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Enhancing Real-Time Adaptability in Tourism Recommendation Systems through Knowledge Graph Techniques: A Quantitative Study

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Abstract

Traditional tourism recommendation systems (TRS) often fail to deliver highly personalized, context-aware, and adaptive travel suggestions due to limitations in algorithmic complexity, fragmented data sources, and insufficient real-time processing capabilities. This study quantitatively examines how knowledge graph-based approaches can address these shortcomings by improving TRS performance in terms of accuracy, coverage, integration, and adaptability. Using a structured survey administered to 200 participants, including travelers and tourism industry stakeholders, the research measures perceptions of TRS effectiveness across ten key performance indicators, each assessed on a 5-point Likert scale. Data were analyzed using SPSS, applying descriptive statistics, correlation, regression, t-tests, and ANOVA to identify significant relationships and trends. Findings reveal moderate to strong agreement that knowledge graphs enhance TRS efficiency by integrating heterogeneous data, reducing information overload, and enabling hybrid methodologies combining machine learning with semantic data modeling. However, results also show variability in perceptions, particularly regarding the tangible benefits of real-time adaptability, suggesting that user experience and awareness significantly influence evaluations. While participants generally support increased investment in knowledge graph technologies, the initial reliability analysis indicated the need for refinement of survey items to improve internal consistency. Overall, the study provides empirical evidence that integrating knowledge graphs into TRS can support more dynamic, personalized, and contextually relevant recommendations, ultimately contributing to improved user satisfaction and competitive advantage for tourism service providers. These insights inform practical strategies for designing next-generation TRS

architectures capable of adapting in real-time to evolving traveler needs and environmental changes.
Keywords: Tourism Recommendation Systems, Knowledge Graphs, Real-Time Adaptability, Quantitative Research, User Satisfaction

Introduction

Despite the advancements in technology, traditional tourism recommendation systems (TRS) still face significant challenges in providing accurate, personalized, and context-aware recommendations to travelers. These challenges stem from the limitations of existing recommendation algorithms, data fragmentation, and the inability to effectively utilize the wealth of available data in the tourism domain. As a result, travelers often encounter suboptimal recommendations that do not fully align with their preferences, interests, and situational factors. Addressing these challenges requires a paradigm shift in the approach to designing and implementing tourism recommendation systems. One of the primary challenges faced by traditional TRS is the reliance on simplistic recommendation algorithms such as collaborative filtering and content-based filtering (Morishima, 2021). While these algorithms have been effective to some extent, they often struggle to capture the nuanced and dynamic nature of travelers' preferences. For example, traditional approaches may overlook contextual factors such as weather conditions, local events, and real-time feedback from other travelers, leading to recommendations that are generic and outdated.

Furthermore, the tourism domain is characterized by a vast amount of heterogeneous and fragmented data, including information about destinations, attractions, accommodations, transportation options, user preferences, and reviews. This data is often siloed across various platforms and systems, making it challenging to extract, integrate, and leverage for recommendation purposes. Traditional TRS lack the capability to effectively aggregate and analyze this diverse range of data sources, resulting in suboptimal recommendations that do not fully leverage the available information (Nitu, Coelho and Madiraju, 2021)). Another critical challenge is the lack of personalized and context-aware recommendations in traditional TRS. While some systems attempt to personalize recommendations based on user preferences, they often fail to consider the broader context of a traveler's journey. For example, recommendations may not take into account situational factors such as travel purpose, travel companions, budget constraints, and time constraints. As a result, travelers may receive recommendations that are not relevant or practical for their specific needs and preferences.

Moreover, traditional TRS face challenges in handling real-time data and adapting recommendations dynamically based on changing circumstances. For example, sudden changes in weather conditions, road closures, or unexpected events may significantly impact travel plans, requiring real-time adjustments to recommendations. Traditional systems may lack the agility and flexibility to incorporate such real-time data and adapt recommendations accordingly, leading to suboptimal user experiences. The existing literature highlights the potential of knowledge graph approaches to address these challenges and revolutionize tourism recommendation systems (Ahmedov, 2020). However, there is a gap in the research regarding the practical implementation of knowledge graph-based TRS and their effectiveness in delivering personalized, context-aware recommendations to travelers. The lack of empirical evidence and case studies showcasing the real-world application of knowledge graph approaches in TRS hinders the advancement and adoption of these techniques in the tourism industry.

Traditional tourism recommendation systems cannot deliver personalized and context-aware recommendations to travelers, leading to suboptimal user experiences and decreased user satisfaction. The tourism domain is characterized by fragmented and heterogeneous data sources, making it challenging to extract, integrate, and leverage data for recommendation purposes. Traditional TRS struggle to aggregate and analyze diverse data sources effectively, limiting their ability to generate accurate and relevant recommendations (Keeley et al., 2019) . Traditional TRS face challenges in incorporating real-time data and dynamically adapting recommendations based on changing circumstances such as weather conditions, road closures, and unexpected events. This lack of real-time adaptability can lead to outdated and irrelevant recommendations for travelers. By addressing these challenges and leveraging the capabilities of knowledge graph approaches, the study aims to architect next-generation tourism recommendation systems that deliver highly personalized, context-aware, and real-time adaptive recommendations to travelers, thereby enhancing the overall tourism experience and contributing to the growth and sustainability of the tourism industry. Based on the research, the research question is elaborated below

- What approaches can be utilized to improve the real-time adaptability of tourism recommendations using knowledge graph techniques?

Literature Review

According to Ko et al. (2022), a recommendation system can be recognised as an information filtering system that is significantly utilised for the purpose of giving recommendations to each user on the basis of their previous history and preferences related to tourism. With the aim to develop a recommendation system, the rate of dependency on artificial intelligence and machine learning is significantly high. In modern time, the rapid growth of the internet has significantly supported users' overload with information related to different things and items, which made an overload of information and increase the rate of challenges in identifying which particular information need to be used to ensure developing better decision and taking an appropriate approach to meet an aim. Due to such reasons, the need and demand for filtering information from the big pool of information have increased at a significant rate. It also encourages the development of a recommendation system in the mid-1900 with the aim of helping individuals select useful information or product from a number of available options to make an appropriate decision. In this, it needs to be mentioned that the development of the recommendation system has only become possible due to the active application of machine learning. Hence, the role of machine learning in the context of a recommendation system and developing an effective platform to support people understanding and identifying essential data and information as well. The utilisation of recommendation systems within the tourism industry has played a significant role in helping tourists by providing adequate and essential information related to their specific tourist destinations. Similar to this context, as identified by Pu et al. (2020), recommendation systems can be recognised as a useful technology that is highly capable of alleviating the problem of overload of information that is shared and provided by users. It is significantly associated with predicting the grade of items to be recommended to each user and creating a list of recommended items for each user and making it possible to recommend items related to the users. There are several types of platform services present that are associated with actively recommending personalised items that are highly capable of meeting the needs of users through the introduction of a recommendation system. However, in order to improve the performance of this recommendation utilisation of different types of filtering models and data mining techniques are significantly conducted to ensure a better decision-making process for each user to ensure a better rate of satisfaction.

However, as identified by Chujai et al. (2020), rather than only helping tourists with tourism destination travel agencies and associated organisations also emphasise utilising a recommendation system to recommend tour packages, the best destination place according to user preference, giving information related to best travel routes and some attractive and off-beat destinations as well. Along with the aspects related to machine learning, the utilisation of data mining techniques is also prominent in the case of tourist recommendation systems. It is mainly associated with vising the history of users and analysing patterns of travel of each tourist to provide them with the best deals and grab their attention. In addition to this, these techniques are also significantly used for further activities as well, such as re-ranking the tourist locations and searching city-wise tourist locations and the number of tourists in a particular destination. The utilisation of the pattern-matching algorithm is also prominent in the case of tourism recommendation systems. The primary rationale behind the use of such information is to find patterns by filtering the information associated with a particular tourist. The pattern can be easily found through the help of analysing the user profile and the user search history as well. In addition to this, the incorporation of some specific rule data related to mining is significantly used for finding frequent patterns, associations, correlations and causal structures in the large volume of datasets. The utilisation of this particular technique has also supported finding the interrelationship between each item associated with the tourism industry and the decision-making process of customers as well.

On the other hand, as deduced by Logesh & Subramaniyaswamy (2019), the utilisation of Hierarchy sampling statistics and the SVD++ algorithm is also significantly popular in the case of tourism recommendation systems. This particular recommendation system is significantly dependent on the dataset related to Smart Travel, the HSS model, and SVD++ algorithm along with a hybrid recommendation system. The primary rationale behind using them is to gather adequate data and information to provide accurate recommendations to each user without any sort of consequence. However, the first stage associated with this particular recommendation system is to collect user travel preferences through the use of a well-designed questionnaire. Further, the ratings of some specific tourist spots are obtained from different types of tourist websites that can be discretized between 0-5 to represent the preferences of users. As a result of this, an effective database has been formed that has been recognised as Smart Travel. In addition to this, in this context, it needs to be mentioned that in order to successfully find the user preferences utilisation of the HSS model is significant. In order to successfully do this appropriately utilisation of three target variables is also high that include travel season, travel interest and travel method that must be chosen to provide each tourist with appropriate recommendations and support them continuously in the travelling period to ensure a higher level of satisfaction. However, the preferences and perceptions of tourists can be influenced by some specific external factors, such as gender age, wage, education, district and job (Kulkarni, & Rodd, 2020). In order to successfully determine and evaluate each of the tourists, the targeted group of samples are divided into several subsets based on their characteristics and background to provide them with the effective recommendation.

Conceptual Framework

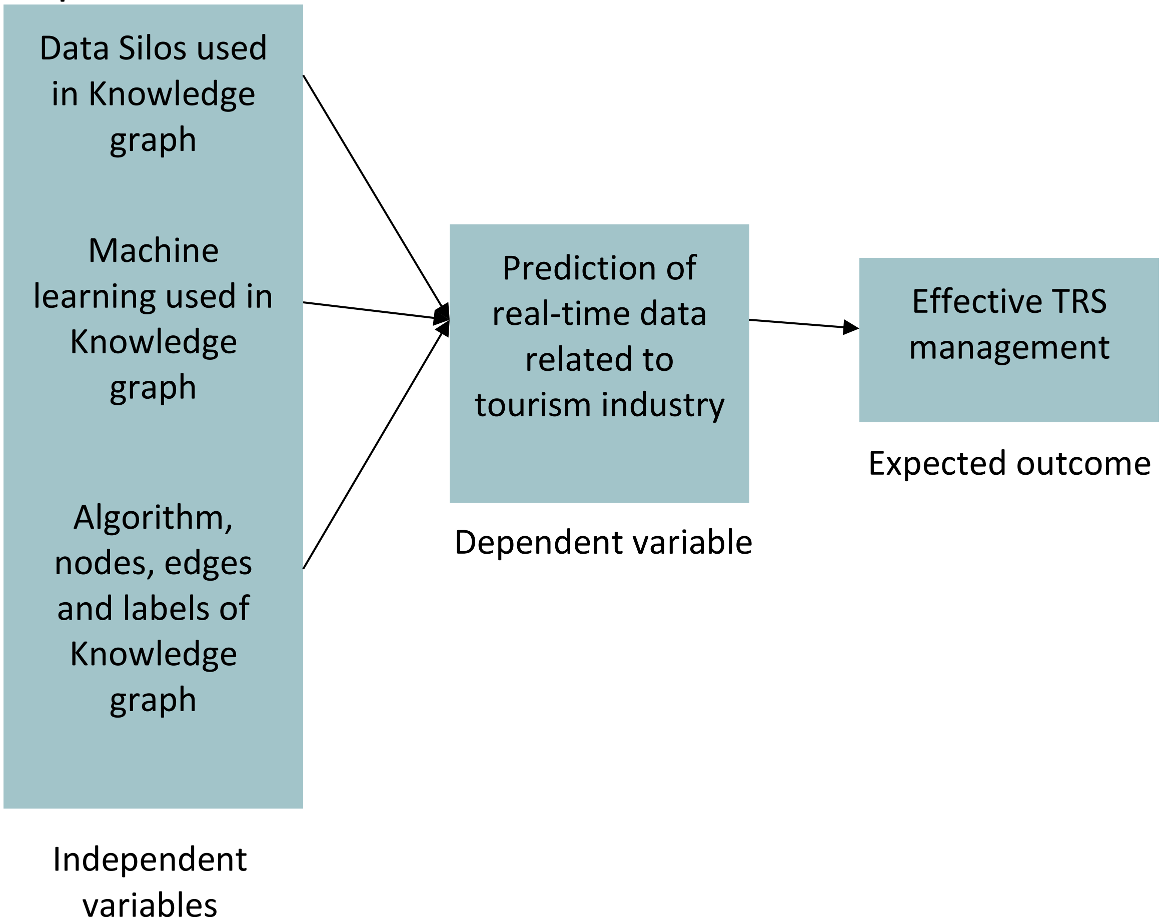

Figure 1: Conceptual framework
(Source: As created by self)

Research Methodology

The quantitative methodology in this study focuses on measuring and analyzing the performance of knowledge graph-based Tourism Recommendation Systems (TRS) using structured surveys as the primary data collection tool. A total of 200 participants—comprising travelers and tourism industry stakeholders—were selected through random sampling to ensure representativeness and minimize bias. The survey items were designed to capture measurable variables such as recommendation accuracy, coverage, response time, and user satisfaction on a 5-point Likert scale. These numerical data allow for objective evaluation of TRS performance, with the aim of testing predefined hypotheses about the effectiveness of knowledge graphs in enhancing system efficiency.

Data analysis is conducted using SPSS (Statistical Package for the Social Sciences), applying both descriptive and inferential statistical techniques. Descriptive statistics, including means, standard deviations, and frequency distributions, summarize participant responses, while inferential tests such as correlation analysis, regression analysis, t-tests, and

ANOVA identify relationships, patterns, and significant differences between groups. This statistical approach ensures that the findings are supported by empirical evidence, allowing for the validation of theoretical assumptions and the formulation of data-driven conclusions about TRS optimization.

Reliability and validity are maintained through careful survey design, alignment of items with research objectives, and pilot testing to identify and address weaknesses in measurement. While the initial Cronbach's Alpha score indicated low internal consistency (0.167), highlighting the need for questionnaire refinement, the quantitative approach still offers a structured, objective, and replicable means of evaluating TRS performance. By focusing on numerical data and statistical testing, the methodology provides concrete, generalizable insights into how knowledge graphs can improve tourism recommendation systems.

Results

RQ: What approaches can be utilized to improve the real-time adaptability of tourism recommendations using knowledge graph techniques?

No.	Survey Question	N	Min	Max	Mean	Std. Deviation
1	The Tourism Recommendation System (TRS) improves the overall tourism experience by offering personalized travel suggestions.	200	1	5	3.52	0.868
2	Knowledge graph technology enhances the efficiency of tourism recommendation systems by connecting relevant data such as locations, user preferences, and travel routes.	200	1	5	3.56	1.045
3	The use of machine learning in tourism recommendation systems significantly improves the accuracy of travel recommendations.	200	1	5	3.39	1.083
4	Tourism Recommendation Systems based on knowledge graphs are better at providing real-time adaptable recommendations than traditional systems.	200	1	5	3.39	1.133
5	Data fragmentation and the lack of data integration are major challenges that affect the performance of traditional tourism recommendation systems.	200	1	5	3.46	1.097
6	The introduction of knowledge graph-based recommendation systems has reduced the problem of information overload for travelers.	200	1	5	3.37	1.003
7	Nodes, labels, and edges within the knowledge graph model effectively enhance the connection between various data points in tourism recommendation systems.	200	1	5	3.47	1.084
8	The hybrid methodological approach combining machine learning and knowledge graphs provides better recommendations for travelers.	200	1	5	3.46	1.102
9	The implementation of knowledge graphs in TRS systems significantly improves the quality of recommendations by integrating data from various sources.	200	1	5	3.46	1.065
10	Tourism organizations should invest more in knowledge graph technologies to enhance customer experience and satisfaction.	200	1	5	3.38	1.063

The first survey item explored whether participants believed that the Tourism Recommendation System (TRS) improves the overall tourism experience by offering personalized travel suggestions. The mean score for this item was 3.52, with a standard deviation of 0.868. This result suggests a generally positive agreement among respondents, indicating that a significant proportion perceive TRS as effective in enhancing the tourism experience. The relatively low standard deviation points to a moderate consensus, meaning that while there is some variation in perceptions, most participants lean toward agreement rather than disagreement. This supports the notion that TRS systems are increasingly recognized as valuable tools for personalizing travel planning and enhancing user satisfaction through tailored suggestions.

The second item assessed perceptions regarding whether knowledge graph technology enhances the efficiency of TRS by connecting relevant data such as locations, user preferences, and travel routes. The mean value here was slightly higher at 3.56, with a standard deviation of 1.045. This result reflects a moderate to strong agreement that knowledge graphs play an important role in increasing the operational efficiency of recommendation systems. However, the standard deviation, which is slightly higher than the first item, reveals more variability in respondents' opinions. This variation may stem from different levels of awareness or familiarity among users regarding how knowledge graphs function behind the scenes, or differences in exposure to graph-based systems versus more traditional recommendation methods.

The third survey statement evaluated the belief that the use of machine learning significantly improves the accuracy of travel recommendations within TRS. The mean score was 3.39, accompanied by a standard deviation of 1.083. The lower mean compared to the first two items suggests that although there is moderate agreement, participants are slightly less convinced about the direct contribution of machine learning relative to knowledge graphs or general TRS effectiveness. The relatively high standard deviation indicates greater diversity in participant views. Some travelers may recognize the value of machine learning in refining recommendations, while others may either be unaware of its influence or skeptical about its accuracy improvements without seeing tangible benefits themselves.

The fourth item focused on whether tourism recommendation systems based on knowledge graphs are better at providing real-time adaptable recommendations than traditional systems. The mean here was also 3.39, with a standard deviation of 1.133, reflecting very similar patterns to the previous question. This suggests moderate agreement but with a considerable spread of responses. Real-time adaptability is a complex capability that many users may not directly perceive unless they experience clear examples, such as instantaneous re-routing during travel disruptions or dynamic attraction suggestions. The slightly high variability may indicate that although users appreciate general improvements in recommendations, the specific advantage of real-time adaptability via knowledge graphs remains somewhat abstract or inconsistently experienced.

For the fifth item, respondents evaluated whether data fragmentation and lack of integration are major challenges affecting traditional TRS performance. The mean score was 3.46, with a standard deviation of 1.097. This relatively strong agreement reflects participant awareness that inconsistencies and isolated datasets negatively impact recommendation quality. The standard deviation points to a moderate spread of opinions, suggesting that while many users recognize the fragmentation problem, others may not have consciously noticed its effects or are satisfied with the performance of existing systems. Nevertheless, this finding supports ongoing efforts to use knowledge graphs to unify fragmented tourism information under a coherent, accessible structure.

The sixth survey question investigated whether the introduction of knowledge graph-based recommendation systems has reduced the problem of information overload for travelers. The mean for this item was 3.37, and the standard deviation was 1.003. This finding reflects moderate agreement, but it also reveals that the impact of knowledge graphs on reducing information overload is less strongly felt compared to their perceived contribution to general recommendation effectiveness. The relatively moderate spread in responses suggests that while some users feel a clear reduction in overload — receiving more targeted, relevant suggestions — others may still encounter an overwhelming volume of options, hinting that information curation techniques within TRS could be further refined.

The seventh item measured the extent to which participants believe that nodes, labels, and edges within knowledge graphs effectively enhance connections between tourism data points. Here, the mean score was 3.47, and the standard deviation was 1.084. The finding suggests a moderate to strong agreement that the graph model's internal structure meaningfully improves data interconnectivity. However, the noticeable variability in responses suggests that while some participants appreciate the technical underpinnings of the recommendation logic, others either lack visibility into the structure or are indifferent to how the system organizes and presents travel suggestions as long as the recommendations are perceived as helpful.

In the eighth survey item, respondents evaluated whether a hybrid methodological approach combining machine learning and knowledge graphs provides better recommendations for travelers. The mean score was 3.46, with a standard deviation of 1.102. This indicates general agreement that hybrid systems offer advantages, but the standard deviation reflects variability in participant confidence regarding hybrid system performance. Some travelers, possibly those who have experienced cutting-edge recommendation systems, perceive distinct improvements, while others may either be unaware of the underlying hybrid mechanisms or find it difficult to attribute improvements specifically to the combination of technologies rather than to general system improvements over time.

The ninth item assessed whether implementing knowledge graphs significantly improves the quality of recommendations by integrating diverse sources. The mean was 3.46, and the standard deviation was 1.065, which suggests that respondents largely agree on the value added by multi-source integration. The moderate standard deviation implies that while the majority appreciate the comprehensive nature of graph-driven recommendations, there is still a portion of users who may either not perceive a noticeable difference in the breadth or depth of suggestions or who remain neutral until directly exposed to more diverse, contextually richer recommendations.

Finally, the tenth survey question asked whether tourism organizations should invest more in knowledge graph technologies to enhance customer experience and satisfaction. The mean value was 3.38, with a standard deviation of 1.063. Although slightly lower than the scores for specific system capabilities, this response shows that participants generally agree on the strategic importance of knowledge graph investment for the future of tourism services. The variability indicates that while many see the promise, others might remain cautious, possibly due to concerns about technological complexity, costs, or skepticism about whether investment would directly translate into better user outcomes.

Conclusion

The findings of this research suggest that improving real-time adaptability in tourism recommendation systems (TRS) through knowledge graph approaches is critical for meeting the evolving demands of modern travelers. Participants noted that knowledge graphs offer a dynamic structure where new information can be easily incorporated, allowing recommendations to stay relevant even as user preferences and external conditions change. This flexibility stems from the graph's ability to model relationships between entities in a non-linear and extensible manner. As Hogan et al. (2021) emphasize, knowledge graphs provide a semantic backbone that can accommodate the constant addition of new nodes and edges without disrupting the integrity of the overall system.

A major insight from the study is the significance of real-time data ingestion in achieving adaptive tourism recommendations. Participants highlighted that live feeds from transportation services, weather updates, social media events, and booking systems must be seamlessly integrated into the knowledge graph to keep recommendations contextually appropriate. According to Ji et al. (2021), real-time data ingestion pipelines linked to knowledge graphs enable TRS platforms to adjust their outputs dynamically based on the most current information available.

Another critical finding revolves around the use of incremental graph updating techniques to support adaptability. Participants agreed that waiting for batch updates or manual interventions significantly reduces the relevance of recommendations in fast-paced travel scenarios. Instead, knowledge graphs must be designed to accommodate continuous, incremental updates at the node, edge, and attribute levels. As Abu-Salih (2020) points out, incremental updating methods ensure that knowledge graphs reflect real-world changes with minimal latency, maintaining the responsiveness and usefulness of the recommendation system.

The research also underscored the role of event-driven architectures in facilitating real-time adaptability. Participants discussed how event-triggered updates, where specific changes in data sources automatically prompt updates to the knowledge graph, allow TRS systems to respond instantaneously to important developments. As Zareian, Karaman, and Chang (2019) assert, coupling knowledge graphs with event-driven mechanisms creates recommendation systems that are more attuned to environmental changes, enhancing their ability to deliver timely and context-sensitive advice.

Participants consistently emphasized the importance of real-time user interaction modeling within the knowledge graph framework. TRS must be able to adjust recommendations based on users' evolving behaviors, such as sudden interest in a new destination or spontaneous changes in travel plans. Real-time updates to user profiles in the knowledge graph ensure that recommendations stay aligned with the traveler's latest preferences. According to Zou (2020), dynamic user modeling enabled by knowledge graphs is fundamental for maintaining personalization and relevance in adaptive TRS platforms.

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