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Digital Transformation in the Tourism Industry: A Smart Tourism Recommendation System Powered by 5G Technology

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Abstract

The rapid evolution of digital technologies, particularly the adoption of 5G, has brought transformative changes across various sectors, including tourism. This paper investigates the role of 5G technology in the creation of a smart tourism recommendation system. The system is designed to enhance the travel experience by offering personalized, real-time recommendations based on tourists' preferences, locations, and contextual information. By leveraging the high-speed connectivity of 5G, the system can provide instant suggestions, thereby optimizing the efficiency and accuracy of the travel planning process. The study highlights the advantages of 5G in tourism, such as improving real-time data processing, enabling enhanced communication, and fostering better customer engagement. Additionally, the paper delves into the system's architecture, emphasizing the significance of machine learning algorithms and big data analytics in refining recommendations. The results indicate that the integration of 5G with smart tourism systems can substantially transform the industry, offering seamless and highly customized experiences for travelers, and driving the expansion of the digital tourism ecosystem.

Keywords: Digital transformation, tourism sector, smart tourism, recommendation systems, 5G technology, personalized travel, real-time analytics

1. Introduction

With the rise of mass tourism and the rapid growth of information technologies such as cloud computing, the Internet of Things (IoT), and 5G communication networks, the development of smart tourism, enhanced scenic spot management, and the ability to meet tourists' individual needs have sparked a major revolution in the tourism sector. This transformation is also improving the operational efficiency of tourism management authorities. In recent years, China's tourism industry has seen significant growth, and the construction of tourism informatization has accelerated. However, the rapid expansion of big data has brought forth various challenges, such as high maintenance costs, inadequate service quality, and limited extraction of relevant information. The advent of big data offers both challenges and opportunities, urging the tourism industry to leverage massive amounts of data more effectively. The efficient mining of tourism data and providing accurate, high-quality tourism information services to visitors have become key research directions in the field of tourism big data. Given the macroeconomic environment of the tourism sector, the opportunities and challenges posed by digitalization, and the shifting needs of customers, many tourism companies have adopted digital transformation as the central focus of their strategic plans. This transformation is not just limited to the modernization of business systems but extends to the digital transformation of operations. The digital economy is rapidly emerging as a key driving force for business growth, prompting more companies to embrace digital strategies. Despite the growing demand for tourism services, current information-based solutions often fall short of providing an optimal experience for tourists. To address these issues, it is essential to integrate advanced platforms and data mining algorithms for improved management and service delivery. The leisure, travel, tourism, and hospitality industries have long been major contributors to the global economy and workforce. The hospitality industry, in particular, is starting to feel the effects of digital transformation. For instance, research by Buyukzkan et al. analyzed the service quality in the digital hospitality industry and proposed a new service model for the digital hotel sector. Meanwhile, Nikitenko focused on the distribution of new communication trends in tourism, emphasizing the role of information technology and the digital tourism economy as driving forces for promoting tourism products globally. Tourism also plays a pivotal role in national economic development, as observed by Marynyak and Stetsko, who highlighted the lack of standardized methods for collecting data on tourism outcomes in Ukraine, making it difficult to assess the tourism sector's true state. Digital transformation impacts socio-economic relations across all sectors, and Stryzhak et al. examined the relationship between human capital in tourism and the level of economic digitization. Using data normalization, cluster analysis, and SWOT analysis, they assessed indicators from different countries. Digital well-being has become an important topic for businesses, consumers, governments, and technology providers alike. Stankov and Gretzer developed new policies and services in tourism based on the role of digital well-being and its adoption in the tourism sector. In the competitive tourism market, businesses are increasingly using digital tools to create memorable experiences. Baranova A. emphasized the importance of combining digital technologies with tourism infrastructure to create lasting positive impressions on tourists. Tourist itinerary planning is crucial for enhancing tourist satisfaction and well-being. Du et al. introduced a novel approach to tourism path mining that considers both the thematic focus of tourist sites and their distinctive characteristics. Their method effectively extracted relevant travel information from vast amounts of tourist data. Wei et al. explored the use of genetic algorithms and big data technologies to mine large-scale tourism data and proposed a comprehensive design for an industrial information service platform based on tourism big data. Nilashi et al. introduced a new recommendation system based on multi-criteria collaborative filtering, which employs clustering, dimensionality reduction, and predictive techniques to improve recommendation accuracy in tourism. As the tourism industry evolves in the era of big data, the integration of IoT and digital technologies has become essential for the development, transformation, and upgrading of the tourism sector. Wu explored smart tourism and the IoT framework, discussing existing challenges and strategies for improving the information service function within smart tourism. Joeng and Kim analyzed the importance of IT services throughout the tourism life cycle and proposed strategies to enhance smart tourism services. Due to the growing amount of online resources, tourists now face the challenge of information overload when planning their trips. This study focuses on the development of personalized recommendation systems for intelligent travel, with performance testing based on user interactions. The testing involved adding 10 users at each stage, with 30-second intervals between each stage, reaching a maximum of 200 concurrent users. At 100 users, the server processing time was 34.45 ms, with a throughput rate of 75.23 requests per second and the shortest user wait time of 45.39 ms. When testing the recommendation module, the number of requests increased from 10 to 200, with the system achieving a maximum throughput of 500 requests per second, stabilizing at 421 requests per second. The average transaction response time was 236.15 ms, with a peak of 7.5 seconds, though this occurred infrequently. In security testing, the minimum processing time was 10 seconds for 10 users, increasing to 85 seconds for 200 users, meeting most user demands. The novelty of this study lies in its exploration of collaborative filtering algorithms and the improvement of recommendation systems to create a personalized smart tourism experience.

2. Digital Transformation of the Tourism Industry and Smart Tourism Recommendation Algorithm

2.1. Digital Transformation of the Tourism Industry

The tourism market has undergone significant changes with the onset of the digital era, creating both substantial opportunities and challenges for tourism businesses. As a result, many tourism companies are embracing digital transformation to stay relevant in the evolving market. The digital transformation of traditional travel agencies is an inevitable consequence of societal progress. The digital evolution of China's economy, driven by advancements in network infrastructure and informatization, has led to an accelerated transformation across industries, including tourism. This transformation is further supported by national policies and the broader industry environment. The tourism sector, as a major part of the service industry's digital economy, has seen rapid digitalization and is now the leading sector in terms of digital value addition. Tourism businesses are focusing on innovation and the integration of big data and networking technologies into their operations to improve customer services. By leveraging technologies such as big data and cloud computing, tourism companies can adopt digital marketing strategies and provide value-added services to customers. However, to remain competitive in an ever-changing market, businesses in the tourism industry must continuously adjust, transform, and upgrade to sustain healthy growth and adapt to industry shifts.

2.2. Ecosystem of the Smart Tourism Platform

To improve the integration and data-sharing capabilities across the various modules of a smart tourism platform, this study proposes the design of a smart tourism ecosystem. The platform should integrate key components such as a cloud system with secure data storage and powerful computing capabilities, and portable terminal devices suited for travel service management. The synergy between these elements is essential for creating a comprehensive smart tourism application. The core features of this platform include competence centers, IoT platforms, monitoring platforms, network data centers, and user terminals, all working in tandem to provide enhanced decision-making, knowledge sharing, and convenience to users. The platform provides tourists with a variety of services, including information dissemination, social interactions, intelligent tour guides, route planning, personalized recommendations, ticketing, and call center support. It also supports comprehensive management of tourist attractions, including security, data mining, visitor flow management, vehicle and parking lot coordination, advertising statistics, and tourism e-commerce services. This integration of user-facing applications with scenic spot management and related departments improves the sharing of resources and services, streamlining the entire tourism experience.

2.3. Collaborative Filtering Algorithm and Its Improvement Methods

The development of a smart tourism recommendation system relies heavily on the use of recommendation algorithms. These algorithms are designed to cater to the personalized needs of users and offer accurate suggestions. Understanding these algorithms is essential to developing effective recommendation systems. Figure 2 illustrates the relationship between users and product recommendations, showing the primary recommendation approaches: content-based recommendation, association rule-based recommendation, knowledge-based recommendation, collaborative filtering, and hybrid recommendation systems.

2.3.1. Content-Based Recommendation

Content-based recommendation systems suggest items based on the content's attributes, using the user's history to identify relevant items. The system calculates the similarity between items and recommends those that align with the user's preferences. A typical method used in content-based recommendation is the term frequency-inverse document frequency (TF-IDF) algorithm, which measures the importance of an item’s attributes by evaluating their frequency across different items.

$$\mathrm{TF}-\mathrm{IDF}(t_k, d_k) = \mathrm{TF}(t_k, d_j) * \log\frac{N}{n_k}.$$

The key advantage of content-based recommendation is its high accuracy and interpretability. However, it has limitations, including the reliance on a limited set of item attributes, which makes it difficult to gather comprehensive data. When multiple attributes are used for recommendations, the system’s processing speed tends to decrease significantly. Additionally, this algorithm suffers from the "cold start" problem, where new users with limited historical data may not receive relevant recommendations.

$$w_{k,j} = \frac{\mathrm{TF}(t_k, d_j)}{\sqrt{\sum_{s=1}^{|T|} \mathrm{TF}-\mathrm{IDF}(t_s, d_j)^2}}.$$

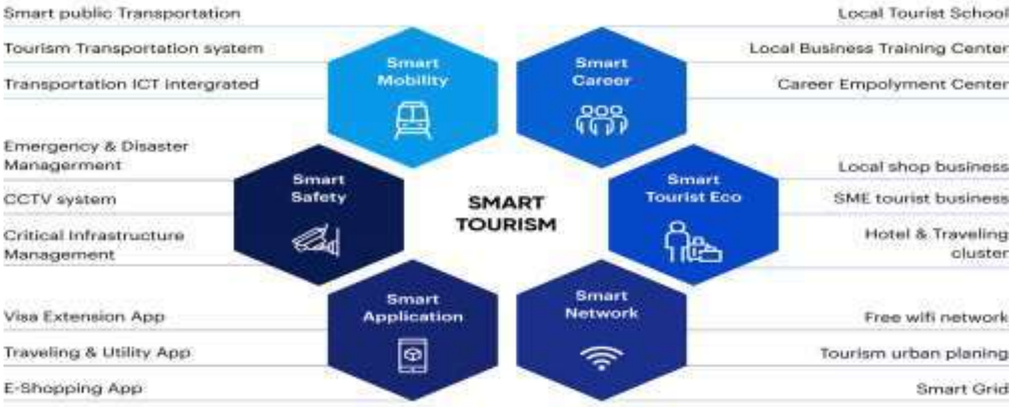

Figure 1: Smart tourism platform ecosystem.

Figure 2: User and product recommendation relationship.

2.3.2. Association Rule-Based Recommendation

Association rule-based recommendation suggests items based on the correlation between items purchased by users. These correlations, derived from a large user database, form the basis of the algorithm's recommendation rules. The formula used to represent the relationships between users is: The similarity between user groups is then calculated using association rule metrics. One advantage of association rule-based algorithms is that they can uncover new areas of interest for users, require minimal domain-specific knowledge, and offer highly accurate and easily interpretable recommendations. However, the method is time-consuming and labor-intensive, requiring significant effort to extract information, and its degree of personalization is often lower compared to other methods.

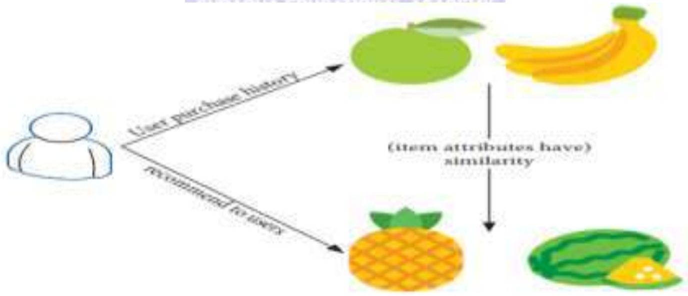

Figure 3: Schematic diagram of content recommendation mechanism

2.3.3. User-Based Collaborative Filtering

User-based collaborative filtering identifies users with similar preferences by calculating the similarity between them. It then uses the ratings of similar users to predict what a target user might like. The schematic diagram for this process is shown in Figure 4, which illustrates how user-based collaborative filtering works.

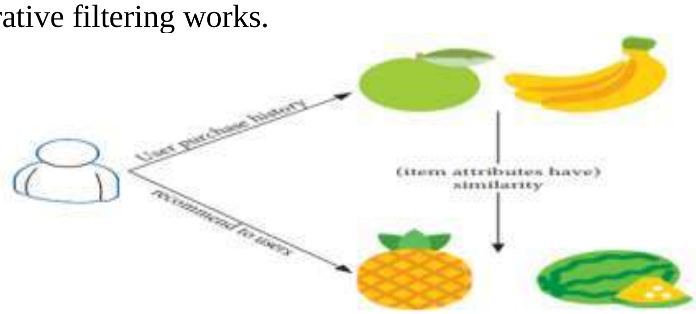

Figure 4: Schematic diagram of user based collaborative filtering recommendation mechanism

To recommend potentially interesting items to a user, for example, user3, the system first identifies the most similar user to user3 based on the similarity formula. Then, the system calculates the interest in specific items, such as item1 and item3, even if the target user, user3, has no previous purchase history for those items. The final recommendation is based on sorting and prioritizing these items according to their predicted interest values. The similarity between users is computed using the formula:

$$\operatorname{sim}(m,n)=\frac{\sum_{x\in I_{mn}}(S_{m,x}-\overline{S}_n(S_{m,x}-\overline{S}_n)}{\sqrt{\sum_{x\in I_{mn}}(S_{m,x}-\overline{S}_m)^2}\sqrt{\sum_{x\in I_{mn}}(S_{n,x}-\overline{S}_n)^2}}.$$

where I_{mn} represents the items jointly rated by users m and n, and $S_{m,x}$ is the rating given by user m for item x.

$$\operatorname{sim}(m,n)=\frac{\sum_{x\in U_{mn}}(W_{m,x}-\overline{W}_n)(W_{n,x}-\overline{W}_n)}{\sqrt{\sum_{x\in U_{mn}}(W_{m,x}-\overline{W}_m)^2}\sqrt{\sum_{x\in U_{mn}}(W_{n,x}-\overline{W}_n)^2}}$$

2.3.4. Item-Based Collaborative Filtering

Item-based collaborative filtering focuses on the similarity between items rather than users. It calculates similarity scores between items based on ratings by users, and then recommends items to a user based on their similarity to previously rated items. The formula for calculating item similarity is:

Here, Um n represents the items rated by both users m and n, and Wm,xWx and Wn,xW_{n,x}Wn,x are the respective ratings for those items.

2.3.5. Model-Based Collaborative Filtering

In large-scale recommendation systems, model-based collaborative filtering is often more suitable, as it can handle the sparsity of rating data effectively. Model-based approaches, such as matrix factorization and neural networks, leverage both user and item data to generate predictions. These models can be trained using association rules, classification algorithms, and neural networks to predict user preferences even when some ratings are missing.

2.3.6. Enhanced User-Based Collaborative Filtering

This study builds upon the user-based collaborative filtering algorithm, improving it to address the challenges posed by traditional methods.

2.3.7. Multilayer Perceptron for Enhanced Recommendations

Multilayer perceptrons (MLP) can be used to replace the traditional matrix factorization technique to learn interactions between user and item representations. The specific process begins by connecting the updated embedding representations of users and items, followed by inputting this into a multi-layer perceptron model. The model calculates the likelihood of a user interacting with an item, as shown in the formula:

$$\overset{0}{x}=\left[E_{u_i}^{(l)}\oplus E_{a_j}^{(l)}\right].$$

Where ⊕ represents the embedding operation, and the output of the model at each layer is updated by applying the weights and biases. Finally, the output is passed through a sigmoid activation function to give the final prediction of user-item interaction:

$$x_1=h(w_1x_0+b_1'),$$

Where $\sigma(x_l)$ is the sigmoid function that ensures the output is in the range [0, 1], indicating the probability of interaction.

2.4. Tourism Seasonal Statistics

Tourism seasonality refers to the uneven distribution of tourism demand over time. Using inbound tourism data from Xi'an as an example, the study analyzes the temporal distribution of tourism flow, the variation in the number of tourists over months, and the relationship between tourist numbers and length of stay. The seasonal intensity index is calculated using the formula:

$$R = \sqrt{\frac{\sum_{i=1}^{12} (x_i - 8.33)^2}{12}},$$

Where xix is the monthly tourist ratio, and the seasonal intensity index R indicates the degree of seasonality in tourism. A value closer to zero implies a more uniform distribution of tourism demand, while a higher R value indicates greater seasonal variation.

2.4.1. Scale of the Tourism Traffic Network

In the tourism flow network, the scale refers to the number of tourist attraction nodes and the possible relationships between them. For a directed network graph, the number of possible relationships is given by:

$k \times (k-1)k$

For an undirected network graph, the number of possible relationships is:

$k \times (k-1)^2$

Where k represents the number of tourist nodes.

2.4.2. Tourism Network Density

The density of the tourism network is calculated by comparing the actual number of connections to the theoretical maximum number of connections, which gives a sense of how tightly connected the attractions are. The formula for tourism network density is:

$$D = \left(\frac{2 \sum_{i=1}^{k} d_i (n_i)}{(k * (k - t1))}, \right.$$

$$d_i(n_i) = \sum_{j=1}^{k} d_i(n_i, n_j),$$

where d_i and n_i represent the connection values between nodes.

3. Construction and Testing of the Recommendation System for Smart Tourism Services

3.1 Framework Design of the Tourism Service Recommendation System in a Cloud Computing Environment

The tourism service recommendation system is implemented on the Hadoop platform, which addresses both the storage challenges of large tourism data and the complex computational problems. Cloud services combine distributed computing, utility computing, load balancing, parallel computing, network storage, hot backup redundancy, and virtualization technologies. The system follows a BS architecture design. The main task of the system is to implement the recommendation algorithm on the cloud computing platform, focusing on four main components: data collection, data analysis, parallelization of the recommendation algorithm, and service recommendation implementation.

3.1.1 Service Recommendation Module

This module consists of a data mining engine centered around the M_CF algorithm. In addition to the offline algorithm, the online recommendation service follows the classic MVC development model, presenting the results to users through a browser.

3.1.2 Recommendation Service Modeling

The recommendation service is divided into two components: offline and online. The offline component generates association rules, while the online component provides the recommendations. In the offline part, the system must preprocess data and convert it into transaction data suitable for the M_CF algorithm. The steps for completing this include setting minimum support, generating frequent item sets, filtering the item sets by minimum confidence, and generating association rules. The system uses two parameters—support and confidence—for association rule mining. Support is determined based on total transaction volume and should be set carefully to avoid too many or too few results. Confidence can be calculated directly, with the top N results (based on confidence) being used to generate final association rules. The online component follows the classic MVC development mode with a three-tier architecture: view layer (presentation layer), business logic layer, and storage layer. These layers interact based on the principle of "high cohesion, low coupling." The online component provides users with popular and personalized travel service recommendations based on their usage patterns.

3.1.3 Service Recommendation Process

The system follows a BS architecture where users access resources through browsers. To obtain recommendation information, users must log in and browse resources. Association rules, browsing records, and user interests are matched, and if relevant results are found, they are returned to the user.

3.1.4 Recommendation Center

The recommendation center is the core of the smart tourism recommendation system. It calculates actual data in the system and uses test cases combined with system database analysis to complete the functional testing. The dataset used contains 5000 ratings from 443 users for 1082 hotels and attractions, along with user tagging information. Test results show that the system recommends 15-20 itineraries that meet user needs, providing specific itinerary details such as starting points. The recommendations pass the tests, and the system's accuracy is verified.

3.2 System Performance Test

Performance testing is essential for evaluating the system's ability to handle high concurrency. The system was stress-tested using a simulation tool with configurable parameters such as the number of test users and new users. The login page was used for performance testing, where the number of concurrent users was varied from 100 to 600. The results indicated that the system performed well under these conditions, with server processing time fluctuating as concurrency increased but stabilizing after reaching a peak.

Table 1: System Dataset Information Record Table

User	User Weight	Banner	Number of Hotels	Number of Attractions
1	2	1	209	508
2	8	1	233	120
3	8	1	398	632
4	8	0	178	453
5	3	0	503	330
6	3	0	45	95
7	5	0	83	66
8	6	0	76	41

Table 2: Trip Module Test Information Schedule

User	Priority	Line Details	Recommended Number of Trips	Is it Accurate
User a	One	Go through	15	Yes
User b	Second	Go through	20	Yes
User c	C	Go through	20	Yes
User d	D	Go through	20	Yes

Table 3: Test Results Under Different Concurrency

Concurrency	Average Server Processing Time (ms)	Throughput (requests/sec)	User Wait Time (ms)
100	34.45	75.23	45.39
200	45.34	74.28	99.83
300	44.81	76.59	205.78
400	43.33	78.52	3049.82
500	50.48	76.65	8946.23
600	48.21	77.23	10668.79

3.2.1 Recommendation Module Performance

The system's performance was tested with both the traditional algorithm and the M_CF algorithm. Results showed that the M_CF algorithm recommended more items at each time point compared to the traditional algorithm, especially for new users. Over time, the gap in recommendations between old and new users decreased, demonstrating the improved algorithm's stability and efficiency.

Stress Test Results

During stress tests, the system handled varying numbers of concurrent users effectively. The tests indicated that the system could maintain a high throughput (maximum 500 requests per second) and responded within acceptable times even under peak loads. The system was deemed stable, meeting all performance expectations. The system's response times, particularly for the recommendation center, were also tested under different user numbers and concurrency levels. The results showed that the system could efficiently manage up to 200 users, maintaining stable performance under high throughput conditions. Overall, the recommendation system demonstrated high stability and met performance requirements.

3.2.2. Security Module

The unique landform contributes to safety concerns and delays in addressing security issues. To address these challenges, a security module has been designed. After completing the functional testing of the module, a performance test is conducted. The single-mode performance test of the security module is carried out by controlling the pressure measurement and configuring the relevant parameters. Using the network column in Google Chrome Developer Tools, the response time of each process can be monitored, with browser developer tools utilized for debugging and testing. The stress test has been completed, evaluating the positioning and reflection time, alarm time, and transaction processing time of the security module under varying user loads. As shown in Table 5, as the number of users increases, the positioning time of the security module also rises but stabilizes over time. The one-key alarm time remains constant at a stable value. When there are 10 users, the security event processing time is at its minimum of 10 seconds. As the user count reaches 200, the processing time increases to its maximum of 85 seconds, which still meets the system's requirements. In conclusion, the security module effectively satisfies the system's performance specifications.

Table 4: Recommended Module Information Collation

User ID	Concurrency	Database Level	Response Time (seconds)
50	2	1000	0.6
200	2	5000	1.3
50	2	5000	0.9
200	2	1000	0.9
50	5	1000	0.8
200	5	1000	1
50	5	5000	1.1
200	5	5000	1.5

Table 5: Security Module Information Organization

User ID	Positioning Time (s)	One-Key Alarm Time (s)	Processing Time (s)
10	0.05	1	10
50	0.1	1	The 50
100	0.1	1.5	70
200	0.1	1.5	85

4. Conclusion

Developing data mining algorithms to address big data challenges in cloud environments is a significant and meaningful task, with practical applications in various domains. This study focuses on solving real-world problems in smart tourism systems. The overall architecture and functional requirements of the smart tourism recommendation system were thoroughly analyzed. The study also delved into existing recommendation algorithms, assessing their advantages and disadvantages, which laid the groundwork for improving collaborative filtering algorithms. Based on this analysis, the collaborative filtering algorithm was enhanced to meet the system's requirements. The system's development plan, including the selection of architecture and functionality, was established. Additionally, a comprehensive test plan was designed, and the system was rigorously tested through functional and performance evaluations. The results of these tests indicate that the smart tourism recommendation system largely meets the expected objectives, performing well in terms of functionality and user satisfaction. While the data used in this study was relatively simple, future research will focus on expanding the data sources to provide a more comprehensive analysis and minimize potential biases.

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