items or on the number of data existing for each item. Nevertheless, there are numerous datasets for recommender systems. Increasing the datasets of serendipitous recommendations can facilitate the presentation of new methods, experiments, relevant analyses, and, finally, the evaluation of the proposed methods.

As discussed in Subsection 4.3, the curiosity theory has become popular in serendipity approaches. Most of these methods attempt to provide the correct amount of unexpectedness for each user. Indeed, curiosity is one of the triggers for serendipitous recommendations. Therefore, it is likely that further research will focus on this theory. The future research employing curiosity should adapt to the previous user's favorite items since serendipity does not end up at the same level of unexpectedness for all users. The mathematical model can be used to deal with this problem. The tunable parameters in the mathematical model make the algorithm perform based on the previous user's records.

Moreover, providing a platform where users can utilize different controllers to discover and evaluate their serendipitous recommendations can be the topic of future research. This platform should include algorithms to generate adaptable serendipitous recommendations. The adaptability will improve the quality of recommendations based on user feedback and how users interact with the system.

The use of contextual information is a factor that affects recommender systems and can result in the development of context-aware recommender systems. However, the use of contextual information in serendipity-oriented recommender systems is a complex task because user interests vary in different temporal and locational conditions. Naturally, it is very complicated to generate a recommendation having the common components proposed by the definition of a serendipitous recommendation (such as unexpectedness and usefulness) and being context-aware (considering the current mental state of users). For instance, a user may normally be uninterested in political drama in a serendipity-oriented recommender system for movies. However, *House of Cards* can be a serendipity-oriented and interesting recommendation to such a user when the society is involved with the presidential election.

Another interesting aspect of serendipity-oriented recommendations is the fact that such recommendations are made to a group of users who have gathered around in one group for various reasons. Basically, such serendipity-oriented group recommendations can face serious challenges, such as the appropriateness of one recommendation to every single user in the group. For instance, assume that a group of users would like to enroll in a course in the electronic education system. The course recommendation should be both relevant to their interests and backgrounds and kind of unexpected so that it can attract the interest and attention of every single user.

Future studies may face a challenge in generating serendipity-oriented recommendations benefiting from multiple information domains to increase serendipity and innovation. Accordingly, it is possible to consider the performance and interest of one user in a specific social network to predict the performance and interest of the same user in other domains. The same approach can be employed to make serendipity-oriented recommendations for items in a domain of interest using the feedback provided by a specific domain.

The users' behavior analysis on social networks is a rich information source to discover the features that could lead to serendipitous recommendations. Indeed, users' interactions, users' clicks on different items, or even the path of the pages that users visit can be much more valuable than the number of users rating in a recommender system. Moreover, the time interval between users' clicks on a website is much less than the time interval between users' ratings in a recommender system. Therefore, more records will be available for analysis purposes. These two factors make it possible to create a time series of users' behaviors. To analyze this time series, the recurrent neural network (RNN) can be one of the most effective solutions. It should be mentioned that Hotjar script or Scraper API can be employed to extract the required information from social networks and other websites. Therefore in the future, researches on serendipitous recommendations pay more attention to social networks to maximize the effectiveness of the recommendations by data fusion.

As discussed in Subsection 4.2, it is predicted that employing general recommender system datasets in the serendipity context will be enriched. For evaluation purpose, (19) inspired from [45] can be used:

$$Ser = \frac{|Unexpected \bigcap Usefull|}{|N|}. \tag{19}$$

Serendipity is regarded as a combination of useful and unexpected recommendations by Shah *et al.*[45]. This equation evaluates serendipity utilizing the ratio of the number of useful and unexpected recommendations to the total number of recommendations.

The following is a summary of the discussions about four research questions mentioned in Table 1.

$Q1$. Do the definitions of serendipity converge? As explained in Subsection 4.1, unexpectedness and usefulness are the most widely-used components in the definition of serendipity from 2013 to 2019.

$Q2$. Which methods have been employed to make serendipitous recommendations? The methods of generating serendipitous recommendations are classified into four categories in Subsection 4.3: collaborative filtering, content-based, context-awareness, and hybrid. Several articles have been reviewed and analyzed in each category. Based on the results of Table 5, the most commonly used approaches were model-based, which employed cosine similarity as the similarity measurement factor.

$Q3$. How are serendipity evaluation criteria related? As discussed in Subsection 4.4, evaluation methods have been classified into three categories: direct evaluation, evaluation of the components of serendipity, and evaluation based on user feedback. Different methods have applied one of these three approaches for evaluation (Fig.5). However, some simple relations such as (6) or (8) can be suitable ways to evaluate serendipity that is almost applicable to all serendipitous recommender systems.

$Q4$. Has there been any improvement in making serendipitous recommendations? The four quality assessment factors are discussed in Subsection 4.5 to determine the progress in serendipity-oriented researches. Based on the results in Fig.6 and Table 6, it is obvious that serendipity-oriented studies have been progressed in recent years.

6 Conclusions

Given the ever-increasing expansion of social networks representing various emotions, interests, and opinions of different users in many contexts, it is absolutely essential to employ recommender systems. Such systems can be used to make appropriate recommendations to users by considering their different interests and backgrounds. Therefore, they will be assisted to find their interests in the turbulent world of information in social networks. However, the main problem that recommender systems face is the over-emphasis on certain recommendations, which can lead to the over-specialization of these recommendations and make them boring and even predictable. Researchers have offered certain solutions, such as novelty and diversity. However, novelty and diversity cannot merely guarantee that the recommended item is noticed by users. Therefore, it is necessary to regard unexpectedness and relevance as the qualitative criteria for recommendations. As a result, the serendipity criterion has been used in recommender systems to make novel, relevant, useful, and appealing recommendations.

At the end, we conclude as followings. 1) There is no convergence between serendipity definitions, but most studies believe that a serendipity recommendations are useful and unexpected. 2) The model-based approaches have been used more than other methods to generate serendipitous recommendations. 3) Simple relations such as (6) or (8) can be suitable ways to evaluate serendipity. 4) Based on Table 6, it's obvious that serendipity-oriented studies have been progressed in recent years.

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