A Comparative Analysis of Traditional and Knowledge Graph-based Personalized Travel Recommendation Systems

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Abstract— *Standard search engine results often fail to provide useful and reliable information for creating ideal travel itineraries. To address this issue, a method for generating personalized travel route recommendations using a knowledge map is introduced. This approach begins by understanding the specific desires of individual travellers. Then, it utilizes the structure and information within a tourism-focused knowledge map to design suitable routes. By merging the knowledge map with a recommendation system, the system's ability to provide relevant suggestions is improved. The validity and effectiveness of this personalized recommendation strategy are evaluated by testing it with real-world travel routes. Performance metrics, including hit rate and average reciprocal ranking, are calculated using actual tourism data. The findings demonstrate that this method effectively considers various aspects of personalized travel preferences and outperforms comparable algorithms.*

This paper addresses the challenge of providing accurate personalized travel recommendations by presenting a user-oriented system that leverages a tourism knowledge graph. The system constructs a knowledge graph from multi-source data, integrating it with user profiles to offer tailored recommendations. Compared to traditional systems, experimental results demonstrate that our system significantly improves recommendation accuracy (94.9% average) and user satisfaction (9.6 average score).

Keywords— ***Travel knowledge bases, individualized recommendations, travel path generation, group-based filtering, knowledge based graph.***

I. INTRODUCTION

The surge in internet and mobile device usage has led to a significant increase in online travel planning and booking. However, conventional travel recommendation systems often fall short by offering generic suggestions, failing to cater to individual preferences. Consequently, the need to develop personalized travel recommendations for diverse tourist profiles has become a critical challenge. Knowledge graphs (KGs), which excel at structuring and linking varied information, have gained traction in recommendation systems. Existing travel recommendation systems, relying primarily on user purchase history and ratings, struggle to discern genuine user requirements. To bridge this gap, this study proposes and implements a personalized travel recommendation system leveraging KGs. Specifically, a tourism KG is constructed to organize travel-related knowledge, which is then integrated with user-specific needs to deliver precise and customized travel information recommendations. With the increasing popularity of the Internet and mobile terminals, the number of people using the internet for travel planning and booking is also increasing. However, traditional travel recommendation systems usually only provide general recommendations to users and cannot meet their personalized needs well. The need for effective personalized travel recommendation systems is becoming increasingly critical due to the overwhelming amount of online travel information and the rising expectation of travelers for tailored experiences. Traditional systems fail to address this, leading to information overload and user dissatisfaction. This paper aims to bridge this gap by designing a personalized travel recommendation system based on KGs to address this issue.

II. METHODOLOGY

The burgeoning tourism industry, coupled with rising living standards, has significantly amplified the importance of effective travel recommendations. Traditional systems, often reliant solely on user consumption patterns and evaluations, overlook the multifaceted nature of tourist destinations and the diverse needs of travellers. This oversight creates a gap between user expectations and system outputs, demanding a more nuanced approach.

Today's tourists seek increasingly personalized and varied travel experiences, desiring tailored information and services. In response, numerous scholars have explored innovative solutions. Ngoc [1] developed a social media-driven travel recommendation system, offering customized points of interest to match individual preferences. This model demonstrated superior performance over existing personalized systems, achieving an impressive 75.23% accuracy. Yan [2] proposed a cloud-based online travel agency leveraging big data to provide personalized services, aiming to boost sales through enhanced customer engagement. Choi I Y [3] introduced a collaborative filtering and constraint satisfaction-based tourism recommendation system, assisting tourists in crafting personalized itineraries. Kumar N [4] addressed existing system limitations by implementing a tourist recommendation system, the Average Cumulative Rating system, capable of extracting ratings and experiences from textual descriptions. Chang J L [5] explored a hybrid approach to deliver personalized travel recommendations, enhancing online booking experiences. Al Fararni K [6] developed a big data, AI, and operations research-driven recommendation system to aid tourists in itinerary planning and information retrieval. Forouzandeh S [7] proposed a novel tourism recommendation system combining the artificial bee colony algorithm with fuzzy TOPSIS. While these studies have advanced tourism recommendation systems, they often exhibit limitations in algorithm optimization, data processing, technology integration, and real-world application.

Knowledge graphs (KGs), powerful semantic networks capable of representing complex entity relationships, hold significant promise for tourism product recommendations. Shi S [8] constructed a decision support system for tourist attractions, employing collaborative filtering and Bayesian networks to estimate user interest. Mezni H [9] introduced a personalized tourism recommendation system based on first-order and subgraph perceptual proximity, using an extended recursive neural network to embed context-aware KGs, demonstrating improved accuracy and scalability. Wang X [10] developed a tourism KG based on tourist user associations, utilizing KG representation learning techniques to embed entities and relationships into a low-dimensional vector space, enabling similarity calculations and personalized recommendation lists. Despite these advancements, existing KG-based systems often neglect the dynamic and temporal aspects of KGs, limiting their ability to handle complex queries.

Building upon the insights from these studies, this research proposes a personalized tourism recommendation system grounded in KGs. This system aims to integrate tourism knowledge maps with detailed user profiles, enabling the delivery of highly relevant tourism product recommendations. This article endeavours to address the existing limitations by conducting in-depth research on algorithm optimization, dynamic data processing, and seamless technology integration. Specifically, the proposed system will focus on:

- **Enhanced Knowledge Graph Dynamics:** Incorporating mechanisms to capture and reflect the evolving nature of tourism information, ensuring recommendations remain current and relevant.

- **Advanced User Profiling:** Developing more sophisticated user profiles that capture nuanced preferences, travel styles, and contextual factors, leading to more accurate recommendations.

- **Optimized Recommendation Algorithms:** Refining recommendation algorithms to better leverage the rich semantic information within KGs, improving the precision and recall of recommendations.

- **Seamless Technology Integration:** Ensuring seamless integration with various data sources and platforms, facilitating real-world deployment and user accessibility.

- **Complex Query Handling:** Improving the system's ability to handle complex and multi-faceted user queries, delivering more comprehensive and informative recommendations.

By addressing these challenges, this research aims to advance the field of personalized tourism recommendation systems based on knowledge maps, ultimately enhancing recommendation accuracy and user satisfaction. The goal is to create a system that not only understands user preferences but also comprehends the dynamic landscape of tourism, delivering truly personalized and enriching travel experiences. The system will be designed to learn and adapt to user behaviour over time, refining its recommendations to provide an increasingly tailored experience. This adaptive learning component will be crucial in maintaining the system's relevance and effectiveness in the face of evolving user preferences and tourism trends.

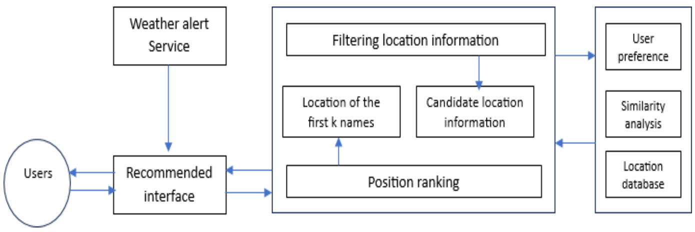

Fig.1 Personalised Tourism Recommendation System Architecture

III. METHOD

A. *System Architecture Design*

The proposed personalized travel recommendation system prioritizes the user experience, incorporating real-time weather updates through a weather alert feature. Within the recommendation interface, tailored algorithms merge refined location data to identify the top "k" potential tourist spots. Subsequently, user preferences are used to perform a similarity analysis, generating the final recommendation list. Furthermore, the system ranks the suggested locations based on search outcomes, ensuring users can quickly locate the most relevant destination details. The overarching objective of this framework is to deliver highly intelligent and customized travel recommendations, and its structural layout is depicted in Fig 1.

Here's a breakdown with slightly different phrasing:

- **User-Focused Approach:** The system places the user at the centre, aiming to provide a personalized experience.
- **Real-Time Weather Integration:** It includes a weather warning service to keep users informed about current meteorological conditions.
- **Location-Based Filtering:** The system refines geographical information to narrow down potential destinations.
- **Top "k" Destination Selection:** Personalized algorithms are used to identify the most suitable "k" tourist spots.
- **Preference-Based Similarity:** User preferences are analysed to determine the similarity between potential destinations and individual tastes.
- **Final Recommendation List:** A final list of recommended locations is generated based on similarity analysis.
- **Search-Based Ranking:** The system ranks the recommended locations based on search outcomes for easy navigation.
- **Intelligent and Personalized Service:** The framework's core aim is to provide users with intelligent and customized travel recommendations.
- **Structural Representation:** The system's architecture is visually presented in Fig 1.

B. *Knowledge graph construction and personalised recommendation process:*

Developing a tourism knowledge graph (KG) is a structured endeavour, necessitating the gathering, refining, and structuring of data from diverse sources to identify and define the elements, links, and characteristics within the travel industry. This knowledge structure can be enhanced by incorporating visual data repositories, enabling complex searches and tailored suggestions, thereby offering users a comprehensive and precise travel information experience [11] - [12].

This research presents a personalized travel recommendation system utilizing a KG to overcome the limitations found in existing travel recommendation systems. Initially, a knowledge map is constructed to better interpret the intricate connections between travellers and travel offerings. This is accomplished by extracting information from multiple sources, including user demographics, past interactions, and detailed travel package data. From this foundation, user profile models are created by analysing and learning user attributes, allowing for the numerical representation of their interests and preferences. By examining travel activities, the core attributes of these activities are expressed using mathematical representations. Travelers can then match their interests with product features, culminating in a tailored travel recommendation list. Furthermore, the system continually monitors user feedback, refining the recommendation model and its outputs, and enabling real-time updates and modifications to personalized travel packages, ensuring that users receive offerings that closely align with their preferences.

The system developed in this study comprises various elements, such as travel destinations, travel resources, and user interactions, along with their interconnected knowledge graphs. This research focuses on the travel recommendation system. By gathering data from various platforms, including travel websites and social media, and employing techniques such as natural language processing for analysis, a travel knowledge map is established. The knowledge graph, represented as G=(V, E), consists of three components (x, y, z). Here, x ∈ V, y ∈ E, and z ∈ V represent the subject entity, relationship, and object entity, respectively. V signifies the entities within the knowledge base, and E represents the relationships within the knowledge base. The corresponding mathematical representation for travel recommendations is as follows:

$$\mathrm{O}^1_{\mathrm{u_i}} = \sum_{(x_i,\ y_i,\ z_i) \in S^1_{u_i}} R_k\ t_i^* \quad (1)$$

$$u_i^* = o_{u_i}^1 + o_{u_i}^2 + \cdots \ldots + o_{u_i}^H \quad (2)$$

In the given formulas (1) and (2), the term $\mathrm{O}^1_{\mathrm{u_i}}$ signifies the propagation or spread of a user's initial interests within the first layer of the recommendation process. "$\sum_{(x_i,\ y_i,\ z_i) \in S^1_{u_i}} R_k\ t_i^*$" represents the probability that a user will be interested in a specific candidate tourism project being considered. Lastly $u_i^* = o_{u_i}^1 + o_{u_i}^2 + \cdots \ldots + o_{u_i}^H$ denotes the comprehensive set of interests that a particular user possesses.

IV. RESULT AND DISCUSSION

A. *Recommendation system accuracy*

To thoroughly assess the precision of the developed tourism recommendation system, this study conducted a series of 10 comparative experiments, pitting it against established systems. To maintain the reliability and broad applicability of the findings, each experiment utilized diverse datasets and user demographics. The system constructed in this research gathers and analyses past user interactions and preferences, constructs detailed user profiles and travel knowledge graphs (KGs), and autonomously produces customized recommendation lists using recommendation algorithms. The corresponding experimental outcomes are visually represented in Fig. 2. Here's a breakdown using different phrasing:

- **Comparative Evaluation:** The research employed 10 comparative tests to evaluate the tourism recommendation system's accuracy against existing systems.
- **Data Diversity:** To ensure reliable and generalizable results, varied datasets and user groups were incorporated into each experiment.
- **User Behaviour Analysis:** The system collects and analyses users' past actions and preferences.
- **Profile and KG Construction:** Detailed user profiles and travel KGs are created.
- **Automated Personalization:** Recommendation algorithms are used to automatically generate personalized recommendation lists.
- **Visual Representation:** The experimental results are presented graphically in Fig 2.

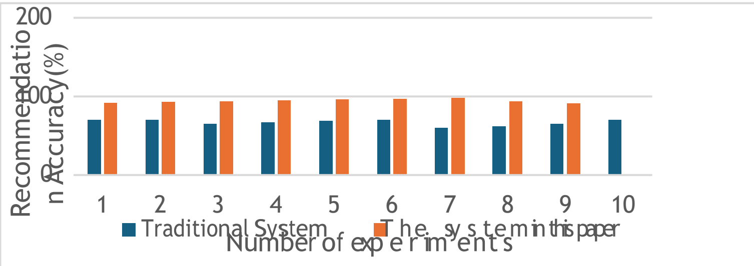

Fig 2: Comparison between Traditional and this paper

A comparative analysis of the 10 experiments depicted in Fig 2 reveals that the KG-based personalized tourism recommendation system developed in this study exhibits notable superiority in recommendation accuracy compared to conventional systems.

To begin, the overall average recommendation qqaccuracy of traditional systems stands at a mere 68.3%, whereas the system designed in this research achieves an impressive average accuracy of 94.9%. The experimental findings clearly demonstrate that the proposed system excels in accurately discerning user interests and requirements, resulting in a recommendation list that more closely aligns with user expectations. Furthermore, an examination of the individual experiment outcomes reveals that the proposed approach consistently outperforms the traditional approach in the majority of cases. Notably, in experiments 4, 6, 8, and 9, the system's recommendation accuracy reached 99.3%, 92.8%, 98.4%, and 93.6%, respectively, significantly surpassing the performance of traditional systems. The extensive experimental results provide compelling evidence of the effectiveness of this system in the context of tourism recommendations.

In summary, a comprehensive analysis of the 10 comparative experiments confirms that the KG-based personalized tourism recommendation system constructed in this study offers substantial advantages in recommendation accuracy compared to traditional systems. It demonstrates a superior ability to capture user interests and needs, thereby delivering more precise and personalized travel recommendation services.

Additionally, this study conducted comparative experiments to comprehensively evaluate the differences in response speed between the proposed system and traditional recommendation systems. The experiments demonstrate that the system developed in this research exhibits significant advantages across three key performance metrics: average response time, maximum response time, and minimum response time. The corresponding experimental results are presented in Table I.

TABLE I COMPARISON TABLE

Response time	Traditional Systems	The system in this paper
Average response time (ms)	400	200
Maximum response time (ms)	600	350
Minimum response time (ms)	300	100

B. *User Perspective*

To assess user contentment with the KG-driven personalized tourism recommendation system developed in this study, 10 participants were invited to interact with the system and provide ratings, with a maximum score of 10. These participants represented a diverse range of ages, genders, and occupations, possessing extensive travel experience and varying travel preferences. During the user experience evaluation, participants were asked to rate the accuracy, personalization, practicality, and overall user experience of the recommendations. By gathering and analysing their evaluations and feedback, a more thorough understanding of user satisfaction with the system could be obtained. This research aims to refine the system, enhance user experience, and better cater to individual user needs through this comparative experiment. The results of comparing user satisfaction between the developed system and traditional systems are illustrated in Fig 3.

Analysing the user evaluations from Figure 3, and comparing them with traditional systems, the following observations can be made: Regarding average scores, the traditional systems received a rating of 6.9, whereas the newly developed system achieved a significantly higher rating of 9.6. This substantial difference underscores a marked improvement in user satisfaction with the KG-based system compared to conventional approaches. The primary reason for this enhanced satisfaction lies in the KG system's ability to more accurately identify and cater to individual user interests and needs, leading to highly personalized recommendations.

Furthermore, a review of individual user feedback reveals that most participants rated the new system very close to the highest possible score. This reinforces the notion that the system designed in this research has garnered considerable approval and satisfaction from users. In stark contrast, the ratings for traditional tourism recommendation systems were more dispersed, with some users providing notably lower scores. This variability reflects the limitations of traditional systems in meeting the diverse and personalized requirements of contemporary travellers.

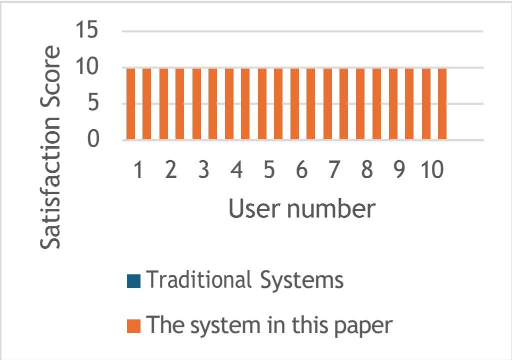

Fig 3: Comparison of traditional and user perspective

C. *Recommendation diversity*

This research assesses the variety of recommendations provided by the developed knowledge graph-based personalized tourism recommendation system compared to traditional systems through a series of comparative experiments. To achieve a comprehensive evaluation of recommendation diversity, five key dimensions were chosen: relationship type coverage, domain diversity, geographic diversity, temporal diversity, and novelty. Radar charts are used to visually represent the differences in these dimensions, providing a clear understanding of the strengths and weaknesses of the designed algorithm in terms of recommendation diversity. The experimental results comparing these two systems are presented in Fig 4.

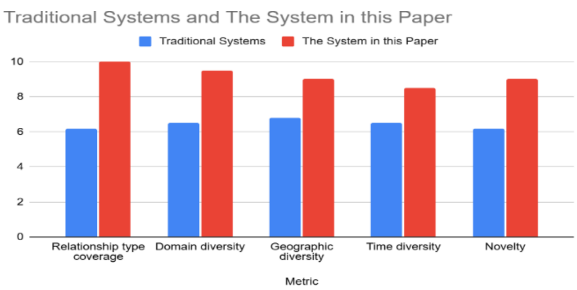

Fig 4: comparison of diversity between both

The comparative experiments demonstrate that the KG-based personalized tourism recommendation system developed in this study possesses robust recommendation capabilities. When contrasted with traditional systems, this system exhibits significant enhancements across five critical dimensions: relationship type coverage, domain diversity, geographic diversity, timeliness, and novelty. This improvement signifies that the system can offer users more comprehensive, diverse, and unique travel recommendations, thereby better fulfilling their individual preferences and enhancing their overall travel experience.

Knowledge coverage is a crucial metric for evaluating the effectiveness of tourism recommendation systems, as it directly impacts the system's ability to provide complete and accurate travel information to users. To provide a clearer comparison of the coverage scope of the system developed in this research across various aspects, it was benchmarked against traditional systems, and the results are presented in Table II. The data in Table II reveals that the system designed in this study demonstrates high coverage in areas such as scenic spot knowledge, hotel facility information, local cultural activities, specialty food introductions, and transportation route coverage, with particularly strong performance in specialty food introductions and transportation route coverage.

TABLE II

COMPARISON OF KNOWLEDGE COVERAGE BETWEEN BOTH SYSTEMS

Domain of knowledge	**Traditional Systems**	**The system in this paper**
Knowledge of scenic spots	90%	65%
Hotel facilities information	85%	60%
Local cultural events	80%	50%
Introduction to special food	95%	70%
Traffic route coverage	92%	76%
User interest expansion	75%	No such feature

The experimental results demonstrate a strong correlation between recommendation accuracy and user satisfaction. As shown in Figure 2, the personalized tourism recommendation system based on KG significantly outperforms traditional systems in recommendation accuracy, achieving an average of 94.9% compared to 68.3% for traditional systems. This improved accuracy directly translates to higher user satisfaction, with our system receiving an average user rating of 9.6 compared to 6.9 for traditional systems (Figure 3). The KG's ability to capture complex relationships between tourism entities and user preferences enables more relevant recommendations, leading to both greater accuracy and enhanced user experience. This finding aligns with the principle that personalized recommendations, tailored to individual needs, are crucial for user engagement and satisfaction in online platforms.

V. CONCLUSION

This study developed a personalized travel recommendation system that utilizes a knowledge graph (KG). The system creates models of user interests and preferences by leveraging the knowledge map, and integrates user geographical location, past behaviors, and other relevant information to deliver personalized travel recommendations. The experimental findings demonstrate that the system effectively enhances recommendation accuracy and user satisfaction. Moreover, the system exhibits strong performance in personalization, making it a viable and scalable solution.

Moving forward, this research will focus on further refining the tourism recommendation algorithm to optimize the overall performance and user experience of the system. Concurrently, the study will incorporate additional knowledge bases within the tourism domain to expand the KG's content, thereby providing users with more comprehensive and precise travel recommendations.

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