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Original Article

A Hybrid Tourism Recommendation System with Modified Similarity and Weighted Popularity Scores

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Abstract:

Obtaining valuable and accurate tourism information can become an overwhelming and time-consuming task to tackle given the vast pool of options available to the consumer. Having a plethora of options with no clear guidelines on how to manage and narrow down choices presents a challenge that can be unwanted for many looking to plan trips and activities in the future. Tourists often spend hours researching different destinations and may still not find the perfect match. Creating a streamlined option to eliminate these issues is, therefore, a worthwhile endeavor. A tourism recommendation system provides a solution by providing tourists with personalized recommendations that are tailored to their specific needs. Recommendation systems, or recommender systems, are a class of artificial intelligence and big data designed to suggest items to users based on prior opinions and preferences, product engagement, and interactions. This can save tourists time and money, and it can help them to have a more enjoyable and memorable travel experience. In this work, we develop a recommender system for Ghanaian tourism websites to provide personalized recommendations to users based on their travel preferences, behavior, and tastes. A combination of collaborative filtering and content-based filtering algorithms have been utilized for this work. This hybrid approach combines the advantages of both methods to create an improved recommendation system. The results obtained ascertain the efficiency of our proposed method.

Keywords:

Hybrid Recommender Systems, Collaborative Filtering, Content-Based Filtering, Modified Similarity Measures, Weighted Popularity Scoring, Personalized Recommendations, User Preference Modeling, Travel Decision Support Systems.

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1. Introduction

Tourism is a major economic driver, generating billions of dollars in revenue each year. In 2019, the global tourism industry generated $1.9 trillion in revenue and supported 334 million jobs (WTTC, 2019). The tourism industry is constantly evolving, and one of the most significant trends in recent years has been the rise of online travel agencies (OTAs). OTAs have made it easier than ever for tourists to find and book travel destinations and activities. However, the sheer volume of information available on OTAs can be overwhelming, and it can be difficult for tourists to find the right matches for their interests. This is where a tourism recommendation (RS) system can help. A tourism recommendation system is a software application that uses artificial intelligence to recommend destinations and activities to tourists. The system considers the tourist's interests, and travel preferences to generate personalized recommendations. In other words, a recommendation system is an intelligent tool that learns users' preferences through their interactions with different items and then suggests new items likely to satisfy them. By gathering information about people's experiences with items, RS are educated to comprehend people's preferences, past choices, and traits (Carole,2024).

The development of machine learning and data analytics has had a major impact on the progress of tourism recommendation systems. Hybrid, context, content, and collaborative filtering are the categories into which most recommender algorithms and techniques fall. Collaborative Filtering (CF) analyses similarity patterns among users based on their interaction with data. In this case, users who purchase similar items are considered to have similar preferences. Content-Based Filtering (CBF), on the other hand, relies on analysing the content and attributes of items to build item profiles and generate recommendations based on how item characteristics match user preferences. Hybrid filtering combines the strengths of both methods mentioned above to develop a more robust and comprehensive recommendation system (Afoudi,2024).

The tourism recommendation system developed in this work will use a combination of collaborative filtering and content-based filtering algorithms. We incorporate a similarity score measure and a weighted popularity score for the purpose of creating a recommendation system for Ghanaian tourism. The system will be designed to recommend destinations and activities to tourists who are traveling to specific cities in the country.

1.1. Collaborative filtering

CF is the most used technique for online recommendations (Iftikhar, 2020). In collaborative filtering, one identifies users whose tastes are like those of the given user and recommends items they have liked (Shoham, 1997). It operates on the principle that, if two users share a similar opinion on one matter, they are likely to have similar opinions on other matters as well. These systems analyse the taste information of users to make automatic predictions and recommendations (Javed, 2021). CF is particularly effective because it can uncover hidden preferences that users may not explicitly state. Pure collaborative recommendation systems resolve all the problems with pure content-based systems. We can deal with any form of content and receive goods with content that differs from what we have previously viewed by utilising the recommendations made by other people. Given fewer evaluations from any one user, there is a chance to retain effective performance because recommendations are influenced by the comments of other users (Shoham, 1997). User-based and item-based techniques are the two main categories into which traditional CF methods may be divided. Whereas item-based CF finds items that users have rated similarly, user-based CF looks for users with similar tastes (Iftikhar, 2020) (Ajaegbu, 2021). CF methods encounter certain challenges, such as the "cold start" issue, which arises when there is little to no data available for new users or items, making it challenging to produce accurate recommendations. Despite its challenges, it has been widely adopted and implemented in various real-world applications. Among other sources, movie recommendation systems, social networks, and e-commerce platforms have demonstrated their efficacy.

1.2. Content-Based Filtering

CBF is a recommendation system approach that generates recommendations based on the attributes of items rather than the similarity between users. It relies on the characteristics of the items themselves, such as their features, attributes, or content, to recommend new items to users (Schedl, 2019). This method involves analyzing the content of items to create user profiles and then matching these profiles to new items (Javed, 2021). A primary obstacle is an inclination to offer suggestions that centre around products with comparable attributes, perhaps resulting in a deficiency of diversity and variation in suggestions. However, it has been successfully applied in many recommendation systems despite its challenges. In tourist recommendation systems, it can suggest locations based on the country of origin of the tourist, past places visited, popular tourist sites, or the cost of travelling to the destination.

1.3. Hybrid filtering

Recent studies have shown that a hybrid approach can sometimes be more effective. Essentially, the two most used methods in information-filtering applications are collaborative filtering and content-based filtering (Thorat, 2015). Hybrid filtering in the context of recommender systems refers to a technique that combines the strengths of multiple recommendation strategies to improve the quality of the recommendations provided to users (Song, 2012). The hybrid approach's primary goal is to increase recommendation accuracy by combining content-based and collaborative filtering. Several strategies can be used to implement hybrid approaches (Sridevi, 2019):

1. Use content-based and collaborative methodologies on an individual basis, then compile their predictions. 2. Incorporate certain content-based features into a cooperative strategy, 3. Incorporate some collaborative features into a content-based methodology. 4. Develop an all-encompassing consolidative model that uses a different approach.

2. Literature Review

Crafting high-quality recommendations is challenging due to the diversity of destinations and the cultural differences between users that shape how they experience and evaluate places. Some studies have found that incorporating multiple criteria, like affordability, safety, and availability of activities, into recommendation systems can improve their effectiveness. (Alrasheed, Alzeer, Alhowimel, Alshameri, & Althyabi, 2020) proposes a multi-level recommender system framework that first provides a list of destinations liked by similar users, and then ranks them based on the user's inputs. Similarly, (Ojha & Mishra, 2018) use multi-criteria decision-making to recommend destinations aligned with tourists' preferences. Culture is another key factor that influences how people experience destinations. (Hong & Jung, 2021) developed tensor models that consider both multiple criteria and cultural groups, finding that these improve recommendation accuracy, especially when distinguishing between Western and Eastern cultures. Scholars have emphasized the importance of balancing customization and generalization to keep recommendations relevant while recognizing cultural and individual diversity in travel expectations. There is a consensus that personalization of services and products should strike a balance between customization tailored to individual needs and generalization that remains universally applicable (Not & Petrelli, 2014; Musterd & Kovacs, 2013; Thomann, 2018).

Customization allows for relevance but risks becoming overly niche, while generalization promotes inclusiveness at the cost of precision. In the context of travel and transportation, customization is key to providing recommendations and itineraries that match travelers' diverse interests, styles, and constraints (Erbil & Wörndl, 2022; Mohan, Klenk, & Bellotti, 2019; Mahdi, Soui, & Abed, 2014). Furthermore, the growth of user-generated information on websites like social media has created opportunities for utilizing current, accurate data to improve the timeliness and quality of recommendations. Several studies have shown how this real-time data from platforms like Twitter and Facebook can be leveraged to improve the accuracy and timeliness of recommendation systems. (Narducci, Musto, Semeraro, Lops, & de Gemmis, 2013) argues that the "explosion of Big Data" from social networks offers new opportunities for personalized recommendations. Social networks offer new opportunities for personalized recommendations. The masses of data people share about their "preferences, feelings, and friendships" can help address the "cold start problem" of recommender systems by providing information to build user profiles. Creating these user profiles is one way of enabling a tourism recommendation site to generate a more personalized output.

The effectiveness of tourism recommendation systems is not only measured by their accuracy but also by user satisfaction. Research has shown that personalized travel recommendations significantly enhance travel experiences by simplifying planning and uncovering hidden gems (Sarkar et al. 2023). However, a balance is needed between providing familiar recommendations that match user preferences and serendipitous options that encourage exploration. Offering too much familiarity can trap users in a "filter bubble," while serendipity can foster long-term satisfaction but carries the risk of suggesting unsuitable options (Tintarev et al. 2010).

User-generated content (UGC), like online reviews and ratings, plays a significant role in enhancing tourism recommendation systems. UGC offers a direct and authentic way for tourists to share their experiences and for businesses to learn from customer feedback (Naab & Sehl, 2017). Analyzing these reviews helps improve the system's accuracy by incorporating the real-time preferences of users. Sentiment analysis is a method that helps uncover hidden emotions or preferences that may not be explicitly stated in the reviews. However, the inconclusive nature of some reviews and ethical concerns regarding the authenticity and bias of UGC require careful consideration (Rossetti et al. 2016).

Tourism recommendation systems offer a promising solution for modern travelers looking for personalized travel experiences. The field has made progress in overcoming challenges related to itinerary planning, cultural differences, and balancing personalization with generalization.

3. Methodology

This work implements a hybrid recommendation system that combines collaborative filtering and popularity-based recommendations using a weighted popularity score. Our method used a modified similarity score calculation combined with the weighted popularity scores for each tourist site based on its location and popularity. The general equation for similarity scores is given as follows:

$$\boldsymbol{similarity\ score} = \mathbf{cos}(\boldsymbol{\theta}) = \frac{\boldsymbol{A} \cdot \boldsymbol{B}}{|\boldsymbol{A}||\boldsymbol{B}|} = \frac{\sum_{i=1}^{n} \boldsymbol{A}_i \boldsymbol{B}_i}{\sqrt{\sum_{i=1}^{n} \boldsymbol{A}_i^2}\sqrt{\sum_{i=1}^{n} \boldsymbol{B}_i^2}} \tag{1}$$

Where AI and B_i are the ith components of vectors **A** and B, respectively. We use the adjusted cosine similarity (Xiong, 2012), (Zhang, 2022) in order to consider the difference in ratings of users. The adjusted cosine similarity offsets the drawback of the general cosine similarity by subtracting respective user's average rating from each co-rated pair. Using the adjusted cosine similarity in equation (2), the top-N locations with the highest similarity target locations are taken as neighbors, and the prediction score of tourists/users on target locations is obtained by using the prediction formula in equation (3):

$$\boldsymbol{Sim(i,j)} = \frac{\sum_{u\in U_{ij}}(r_{ui}-\bar{r}_i)(r_{uj}-\bar{r}_j)}{\sqrt{\sum_{u\in U_{ij}}(r_{ui}-\bar{r}_i)^2}\sqrt{\sum_{u\in U_{ij}}(r_{uj}-\bar{r}_j)^2}} \tag{2}$$

$$\boldsymbol{P_{ui}} = \bar{r}_i + \frac{\sum_{j\in N}\mathrm{sim}(i,j)\times(r_{uj}-\bar{r}_j)}{\sum_{j\in N}|\mathrm{sim}(i,j)|} \tag{3}$$

Where $\bar{r}_i$ and $\bar{r}_j$ are the average rating values for location i and j users, respectively. r_{uj} refers to the rating value for a location j given by all users. $\bar{r}_i$

3.1. Modified Location Similarity and Popularity Score

The problem of "long tail effect" where only well-known items are sold, and the rest of the items are not sold, well affects good and new items that are not popular. Therefore, the popularity penalty factor was implemented to solve this problem in the recommendation system. The work by (Gao, 2018) introduced a method for punishing popular items. They used the number of popular items and the proportion of total items as punishment in the similarity calculation method. In another work by (Hao, 2013), they included item popularity as a weight factor in the similarity calculation and recommendation process to improve the accuracy of user similarity calculations and the influence of unpopular items in the final item recommendation process.

Similarly, in our recommender system, location popularity is expressed as the number of user/tourist evaluations. The more times a location is evaluated, the higher its popularity will be. Popular locations are more likely to be selected and evaluated by users due to their popularity or the value they offer to users in terms of experience and two popular locations are more likely to be scored by the same user at the same time. When using traditional similarity to calculate the similarity of two popular places, the calculated similarity is greater, but this does not imply that popular places are similar to other places/tourist attractions (Zhang, 2022).

In addition, to reduce data deviation which happens when there is a large difference in numerical value in calculation, because of the large difference in popularity between locations, which can result in higher values in subsequent calculations of the attribute weight function. The result is normalized, as shown in equation (4), to keep the results in the range [0,1].

$$\boldsymbol{Pop(i)} = \frac{\boldsymbol{poplocation(i) - popmin}}{\boldsymbol{popmax - popmin}}, \tag{4}$$

Where, *poplocation (i)* refers to the number of times that *location i* has been evaluated, *popmax* refers to the number of times that the most popular location has been evaluated, and *popmin* refers to the number of times that the least popular location has been evaluated.

The addition of popularity penalty weight improves the algorithm's ability to mine unpopular locations. The algorithm also incorporates a time factor to address dynamic interest changes as done in (Yi, 2005), (Zhang, 2022). By incorporating this time factor, the algorithm improves the validity and effectiveness of each score. Based on the above analysis, combined with the popularity of the location and the differences in popularity, the following popularity penalty weight function is proposed:

$$\boldsymbol{p\_weight(i,j)} = \frac{\mu 2\times \boldsymbol{Pop_i}}{\mu\left(2+\boldsymbol{Pop\_diff_{i,j}}\right)}, \tag{5}$$

Where, Pop_i is the normalized popularity of *location i,* and *Pop_diff (i, j)* is the difference in popularity between *location i* and *location j*. A parameter $\mu 2$ is introduced to reduce the numerical influence of the prevalence difference between two locations which can affect the penalty weight values. Combining the popularity penalty weight function with the adjusted similarity calculation method (Xiong, 2012), (Zhang, 2022), the modified location similarity and popularity score equation is as follows:

$$\boldsymbol{Mod\_Sim(i,j)} = \frac{\sum_{u\in U_{ij}}[(r_{ui}-\bar{r}_i)\,p\_\mathrm{weight}(i)][(r_{uj}-\bar{r}_j)\,p\_\mathrm{weight}(j)]}{\sqrt{\sum_{u\in U_i}[(r_{ui}-\bar{r}_i)\,p\_\mathrm{weight}(i)]^2}\sqrt{\sum_{u\in U_j}[(r_{uj}-\bar{r}_j)\,p\_\mathrm{weight}(j)]^2}} \quad (6)$$

3.2. Steps for proposed method

1. The dataset is processed to combine relevant information and select key columns for analysis. Text data is transformed into numerical features using TF-IDF vectorization, and cosine similarity is calculated between these vectors to measure content-based similarity between spots.
2. In this phase, a recommendation function is defined to generate personalized tourist spot recommendations using our hybrid system. The function selects a random sample spot from the chosen category, calculates its weighted modified similarity to other spots, and identifies the most similar places within the same region. This function forms the core of the recommendation engine. Figure 1 shows an illustration of the pipeline of our proposed system.

3.3. Algorithm

Algorithm 1 Setting Up the recommender system.

Require: Start
    Import necessary libraries.
    Set up the Flask application.
    Preparing the dataset.
    Define the recommend by content-based filtering function.
    Define the coordinate-plotter function.
    Define the make Recommender function.
    Define the Flask
Stop

Algorithm 2 Recommending a tourist spot
Require: Start
Ensure: Select Region, select Category, select Number of locations
If region! == ' ' && Category! == ' ' && Number of location >= 1 **then**
    samples a data sample from the specified category using pandas
    retrieves the index of the data sample in the Data Frame
    finds modified weighted similarity scores (Equation 6) between [data sample] and all other tourist spots using the 'similarity' array.
    Sort and Select Similar Locations
    Iterate and Collect Recommendations.
If recommendations matches' specified region **then**
    Append it to the recommended-tourist-site
else
    Skip to next list
end if
    Control Number of Recommendations
If the length of recommended-tourist-site >= number of location **then**
        break
end if
    Output recommended-tourist-site list with the type of tourism and the description.
    Plot The recommended-tourist-site list coordinate on the map
else
    Send user to step 1.
end if

stop

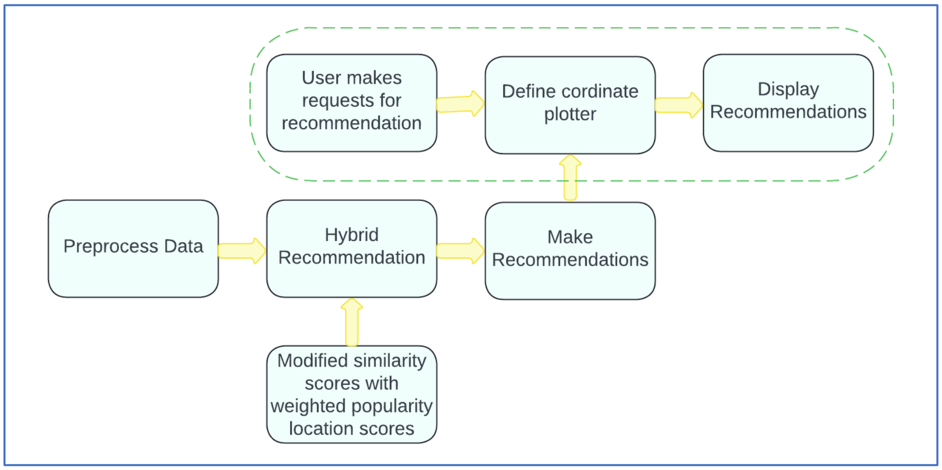

Figure 1. Workflow of the Recommendation System

4. Experiment and Results

Data for this work was obtained from a publicly available dataset that includes thorough data about various tourist sites. Essential features such as place names, categories, regions, descriptions, coordinates, and ratings have been carefully selected for inclusion in this collection. Preprocessing steps include concatenating category and description information into a single ”Tags” column providing the data with semantically significant textual elements for later analysis.

	A	B	C	D	E	F	G	H
1	Place_Id	Place_Name	Description_en	Category	Region	Lat	Long	Rating
2	1	Tagbo Falls	Tagbo Falls is a capti	Eco tourism	Oti Region	7.141965646	0.333406899	1.5
3	2	Digya National Park	Digya National Park i	Eco tourism	Eastern Region	7.524826732	-0.224519844	3.4
4	3	Kete-Krachi Slave Market	The Kete-Krachi Slav	Heritage	Oti Region	7.797158202	-0.048465319	1.9
5	4	Tafi Atome Monkey Sanctuary	The Tafi Atome Mon	Heritage	Volta Region	6.908173881	0.386766714	3.6
6	5	Hanging Village (Shiare village)	Shiare is a village mo	Culture	Oti Region	8.29204495	0.60959339	4
7	6	Larabanga Mosque	The Larabanga Mosq	Heritage	Savannah Region	9.220573638	-1.860049543	4
8	7	Gambaga Escarpment	The Gambaga Escarp	Adventure	Northern East Region	10.51609965	-0.450003512	4.2
9	8	Nayiri Palace	The Nayiri Palace is t	Heritage	Northern East Region	10.52747545	-0.369574183	3.9
10	9	Nakpanduri Mosque	The Nakpanduri Mos	Heritage	Northern East Region	10.63448042	-0.175750885	4
11	10	Bui National Park and Bui Dam	Bui National Park is a	Eco tourism	Brong Ahafo Region	8.394334973	-2.382309283	4.1

Figure 2. Sample Dataset

The evaluation centered around appraising the systems using two specific criteria: the speed of execution and user satisfaction. The main goal of this study was to determine which of the two recommendation systems exhibited superior performance in terms of efficiency.

4.1. Execution Time:

In the first experiment, a comparative experiment that was performed on the travel recommendation system and the movie recommendation system (Rajarajeswari, 2018). The experiment was centered around the system's speed of execution. This was done to find out which of the two uses the least amount of time in execution.

The results depicted in Table 1 and Figure 3 was obtained through algorithmic testing using simulated data. The variables portrayed in the graph correspond to the number of outputs plotted against time in seconds. Within the scope of the two scrutinized recommendation systems, the tourism recommendation system exhibits its lengthiest execution time at 0.022 seconds, observed during the generation of thirty outputs. Impressively, this time is 0.023 seconds faster than the highest recorded time of the movie recommendation system, which recorded 0.045 seconds for producing one hundred outputs. After a thorough examination of the graph, it becomes evident that the execution time for the movie recommendation system consistently ascends with each subsequent rise in the output. Regarding the travel recommendation system, the average execution time is 0.0193 seconds, representing an enhancement of 0.0101 seconds over the movie recommendation system, which reports an average time of 0.0294 seconds.

Table 1. Dataset against Execution Time of Tourism and Movie Recommendation System

Dataset	Execution time for tourism recommendation system(seconds)	Execution time for movie recommendation system(seconds)
10	0.0150	0.0100
20	0.0190	0.0150
30	0.0220	0.0210
40	0.0210	0.0250
50	0.0190	0.0290
60	0.0190	0.0330
70	0.0200	0.0350
80	0.0200	0.0390
90	0.0200	0.0420
100	0.0180	0.0450

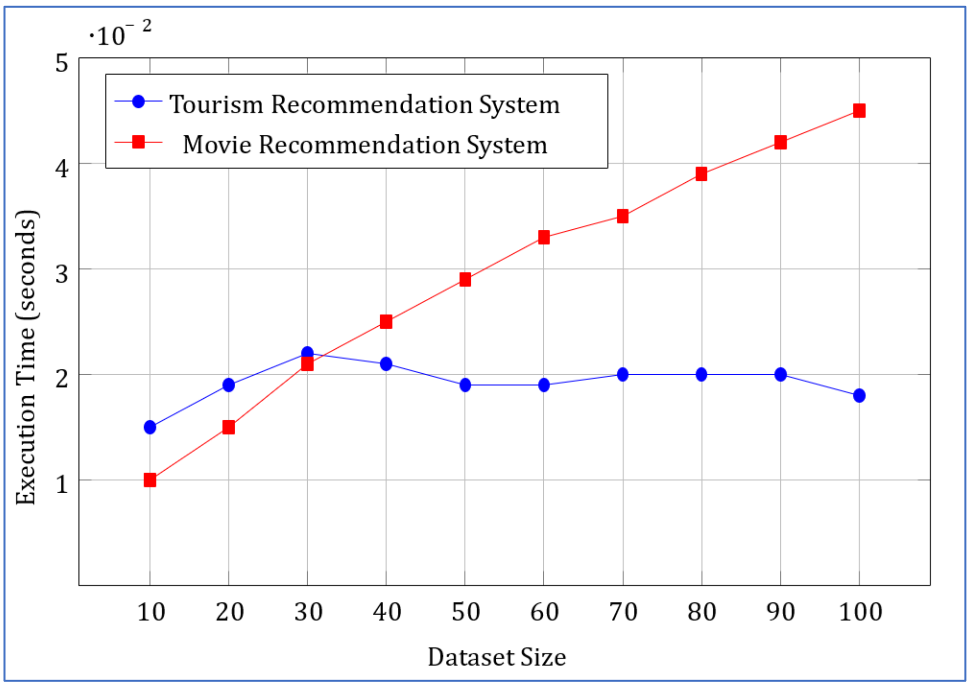

Figure 3. Comparison of the Execution Time of the Movie Recommendation System and our Tourism Recommendation System

4.2. Program Developers System Testing

The second experiment, focuses on the results obtained from the survey, after software developers and final year computer science students, performed various tests on the recommender system to ensure functionality, quality and reliability before approval and hosting of the application. A thorough examination of the insights is provided below.

The participants (software developers and final year computer science students) for the survey were chosen using clustered random sampling. The survey was left open for a week and a total of sixty-seven (67) participants were obtained, all of whom engaged with both the tourism recommendation system and the movie recommendation system (Rajarajeswari, 2018).

Figure 4 offers insights into the functional and user interface testing of the tourism recommendation system among the participants, utilizing a scale from 1 to 5, where 1 represents very difficult and 5 indicates very easy. A significant number of participants opted for the rating of 5, signifying a notable degree of user-friendliness in their interactions.

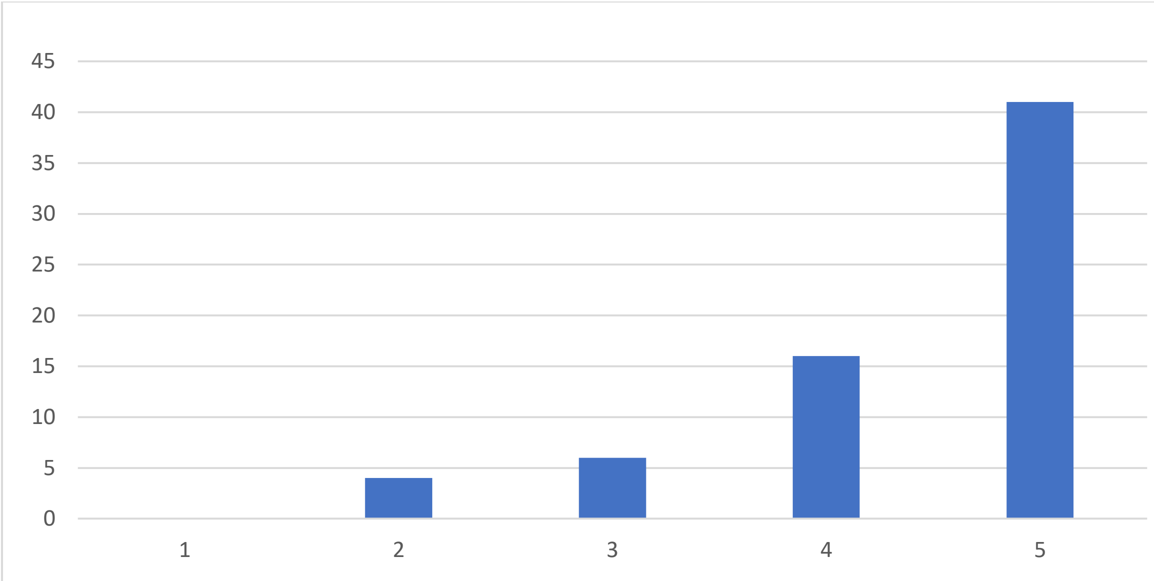

Figure 4. Functional and User Interface Testing

Figure 5 imparts insights into the level of performance testing of the recommender system by the participants. Employing a scale where 1 symbolizes low performance level and 5 signifies a higher performance level, the data underscores that a noteworthy proportion of participants favoured a rating of 4. This underscores a perception of moderate performance level in the results, although not reaching the status of complete precision. Furthermore, a segment of participants chose a rating of 2, signifying a moderate performance level.

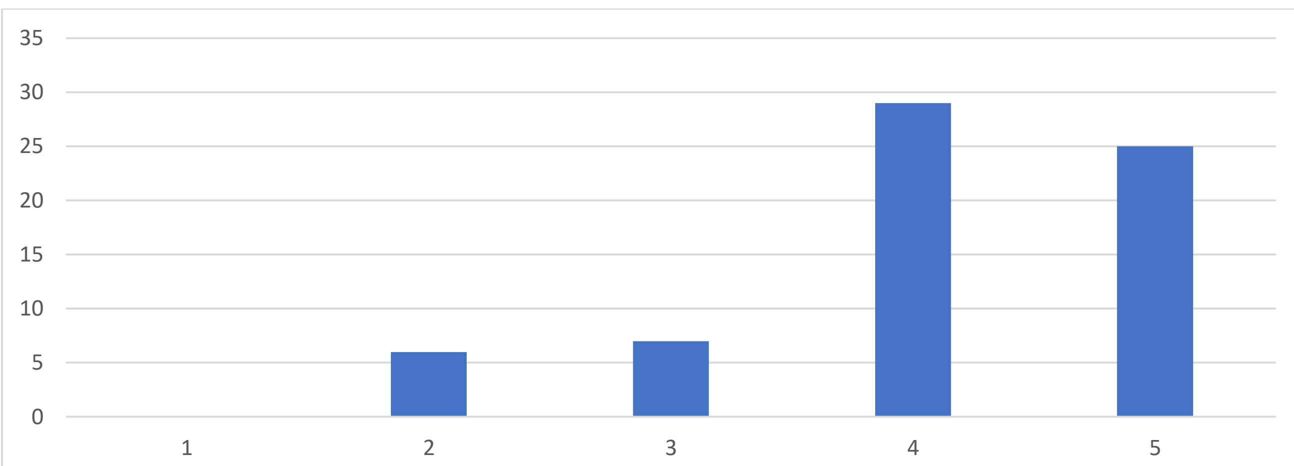

Figure 5. Performance Level of the Recommender System

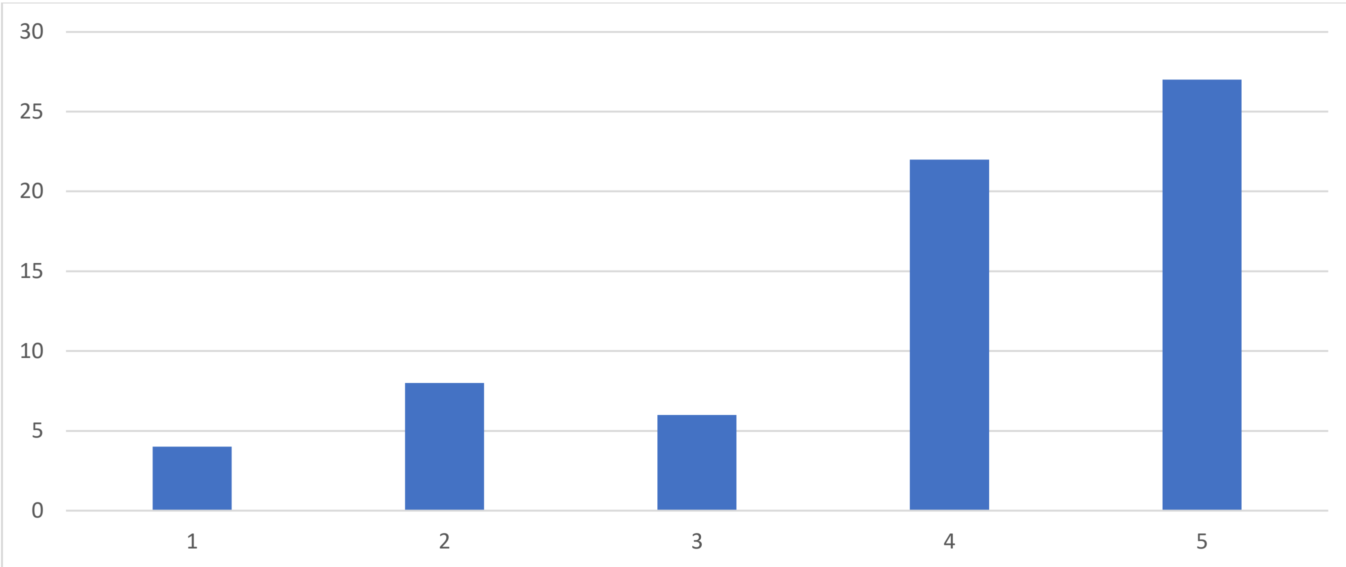

Figure 6. Relevance of the Recommender System ?

Figure 6 provides insights into participants' perceptions of the relevance of outcomes produced by the tourism recommendation system. Participants tested the system taking into consideration some importance of the application such personalization of contents and services, less of user engagements to align with user interests, to help users discover new contents and services, building trust in the platform, addressing diverse needs of users, generating revenue for management and reducing user frustrations. Employing a scale where 1 represents 'no, completely irrelevant,' and 5 denotes 'yes, very relevant,' the data discloses that most participants perceived the results of the tourism recommendation system as markedly relevant. Interestingly, an equivalent number of participants expressed a neutral perspective or slight sense of irrelevance toward the outcomes.

Figure 7 provides insights into the overall satisfaction levels of participants regarding the recommendation system, in terms of system testing and user acceptance testing (UAT), where they conducted tests to ensure the system meets their expectations. The participants also performed a system compatibility test including to confirm it worked across different browsers, operating systems, platforms and interactions with external systems and API. Employing a scale where 1 represents 'low -level acceptability,' and 5 signifies 'high-level acceptability'. The graph depicted in Figure 5 demonstrates that most participants conveyed a strong sense of satisfaction with the tourism recommendation system, while the least common sentiment was neutrality.

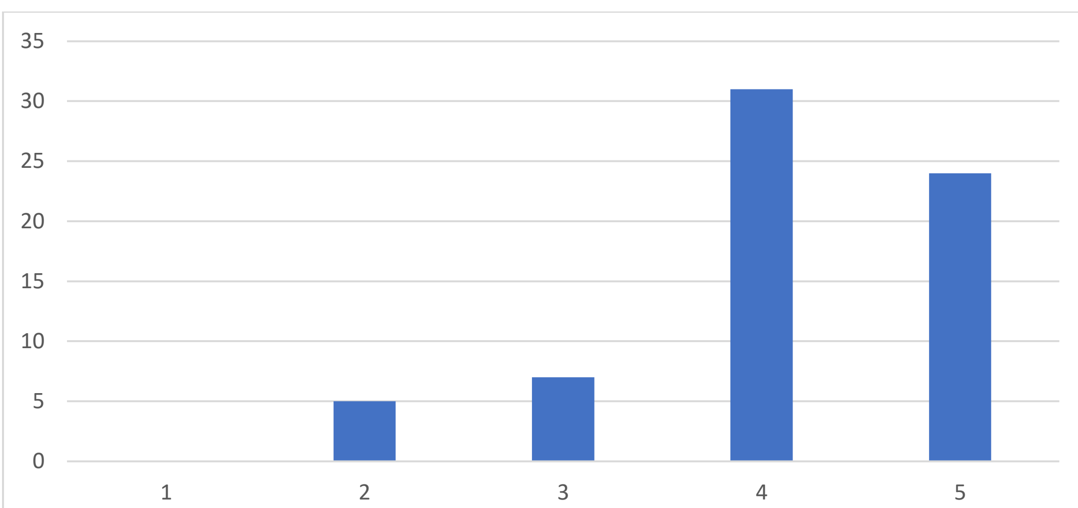

Figure 7. System and Compatibility Testing and User Acceptance Testing (UAT)

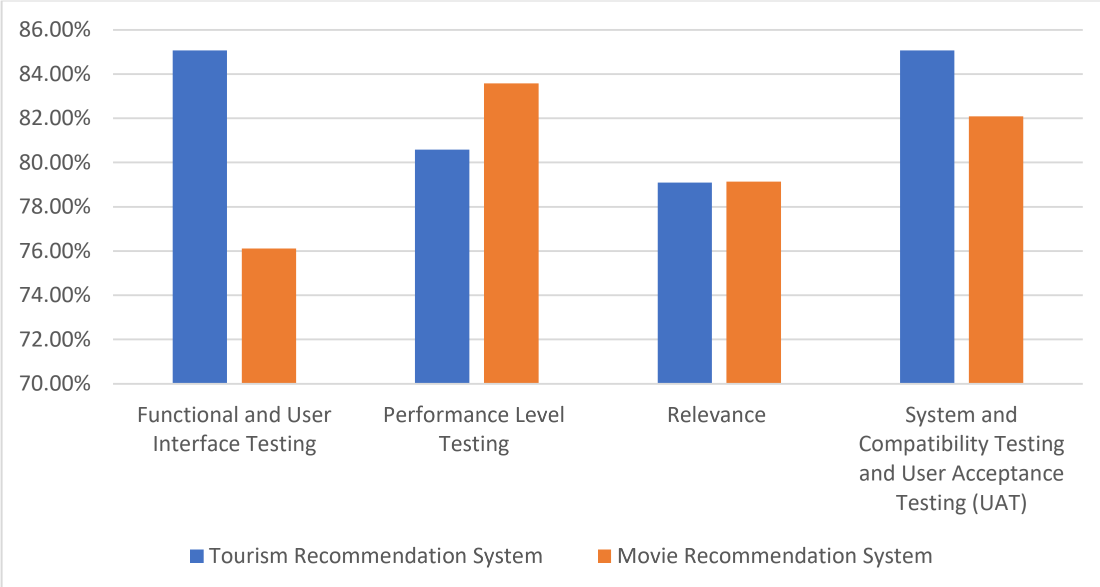

Figure 8. Comparison of the Systems

Shown in Figure 8, the tourism recommendation system exhibits a greater number of positive responses across almost all but one subcategory when compared to the movie recommendation system (Rajarajeswari, 2018).

In summary, it can be inferred that the tourism recommendation system performs better than the movie recommendation system in terms of system performance, compatibility and user acceptance.

To determine the superior system according to participants, a table was generated using the positive responses from participants, specifically responses rated 4 and 5 on a scale of 1 to 5. The table is provided below

Table 2. Comparison of the percentage of positive responses

	Tourism Recommendation System	**Movie Recommendation System**
Functional and User Interface Testing	85.07%	76.12%
Performance Level Testing	80.59%	83.58%
Relevance	79.10%	79.14%
System and Compatibility Testing and User Acceptance Testing (UAT)	85.07%	82.09%

5. Conclusion and Recommendation

This work presented a hybrid tourist site recommendation system that effectively integrates collaborative filtering with popularity-based metrics. The system offers personalized and relevant location recommendations tailored specifically to tourist visiting Ghana. The hybrid approach demonstrated the potential to enhance the user experience by delivering recommendations that resonate with individual tastes and popularity. It is effective in interpreting user input and providing relevant suggestions. The system has been rigorously tested and successfully meets its goal of offering easy access to tourist information in Ghana.

Future work could involve the integration of sentiment analysis and social network data to refine recommendations further, expanding the dataset to include a broader range of respondents and actual tourists, exploring real-time recommendation adjustments based on user feedback and behaviour.

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