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Promoting Sustainable Travel Experiences: A Weighted Parallel Hybrid Approach for Personalized Tourism Recommendations and Enhanced User Satisfaction

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Abstract: With the growing significance of the tourism industry and the increasing desire among travelers to discover new destinations, there is a need for effective recommender systems that cater to individual interests. Existing tourism mobile applications incorporate recommendation systems to alleviate information overload. However, these systems often overlook the varying importance of different items, resulting in suboptimal recommendations. In this research paper, a novel approach is proposed: a weighted parallel hybrid recommendation system. By considering item weights and leveraging parallel processing techniques, this method significantly enhances the accuracy of the similarity between items, leading to improved recommendation quality and precision. With this approach, users can efficiently and effectively explore new destinations that align with their unique preferences and interests, thereby enhancing their overall tourism experience and satisfaction. To evaluate the effectiveness of the proposed weighted parallel hybrid recommendation system, we conducted experiments using a dataset consisting of 20 users. The results demonstrated that the proposed approach achieved an impressive classification accuracy of 80%. A comparative analysis revealed that the proposed approach outperformed that of existing systems and achieved the best results in terms of classification accuracy. This finding highlights the effectiveness and efficiency of the proposed method in generating and promoting sustainable travel experiences by developing a personalized recommendations system for the unique preferences and interests of individual users.

Keywords: social recommender system; mobile application; recommendation system; weighted similarity; cosine similarity; travelers; place reviews; agent-based model; tourism recommendation allocation

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1. Introduction

A social network recommender system can provide personalized recommendations, based on a user's preferences, past travel experiences, and behavior, within the application. This can help travelers discover new destinations and activities that match their interests. The main focus of this study is to improve the effectiveness of hybrid recommender systems in the tourism industry by incorporating weights with cosine similarity. The motivation for developing such systems stems from the fact that planning a trip can substantially boost one's happiness. However, many travelers face the challenge of deciding where to go and may miss out on new places that match their preferences [1]. To address this issue, this study aims to improve the current methods of obtaining travel recommendations. In this study, a new method that utilizes a weighted parallel hybrid recommendation system is proposed. This approach improves the accuracy of the similarity between items and enhances the recommendation quality by exploiting the differences between items. In comparison to existing methods, the proposed approach provides more efficient and accurate results for a recommender system. Typically, travelers rely on friends, family, celebrities, or social media to find destinations. However, these sources have limitations, and it would be beneficial to have a social network mobile application that allows travelers to share their experiences with others.

The proposed method offers various features that enhance user experience, including the ability to access detailed posts and recommendations from other users, share personal experiences, and easily create trip lists. To facilitate list creation, the proposed method incorporates a hybrid recommender system that combines content-based and collaborative filtering techniques. This system suggests lists created by other users based on similarities in their profiles and behavioral patterns within the application.

The tremendous growth in digital information and Internet users has led to the problem of information overload, impeding users' ability to efficiently find relevant content. While search engines like Google have partially addressed this issue, prioritizing, and personalizing available information based on user interests and preferences remains a challenge. Consequently, the demand for recommender systems has surged. Recommender systems aim to alleviate information overload by filtering essential information from vast amounts of dynamically generated data, considering user preferences, interests, and behavior. By analyzing a user's profile, a recommendation system can predict their preferences for specific items [2]. Notably, prominent brands, such as Netflix, Amazon, and Google, have built their platforms around recommender systems.

There are three primary types of recommendation systems: collaborative filtering, content-based filtering, and hybrid systems that integrate both approaches. Collaborative filtering analyzes user behavior, activities, and preferences to predict user preferences based on similarities with other users. One advantage of collaborative filtering is that it does not require in-depth analysis or understanding of the product; the recommendation system selects items based on available user information. Content-based filtering operates on the assumption that if a user likes one item, they will likely enjoy similar items. This algorithm measures item similarity based on the user's preference profile and item de-scription. However, content-based filters have the limitation of recommending only content similar to what the user has already interacted with, potentially resulting in limited recommendations. On the other hand, hybrid recommendation systems leverage both collaborative (metadata) and content (transactional) data. This approach utilizes natural language processing tags to create item tags and employs vector equations to calculate similarity. By utilizing a collaborative filtering matrix based on user behavior and preferences, users can be recommended items. The Netflix recommendation engine serves as a classic example of a hybrid recommendation technology, considering both user interests (collaborative) and content descriptions (content-based) [3,4].

Overall, this study aims to enhance the travel planning experience by providing personalized recommendations and promoting sustainable tourism. By using this technology, travelers can make more informed decisions, discover new destinations, and share their experiences with others in the traveling community.

The rest of the paper is organized as follows: This section presents a brief background about recommender systems. Section 2 introduces the work that has been undertaken in the field of related recommender systems. Section 3 describes the dataset that has been used in this study and the proposed method. Section 4 presents the experiment stages and the results that have been obtained. Section 5 discusses the results. Finally, Section 6 concludes the study.

2. Literature Review

This section explores different applications and tools that use recommender systems to enhance their features and functionality. One such application is Google Maps [5], which allows users to search for places and to view the fastest route to a particular location by walking, car, or train. Google Maps also features a place page that displays ratings and reviews and user profiles, and offers the ability to follow other users, and make lists that can be shared with others. In Google Maps, the recommender system suggests places based on reviews, photos, and updates from people and businesses that users follow on the platform. The system uses collaborative filtering techniques to identify similarities between users' preferences and to generate personalized recommendations [5]. For example, if a user frequently searches for coffee shops and leaves positive reviews, the system may suggest similar or related places.

The RoadTrippers [6] app is designed specifically for road travelers, allowing users to plan their road trips by entering the start and end points of the trip, and to read reviews of places, view travel guides, and see recommended stops endorsed by previous travelers. In RoadTrippers, the recommender system offers recommended stops endorsed by previous travelers. The system uses content-based filtering techniques to match a user's preferences with similar places and activities. For instance, if a user frequently visits museums and historical sites, the system may suggest similar places to visit along the route.

Another popular application is TripAdvisor [7], which provides detailed information on different destinations and uses recommender system technologies to support users in their trip destination tasks. The platform's main features include creating plans, adding saved places to plans, making bookings, and leaving reviews. TripAdvisor also allows users to follow other people and to view their profiles and reviews. In TripAdvisor, the recommender system uses a combination of content-based and collaborative filtering techniques to suggest places and create personalized travel plans. The platform analyzes a user's search and browsing history to identify their preferences and suggest places that match their interests. The system also considers the ratings and reviews of other users to generate recommendations.

Wanderlog [8] is a travel application that enables travelers to create trips and post guides for other users to view and follow. Users can plan future trips on the Wanderlog app, create notes and lists of places they wish to visit, and attach reservations and add notes when building their plans. In Wanderlog, the recommender system suggests places based on a user's destination and preferences. The system uses collaborative filtering techniques to analyze a user's previous searches and activities to generate personalized recommendations. For instance, if a user frequently searches for vegan restaurants, the system may suggest similar places to visit during their trip.

As part of the related work to this research, Lin et al. [9] conducted a study that focused on developing a travel recommendation method that not only considers users' personalized needs, but also aims to maximize team satisfaction. The study was achieved through the utilization of an enhanced collaborative filtering algorithm (CFA) method, and it was grounded in key techniques for recommendation in the context of collaborative filtering algorithm (CFA) applications, encompassing fusion methods and fusion strategies. The fusion method is further classified into two categories: model fusion, where recommendation combinations are generated based on user preference models, and recommendation fusion, which involves fusing prediction scores obtained from traditional algorithms for each user and which can incorporate the list of recommended items. When it comes to fusion strategies, the mean value strategy, the least pain strategy, and the happiest strategy are widely used in recommendation key techniques. The improved CFA technique merges the similarity factor and the correlation factor, which offers a more effective solution to the issue of data sparsity in travel recommendations. The instance validation carried out on https://Qunar.com (accessed on 9 April 2023) revealed that the enhanced CFA method proposed in this study exhibited a significant decrease in both the mean absolute error (MAE) and the root-mean-square error (RMSE) when compared to the non-optimized CFA method, across different values of K. This observation highlights the efficacy of the proposed method in enhancing the accuracy and performance of the recommendation system. The utilization of the satisfaction equalization strategy is aligned with the conventional fusion strategy for varying numbers of users. The effectiveness of the improved method proposed in this study is confirmed through experimental analysis conducted on a relevant tourism dataset from the city of Chongqing, validating its ability to enhance the quality of tourism recommendations.

Jagtap and Borate [10] conducted a study that focused on a tourist destination recommendation system using cosine similarity. Since the early 1990s, for information and even recommendations, we now turn to the Internet. Finding vacation spots on the Internet is a common practice. As a result of the overwhelming number of destinations and information available, a lot of time is wasted before an appropriate tourist destination is determined. To provide cogent and fast recommendations, the destination recommendation system utilizes data analysis and machine learning. In this paper, the cosine similarity algorithm is used to provide generalized recommendations to every user. A variety of tourist locations are represented in the dataset used. The cosine similarity algorithm predicts the most relevant tourist places using some important features of the dataset, such as the tourism category, the minimum budget (per day), and the visa requirement.

Luong et al. [11] presented a novel approach to enhancing user-based collaborative filtering (UBCF) by clustering users based on cognitive similarity across different cultures. To gather feedback from cross-cultural users, the authors deployed a crowdsourcing platform that featured a simple and user-friendly feedback collection process. The experiments on the dataset showed that the proposed approach outperformed the baseline UBPS, which only considers global similarity. However, the study by Luong et al. has some limitations. Specifically, the evaluation methods used to form user clusters were not examined, and demographic and personal information that could have been collected from users were not taken into account. For this reason, this research aims to introduce a more advanced approach to splitting the user list into preferred clusters by using a priority and weighted cosine similarity measure to improve the recommendation performance. Overall, while the approach presented by Luong et al. [11] is promising, further research is needed to address the limitations of the study and to advance the field of cross-cultural recommender systems.

Abbas et al. (2022) [12] implemented new trip recommendations using the concept of serendipity. The challenges of personalized trip recommendations lie in discovering relevant, novel, and unexpected points of interest (POIs) while ensuring high user satisfaction. To address these challenges, a novel method called serendipity-oriented personalized trip recommendation (SOTR) was proposed by Abbas et al. (2022) [12]. SOTR uses serendipity to discover users' satisfaction based on relevance, novelty, and unexpectedness. The proposed recommendation algorithm aims to efficiently plan the trip and maximize the user experience.

However, one possible weakness or limitation of SOTR [12] is that it may require a significant amount of relevant and accurate user data to provide personalized and effective recommendations. Additionally, while the novelty and unexpectedness of some recommendations may be appreciated by some users, others may prefer more conventional and familiar options, which could limit the overall acceptance and adoption of the method.

Overall, these applications demonstrate the potential of recommender systems in the tourism industry, providing users with personalized recommendations, enhancing the travel planning experience, and promoting sustainable tourism. These applications use different recommender system techniques to generate personalized recommendations, enhance the travel planning experience, and promote sustainable tourism.

3. Methodology

This study outlines the data collection and preparation process, as well as the proposed hybrid recommender system that combines content-based filtering and collaborative filtering. The goal of this section is to provide a detailed explanation of the methodology employed in developing the recommendation system.

3.1. Data Collection and Preparation

Data was collected and prepared to train and test the recommendation system module. As an appropriate dataset meeting the requirements of the weighted recommender system module was not readily available, we decided to build our own dataset. The dataset was crowdsourced, allowing us to outsource questionnaires, gather data in real-time, and to obtain a larger and more diverse set of observations compared to traditional data collection methods [13].

3.2. User Characteristics and Preferences

The collected data included the following user characteristics: user ID, age (ranging from 12 to 61 years old), marital status (for users aged 18 and above), presence of children (for users aged 18 and above), gender, preferred country for travel, preferred places to visit, user-assigned tags used in created lists, and the lists that the user saved.

3.3. Proposed Hybrid Recommender System

This section presents the proposed method, which utilizes a hybrid recommender system combining content-based filtering and collaborative filtering to recommend lists of posts to users. The method involves two main components: the content side and the collaborative side.

- Content-Based Filtering: The content side of the recommender system is based on the user's characteristics. These characteristics include the user's age, gender, social state, whether they have children or not, the countries they prefer (e.g., Middle Eastern, Asian, European, American, African), and the types of places they enjoy (e.g., restaurants/cafes, shopping malls, parks, museums, sports attractions). These attributes contribute to creating a personalized recommendation for each user. To incorporate these characteristics, this study employs techniques such as the TfidfVectorizer for normalization of the tf-idf representation. This transformation converts the count matrix into a normalized or tf-idf (term frequency inverse document frequency) representation. The tf-idf algorithm provides a meaningful numerical representation for machine learning algorithms and predictions. The TfidfVectorizer produces output vectors, including Vec Places, Vec Tags, Vec Age, Vec Country, Vec Social state, Vec Children, and Vec Gender.
- Collaborative Filtering: On the collaborative side, the recommendations are based on the tags attached to the lists that the user has saved. Each tag is assigned a weight based on its importance, with higher weights given to more significant values. This weighting scheme allows us to prioritize and emphasize the most relevant tags in the recommendation process.

To combine the content-based and collaborative filtering components, this study employs a weighted recommender system based on cosine similarity. The proposed recommender system method is illustrated in Figure 1. The implementation of the method is carried out using the Python programming language. We utilize the Pandas library to manipulate the data.

The first step employs the TfidfVectorizer [14] for the normalization of the tf-idf representation. This process converts the count matrix into a normalized or tf-idf (term frequency inverse document frequency) representation. The tf-idf algorithm is commonly used to convert text into a meaningful numerical representation suitable for machine learning algorithms and predictions. The "tf" in tf-idf refers to term frequency, representing the number of times a term "t" appears in a document "d". The inverse document frequency (idf) denotes the weight of a term. The defined idf is illustrated in Figure 2.

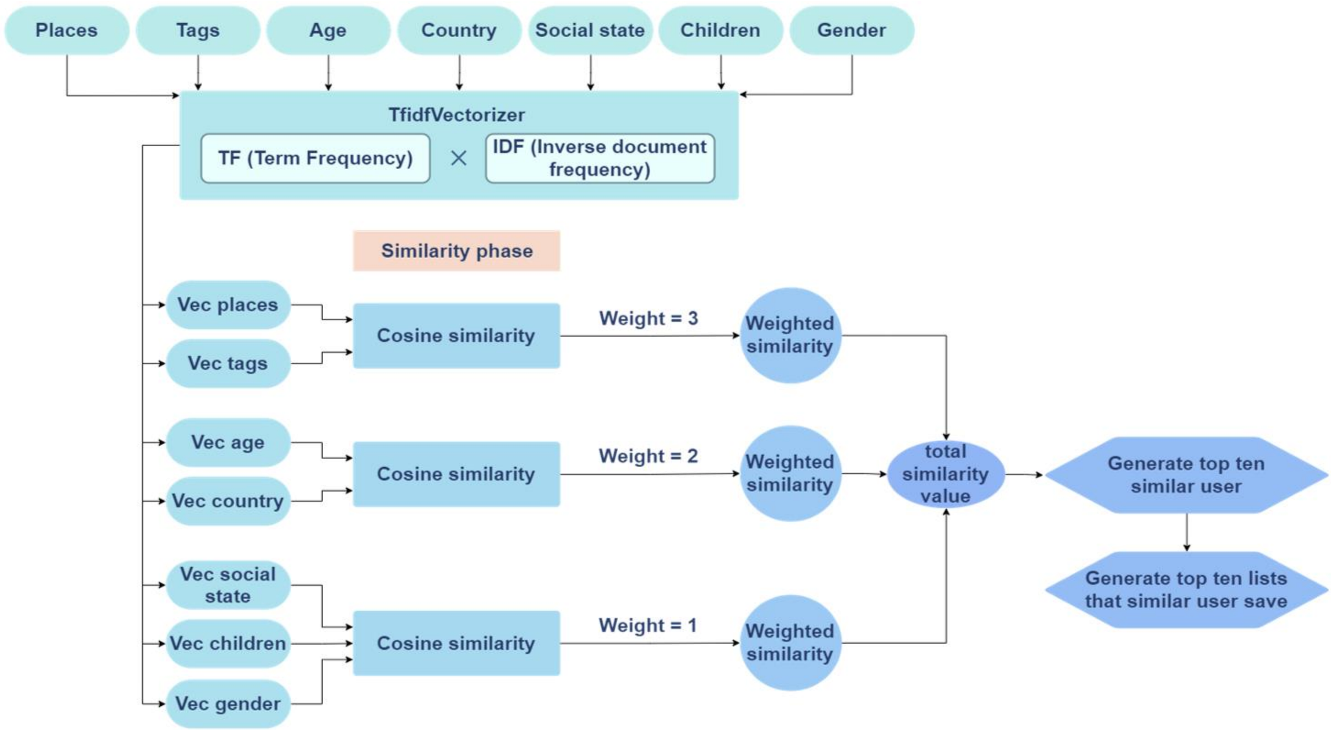

Figure 1. The proposed recommender system method.

$$\mathrm{idf}(t) = \log \frac{|D|}{1 + |\{d : t \in d\}|}$$

Where $|\{d : t \in d\}|$ is the **number of documents** where the term t appears, when the term-frequency function satisfies $\mathrm{tf}(t, d) \neq 0$, we're only adding 1 into the formula to avoid zero-division.

Figure 2. Idf(t) formula [13].

The TfidfVectorizer (Vec Places, Vec Tags, Vec Age, Vec Country, Vec Social state, Vec Children, and Vec Gender) produces the output. The count vectorizer provides frequency counts relative to the vocabulary index, while the tf-idf takes into account the overall document weights of words. The data is then fed into the cosine similarity calculation. The formula for the tf-idf is shown in Figure 3.

$$\mathrm{tf} - \mathrm{idf}(t) = \mathrm{tf}(t, d) \text{ x } \mathrm{idf}(t)$$

Figure 3. Tf-idf(t) formula [13].

The weights assigned to each feature category are justified based on empirical evidence and user feedback. Three categories are defined based on importance:

Category 1: Contains tags and places, assigned weight 3. This category is extremely important for generating similar lists aligned with the user's interests on the explore page.

Category 2: Contains age and country, assigned weight 2. This category is less important than Category 1 but still contributes to generating relevant lists for users on the explore page.

Category 3: Contains social state, children, and gender, assigned weight 1. This category has the lowest weight as it is less influential than Category 1 and 2 in generating similar lists for user interests on the explore page.

To determine the weight of each category, crowd-sourcing methods were utilized to gather user feedback and preferences. By analyzing the results, we identified the features that were most closely related to user choices and had the greatest impact on generating similar lists. Based on this analysis, the weights were assigned to each category according to their importance in generating recommendations aligned with the user's interests on the explore page. Cosine similarity is a metric used to measure the similarity between documents regardless of their size. It calculates the cosine of the angle between two vectors projected in a multi-dimensional space. Even if two similar documents are widely separated by Euclidean distance, they can still be considered closer together based on cosine similarity. The advantage of cosine similarity is that even if two documents are separated by a large Euclidean distance, they can still be considered similar. A smaller angle corresponds to a higher cosine similarity [15]. Figure 4 illustrates the assignment of different weights to each feature based on their importance and relationship.

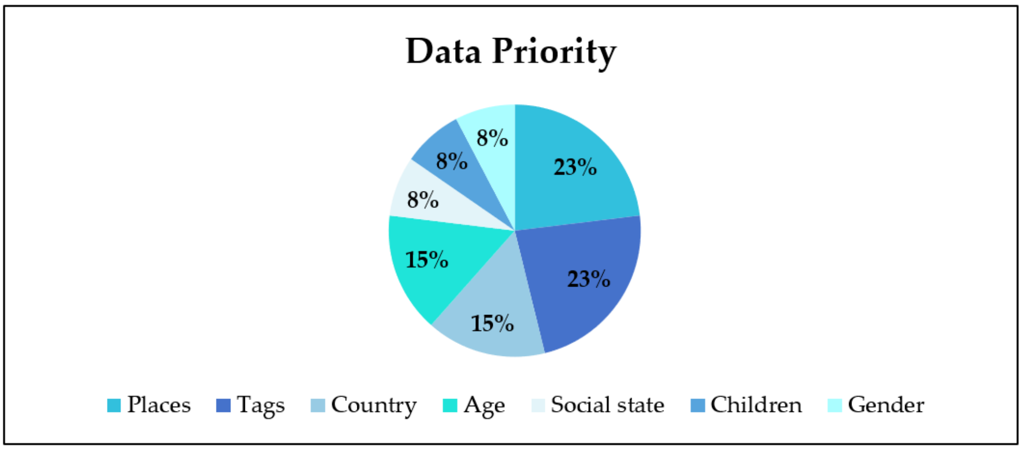

Figure 4. Data priority.

Based on this analysis, the weights were assigned to each category according to their importance in generating recommendations aligned with the user's interests on the explore page. Table 1 summarizes the weighted data, indicating the assigned weights for each item.

Table 1. Weighted data.

Item	Priority
Places	3
Tags	3
Country	2
Age	2
Social state	1
Children	1
Gender	1

Afterwards, the method displays the top 10 similar users and concludes by displaying the recommendations.

4. Analysis and Results

To investigate the performance of the recommender system by using a weighted parallel hybrid method with cosine similarity, different types of cases were tested, and the results were compared. Rather than comparing the methods to excellent state-of-the-art recommendation algorithms, the aim of this experiment was to demonstrate that weighting coefficients can be combined with cosine similarity and that the weighted cosine similarity measure improves recommendation performance.

4.1. Data

Data were collected and prepared in order to train and test the recommendation system module, which is available on the GitHub platform [16]. In order to provide academic support to the text, this section discuss the data and refers to the relevant literature.

When searching for a suitable dataset for the proposed weighted recommender system module, difficulties were encountered in finding one that fulfilled all the requirements. As a result, we made the decision to construct our own dataset. It is important to note that the minimum number of observations that a dataset should have is approximately 500 observations, as suggested in the literature [13].

To collect the data, we employed a crowdsourcing approach, which allowed us to outsource questionnaires and gather data in real-time. This method enabled us to obtain a significantly larger and more diverse set of observations compared to traditional data collection methods. By leveraging crowdsourcing, we were able to collect a rich and comprehensive dataset for the proposed recommender system [17].

Table 2 provides a detailed explanation of each item present in the dataset. The construction of our own dataset ensures that it meets the specific requirements of our weighted recommender system module and allows us to conduct thorough evaluations and experiments [18].

Table 2. Items and their characteristics.

Item Name	Characteristics
user_id	The number of the user's ID
age	Age of the user that ranges from 12 to 61 years old
married	Whether the user is married or not if he/she is 18 or above
children	Whether the user has children or not if he/she is 18 or above
gender	Whether the user is male or female
most_liked_country	The preferences of the user's most liked country to travel to
most_liked_place	Preferences of the user's most liked places to go to when traveling
user_assigned_tags	Tags that are used by users in their created lists
lists_id_save	The ID of lists that were saved by the user

4.2. Experimental Results

The recommender system will generate the top 10 similar users and then generate the lists saved by the top 10 similar users for each user for 20 users who were randomly selected to test the accuracy of the recommender system module. Table 3 shows the synthetic representation of users that contains a summary of the experimental results.

Table 3. Synthetic representation of users.

Category	Sub-Category	Number of Times Used
Gender	Female	12
	Male	8
Age	19–28	6
	30–42	7
	44–61	7
Country Preference *	European	17
	American	7
	African	4
	Middle Eastern	8
	Asian	8

Table 3. *Cont.*

Category	Sub-Category	Number of Times Used
Places Preference *	Restaurants/cafes	8
	Shopping malls	10
	Sports attractions	11
	Museums	9
	Parks	7
Have Children	Yes	12
	No	8
Social Status	Single	9
	Married	11
Used Tags *	#coffee	1
	#friends	1
	#waterParks	5
	#fun	5
	#america	5
	#Yummy	1
	#London	1
	#UK	1
	#food	1
	#hotel	11
	#art	3
	#swimming	6
	#History	3
	#families	3
	#flowers	5
	#fresh air	3
	#libarary	1
	#nature	1
	#castle	2
	#hiroshima	2
	#Mountain	2
	#games	1
	#mario	1
	#studio_ghibli	1
	#anime	1
	#activities	2
	#kids	3
	Did not use tags	7

* A user can have multiple values in the country and places preferences and tags.

Appendix A shows each users' characteristics and their explore page after generating lists by the 10 most similar users.

Accordingly, the proposed method produces lists of places for different countries or for the same country based on the data input. The lists contain different places related to specific categories, such as restaurants, breakfast places, and countries. We noticed the recommender system module detected (16) correct and (4) incorrect, so, the accuracy of the module by using this formula for calculating the accuracy of module is:

$$Accuracy = \frac{Number\ of\ attempts\ correct\ detected}{Number\ of\ test\ uusers} = \frac{16}{20} \times 100 = 80\%$$

In order to evaluate the proposed method, the precision and recall of the module were calculated using the following equations [8], where the true positives equal 11, the true negatives equal 5, the false positives equal 1, and the false negatives equal 3.

$$Precision = \frac{True\ Positives}{(True\ Positives + False\ Positive)} = \frac{11}{11+1} = \frac{11}{(11+1)} = 0.916 = 91.6\%$$

$$Recall = \frac{True\ Positives}{(True\ Positives + False\ Negatives)} = \frac{11}{(11+3)} = 0.785 = 78.5\%$$

To thoroughly evaluate the performance of the proposed method, a comparison was performed with two related tourism recommendation systems: user-based Pearson similarity (UBPS) [11] and a recommender system based on the cognitive similarity between cross-cultural users (CSBCC) [11]. The comparison was conducted based on accuracy, and the results are presented in Table 4. The comparison results for the proposed method and other related methods are shown in Table 4. The results indicate that the proposed method outperformed UBPS and CSBCC in terms of accuracy. Specifically, the proposed method achieved an accuracy of 80%, while SOTR [12], UBPS [11], and CSBCC [11] had accuracies of 54%, 75%, and 76%, respectively. These findings suggest that the proposed method represents a more effective approach for tourism recommendation systems.

Table 4. The performance measurement of the proposed method and comparison with more recent and related works in the literature.

RS\Performance Measurements	NO of Users	Accuracy	Precision	Recall
Proposed Method	20	80%		
SOTR [12]	11	54%	91.6%	78%
UBPS [11]	20	75%	45.1%	50.7%
CSBCC [11]	20	76%		

In conclusion, the proposed method has been shown to be a better approach for tourism recommendation systems than SOTR [12], UBPS [11] and CSBCC [11]. It has a higher accuracy rate, which indicates that it is a more effective approach for tourism recommendation.

5. Discussion

This section highlights the potential benefits of using recommendation systems in the travel industry. These systems can recommend suitable deals, such as for hotels, flights, or activities, making it easier for travelers to identify suitable places quickly and easily. The proposed solution enhances the accuracy of the recommender system by using a weighted parallel hybrid method with cosine similarity. This approach assigns a value to each item, thereby recognizing that some items are more important than others.

The experimental results presented in the previous section demonstrate that the proposed method is efficient and provides good results for a recommender system by improving the accuracy of the similarity between items, thus enhancing the recommendation quality accuracy. This approach is novel and advanced, and its application in the tourism field can benefit both local and global economies by helping people to discover the world in a way they enjoy.

Moreover, the proposed system can be useful for both travelers and local businesses. For travelers, the system helps them find suitable destinations and activities, while for businesses, it provides an opportunity to showcase their offerings to a wider audience. The use of such technology in the tourism industry can also help promote sustainable tourism by encouraging travelers to explore lesser-known destinations and reducing over-tourism in popular areas.

In conclusion, the proposed method for a recommender system in tourism is innovative and has the potential to transform the way people discover and explore the world. By using this technology, travelers can make more informed decisions, and local businesses can benefit from increased exposure. The application of such a technology in the tourism industry can also have positive economic and social impacts, making it a promising area for future research and development.

6. Conclusions

The main objective of the proposed recommender system, as described in this paper, is to enhance the accuracy of recommendations by taking into account the differences between items. The system serves as a social network for travelers, helping them plan their next trip, discover new places in a city, and save time and effort when searching for a new place by recommending lists based on the similarity between the user and other users. To achieve this goal, a novel method that utilizes a weighted parallel hybrid approach is proposed. This method assigns each item a value, recognizing that some items are more important than others, thereby improving the accuracy of the similarity between items and enhancing the quality and accuracy of recommendations.

The proposed method outperforms existing recommendation systems, providing efficient and effective results for a recommender system. It has the potential to transform the way people explore new destinations, making travel planning more efficient and enjoyable. In conclusion, the proposed recommender system method is a significant contribution to the tourism industry, providing travelers with a reliable and accurate source of information and recommendations. The use of a weighted parallel hybrid approach is a novel and advanced technique that improves the accuracy of the similarity between items and enhances the quality of recommendations. This method has the potential to promote sustainable tourism, reduce over-tourism, and to benefit local and global economies. However, the application has certain limitations, including the lack of statistics on post/list views and list additions for users. Additionally, the recommender system currently only supports Android devices and the English language, requiring improvement in accuracy, iOS device support, and language options (such as Arabic).

Future work will aim to address these limitations and to enhance the system by incorporating more statistical data on post/list views and list additions for users, improving accuracy, and expanding language support. Moreover, alternative approaches will be investigated to further improve the system's performance, such as incorporating deep learning or other advanced techniques. These enhancements aim to enable the system to provide more accurate and personalized recommendations for travelers, thereby enhancing their overall experience.

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Data Availability Statement: The data used to support the findings of this study are available and can be accessed online through the GitHub platform [15].

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Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. The experimental results of user #1.

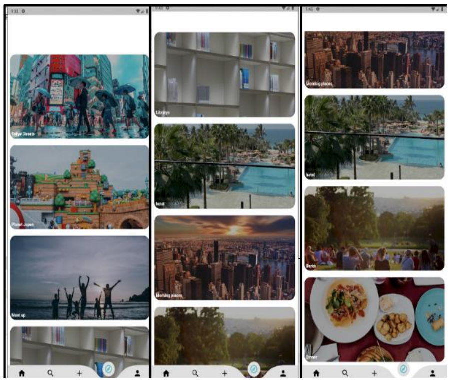
User Number	User Details	User Explore Page
User #1	• Female; • 25 years old; • Likes the countries (European, American); • Likes the places (restaurants/cafes, shopping malls) • Single; • Does not have children; • Uses tags (#coffee #friends #waterParks #fun #america).	

Table A2. The experimental results of user #2.

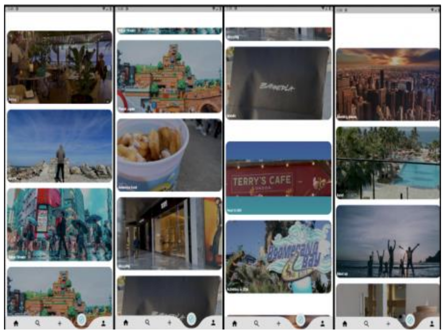
User Number	User Details	User Explore Page
User #2	• Female; • 30 years old; • Likes the countries (European, American); • Likes the places (restaurants/cafes, shopping malls, sports attractions); • Single; • Does not have children; • Uses tags (#Yummy #London #UK #food #waterParks #fun #america).	

Table A3. The experimental results of user #3.

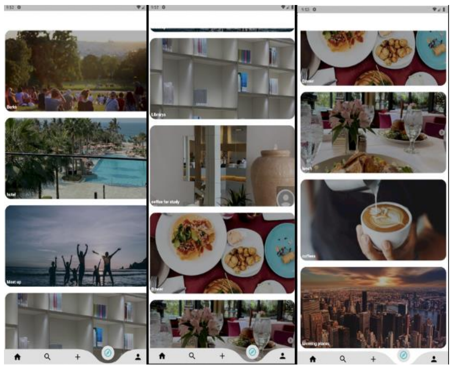
User Number	User Details	User Explore Page
User #3	• Female; • 45 years old; • Likes the countries (European, African); • Likes the places (museums, parks); • Single; • Does not have children; • Uses the tag (#hotel).	

Table A4. The experimental results of user #4.

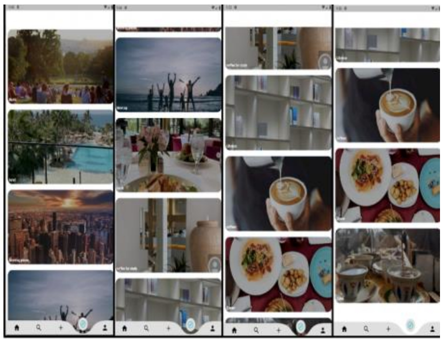
User Number	User Details	User Explore Page
User #4	• Female; • 34 years old; • Likes the countries (European); • Likes the places (shopping malls, parks); • Married; • Has children; • Does not use tags.	

Table A5. The experimental results of user #5.

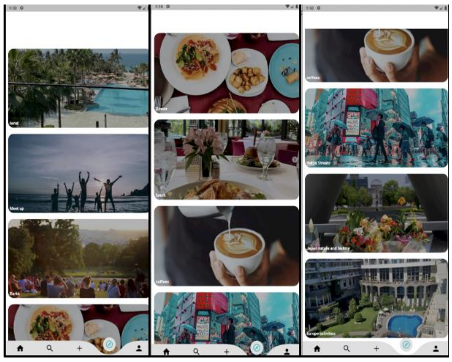
User Number	User Details	User Explore Page
User #5	• Female; • 36 years old; • Likes the countries (European, American, Middle Eastern); • Likes the places (restaurants/cafes, museums); • Married; • Has children; • Does not use tags.	

Table A6. The experimental results of user #6.

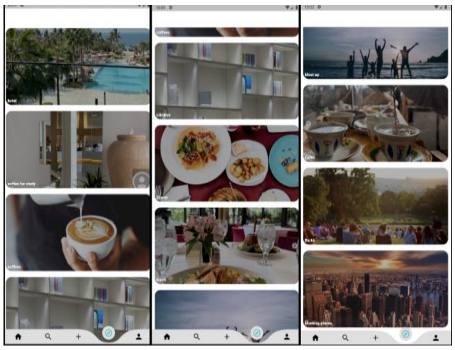
User Number	User Details	User Explore Page
User #6	• Female; • 20 years old; • Likes the countries (Middle Eastern, American); • Likes the places (restaurants/cafes, sports attractions); • Single; • Does not have children; • Does not use tags.	

Table A7. The experimental results of user #7.

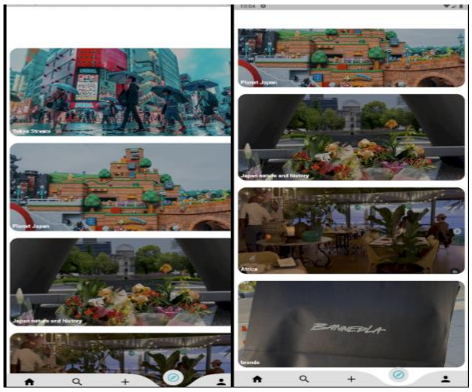
User Number	User Details	User Explore Page
User #7	• Female; • 49 years old; • Likes the countries (African, European); • Likes the places (museums, parks, sports attractions); • Married; • Has children; • Does not use tags.	

Table A8. The experimental results of user #8.

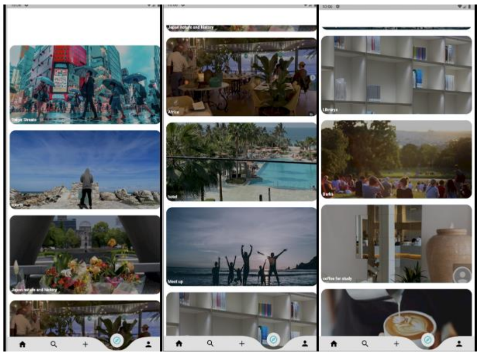
User Number	User Details	User Explore Page
User #8	• Female; • 30 years old; • Likes the countries (Middle Eastern, European); • Likes the places (shopping malls, sports attractions); • Single; • Does not have children; • Uses tags (#art #swimming #History #families #flowers #freshair).	

Table A9. The experimental results of user #9.

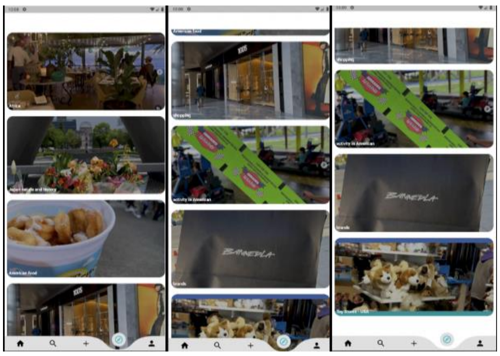
User Number	User Details	User Explore Page
User #9	• Female; • 50 years old; • Likes the countries (Middle Eastern, European, African, Asian); • Likes the places (shopping malls, sports attractions, parks, museums); • Married; • Has children; • Uses tags (#libarary #nature #castle #hiroshima #flowers #Mountain).	

Table A10. The experimental results of user #10.

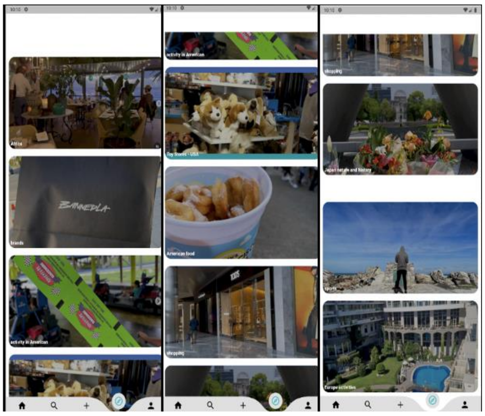
User Number	User Details	User Explore Page
User #10	• Female; • 42 years old; • Likes the countries (European, Asian); • Likes the places (museums, sports attractions); • Married; • Has children; • Uses tags (#games #Mountain #flowers #castle #hiroshima).	

Table A11. The experimental results of user #11.

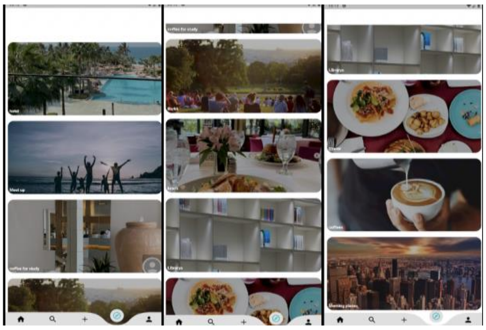
User Number	User Details	User Explore Page
User #11	• Female; • 19 years old; • Likes the countries (European); • Likes the places (shopping malls); • Single; • Does not have children; • Uses tags (#swimming #art #History).	

Table A12. The experimental results of user #12.

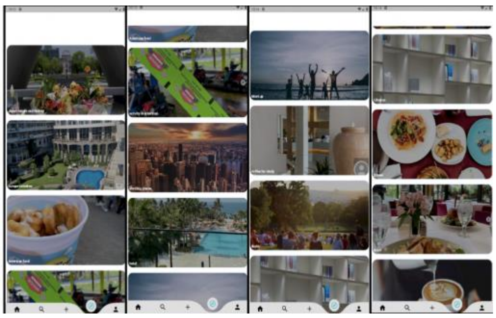
User Number	User Details	User Explore Page
User #12	• Male; • 28 years old; • Likes the countries (Middle Eastern, Asian); • Likes the places (parks, restaurants/cafes); • Single; • Does not have children; • Uses tags (#families #flowers #freshair).	

Table A13. The experimental results of user #13.

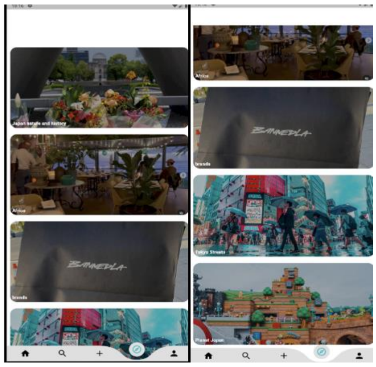
User Number	User Details	User Explore Page
User #13	• Male; • 26 years old; • Likes the countries (European, American); • Likes the places (museums, shopping malls, sports attractions); • Married; • Has children; • Uses tags (#art #swimming #History).	

Table A14. The experimental results of user #14.

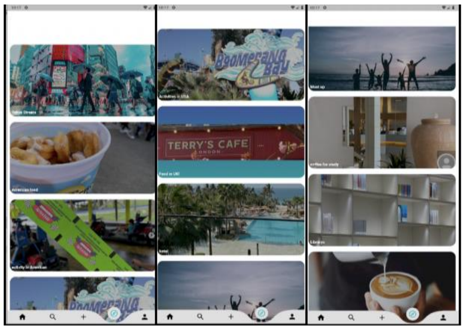
User Number	User Details	User Explore Page
User #14	• Male; • 61 years old; • Likes the countries (Asian, European, Middle Eastern) ; • Likes the places (museums, restaurants/cafes, sports attractions); • Married; • Has children; • Uses tags (#families #flowers #freshair).	

Table A15. The experimental results of user #15.

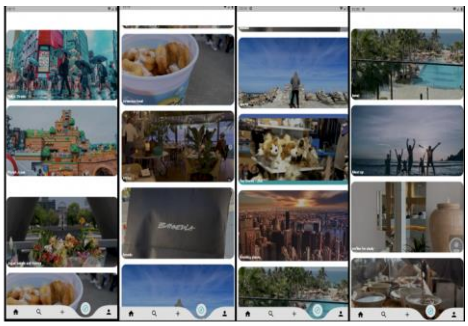
User Number	User Details	User Explore Page
User #15	• Male; • 33 years old; • Likes the countries (Asian, American); • Likes the places (restaurants/cafes, sports attractions); • Married; • Has children; • Uses tags (#activities #america #waterParks #fun #swimming #kids).	

Table A16. The experimental results of user #16.

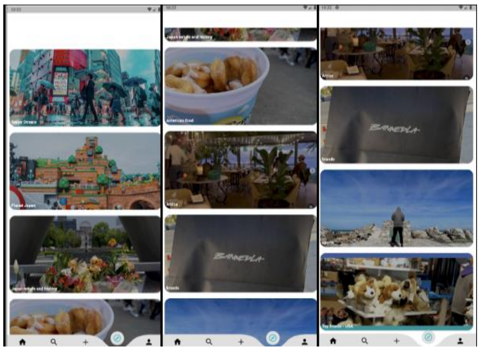
User Number	User Details	User Explore Page
User #16	• Male; • 44 years old; • Likes the countries (Asian, Middle Eastern, European, American); • Likes the places (sports attractions, restaurants/cafes, parks, shopping malls); • Married; • Has children; • Uses tags (#america #waterParks #fun #swimming #kids).	

Table A17. The experimental results of user #17.

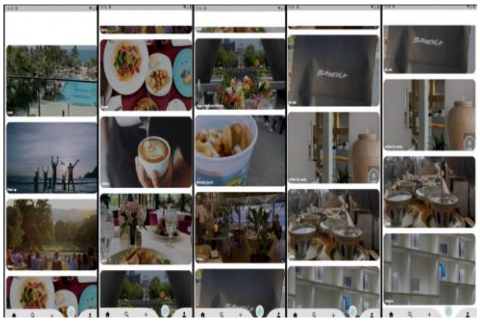
User Number	User Details	User Explore Page
User #17	• Male; • 49 years old; • Likes the countries (Asian, Middle Eastern, European); • Likes the places (museums, parks, shopping malls); • Married; • Has children; • Uses tags (#activities #waterParks #america #swimming #kids #fun).	

Table A18. The experimental results of user #18.

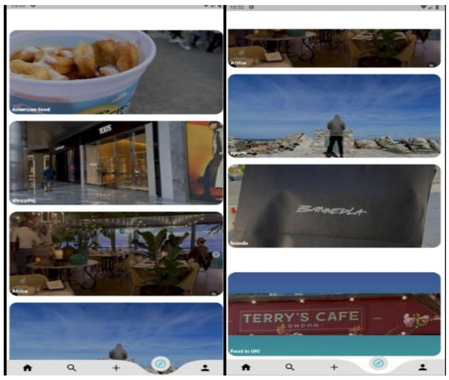
User Number	User Details	User Explore Page
User #18	• Female; • 19 years old; • Likes the countries (European); • Likes the places (shopping malls); • Single; • Does not have children; • Does not use tags.	

Table A19. The experimental results of user #19.

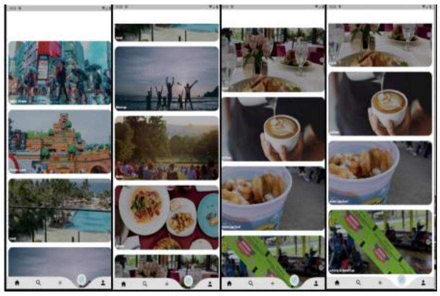
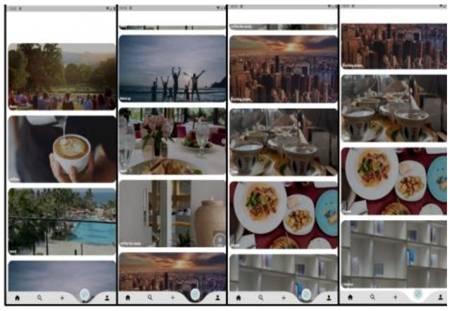
User Number	User Details	User Explore Page
User #19	• Male; • 60 years old; • Likes the countries (European, Asian); • Likes the places (museums); • Married; • Have children; • Do not uses tags.	

Table A20. The experimental results of user #20.

User Number	User Details	User Explore Page
User #20	• Male; • 31 years old; • Likes the countries (European, African); • Likes the places (sports attractions); • Married; • Has children; • Does not use tags.	

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