Towards Ideal and Efficient Recommendation Systems Based on the Five Evaluation Concepts Promoting Serendipity

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Abstract*—Nowadays, recommendation algorithms allow users to fulfill their desires more easily. It may be used to propose things in various fields, including e-commerce, medical, education, and more. E-commerce industry is where most research is happening to help people find what they want. A recommendation system provides users helpful information regarding their possible activities and interests. The serendipity problem occurs when people become bored with identical recommendations to their profiles. Serendipity offers users limited and predictable content without a systematic approach to delivering new and surprising insights. The user only receives objects that are highly correlated with what he is interested in. We saw in our previous research that novelty and diversity represent ways to diversify recommendations that users did not know they needed. However, there are several criteria to study to have serendipitous suggestions. After studying and analyzing the concept of serendipity, this research aims to challenge several metrics often overlooked concerning accuracy. In this paper, we propose a novel methodology, capable of analyzing the user preferences and extracting their disapprovals that are incorporated into the recommendation process. This paper describes an Ideal Recommender System based on Five Qualities called IRS5Q, which gives a nice surprise, implying that a recommendation should be unexpected yet helpful to the user. Experiments show that the algorithm can propose many products that each user will enjoy. The results of IRS5Q were evaluated against the recommendation results of the content-based filtering approach. The outcomes showed the efficiency of IRS5Q with the MovieLens dataset and its capability to predict more accurately than the alternative approaches. We take an improved approach to assisting users to get out of their filtering bubble, monotony and redundancy in the recommendations made by achieving more than 83% in the diversity metric, 77% in the unexpectedness metric.

***Keywords*—recommender system, content-based filtering, serendipity, over-specialisation, novelty, diversity, unexpectedness, relevance, utility**

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I. Introduction

Recommendation systems are ubiquitous in our daily lives. When we are faced with an important choice, whether it is choosing a doctor or deciding which movie to see, we often seek the advice of others [1]. Friends, family members, and, increasingly, product reviews on the internet are among the people we consult. We get recommendations for books, music, food, buying items, hotels, travel, and even opinions and ideas. Recommendations are so much a part of our experience that we may not even be able to conceive of our lives without them [2]. Nonetheless, we make most of our decisions based on ideas or advice that we get or seek.

Recommender systems are pre-processing devices that recommend items or materials of interest to users. These systems look at a user's previous actions, create a profile with information about their interests, and then use it to discover potentially relevant products. If too much emphasis is placed on the precision of suggestions, the information can become too specialized, making the advice boring or even predictable. Some criteria, such as novelty and diversity, have been introduced by researchers to solve this problem [3]. Novelty refers to the ability of a recommender system to make novel and unrepeated recommendations. Otherwise, diversity refers to differences in the recommendations of a list. Recommender systems would have to suggest unexpected products, which is problematic. A recommender system calculates the chance a specific user selects a particular item. According to how the recommendation is generated, the recommendation methods are classified into eight different approaches, as mentioned in Fig. 1.

User satisfaction remains a crucial element in proving the quality and performance of a recommender system, even if they have reached a considerable level of profitability in several areas. We focus our research on the two types of recommender systems: item-based filtering and content-based filtering. These types only suggest recommendations that the user has enjoyed before, which causes the problem of serendipity.

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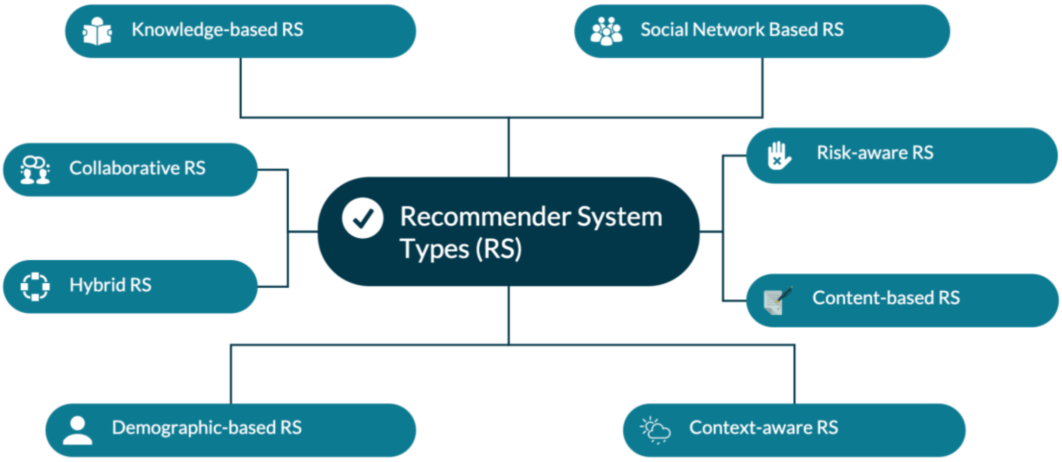

Figure 1. Different recommender systems approaches.

Serendipity is a fascinating and complicated concept to study [4]. It represents a crucial aspect of improving recommender systems that can significantly increase suggestions overall performance and usefulness. The complication and ambiguity of serendipity stem primarily from its emotional connotation [5]. Increasing the serendipity in the recommendation system is one method to combat the problem of over-specialization. We assume that a recommendation system provides serendipitous suggestions if it can offer new, intriguing, and unusual items to a given consumer at a particular moment. Considering the solid emotional component linked to the concept of serendipity, we have made two small but essential contributions, firstly, a more precise definition and, secondly, the steps to follow to measure serendipity. For this reason, the proposed approach is based on the definitions of serendipity and how to measure this concept. In this research, we will address multiple shortcomings. We make various interventions, which include the most significant:

- Presenting a clear definition of the serendipity concept and its usage in recommendation systems.
- Developing a novel approach for making serendipitous recommendations using hybrid methods, described by Ideal Recommender System based on Five Qualities called IRS_{5Q}, which uses other qualities that best evaluate the recommender system rather than precision to mitigate the serendipity problem.

The remaining sections of this article are classified as indicated below: we discuss our related works about content-based filtering, item-based filtering, and serendipity components in Section II. Section III focuses on describing our research problems. Section IV describes our research contribution. Our theoretical contribution is detailed in Section V. The proposed suggestion method, IRS_{5Q} and our contribution is seen and described in Section VI. The purpose of Section VII is to provide a focus on the testing and discussion of the experimental outcomes of IRS_{5Q}. We reference the analysis of our work in Section VIII. Finally, Section IX concludes the article and evokes opportunities for further investigation.

II. Related Work

A. Content-Based Filtering Methods

Content-based methods make connections between a user's preferences and items on social networks using information such as movie genres and actors through labeling.

The workflow of a content-based recommendation system is mainly determined by the user's preferences on the one hand and by his new interests on the other [6]. The approach followed by this kind of system is first to know the user's behavior and then compare it with the object in question. It is a strategy that generates an answer about the character of each person and what he likes and does not like as mentioned in Fig. 2. Reddy and Nalluri *et al.* [7] proposes a technique that provides recommendations in the field of entertainment, more precisely, the recommendation of movies like the Netflix platform. For this purpose, it recommends movies based on the genres of movies that a user can follow. Peng and Zhang *et al.* [8] introduced three elements to the memory-based collaborative filtering method to enhance serendipity. These elements include Cinsight, which involves creating a user profile, Cunexpected, which filters out predictable recommendations, and Cusefulness, which evaluates the worth of the recommendation. The final recommendations are sorted and displayed in a descending order based on their value.

In 2019, Park and Kim *et al.* [9] created a framework for serendipitous recommendation that utilizes social network analysis. Instead of relying on user preferences or content analysis, the framework uses tie strength and link clustering to generate recommendations. Tie strength represents the link between users and helps to determine their social connections. However, this approach has some drawbacks, such as the difficulty in accurately measuring tie strength for users without a frequent rating matrix. Additionally, as more publications are added to social network platforms, there may be fewer overlapping likes among reciprocal friends, leading to less serendipitous recommendations.

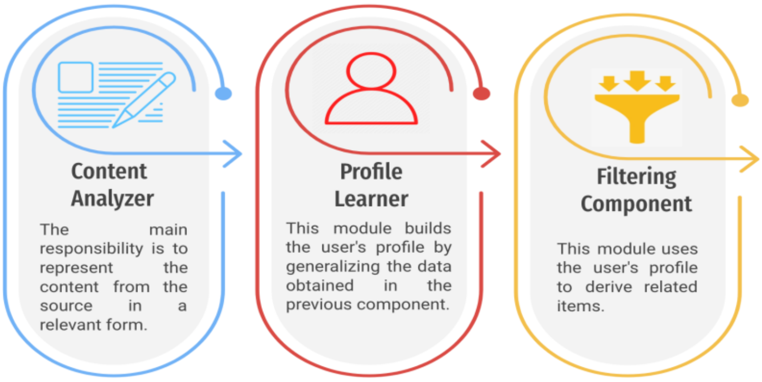

Figure 2. Content-based filtering.

B. Item-Based Collaborative Filtering Methods

Item-based collaborative filtering considers the proximity of items to make suggestions. In contrast to user-based collaborative filtering, it determines the similarities between items and then recommends unevaluated items similar to those that the targeted user evaluated previously. Item-based filtering calculates items similarity according to item preferences and recommends the most similar items to the unevaluated items by the targeted user.

For example, Item A and Item D are substantially similar, as seen in Fig. 3. Item-based collaborative filtering can propose Item D to a user who loves Item A. Item-based collaborative filtering requires the presence of several objects evaluated by the user to measure the similarity between the item in question and these objects. Then, based on these item similarities, it makes a forecast for the target item by integrating the target user's past preferences. User preferences may be collected in two methods in item-based collaborative filtering. One is that the user actively assigns a rating score to each item on a number scale. The other is that it indirectly evaluates the user's purchasing history or click-through rate.

Wang and Fu [10] describe a unique strategy for item-based collaborative filtering, which relies on BERT to recognize items and assess relevance between them. They tested the suggested technique on a large-scale real-world dataset with a complete cold-start scenario, and it substantially outperformed the popular Bi-LSTM model. Chen and Yang *et al*. [11] analyzed the effects of curiosity, novelty, unexpectedness, and time on serendipity. This analysis was performed in an online test by evaluating multiple algorithms of collaborative filtering type. According to their results, the more curious users showed appropriate feedback to unexpected items at higher probabilities. This study can be developed by running some tests on social networks or e-tourism platforms. Jain and Singh *et al*. [12] developed a framework for the trade-off between popularity and diversity. For this purpose, Jain and Singh *et al*. [12] attempted to solve a multi-objective optimization problem. They employed Bhattacharyya Coefficient to create a new similarity model to increase prediction accuracy instead of cosine similarity in traditional collaborative filtering. Furthermore, they introduced a multi-parent crossover mechanism that preserves the order and the frequency in the parents genes to bring more objectivity in a trade-off of recommending popular and diverse items. This work can simultaneously extend to recommendation objectives beyond accuracy, such as item coverage, novelty, and diversity. Moreover, this algorithm could employ pre-filtering to decrease the number of items to increase the search process performance.

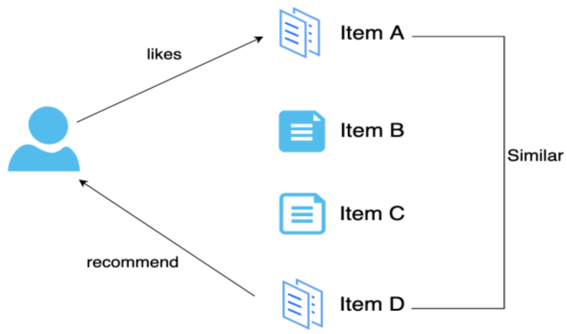

Figure 3. Item-based collaborative filtering.

C. Hybrid Methods

Li and Jiang *et al*. [13] proposed the Hybrid Approach for movie recommendation with Elastic Serendipity (HAES). They aimed to maximize genre accuracy and content difference. Genre accuracy refers to the similarity of a movie genre with a user's recent profile. The content difference means the low similarity between a movie and the target user's preferences. The goal of the content difference is to make unexpected recommendations. The HAES method introduces the concept of user elasticity, which refers to a target user's ability to accept a movie different from the user's profile. Bertani *et al*. [14] proposed a machine-learning algorithm to generate customized recommendations by combining novelty and popularity [14]. They proposed a User Profile Oriented Diffusion (UPOD) algorithm that extracts features from the user profile. UPOD uses a λ value, especially learned for the target user, to generate customized recommendations. The diffusion-based algorithm represents the recommendation system as a user-item bipartite graph that includes the user set, the item set, and the set of graph edges, respectively. This work can be extended to incorporate the rating values assigned to items during the mass diffusion process in the bipartite graph.

Thus, better-rated items in the system would be recommended more strongly than poorly rated items.

D. Serendipity Components in Recommender Systems

One of the most significant components of a recommendation system is originality, known as novelty [3], which is identified as among the essential aspects of a recommendation system. It increases accuracy by increasing effectiveness and adding a new item to the list of suggestions. Serendipity is an imprecise term and a complex aspect of information systems. It is impractical to use a controlled, automatic approach to handle the phenomenon of serendipity. However, several kinds of research have shown the progress that can be made in serendipity. There are many challenges, as shown in Fig. 4. Lee *et al.* [15] focuses on the development of a recommendation system that takes into account various contextual factors to provide serendipitous recommendations. A serendipitous recommendation refers to suggesting items that the user might not have considered before but could still be of interest to them.

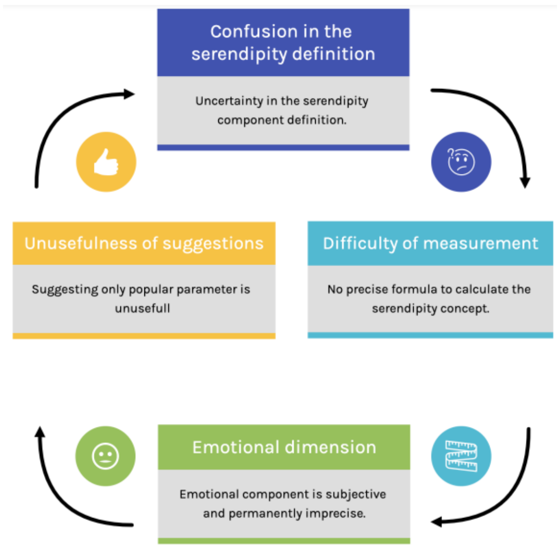

Figure 4. Serendipity challenges.

Context-aware recommendation systems consider factors such as time, location, user behavior, and previous interactions to make recommendations that are relevant to the user's current situation. By incorporating these contextual factors, the system can provide more personalized and relevant recommendations, and increase the likelihood of serendipitous discoveries. Lee *et al.* [15] describes the methodologies and algorithms used to develop this type of recommendation system, and may also provide results and evaluations of the system's performance. Overall, the paper likely provides insights into the importance of considering context in recommendation systems and how this can enhance the user experience.

Felicioni [16] describes an important contribution to the field of recommendation systems and can help improve their performance and usefulness. It explores ways to improve the evaluation and training of recommendation systems using counterfactual reasoning. Alhijawi and Awajan *et al.* [17] focuses on the objectives of recommender systems, including measures of effectiveness, solutions for addressing these objectives, evaluation methodology, and new perspectives in the serendipity concept. Table I summarize some articles defining the serendipity concept.

Serendipitous recommendations refer to suggestions that are not directly related to a user's previous behavior or preferences, but may still be of interest to them. By presenting users with unexpected recommendations, they are exposed to new and diverse content that they may not have otherwise discovered. This can lead to increased engagement and a more enjoyable user experience. Cui and Rajan *et al.* [18] explores how serendipitous recommendations, or unexpected recommendations, can be used to engage users in new and unique ways. It discusses various methods for generating serendipitous recommendations, such as incorporating contextual information or using machine learning algorithms that consider diverse factors beyond just user behavior. In recent years, the use of recommender systems has become widespread in various domains such as e-commerce, online media, and social networks. However, users are becoming increasingly concerned about the privacy and security of their data, as well as the transparency and accountability of the algorithms used by recommender systems. Ge and Liu *et al.* [19] review existing research on the topic of trustworthy recommender systems, covering areas such as privacy-preserving recommendation algorithms, explainable AI techniques, and the design of transparent and accountable recommender systems.

TABLE I. SUMMARIZATION OF ARTICLES DEFINING SERENDIPITY CONCEPT

References	Proposed Approach	Application domain	Advantages	Limitations
[20]	Machine learning-based methods.	General	Recommending entities with serendipity related to both a given query and a user.	Lack of clear definition of serendipity concept.
[21]	Graph-based learning	Education-Book	Recommendation based on user control can impact the surpriseful experience of the user in the learning environment	The proposed approach doesn't demonstrate if the used algorithm can be appropriate in other domains.
[22]	Deep Learning methods	Movie	Useful for accuracy and scalability.	Lack of user feedback
[23]	Deep Learning methods	General	-	-
[8]	Hybrid methods	Movie	Good optimization	Lack of parameter extendibility.
[24]	Optimization-based methods	Movie	Measuring user satisfaction	Investigate the effect of serendipity on users.

III. Research Problematic

Users find serendipitous items interesting, novel, and surprising. Serendipity is therefore composed of five elements: novelty, diversity, unexpectedness, relevance, and usefulness. Serendipity is a challenging and attractive research concept [24]. The primary cause of the difficulty and uncertainty of serendipity is its connection with the emotional component. Consequently, the definition of serendipity in recommendation systems is still a hard task. Serendipity isn't only a concept in computer science. It's also employed in business, cognitive science, and computer science.

Previously, a personalized recommendation system's item prediction accuracy was insufficient to satisfy consumers [25]. A sound recommender system should offer relevant recommendation lists containing various items to meet all user's needs and tastes. Monotony and redundancy are major drawbacks of content-based filtering, which leads us to think about diversifying the recommendation results so that the user is not bored by proposals perfectly correlated with his intentions. Serendipity is a criterion for producing recommendations that are both appealing and useful. The essential advantage of these criteria over novelty and variety is the usefulness of serendipitous recommendations [26].

Serendipity represents an emotional component, and chance encounters are incredibly infrequent, making the concept of serendipity difficult to examine and analyze. Fig. 5 mentions the definition of serendipity in its broadest sense. Based on this general definition serendipity encompasses many different components, including "novelty", "diversity", "unexpectedness", and "relevance" of valuable or delightful things. These elements can interact in a variety of ways, leading to a range of experiences that can be classified as serendipitous. Serendipity is a complicated term that involves relevance. Therefore, it depends more on the current mood of the user.

Traditional recommendation systems offer suggestions based on the user's concerns, tastes, and hobbies but cannot build a true emotional connection with the user. A deep sense of closeness between the user and the brand can increase brand loyalty and improve the likelihood that the user will act on a recommendation.

The serendipity issue is described as limited information and providing proposals with a poor degree of innovation and the absence of a strategy to discover unusual items to propose to the user. When someone likes a new item, the system only suggests items comparable to what the user currently likes. The challenge of serendipity arises in two types of recommendation systems as mentioned in Fig. 6:

- Content-based filtering
- Collaborative filtering, particularly item-based collaborative filtering.

Both types recommend only items that the user has already liked. The difficulty with serendipity is that neither type has a built-in mechanism for discovering unexpected items. For example, in a movie recommendation system, the customer receives recommendations for movies similar in genre or actors to those they have previously enjoyed.

Serendipity represents the capacity to receive a surprising and accidental item selection in a recommendation system. It is a way to shuffle the suggestions around. Optimizing recommendation qualities remains a good practice to implement to obtain incidental recommendations. We eliminate the risk of over-specialization while bringing unexpected proposals to the user.

Figure 5. Serendipity definition.

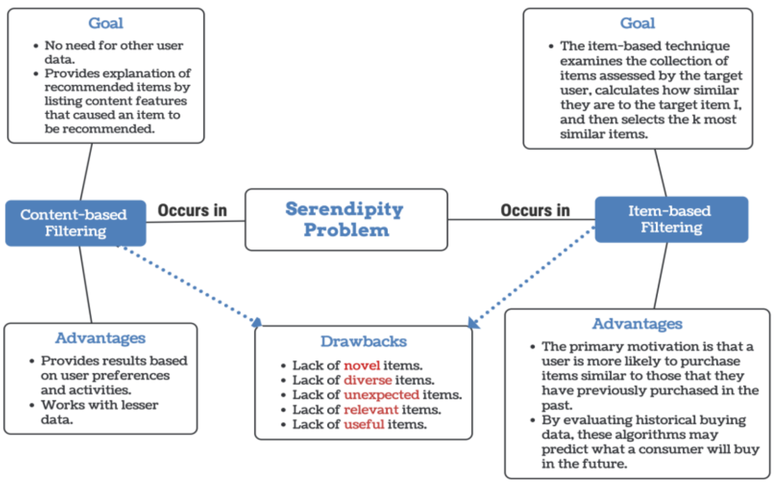

Figure 6. Serendipity problem in recommender system.

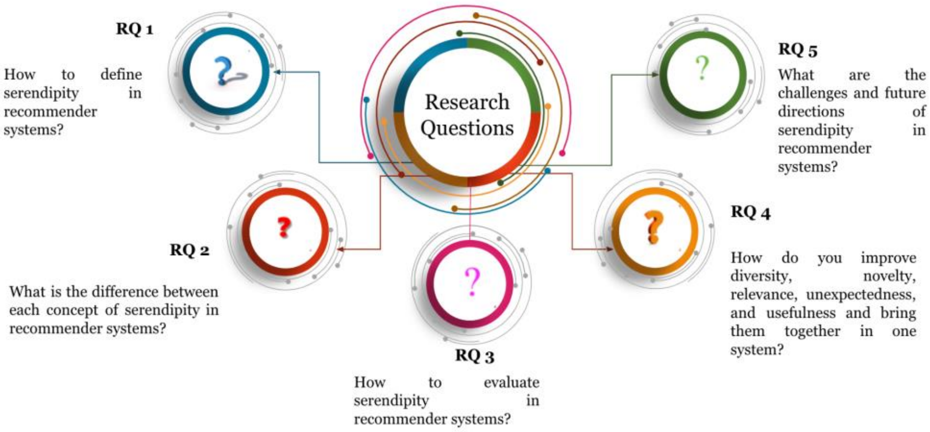

Figure 7. Our research questions regarding serendipity concept.

In this regard, this work aims to achieve our goal of mitigating the serendipity problem by using a hybrid technique. Our approach will rapidly adjust and grow from user selections in the initial steps to eliminate the issue of over-specialization. This will allow us to provide freshness-related recommendations for users depending on their preferences. Our proposed approach is quickly adaptable and changeable based on the user's choices in the first part to minimize the serendipity challenge. For this purpose, our research will focus on serendipity, which will deeply impact the satisfaction of consumers. In the next sections, we will mention answers to the research questions displayed in the Fig. 7.

IV. Research Contribution

A. *Motivation*

Using only accuracy to evaluate a recommendation system can lead to redundancy in the recommendations given to a user. This is because a purely accuracy-based system will prioritize recommending items that are similar to items the user has previously consumed, rather than presenting the user with new and diverse options. On the other hand, incorporating serendipity into the evaluation and design of a recommendation system can lead to more diverse and unexpected recommendations, reducing the risk of redundancy.

Incorporating serendipity into recommendation systems can also increase user engagement and satisfaction. By providing users with unexpected and novel recommendations, the system can challenge their prior expectations and encourage exploration and discovery. This can lead to a more enjoyable and fulfilling user experience. Therefore, while accuracy is still an important factor to consider in recommendation systems, incorporating serendipity can lead to a more well-rounded and diverse set of recommendations, and can ultimately result in a better user experience.

Serendipity plays an important role in recommendation systems, as it helps to avoid the problem of redundancy and improve the overall user experience. When a recommendation system is solely based on accuracy, it may often recommend items that the user has already seen or is aware of, leading to a repetitive and boring experience. On the other hand, incorporating serendipity into a recommendation system encourages the exploration of new and unexpected items, keeping the user engaged and interested in the recommendations they receive. This can lead to increased user satisfaction and engagement with the recommendation system. In summary, while accuracy is an important aspect of a recommendation system, incorporating serendipity into the evaluation process can help to provide a more diverse and engaging experience for users, and avoid the problem of redundancy in recommendations.

B. *Demonstration of the Choice of Serendipity*

In the context of recommendation systems, serendipity refers to the phenomenon of discovering items or content that are unexpected or fortuitous, but still enjoyable or relevant to the user. This can refer to recommendations that are outside of a user's usual preferences or interests, but still provide a positive experience. For example, if a music streaming service recommends a new album to a user who primarily listens to rock music, but the album is a fusion of rock and classical music, this can be considered a serendipitous recommendation. The user may not have explicitly searched for or indicated an interest in classical music, but the recommendation can still provide a pleasant surprise and expand their musical tastes. Serendipity is an important aspect in recommendation systems as it can help users discover new and interesting items, and keep the recommendations fresh and engaging. However, striking a balance between serendipitous recommendations and personalized recommendations that align with a user's interests can be challenging.

Based on this observation, serendipity takes into consideration several evaluation concepts so that it is well defined:

- Novelty: The ability of a recommendation system to suggest items that are unique and new to the user.
- Diversity: The ability of a recommendation system to present a variety of items to the user, rather than just a few popular ones.
- User Engagement: The ability of a recommendation system to encourage users to explore and discover new items, by providing

them with recommendations that challenge their prior expectations.
- Surprise: Recommending items that are unexpected, based on the user's history or preferences.
- Relevance: Recommending items that are appropriate for the user's needs or interests.

C. Contribution

In summary, the paper presents the following key contributions:

- We presented and demonstrated a clear definition of serendipity in recommendation systems and its usage.
- We have developed and evaluated a new approach for making serendipitous recommendations, using hybrid methods that explicitly accounts for the user's preferences and emotion expressed for specific items.
- We named our proposed approach by the Ideal Recommender System based on Five Qualities IRS_{5Q}, which uses other qualities that best evaluate the recommender system rather than precision to mitigate the serendipity problem
- We compared the proposed model with the other state-of-the-art serendipity recommender systems and demonstrated the feasibility, technical soundness and stable performances of the proposed model.
- We evaluated our proposed recommender system, in movieLens application scenarios and showed that utilizing the defined criteria, the recommendation process can substantially improve the quality of the recommendation rather than just precision.

V. Our Proposed Theoretical Definition

A. Serendipity Components

Serendipity is a highly complex topic with other components. The concept of serendipity has been identified as being among the most difficult words to translate. This section describes this associated and complementary component in Fig. 8.

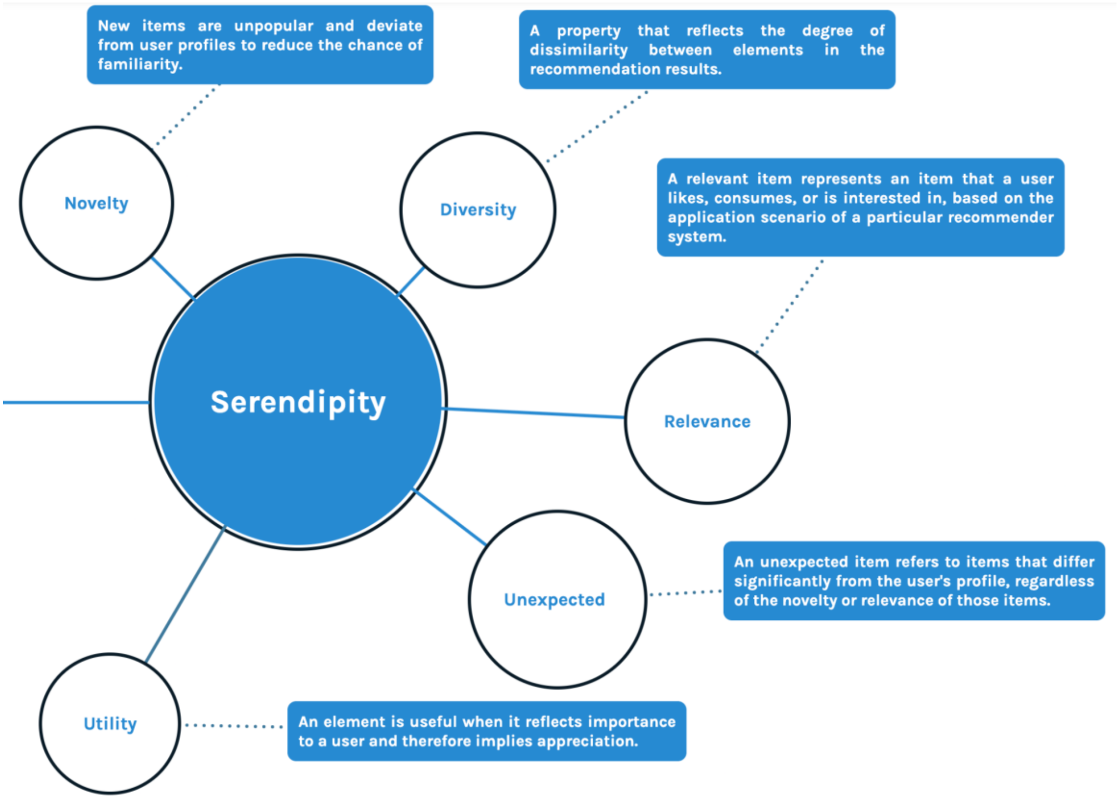

Figure 8. Relevant aspects of serendipity concept.

We have included an illustration to help readers distinguish between novelty, variety, and serendipity. In the list of suggested action films, the client could also come across an unexpected film that attracts them. As he uncovered this action movie on his own, it is referred to as a novelty recommendation rather than a serendipity recommendation. If we discover that individuals who prefer action movies also enjoy comedy films, we may add a comedy film to the suggestion list to further broaden the list.

Relevance and usefulness represent two related components but with a slight difference. First, a recommendation is relevant if the user receives it and gives it a high score according to a predefined scale, whereas usefulness is perceived based on the user's comments. For example, did they watch the whole recommended movie or finish reading an article and give recommendations to their friends? This is then a diverse recommendation and not an occasional recommendation, as the user could not be shocked by the suggestion.

This study defines serendipity as a characteristic that combines the five qualities and components: novelty, diversity, relevance, unexpectedness, and usefulness. In other words, something is serendipitous if it is new, diverse, unexpected, relevant, and valuable. Table II shows the definition of serendipity in previous related work.

From our bibliography, it is clear that the concept of serendipity lacks an exact definition. Therefore, we have chosen the five most common variations of the description of serendipity. We have verified them in our consumer research and examined the practicability and advantages of the suggestion of these items.

1) Novelty

Novelty refers to items that people have never heard of before the suggestion. Unfamiliar items are unpopular and deviate from the consumer profile to minimize the likelihood of familiarity. The term novelty refers to the distinction between current and previous experiences.

Novelty describes the capacity of a recommendation system to produce novel and unfamiliar recommendations. Diversity is identified as the metric that represents the distinction between items. Adding a new item to the list of recommendations is one of the essential and primary techniques to satisfy the user and get him out of his filtering bubble. This increases the efficiency of a recommendation system. Table III displays the definition of novelty in previous work.

Let U_i stand for the number of recommended items unknown, and T_r mention the total number of provided recommendations.

$$\text{Novelty}=\frac{U_i}{T_r}$$

2) Diversity

The individual diversity of recommendations for a specific user can be measured by the difference between the set of associations of items recommended to the user. This diversity at the recommendation results level consists of expanding the range of suggested objects in the recommendation results.

The distinctions between the pieces of an experience are what diversity is all about. In recommender systems, diversity may be quantified in two directions. Individual and aggregate diversity are the two types of diversity. For the user, individual variety results in a single item. This item is what people are looking for. However, even if the result is satisfactory, the customer will be dissatisfied with this one item. Aggregate diversity is called when you want to offer a non-negligible element for several user alternatives.

$$\text{Diversity} = 1\text{-Similarity}$$

TABLE II. CLASSIFICATION OF ARTICLES FOCUSING ON SERENDIPITY CONCEPT

References	Definition	Novelty	Diversity	Unexpectedness	Relevance	Utility
[20]	Find amazingly unusual suggestions that enhance information retrieval			✓	✓	✓
[21]	Recommendations related to the unexpected	✓	✓	✓		
[26]	A serendipity component defines a fresh, surprising, appropriate, and difficult to find suggestion for users.	✓	✓	✓		
[22]	Serendipity pertains to a suggestion that possesses four characteristics: newness, surprise, pertinence, and difficulty in being found by users.	✓	✓	✓		
[23]	Serendipity is marked by a low level of initial interest but a high level of satisfaction.	✓				
[8]	Its goal is to merge three primary measures centered on user experience of serendipity, namely, value, unexpectedness, and insight.		✓		✓	
[4]	This pertains to how innovative and pleasantly unexpected recommendations are for users.	✓		✓		
[24]	Is the faculty of making fortunate discoveries by accident.	✓		✓	✓	
[27]	Serendipity occurs when an otherwise uninteresting item becomes interesting.		✓	✓	✓	

TABLE III. DEFINITION OF NOVELTY IN SERENDIPITY WORK IN RECOMMENDER SYSTEMS

References	Definition
[28]	Novelty in recommendations means suggesting items that are new or unfamiliar to the users. There are two types of novelty: ● Strong novelty where the user has never heard of the item before. ● Motivational novelty where the user had not thought of purchasing the item until it was recommended to them.
[29]	There are three different levels of novelty: the first is related to new experiences in the user's life, the second is connected to elements that have been presented to the user through their browser and consumption history, and the third level of novelty happens when personalized recommendation lists contain new items.

3) Relevance

Relevance can be defined by the inter-change of user interests for a future item. Relevance refers to items that predict or guarantee that they match consumer choices in the movie domain [7]. For example, a movie may be considered relevant if the user has seen the entire movie. In another situation, the user would have to give it a high rating for a movie to be considered relevant.

The user always judges the relevance of a recommendation in different ways:

1) The user rated and ranked the recommendation very well.
2) The user has bought the proposed item.
3) The user has liked and consumed the proposed item.

Most recent contributions to RS research have been judged on their relevance. Predictive accuracy, comprehensive suggestion lists, and ranking-based methods have been explored in the literature to evaluate the relevance of recommendations.

$$P(c \mid i) = \frac{P(c)\,P(i \mid c)}{P(i)}$$

There are two forms of feedback to predict the relevance of an element for a user: explicit feedback and implicit feedback.

- Explicit feedback: a direct response from the user about an item. This direct feedback can be presented by the user's favorable or unfavorable opinion on a recommendation using scores or written comments.
- Implicit feedback: is the collection of actions that users take on items; these responses indirectly express the user's opinion on the item.

4) Unexpectedness

Unexpectedness is defined by Kotkov [28] as avoiding direct suggestions of goods meant to be taken to decrease user boredom and irrelevant recommendations. Customers' expectations differ from the unexpectedness or surprise of suggested recommendations.

Unexpectedness refers to new recommendations being taken in a direction that is different or unfamiliar to the user's experience. To identify unexpectedness, we begin with the user's intentions. Based on the characteristics of content-based filtering, we can say that a user's daily article can be described by the set of objects he consults within a recommender system. A novel recommendation can be unexpected. However, novelty is defined purely as non-redundant, previously unfamiliar items when we compare novelty to unexpectedness without considering available but unexpected items.

Let R_s stand for the suggestions provided by content-based filtering and R_d for the recommendations made by our dissimilarity-based recommender system.

We consider an item in R_d as an unexpected recommendation if it does not belong to R_s.

$$\text{Unexpectedness} = \frac{R_s}{R_d}$$

Let R_{si} be an element of the list R_s, if this element R_s does not belong to the list R_d then:

$$\text{Unex}(R_{si}) = 1$$

else $\quad \text{Unex}(R_{si}) = 0$

5) Utility

Serendipity is a criterion for producing recommendations that are both appealing and useful. The utility of spontaneous proposals is the primary benefit of this criterion above novelty and variety. In truth, the essential advantage of serendipity over novelty and diversity is the benefit of suggestions.

However, it is not as easy to make spontaneous suggestions as it is to make unique and varied ones. Utility and positive feedback are two aspects of the idea of serendipity. The most commonly used components in the definitions of serendipity were unexpectedness and usefulness. Serendipity could be a mixing of the surprising and the necessary.

Recommendation systems should consider other key criteria besides accuracy, including serendipity, unexpectedness, and usefulness. The utility of a recommendation can be determined by how consumers evaluate a specific object. The quantity to which an object appeals to a user is referred to as utility. In practice, the users projected ratings for the item are frequently used to assess utility.

The user can judge the value of suggestions or, in an offline situation, user ratings of goods can be used to approximate it.

B. Serendipity Based on Recommendation Algorithms

Serendipity-oriented methods are classified according to the data they use or their design. Collaborative, content-based, and hybrid filtering are the three types of data-based classification. There are three categories of design-based categorization:

- Reranking algorithms: an algorithm can use the projected evaluations of an accuracy-oriented algorithm to rerank the output. This can improve serendipity in the recommender system.
- Serendipity-oriented modification (Modification): This modification refers to precision-oriented algorithm changes. The most important limitation between modifying and re-ranking algorithms is that re-ranking strategies can use whatever precision-oriented algorithm provides ranking scores to items. In contrast, modifications can only be made to a specific method.
- New Algorithms: This category contains serendipity-oriented algorithms that do not enter the re-ranking or modification categories.

The serendipity-enhancing phase is the basis for the paradigm categorization:

- Pre-filtering: a recommender algorithm pre-processes the input data of a precision-oriented method.

- Post-filtering: recommender algorithms reorganize the results of precision algorithms after they have been filtered.
- Modeling: actions to increase serendipity can be implemented during the recommendation generation phase.

VI. Proposed Approach

A. Problem Definition

Users of a movie recommendation system frequently complain that the suggestions are annoying and apparent. Such systems eventually drive consumers away. Even though most of the previous work was accurate to their ability, the user still complains of a lack of variation. However, suggesting a wide range of movies to them would not solve the problem as it might alienate them from their general tastes. Therefore, following our future work already cited in the previous article [3], The problem of monotony in the recommendation results we mentioned before is solved in three consecutive ways:

- First, we generate a recommendation that perfectly matches the user's preferences.
- Secondly, we generate new and unexpectedly diverse recommendations.
- Thirdly, we combine the first two results to obtain a list that will simultaneously contain data seen before in addition to incidental recommendations.

B. Approach Overview

1) The proposed IRS_{5Q} approach

This research study aims to recommend a chance list to the user while eliminating recommendations similar to the user's preferences. To this end, our suggested strategy provides a multi-phase procedure for dealing with this challenge. This fortuitous list provides support for four concepts:

- Diverse recommendation: Description of new items in the recommendation results far from the user's tastes.
- Novel recommendation describes the difference between the user's present and past experiences.
- Unexpected recommendation: unfamiliar recommendation, unusual to the user experience.
- Relevant Recommendation: which refers to elements that guarantee to adapt to user preferences.
- Useful recommendation: the user scores or comments on the recommendation results.

Our global proposed approach contains two sub-approaches: the first one is used for content-based filtering, and the second one is for item-based filtering. We discuss each case in a specific algorithm, and both have a similar idea in terms of approach. The proposed architecture can solve the serendipity problem in both types of filtering. In content-based filtering, the input to the algorithm must represent the user's preferences and derive a list of dislikes for each user. Except that in element-based filtering, the algorithm's input should describe the element's characteristics and derive the dislikes for each element.

2) The proposed approach for content-based filtering

Algorithm 1 presents the main procedure of our proposed approach for content-based filtering as it is mentioned in Fig. 9.

Algorithm 1: The main procedure of our proposed content-based filtering approach.

Input: User Preferences.
Output: Recommendation list based on user disapprovals.

1: Generate the list of user preferences with high rated movies.
2: Generate the list of user disapproval.
3: Select list of popular movies having rating>=4
4: Store only preferences of popular movies having similar genres cited in user disapproval.
5: for each dissimilar and popular movie **do**:
6: Calculate Unexpected metric
7: Calculate Diversity metric
8: Calculate Novelty metric
9: Calculate Utility metric
10: Select Recommendation list based on high metrics values.

---

3) The proposed approach for item-based collaborative filtering

Algorithm 2 outlines the primary process of our suggested algorithmic procedure for feature-based collaborative filtering as it is mentioned in Fig. 10.

Algorithm 2: The main procedure of our proposed approach for item-based collaborative filtering.

Input: Movie i.
Output: Recommendation list to users who like the movie in input.

1: Generate the list of dissimilar movies to the film entered in input.
2: Group popular movies based on the high count of rating
3: if popular movies have rating >=3 **do**:
4: Select list of popular movies with rating>=3
5: Store only popular movies which are in the list of dissimilar ones.
6: for each dissimilar and popular movie **do**:
7: Calculate Unexpected metric
8: Calculate Diversity metric
9: Calculate Novelty metric
10: Calculate Utility metric
11: Select Recommendation list based on high metrics values.

C. Methodology and Overall Approach

We started with a content-based recommendation that organizes all matched movies by the user's preferences. It uses a content-based filtering algorithm to make the main recommendation. If a user has previously enjoyed a particular film in a genre, "Action," the content-based main suggestion, will suggest all films in that genre to the user. The general design is shown in Figs. 9, 10. The method entails the following steps:

- **Step 1:** We generated resemblance matrices based on a cosine similarity feature between the movies. We then created a list containing the set of non-similar movies for each. In other words, we try to make a dissimilarity matrix between the movies.
- **Step 2:** We have adjusted a group of popular films and have a high number of ratings. We try to store only the famous films in the list of different films made in the first phase.
- **Step 3:** We calculate the different metrics we use to evaluate the concept of serendipity: diversity, novelty, relevance, and unexpectedness.
- **Step 4:** We conclude with the recommendation list, characterized by a random list.

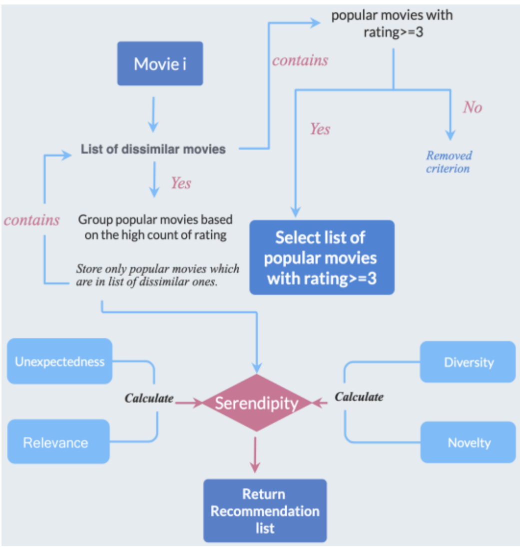

Figure 9. Our proposed Approach for content-based filtering.

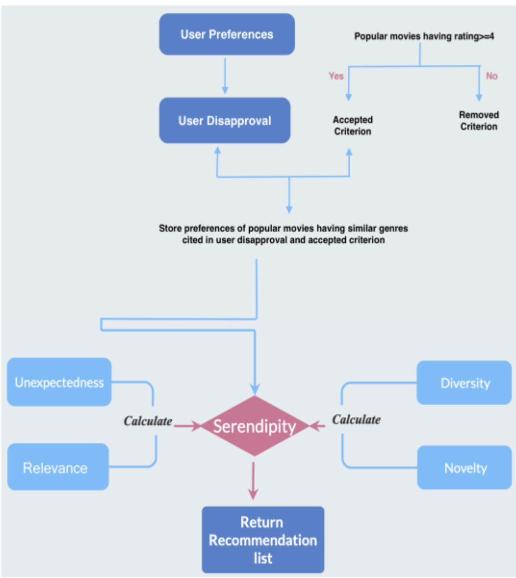

Figure 10. Our proposed approach for item-based collaborative filtering.

D. Advantages of the Proposed Approach

Our approach has several advantages that can be summed up in the following way:

- Collaborative filtering is a good method, but it does not understand user and content-based filtering. The only problem with the latter is the monotony at the recommendation level.
- The lack of diversity in previous work based on old datasets led us to think of introducing the five qualities: novelty, diversity, unexpectedness, relevance, and usefulness into a single term of serendipity.
- Serendipity concept definition: the key is to broaden the user's preferences while ensuring they like and appreciate the item. It is important to guarantee the user a recommendation that will take him out of his filtering bubble, but only if he is not too far from his usual preferences.

Serendipity and accuracy are two different aspects that are important in providing recommendations, and each has its own advantages. For that it is important we have given importance to strike a balance between serendipity and accuracy in recommendation systems in order to avoid a lack of relevance and a decrease in user trust. Here are some of the benefits of using serendipity over accuracy:

- **Surprising and enjoyable experience:** One of the main benefits of serendipity is that it can provide users with unexpected and enjoyable experiences. By suggesting items that they wouldn't have otherwise considered, it can help users discover new things and broaden their horizons.
- **Encourages exploration and experimentation:** When recommendations are too accurate, they can become predictable and boring. Serendipitous recommendations, on the other hand, can encourage users to explore and experiment with new items, which can lead to a more engaging and dynamic experience.
- **Increases user engagement:** Serendipitous recommendations can keep users interested and engaged with the recommendation system. By providing unexpected results, it can foster a sense of curiosity and excitement, encouraging users to continue using the system.
- **Helps break out of filter bubbles:** When recommendations are too accurate, they can reinforce existing biases and opinions, leading to the creation of "filter bubbles." Serendipitous recommendations can help users break out of these bubbles and expose them to new ideas and perspectives.

E. Limitation of the Proposed Approach

This approach has some limitations:

- First, to define our serendipity metric, we have collected the five qualities that can be found in an ideal recommendation system. Since the concept of serendipity is subjective, there are several definitions. Although novelty, diversity, unexpectedness, and relevance showed the best results, we still cannot measure the use concept because it represents a problematic finding metric since it requires user feedback.

- Second, to demonstrate our algorithm and the serendipity metric, we used datasets collected in MovieLens. Evaluation results using datasets collected in another recommender system might yield different results.
- Third, the offline evaluation may not match a real-world scenario because we will have more accuracy if we enter into communication with the user.

VII. Evaluations and Results

This section describes the simulation platform and dataset we utilized in our tests, the benchmark algorithms and evaluation metrics used to assess the proposed technique, and the values assigned to its various parameters. The five principles of novelty, variety, relevance, unexpectedness, and utility can be used to evaluate serendipity.

The assessment criterion for evaluating serendipity in recommender systems is still debatable. Our strategy focuses on combining the five characteristics of recommender systems in this study to improve the system's serendipity. Using a MacBook Pro with 16GB RAM, the assessment procedure consists of four separate trials (Apple, Cupertino, CA, USA).

A. Technical Detail

There are various metrics for evaluating recommendation systems beyond accuracy, including coverage, diversity, novelty, unexpectedness and serendipity. Depending on our research problematic, the choice of metrics to use will be articulated around:

- Novelty: This is a measure of how new or unexpected the recommended items are to the user.
- Diversity: This is a measure of how different the recommended items are from each other, to avoid recommending similar items repeatedly.
- Unexpectedness: This is a measure of how surprising or unexpected the recommended items are to the user, leading to a positive experience.

Finally, to measure the serendipity metric of a recommendation system, we can use metrics such as novelty, unexpectedness, diversity, and inject utility which needs user feedback.

B. Experiment 1: Data Distribution

The Movielens 100K dataset has been used in all these experiments. Table IV provides the experimental data statistics. Movielens created the Movielens 100K dataset. This dataset contains 100,000 ratings (1–5) on 1682 films gathered from 943 individuals. Each user has given ratings to at least 20 films, which fall into one of the 18 categories. The poor film receives a one-point rating, while the outstanding film receives a five-point rating. Users and items are numbered sequentially, starting from 1.

TABLE IV. Specifications of the Datasets Used

	MovieLens
Number of users	94
Number of movies	2113
Number of genres	18
Number of actors	0
Number of directors	0
Number of evaluations	100000
Evaluation scale	1–5
Level of spartiality	93.7%

C. Experiment 2: Exploratory Data Analysis

Fig. 11 shows that film genres like "Animation", "Adventure", "Comedy", and "Children" are the most likely ones for some users.

Figure 11. WordCloud of preferences for specific users.

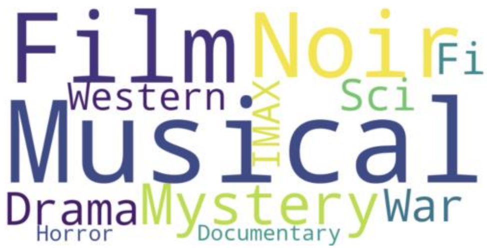

Figure 12. WordCloud of disapproval for specific users.

Some users are unlikely to prefer film genres such as "Musical", "Film Noir", "Comedy", and "Children" as mentioned in Fig. 12.

D. Experiment 3: Results

By comparing our methodology to usual benchmark techniques under experimental situations, we want to prove that the suggested strategy effectively reflects the notion we created to characterize the serendipity concept and succeeds better in terms of classical accuracy metrics. We opt for a ranking-based evaluation. In such an evaluation, two steps are necessary: dividing the data sets into training and test subsets and selecting the items to be ranked.

Table V explains the difference in results diversity between our proposed method and other recommender system approaches, which is lower when we use traditional content-based filtering and increases when we use the proposed approach, generating new, diverse, and unexpected items in the recommendation lists. Furthermore, in our suggested strategy, the effect of overspecialization is reduced.

The term "Less" means that the property concerned lacks the approach that suits it. The term "Medium" indicates that the property concerned exists with 50%. The term "High" denotes that the property involved exists with 100%. For example, the effect of over-specialization exists in content-based filtering; that is why we mention the term "High", and it exists with 50% in the clustering approach. Still, it is absent in our proposed method, which means "Less."

TABLE V. COMPARISON OF OUR PROPOSED APPROACH WITH RECOMMENDER SYSTEMS

Properties	**CBF**	**Clustering**	**Proposed approach**
Diversity	Less	Less	High
Novelty	Less	Less	High
Unexpectedness	Less	Less	High
Scalability	Low	Low	Good
Effect of over-specialization	High	Medium	Less

The Table VI describes the results of the diversity metric ranging from two recommendations to 12 recommendations and shows the results of the collected novelty. The reader will see that the method utilized outperforms alternative methods for making recommendations. The originality of the applied method extremes at the Top 4 and 6, after which it declines. The collected findings show that the proposed strategy is superior.

TABLE VI. DIVERSITY METRIC RESULTS

Method Recommendation	**K=2**	**K=4**	**K=6**	**K=8**	**K=10**	**K=12**
Our proposed approach	0.83	0.92	0.93	0.91	0.87	0.89

Table VII describes the novelty, diversity, and unexpectedness metrics results. The results for the unexpected metric are more significant than the diversity metric, which can be explained by the relationship between disapproval and user preferences. Top-n recommendation means the number of novel, unexpected, and diverse elements. For example, Top-1 denotes that we have one new recommendation, and Top-2 means two novel recommendations.

TABLE VII. THE RESULTS OF THE DIVERSITY, UNEXPECTED, AND NOVELTY METRICS

	Top-1	**Top-2**	**Top-3**	**Top-4**
Diversity	0.57	0.64	0.57	0.65
Unexpectedness	0.77	0.74	0.83	0.90
Novelty	0.22	0.23	0.09	0.04

E. Experiment 4: Experiment Comparison

Fig. 13 shows the comparison of serendipity definitions between our proposed approach and other research. While some researchers do define serendipity as involving novelty and diversity, the concept of serendipity encompasses a range of different aspects and definitions depending on the context and field of study. Serendipity can be understood as a fortunate accident or unexpected discovery, which may involve factors such as creativity, curiosity, openness to new experiences, and the ability to recognize and capitalize on unexpected opportunities. Fig. 14 represents the evolution of the novelty metric, which describes the ratio of unseen items to recommended items, diversity, which displays the degree of difference between recommendations with user preferences; and unexpectedness, which calculates the degree of difference between user disapproval and the preferences of the user in question. Fig. 15 represents the novelty metric for an example of 20 users, as it is mentioned that users 15, 16, 17 are very similar to others.

Fig. 16 represents the metric novelty from Top-2 to Top-10 recommendations for different users. The interest behind providing a list of recommended items is limited to show the top few options to the user to save user time and make the recommendations more actionable. Showing the Top-2 to Top-10 recommendations allow for a good balance between providing enough options for the user to consider, while not overwhelming the user with too many choices. The exact number of recommendations shown can vary depending on the context and the user's preferences. It is visible that moving from two recommendations to 10, the percentage of novelty decreases. Fig. 17 represents ten user metrics, novelty and diversity.

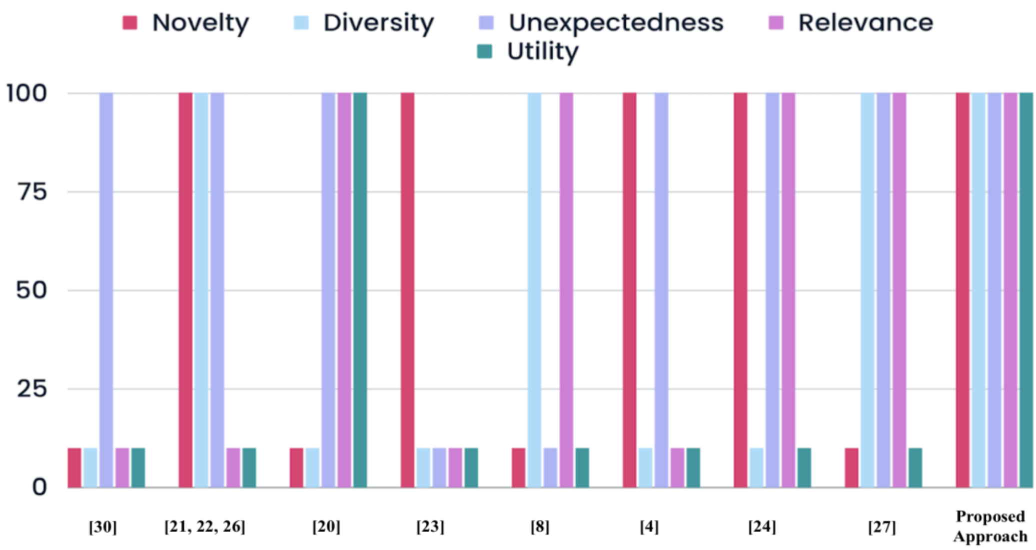

Figure 13. Comparison of serendipity definitions between our proposed approach and other research.

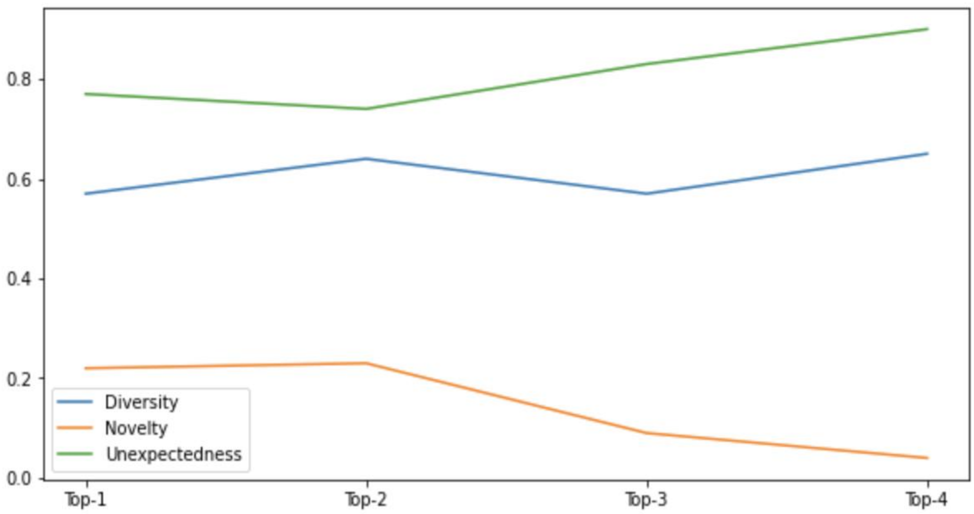

Figure 14. The evolution of serendipity.

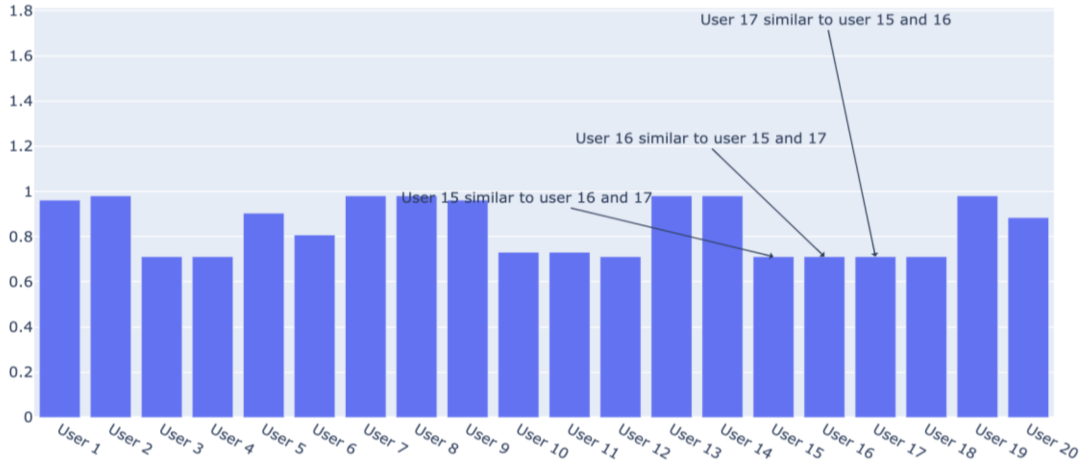

Figure 15. The novelty metrics for the first 20 users.

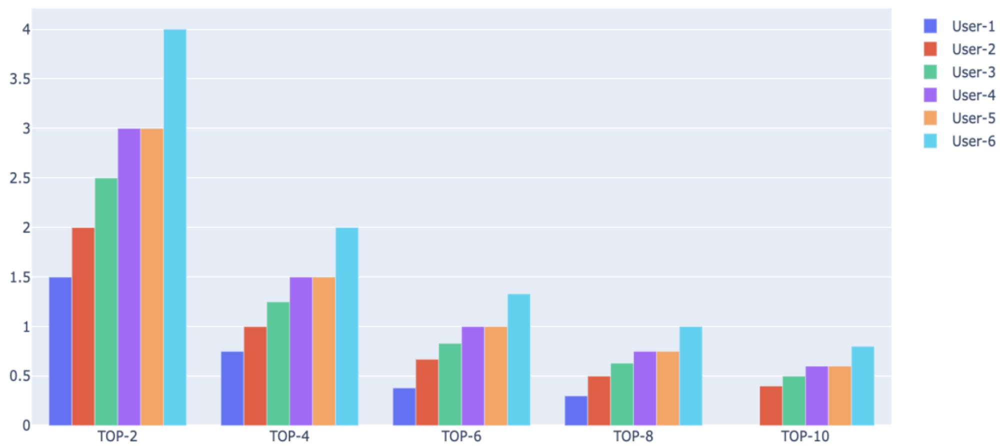

Figure 16. Top novelty metrics for the first users.

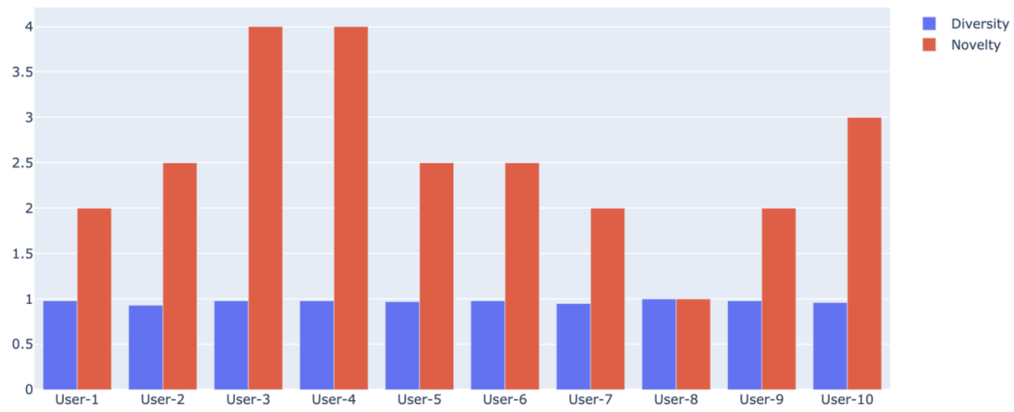

Figure 17. Novelty and diversity metrics for 10 users.

VIII. Discussion

The fundamental principle of this research is to investigate possible suggestion lists and then build a recommendation list that simultaneously guarantees correlated semantic proposals and diverse, novel, and relevant proposals. Therefore, IRS_{5Q} examines for a recommended list that fulfills three fundamental characteristics:

- The proposed items are functionally equivalent to the item that was researched.
- The suggested items cover a wide range of users' desires.
- Items discovered by coincidence must be recommendable to users.

The suggested system IRS_{5Q} varies the suggestion list and finds a list that fits the requirements by employing novel methodologies. The length of the dataset and the number of proposed objects, according to the authors, influence the proposed system's performance. The Top-n recommendation must be determined experimentally and accurately to acquire the most excellent possible performance with acceptable dataset size. The data considerably improves the proposed system's IRS_{5Q} serendipity suggestion quality.

The observed results can be analyzed to provide insight into the research questions being addressed.

1) The first research question aims to examine a clear definition of serendipity concept. To answer this question, it is necessary to check the broadest sense in literature and compare the definition to previous studies and relevant literature in the field to determine if the proposed definition does not exist before as it can be experienced in many different areas of life, from personal relationships and creative pursuits, to scientific and technological advancements.
2) The second research question is aimed at discovering each component individually. One can gain a deeper understanding of the various factors that contribute to serendipitous recommendations. In this case, the results are evaluated to each of these components which contributes to the overall experience of serendipity, and all play a role in creating the unexpected, diverse, and useful outcomes that define the concept. By understanding each component separately, it becomes easier to understand the full picture of serendipity and how to foster it in various settings and contexts.
3) The third research question is aimed at evaluating the serendipity concept which can be evaluated by examining the five components that make up the concept: novelty, diversity, unexpectedness, relevance and utility.
4) The fourth research question is aimed at improving diversity, novelty, relevance, and unexpectedness in a one system which is a complex task, to achieve this goal we use metrics that evaluate each component separately.
5) The last research question is aimed at describing challenges of serendipity. Serendipity, the idea of discovering unexpected but pleasing results, is a desirable aspect of recommender systems, as it helps users to find items that they may not have known about or considered before. However, implementing serendipity in recommender systems is challenging, and there are several issues that need to be addressed. Here are some of the challenges and future directions of serendipity in recommender systems:
   a) **Balancing serendipity and accuracy:** Recommender systems are often evaluated based on their accuracy, but adding serendipity to the mix can make it difficult to maintain high accuracy. There is a need for algorithms that can balance serendipity and accuracy and provide recommendations that are both surprising and relevant to the user.
   b) **User feedback and engagement, Sparsity issue:** In order to implement serendipity effectively, recommender systems need to be able to collect and use high quantities of user feedback to understand what users consider to be serendipitous. This requires user engagement, as users need to be willing to provide feedback and rate the serendipity of their recommendations.

In conclusion, the future of serendipity in recommender systems lies in developing algorithms and systems that can effectively balance serendipity and accuracy, provide a balance between personalization and diversity, effectively use user feedback, and integrate seamlessly with other systems.

Fig. 15 shows the evolution of serendipity in terms of diversity, novelty, and unexpectedness. That's correct. Diversity, novelty, and unexpectedness can be quantitatively measured using various metrics such as entropy, cosine similarity, and information gain. However, utility is subjective and depends on user feedback and their individual preferences and needs. Therefore, measuring utility requires direct user feedback.

However, it's important to also compare the time complexity between different approaches. Table VIII compares the classical algorithm "content-based filtering", clustering and our proposed approach in terms of different factors such as memory usage, ease of implementation, and readability.

TABLE VIII. TIME COMPLEXITY FOR ALL APPROACHES

Method	Complexity Time (Memory usage)	Ease of implementation
Content-based filtering	12	Medium
Clustering	15	High
Our proposed approach	10	Less

The most significant drawback of content-based filtering is the issue of serendipity. Consequently, IRS_{5Q} aims to solve the issue of serendipity in order to improve the quality of recommendations [20] and user satisfaction. MovieLens was the dataset used to test IRS_{5Q} . The proportion of enhancements was more significant when IRS_{5Q} used Movielens instead of more traditional approaches.

In terms of originality, recommendation quality, and the number of fortuitous items offered to the user, the IRS_{5Q} exceeds the other RSS. Overall, IRS_{5Q} significantly improved the quality of its recommendations. This indicates its effectiveness in addressing the content-based filtering problem that plagues serendipity.

In this new article, we have expanded our future research described in [3, 31] by incorporating additional evaluation metrics to further define and measure the concept of serendipity.

Recommendation systems are widely used to help customers in their decision-making process and build customer loyalty based on their preferences. However, the user needs a system that recommends items outside of his preferences, pushing him beyond his filtering bubble, monotony, and redundancy in the recommendations made. In our previously published article [3] we addressed the problem of over-specialization by injecting novelty and diversity to recommendation results which opened up another research direction in order to fix the serendipity problem. Table IX shows the comparison of both approaches RRS_{GA} and IRS_{5Q} in terms of the best evaluation metrics because accuracy is a commonly used evaluation metric.

TABLE IX. COMPARISON BETWEEN OUR PREVIOUS APPROACH AND THE NEW ONE

Approaches	Genetic Algorithm	Dissimilarity	Metrics Used
RRS_{GA}, [31]	✓		• Novelty • Diversity
IRS_{5Q}		✓	• Novelty • Diversity • Unexpectedness • Utility • Relevance

IX. CONCLUSION AND FUTURE WORK

Due to the abundance of data, recommender systems have become increasingly important. Our study aimed to address the serendipity problem in content-based recommender systems and generate new recommendations for users using a new approach. The IRS_{5Q} was used for content-based filtering, and the system combines item popularity with user disapproval to achieve serendipity. While many recommendation systems focus on improving accuracy, serendipity is often overlooked as a crucial aspect of recommendation quality. A serendipitous recommendation should be unexpected but helpful, providing users with a pleasant surprise.

Serendipity has an advantage over other evaluation concepts in that it allows for the discovery of unexpected and valuable results, which may not have been anticipated by the user or system. This can lead to new insights and opportunities that may not have been identified through other evaluation methods. Additionally, Serendipity can help to mitigate the issue of "filter bubbles" and provide a more diverse and inclusive user experience by exposing users to content they may not have otherwise encountered.

We plan to introduce feedback from real users for the evaluation of serendipity as well as explore other solutions for our future work. Furthermore, we want to develop and research other criteria, compare recommendation effectiveness across various parameters, and expand the definition of serendipity, combining user demographics with data from other areas to predict the needed parameters better and satisfy a customer's wishes. Overall, the study of serendipity in suggesting systems is a relatively young and understudied area of research. Much more effort is needed to tackle this important, intriguing, and useful problem.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

O.S conducted the research, analyzed the data, and wrote the draft and the revised version of the paper. S.K. and O.B supervised the research, and all authors had approved the final version.

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