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Trends In Tourism Recommendation Systems: A Review

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ABSTRACT

Tourism Recommendation Systems (TRS) are increasingly important in the tourism industry to provide personalized recommendations based on diverse tourist preferences. Technology and big data have transformed TRS from traditional travel agencies to modern digital platforms, enabling the processing of vast amounts of user-generated data for precise recommendations. The study aims to identify strengths and weaknesses within existing TRS frameworks and techniques, propose recommendations to mitigate these weaknesses, and provide insights for practitioners and researchers. Key findings are the effectiveness of personalized and context-aware recommendations, the importance of multimodal data integration, the need for ethical and fair recommendation practices. Future directions in TRS research should focus on exploring and developing explainable AI and transparency, personalization at scale, enhancing multimodal recommendation capabilities, and ensuring ethical and fair recommendation. This review contributes to a deeper understanding of contemporary TRS methodologies and provides actionable insights for enhancing TRS performance. By addressing current trends and proposing recommendations for future research, this paper aims to advance the field of TRS and improve travel experiences for tourists.

1. INTRODUCTION

The tourism sector has expanded significantly in recent years, and a wide range of in-person and online travel services are now offered. Tourists navigate complex destinations with unpredictable visit sequences and varying preferences. Effective tour planning involves evaluating local conditions, time constraints, financial limitations, and weather forecasts (Mahdi & Esztergár-Kiss, 2023). The digital era presents overwhelming options, including destinations, accommodations, and activities, leading to decision paralysis (Sarkar et al., 2022). The increasing number of service providers makes it challenging for tourists to choose the best travel plan (Chaudhari & Thakkar, 2019). Travel and tourism recommendation systems (TRS) have been developed to simplify the planning process, offer relevant suggestions, and enhance

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overall experiences by reducing effort. TRS uses data from user profiles, historical bookings, reviews, and social interactions to generate personalised recommendations (Hamid et al., 2021; Yuan & Zheng, 2024).

TRS has revolutionised the travel industry by providing personalised recommendations based on individual preferences, interests, and constraints. This approach not only helps discover new destinations but also boosts business growth and competitiveness for travel service providers (Banerjee et al., 2023; Wilcox, 2022). However, TRS faces challenges such as dynamic itinerary planning, mobile platforms, evaluation methods, group recommendation, social networks, integration, user modelling, privacy, and robustness. Traveller preferences significantly influence itinerary design. Current TRS requires travellers to predefine individual preferences for each point of interest (POI), which can be laborious in large-scale locations (Mahdi & Esztergár-Kiss, 2023). Additionally, TRS designs often rely on assumptions of certainty and consistency, which can lead to erroneous preference inputs. Decision-making in tourism involves balancing variables such as preferred destinations, activities, lodging, transportation, financial restrictions, personal interests, cultural background, and psychological factors. Travellers often alter travel plans due to unpredictable traffic, environmental conditions, and waiting hours. Thus, unpredictable tourist behaviour requires careful consideration of various locations, visit orders, and visitor demands. (Banerjee et al., 2023; Mahdi & Esztergár-Kiss, 2023; Wilcox, 2022).

The tourism industry is increasingly integrating social networks (SNs) with personalised recommendations based on social media data (Menk et al., 2019; Sarkar et al., 2022). Chaudhari and Thakkar (2019) also delve into tourism-related aspects such as hotel, restaurant, and attraction planning. Borràs et al. (2014) explore TRS technical aspects with a focus on traditional and tourism-specific technologies, artificial intelligence (AI), algorithms, datasets, and evaluation methods. Kontogianni and Alepis (2020) consider the broader context of smart tourism, emphasising privacy protection, user experience, and big data analytics. This diversity highlights the multifaceted nature of this research area and opens up various avenues for future exploration. There is a recognised need for further research into quality of service (QoS) improvement (Sarkar et al., 2022), unbiased data (Chaudhari and Thakkar, 2019), integration of social network-based recommender systems, and incorporation of user personality into recommendations (Menk et al., 2019). Additionally, there have also been calls for more research on diversity and trust in social recommendations (Borràs et al., 2014), as well as the need for large-scale user studies to evaluate the proposed systems (Kontogianni & Alepis, 2020).

The main research question is: How can TRS provide better recommendations for travellers by addressing the issues and challenges identified in the literature? This research aims to review contemporary TRS methodologies, assess strengths and weaknesses within existing frameworks and techniques, and propose recommendations to mitigate identified weaknesses and improve TRS performance. This can provide valuable insights and practical solutions for academic researchers and industry practitioners in TRS, as AI advancements have significantly impacted tourism, leading to smart tourism. Future research should evaluate proposed systems with real users to assess effectiveness, user acceptance, and practical challenges (Kontogianni & Alepis, 2020). The future of TRS depends on ethical concerns such as data privacy and user experience, as well as utilising advanced AI techniques like deep learning and natural language processing (NLP) to enhance accuracy and personalization. Collaboration across disciplines can help evolve TRS to provide a personalised, efficient, and enriching tourist experience.

2. LITERATURE REVIW

2.1 Data Collection and Pre-processing

Fundamental to building a robust TRS is an effective data collection and pre-processing technique (Belaidan et al., 2019) from sources such as user profiles, historical booking data, reviews, and social interactions (Cai et al., 2024; Olshannikova et al., 2017). Common data sources for developing TRS are

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TripAdvisor, Dataset_tsmc, Hotel Reviews, dataset ubicomp, Flickr, and Agoda.com (Chouiref & Hayi, 2022). Data is collected, pre-processed, and transformed into a suitable format for analysis using techniques like data cleaning, normalization, and feature engineering to improve data quality and relevance (Arinez et al., 2020). Additionally, data anonymization and privacy protection measures may be implemented to safeguard sensitive user information.

2.2 Feature Representation and Selection

Feature representation and selection are crucial for extracting meaningful patterns and insights from the pre-processed data that significantly influence the effectiveness and precision of TRS recommendations. This involves encoding relevant attributes of items like destinations, accommodations, and users into a structured format for recommendation (Pérez-Núñez et al., 2019). Feature selection techniques, such as dimensionality reduction and feature importance analysis, help identify informative features for modelling (Partridge & Calvo, 1998). Moreover, word embeddings (Bakarov, 2018) and image representations enable the integration of multimodal data sources, like textual descriptions and visual content, to enrich the representation of items and users in recommendations.

2.3 Types of Tourism Recommendation Systems

TRS employs various methodologies, like collaborative filtering (CF) (Goldberg et al., 1992), which uses the preferences and behaviours of similar users to make recommendations; content filtering-based (CFB) (Pazzani & Billsus, 2007), where recommendations are based on the similarity of items to those previously viewed by the user; and hybrid-based TRS (HTRS) (Burke, 2002), which combines both content and collaborative approaches. Additionally, Adomavicius and Tuzhilin (2005) design context-aware recommendation systems to provide relevant and timely recommendations based on various factors such as time, location, weather, and user activity. These systems dynamically adjust the recommendation to align with users' current situations and preferences.

Moreover, HTRS is a sophisticated approach that combines multiple recommendation techniques to improve personalized travel suggestions. These systems offer complementary strengths, overcome weaknesses, and enhance personalization by integrating collaborative filtering, content-based, and context-aware methods. For instance, there are seven HRS techniques, such as weighted, mixed, feature combination, switching, feature augmentation, metalevel, and cascade. Weighted aggregates votes; switching applies techniques based on circumstances; mixed generates simultaneous recommendations; feature combination amalgamates data sources; and cascade refines outputs (Çano & Morisio, 2017; Lathia et al., 2009).

Other than that, knowledge-based TRS (KBTRS) (Burke et al., 1996) consider constraints and user-item interactions, while demographic recommendation systems use demographic information and contextual data. KBTRS uses prior knowledge to cater to user preferences and ensure recommendations align with user requirements. It encodes knowledge into three types, such as catalogue, functional, and user. The knowledge base (KB) is the central component to serve as input data for the system (Gemmell et al., 2012). The growing user base of social networks presents a potential for intelligent recommendation systems (IRS) in the tourism sector, which utilise user-generated content and interactions to provide personalized and engaging recommendations. Group-Based Tourism Recommendation Systems (GBTRS) are a new approach to traditional recommendation systems that focus on providing recommendations for groups of users with shared interests or preferences. In addition, the use of AI techniques like knowledge representation, optimisation, clustering algorithms, multiagent systems, and natural language processing enhances recommendations and creates context-based, time-sensitive, and location-based social recommendation systems. These systems help identify industry strengths, weaknesses, opportunities, and threats.

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2.4 Existing Tourism Recommendation Systems

Table 1 provides a summary and comparative analysis of each TRS that offers unique features and approaches to assist travellers in planning trips. PersonalTour (Lorenzi et al., 2011) and TravelBuddy (Fu et al., 2014; Jain et al., 2021) focus on personalized recommendations and real-time adjustments, while Photo2Trip (Gaggi, 2013; Wang et al., 2022; Yin et al., 2010) and TravelWithFriends (De Pessemier et al., 2015) use visual content and collaborative filtering. TripAdvisor (Amaral et al., 2014; Belaidan et al., 2019; Filieri et al., 2020; Valdivia et al., 2019) and TripHobo offer user-generated content and comprehensive trip planning, but have limitations such as authenticity concerns and a lack of detailed time management (Belaidan et al., 2019). Overall, the choice of recommendation system depends on individual preferences and the specific needs of travellers.

Table 1. Existing TRS

TRS	Key Features	Advantages	Disadvantages
PersonalTour[a]	Uses distributed AI and multiagent systems, autonomous agents, and flexible recommendations	Outperformed manual travel agents with 76.59% accuracy compared to human experts	May not fully replace human expertise
TravelBuddy[b]	Real-time route planning algorithm, knowledge graph attention network, interactive interface	Continuously customises routes based on user feedback and offers personalised advice	Requires active user input and interaction
Photo2Trip[c]	Uses geotagged photos, mean-shift clustering, and collaborative filtering	Recommends popular routes, considers visit time, location, and duration	Relies heavily on visual content
TravelWithFriends[d]	Hybrid system using content-based, collaborative filtering, and knowledge-based methods	Provides personalised recommendations based on user constraints and filters destinations by ratings	May not offer detailed explanations for suggestions
TripAdvisor[e]	User-generated content platform, five-point rating scale, content-based method	Offers word-of-mouth reviews, a platform for searches, and bookings	Concerns about cluttered displays and fake reviews
TripHobo[f]	Offers a variety of locations, restaurants, package tours, and a drag-and-drop interface	Covers attractions, itinerary planning, accommodations, and local transportation	May lack consideration of time spent at each location

Note. TRS = Tourism Recommendation Systems. Adapted from [a]Lorenzi et al. (2011). [b]Fu et al. (2014); Jain et al. (2021). [c]Gaggi (2013); Wang et al. (2022); Yin et al. (2010). [d]De Pessemier et al. (2015). [e]Amaral et al. (2014); Belaidan et al. (2019); Filieri et al. (2020); Valdivia et al. (2019). [f]Belaidan et al. (2019).

2.5 Evolution of Tourism Recommendation Systems

Initially, early TRS relied on simple rules or expert knowledge, often provided by travel agencies and guidebooks. However, these early RS had limitations in personalization and adaptability and were subject to bias (Li et al., 2010; Resnick & Varian, 1997). The emergence of online platforms marked a shift towards collaborative filtering algorithms, enabling access to vast amounts of travel-related information and user-generated reviews. Online travel platforms revolutionized travel planning by providing convenience, real-time pricing, and secure booking facilities (Filieri, 2015; Gretzel, 2011; Su et al., 2019; Xiang et al., 2017). Subsequently, personalization and context awareness became prominent (Öğüt & Onur Taş, 2012; Tarek et al., 2022; Xiang et al., 2017), with systems leveraging AI, machine learning (ML), and NLP to deliver personalized recommendations based on real-time contextual information and user data (Huang et al., 2023; Yochum et al., 2020; Zeng et al., 2023). The integration of mobile applications and wearable technology further enhanced the travel experience by offering personalized recommendations, interactive maps, AR experiences, and location-based services (Cibilić et al., 2021; Manggopa et al., 2022; Ojagh et al., 2020). Finally, there is a growing emphasis on incorporating social and environmental factors into

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recommendation systems, with sustainability, community-based tourism, and responsible travel recommendations based on user data and feedback gaining traction (Bargeman & Richards, 2020; Font et al., 2021; Hall et al.,2015; Mathew, 2022; Sharpley, 2020; Sun et al., 2020). Table 2 outlines the evolution of TRS, its key phases, and its ongoing efforts to enhance the travel experience with more personalized, relevant, and ethically conscious recommendations.

Table 2. Evolution of TRS

Phase	Description	Key Features/Technologies	References
Early Recommendation Systems	Recommendations based on simple rules or expert knowledge	Travel agencies and guidebooks	Li et al. (2010); Resnick and Varian (1997)
Emergence of Online Platforms	Online platforms provide access to travel-related information and user-generated reviews	Collaborative filtering algorithms	Filieri (2015); Gretzel (2011); Su et al. (2019); Xiang et al. (2017)
Personalization and Context Awareness	Shift towards personalization, using user preferences and contextual data to tailor recommendations	Sophisticated algorithms Analysis of user data (past travel history, demographics) Realtime contextual factors (location, time)	Öğüt and Onur Taş, (2012); Tarek et al. (2022); Xiang et al. (2017)
AI and ML Integration, Realtime Personalization, NLP Integration, Context-aware Recommendations	Integration of AI and ML for real-time personalized recommendations NLP enhances content processing Context-aware systems adjust based on context	Collaborative filtering Content-based filtering, Hybrid models Predictive analytics NLP techniques Contextual information Dynamic adjustment	Huang et al. (2023); Yochum et al. (2020); Zeng et al. (2023)
Mobile Applications and Wearable Technology	Mobile apps and wearable devices offer personalized recommendations, interactive maps, AR experiences, and location-based services	Mobile technology, AR	Cibilić et al. (2021); Manggopa et al. (2022); Ojagh et al. (2020)
Integration of Social and Environmental Factors	Emphasis on responsible and community-based travel	Sustainable tourism practices and eco-friendly accommodations	Bargeman and Richards, (2020); Font et al. (2021); Hall et al. (2015); Mathew (2022); Sharpley (2020); Sun et al. (2020)

2.6 Recommendation Algorithms and Techniques

A wide range of algorithms and techniques have been developed to tackle the recommendation problem, each with its strengths and limitations. Some common approaches include:

(i) Matrix factorization: Matrix factorization techniques decompose the user-item interaction matrix into lower dimensional latent factors, capturing the underlying preferences and patterns in the (Sarkar et al., 2022; Takács & Tikk, 2012).data. Collaborative filtering-based recommendations commonly employ Singular Value Decomposition (SVD) and Alternating Least Squares (ALS) (Chaudhari & Thakkar, 2019; Tarek et al., 2022).

(ii) Deep Learning: techniques, such as neural networks and deep autoencoders, have gained popularity for their ability to model complex interactions and nonlinear relationships in the data. Deep learning models can learn hierarchical representations of users and items, enabling more accurate and expressive recommendations (Noshad et al., 2021).

(iii) Reinforcement Learning: Reinforcement learning techniques, such as Multiarmed Bandits and Deep QNetworks, enable sequential decision-making Deep learning in recommendation systems. These methods learn to optimize recommendation policies through trial-and-error

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interactions with users, maximizing long-term rewards and user satisfaction (Filieri et al., 2020; Kontogianni & Alepis, 2020; Sarkar et al., 2022).

By leveraging these components and techniques, TRS can deliver personalized and relevant recommendations to enhance user satisfaction, engagement, loyalty, and satisfaction in travel planning.

3. METHODOLOGY

3.1 SWOT Analysis of Tourism Recommendation Systems

SWOT analysis is a strategic tool used to evaluate the TRS's internal strengths and weaknesses, opportunities, and threats. It helps identify TRS capabilities, deficiencies, market opportunities, and threats (Benzaghta et al., 2021; Gürel, 2017; Namugenyi et al., 2019). SWOT analysis provides a comprehensive view of TRS's strengths, weaknesses, opportunities, and threats to facilitate macro-evaluations. It also identifies opportunities and competitive strategies, such as emerging technological trends. SWOT analysis helps researchers understand current trends and potential future actions, using strengths to counter threats and weaknesses (Gürel, 2017). It offers a structured approach to identifying key factors affecting each TRS, as well as support for strategic planning. Its flexibility and comprehensiveness make it an ideal tool for evaluating and enhancing TRS in the rapidly evolving tourism industry.

The process of SWOT analysis in TRS involves identifying industry strengths, weaknesses, opportunities, and threats, establishing priorities, and developing strategies (Namugenyi et al., 2019). The SWOT matrix has four strategies, which are strengths-opportunities (SO) strategies, strengths-threats (ST) strategies that mitigate threats, weaknesses-opportunities (WO) strategies that create opportunities by addressing weaknesses, and weaknesses-threats (WT) strategies that minimise weaknesses to avoid threats (Benzaghta et al., 2021). Different types of TRS, such as collaborative filtering, content-based filtering, context-aware systems, hybrid systems, knowledge-based systems, social network systems, and group-based systems, are selected for SWOT analysis due to respective prominence, diversity, and relevance in understanding the full spectrum of TRS capabilities. Therefore, this study reviewed, analysed, and compared existing literature and findings to identify common SWOT associated with each type of TRS.

3.1.1 Collaborative Filtering Based TRS

The cold start problem is a significant challenge in TRS, where CF struggles to make accurate recommendations for new users with limited interaction history. In these cases, the system lacks the necessary data to identify similar users with relevant preferences. To overcome this, hybrid approaches have been proposed to improve recommendation accuracy, such as combining CF with content-based filtering (Sarwar et al., 2001). These methods can analyse travel options' features like location, price, and amenities, as well as user characteristics like age and travel style. The research community has extensively explored memory-based CF (Adomavicius & Tuzhilin, 2005). Researchers have also explored advanced techniques like matrix factorization (Ren et al., 2017) and deep learning (Zhang et al., 2020) to further enhance CF in TRS. These methods capture implicit relationships between users and travel items and demonstrate promising results in recommendation quality. In the travel industry, the use of CF in recommendation systems has gained significant traction. While facing challenges like the cold start problem, the integration of CF with other techniques and the exploration of advanced methods offers promising avenues for further development and enhancement.

3.1.2 Content Filtering Based TRS

In the context of TRS, CFBTRS plays a crucial role in suggesting relevant destinations, activities, and services based on users' profiles and preferences. However, CFBTRS has limitations, such as the possibility of reducing the novelty and diversity of recommended items, which can limit user exposure to new and

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varied experiences. Additionally, CFBTRS faces challenges in addressing the cold-start problem, particularly for new users with limited interaction history within the system. Experts suggest combining CFBTRS with other computer intelligence methods to address this problem. This has led to the creation of composite intelligence-based recommendation systems (CIRS). Further research by Adomavicius et al. (2005) compared various recommendation approaches, including content-based filtering. Researchers have explored enhancements such as natural language processing, deep learning techniques, and user profiles that evolve based on user interactions and feedback. Bao et al. (2015) investigated the use of natural language processing to enrich content-based recommendations by analysing user reviews and descriptions. Vargas and Castells (2013) introduced the concept of user profiles that evolve based on user interactions and feedback, potentially allowing the system to recommend options catering to changing preferences. Additionally, Gupta and Katarya (2020) investigated the use of deep learning techniques to model complex relationships between travel features and user preferences, demonstrating promising results in terms of recommendation effectiveness. In summary, while CFBTRS offers personalised and attribute-driven recommendations within TRS, it also poses challenges such as reducing diversity and addressing the cold-start problem. By integrating content-based approaches with other recommendation techniques and addressing these limitations, TRS can deliver more effective and diverse recommendations tailored to tourists' preferences and needs.

3.1.3 Context-Aware Filtering Based TRS

Context-aware TRS can dynamically adjust recommendations based on changing contextual cues, such as time of day, geographical location, and user behaviour. One of the key strengths of context-aware recommendation systems is the capacity to dynamically adjust recommendations based on changing contextual cues (Baltrunas et al., 2015). These systems can offer personalised suggestions that align with users' needs and preferences, such as prioritising indoor activities during rainy weather. However, these systems face challenges such as overspecialization (Zhang et al., 2018), cold start problems, data sparsity, and increased complexity (Adomavicius et al., 2010). To improve performance, future research should focus on developing better algorithms for capturing and processing contextual information to integrate with emerging technologies like the Internet of Things (IoT), which could enhance the richness and granularity of contextual data available for recommendation purposes (Zhang et al., 2020). Furthermore, expanding the application domains of context-aware recommendation systems beyond traditional tourism and leisure contexts could unlock new opportunities for personalised recommendation experiences (Liang et al., 2017). However, it is crucial to address concerns related to user privacy and data consent, as well as mitigate potential biases that may arise from the use of contextual data in recommendation algorithms (Lathia et al., 2009).

3.1.4 Hybrid TRS

HTRS is a sophisticated approach that combines multiple recommendation techniques to enhance personalized travel suggestions. These systems offer complementary strengths, overcome weaknesses, and improve personalization by integrating collaborative filtering, content-based, and context-aware methods. HTRS is a dynamic and versatile approach to tourism recommendation that uses the synergies between different techniques to provide users with tailored and optimized suggestions. Challenges encountered in HTRS development and deployment include the cold start problem for new users or items with limited interaction history, scalability issues, and adaptability to changing user preferences and environments. However, real-world applications of HTRS span various domains within the tourism industry, including hotel recommendations, tourist attractions, and restaurant suggestions, to shape the future of TRS (Aliannejadi & Crestani, 2018). Researchers continue to explore deep learning models and refine HTRS to enhance travel experiences for users. Different types of recommendation systems (RSs) consider various factors to generate suggestions, such as knowledge-based RSs considering constraints and specific cases,

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demographic RSs relying on user demographics, and social recommendation systems catering to specific domains.

3.1.5 Knowledge Based TRS

The KBTRS operates on the principle of catering to user preferences through the utilization of prior knowledge about various items, ensuring recommendations align closely with user requirements (Gemmell et al., 2012). The KBTRS thus operates as a personalized recommendation engine using encoded knowledge to tailor suggestions that best suit individual user needs, thereby enhancing the overall tourism experience.

3.1.6 Social Network TRS

The expanding user base of social networks offers potential for the development of Investor Relations Services (IRS) within the tourism industry. Social network TRS (SNTRS) uses user-generated content and interactions to offer personalized recommendations. By analyzing social interactions, such as tags and comments, SNTRS can gain valuable insights into user preferences and behaviours (Sharma et al., 2024). This enhances the performance of traditional RS by providing a deeper understanding of user interests. SNTRS treats simplified homogeneous SNs as Bayesian networks, modeling probabilistic relationships between users and their preferences. This approach enhances the recommendation process and fosters greater user engagement by facilitating interactions based on shared interests and experiences. SNRS thus represents a promising avenue for enhancing the tourism experience through the integration of social network dynamics and intelligent recommendation techniques (Sarkar et al., 2023).

3.1.7 Group Based TRS

GBTRS is designed to cater to the needs of groups, especially when face-to-face interaction is limited or group members lack clarity about the preferences (Sarkar et al., 2023). It uses algorithms to analyse group members' preferences and interactions, identifying commonalities and patterns to generate recommendations that satisfy the group's collective needs (Sarkar, 2022). This approach is particularly beneficial in areas like entertainment, where group dynamics play a significant role in decision-making. GBTRS allows users to explore new experiences together, fostering camaraderie and enhancing the enjoyment of their tourism activities. Overall, GBTRS represents a novel approach to recommendation systems that optimizes recommendations for collective enjoyment and satisfaction.

3.1.8 Overview of the SWOT Analysis of TRS

Table 3 presents a SWOT analysis of TRS with a variety of strengths and trade-offs. Collaborative filtering (Goldberg et al., 1992) is effective based on collective user behaviour but faces challenges with new users. Content-based filtering (Pazzani & Billsus, 2007) is resourceful but limited, while context-aware filtering (Adomavičius & Tuzhilin, 2010) enhances personalisation but faces overspecialization and data scarcity. Hybrid approaches (Burke, 2002) promise higher accuracy but require complex management. Knowledge-based systems (Burke et al., 1996) offer depth but require ongoing maintenance. Social network-driven TRS (He & Chu, 2010) uses connections, while group-based systems (Masthoff, 2005) cater to collective preferences. The best TRS should be chosen based on specific use cases and priorities, with the potential for method fusion and targeted weakness mitigation to enhance the user experience.

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Table 3. SWOT analysis of TRS

TRS Type	Strengths	Weaknesses	Opportunities	Threats
Collaborative Filtering Based TRS[a]	Leverages user interactions and preferences for accurate recommendations Can handle new items and users effectively	Cold start problem for new users and items Vulnerable to shilling attacks	Personalisation based on user feedback and context Integration with other recommendation techniques for enhanced accuracy	Privacy concerns regarding user data based on active user participation Competing with newer recommendation methods
Content Filtering Based TRS[b]	Personalises recommendations based on item features and user preferences Resilient to the cold start problem for new users	Limited to recommending items with available content metadata Vulnerable to overspecialization	Integration with collaborative filtering for enhanced recommendations Incorporation of hybrid approaches with collaborative filtering	Dependency on accurate and comprehensive item metadata Risk of recommending redundant or irrelevant content
Context-Aware Filtering Based TRS[c]	Increased relevance and personalization	Over-specialisation, cold start issues, data sparsity	Develop better algorithms and increase user trust	Privacy concerns, data consent challenges, potential bias, and competition from emerging technologies
Hybrid TRS[d]	Effective in mitigating the weaknesses of individual methods Combines the strengths of multiple recommendation techniques for improved accuracy	Complexity in integrating different recommendation algorithms Potential for increased computational overhead	Opportunities for innovation and exploration in combining several methods Customisation options to suit specific application domains and user preferences	Challenges in maintaining system robustness and stability Risk of user confusion or dissatisfaction due to complex recommendation logic
Knowledge Based TRS[e]	Can handle cold start problems with explicit knowledge representation Well-suited for domains with structured information and expertise	Dependency on accurate and up-to-date knowledge representation Limited scalability in handling large knowledge bases	Opportunities for domain-specific customisation and fine-tuning Potential for leveraging emerging AI techniques for knowledge representation and reasoning	Competition from more agile and data-driven recommendation systems Challenges in acquiring and maintaining comprehensive domain knowledge
Social Network TRS[f]	Facilitates user engagement and interaction within social networks Offers opportunities for serendipitous discovery and exploration	Privacy concerns regarding user data sharing and analysis Challenges in accurately capturing user preferences and intentions from social interactions	Customisation for incorporating user privacy preferences Potential for leveraging emerging social network analysis techniques for enhanced recommendation quality	Risks of user backlash or distrust due to perceived intrusiveness or manipulation Dependence on social network platform stability and availability
Group Based TRS[g]	Fostering collective decision-making and enjoyment Offers opportunities for group discovery and shared experiences	Complexity in accommodating diverse group preferences Dependency on accurate group profiling and interaction data	Customisation for different group dynamics and preferences Potential for facilitating groups-based promotions and discounts	Challenges in balancing individual and group needs Competition from traditional recommendation systems focused on individual users

Note. TRS = Tourism Recommendation Systems. Adapted from [a]Ren et al. (2017); Sarwar et al. (2001); Zhang et al. (2020). [b]Adomavicius and Tuzhilin (2005); Bao et al. (2015); Cibilić et al. (2021); Gupta and Katarya (2020); Vargas and Castells (2013). [c]Adomavicius et al. (2010); Baltrunas et al. (2015); Lathia et al. (2009); Liang et al. (2017); Zhang et al. (2018); Zhang et al. (2020). [d]Aliannejadi and Crestani (2018); Çano and Morisio (2017); Fayyaz et al. (2020). [e]Gemmell et al. (2012). [f]Sharma et al. (2024); Xiao et al. (2023). [g]Sarkar and Majumder (2022); Sarkar et al. (2023).

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4. RESULTS AND DISCUSSION

4.1 Comparative Suitability of Tourism Recommendation System Based on SWOT Analysis

Table 4 highlights the traveller requirements, suitable TRS types, inputs, and supporting evidence to understand how different TRS meet various travel situations.

Table 4. Comparative suitability of TRS

TRS Type	Situation	Traveller Requirements	Inputs	References
Collaborative Filtering Based TRS	Personalized solo travel recommendations	Active history of travel, diverse preferences and consistent engagement with user profile platform	User Ratings: Ratings on destinations, hotels, attractions, and activities User Profiles: Demographic information, travel history, and stated preferences Item Information: Descriptions, ratings, reviews, and travel item details Contextual Data: Travel dates, seasons, local events, and current conditions Constraints and Preferences: Budget limits, preferred travel dates, accommodation types, and desired activities Sparsity Management: Techniques to sparse data	Choi et al. (2021); Lin et al. (2022); Sarwar et al. (2001); Zhang et al. (2020)
Content Filtering Based TRS	Frequent travel planning	Frequent travel, detailed preferences and experiences	User Preferences and Interests: Preferred types of destinations, activities, and specific interests User-Generated Content: Reviews, ratings, and comments Geospatial and Temporal Data: Geographic coordinates and timestamps associated with travel photos, check-ins Item Descriptions and Attributes: Descriptions, amenities, and features of travel items Travel Routes and Costs: Information about travel routes, distances, and associated costs Quality Indices and Ratings: Aggregated quality scores and ratings for hotels and attractions Feedback and Usability Data: User feedback and data on system usability	Cibilić et al. (2021); Zhou et al. (2017)
Context-Aware Filtering Based TRS	Context-aware travel planning	Frequent travel and context aware	User Preferences and Profiles: Interests in cultural sites, nature, sports, leisure activities, past travel history, preferred types of destinations, and activities	Achmad et al. (2018); Adomavicius and Tuzhilin (2010); Bahramian et al. (2017); Baltrunas et al. (2015); Barranco et al. (2012);

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			Contextual Information: User’s current context such as location, time, weather conditions, and distance to POIs User Feedback: Explicit feedback such as ratings, reviews and implicit feedback such as clicks, time spent on a page Geospatial and Temporal Data: Geographic coordinates, timestamps, and temporal factors such as the time of day, season, and duration of stay Social Context: Travel companions such as family, friends, solo travel and social media activity Environmental Context: Environmental factors such as weather conditions and local events Travel Routes and Costs: Information about travel routes, distances, and associated costs	Richa and Bedi (2019); Lathia et al. (2009); Liang et al. (2017); Zhang et al. (2018), Zhang et al. (2020)
Hybrid TRS	Comprehensive travel planning	Frequent travel, socially connected	User Preferences and Profiles: Demographic information, travel history, interests, and explicit preferences for types of destinations, activities, and accommodations User Ratings and Feedback: User ratings, reviews, and feedback on POIs, activities, and accommodations Contextual Information: User’s current context such as location, time of day, season, weather conditions, and travel companions Trust and Social Network Data: Trust statements, social ties, and relationships within the user's social network Geospatial Data: Geographic coordinates, distances between locations, and travel routes Temporal Data: Time-related information such as the time of day, day of the week, season, and duration of stay Item Attributes and Content Features: Detailed descriptions and features of travel items such as destinations, hotels, and activities Crowdsourced and Review Data: User-generated content from platforms like Yelp and TripAdvisor	Aliannejadi and Crestani (2018); Çano and Morisio (2017); El Yebdri et al. (2021); Esmaeili et al. (2020); Gavalas and Kenteris (2011); Gonzalo-Alonso et al. (2009); Javed et al. 2021; Kbaier et al., (2017); Logesh and Subramaniyaswamy (2019); Pessemier et al. (2017); Ravi et al. (2019); Vekariya and Kulkarni (2012)
Knowledge Based TRS	Explainable travel recommendations	Active travel history, socially connected, detail-oriented	User Preferences and Historical Data: Data on past travel destinations, types of activities enjoyed, and preferred accommodation styles	Guo et al. (2020); Sharma et al. (2024)

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			Demographic Information: Information such as age, gender, and occupation Social Connections and Influences: Data on social media interactions and relationships Contextual Information: Contextual factors such as time of year, weather conditions, and current events at potential travel destinations User Feedback and Ratings: Continuous feedback from users about their travel experiences and ratings of recommended destinations Knowledge Graph Construction: Integration of various data sources to create a comprehensive and interconnected representation of travel-related entities and their relationships Embedding-Based and Path-Based Methods: Techniques to pre-process the knowledge graph and obtain embeddings of entities and relations, and discover path-level similarities for items Hybrid Approaches and Reinforcement Learning: Integration to optimize recommendations	
Social Network TRS	Socially influenced travel recommendation	Active travel history, socially connected, detail-oriented	User Demographic Information: Demographic data such as age, gender, relationship status, city of residence, and nationality Explicit User Preferences: Explicit preferences about categories of POIs collected directly from users User Ratings of POIs: Ratings of different POIs Social Network Data: Profile information from social networks like Facebook, Google, and Twitter User Interaction Data: Social media interactions, likes, groups, and friendships Tags Created by Users: Tags about POIs User Feedback and Sentiment Analysis: Real-time user feedback and sentiment analysis of social media posts Behavioural Data: Implicit feedback such as clicks, check-ins, and browsing history	Aivazoglou et al. (2020); Ben-Shimon et al. (2007); Esmaeili et al. (2020); A. Garcia et al. (2013); Logesh et al. (2018); Sarkar and Majumder (2022); Yang (2013)
Group Based TRS	Group Travel recommendations	Active travellers,	Tourism Dataset: Detailed information about various tourist attractions,	Ambarwati and Baizal (2019); Dara (2010); I.

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	diverse preferences and budget conscious	including categories, locations, and ratings User Profiles: Detailed profiles including individual ratings of tourist attractions, preferred categories, and budget constraints Tourist Categories: Preferred types of tourist attractions such as natural tourism, water parks, cultural tourism Cost Constraints: Budget limits specified by users Rating History: Historical ratings of tourist items by users Pre-filtering Process: Initial filtering based on user inputs such as categories and costs Recommendation Aggregation: Aggregating individual recommendations using strategies like 'average' to calculate hybrid rating predictions	Garcia et al. (2011); Pérez-Almaguer et al. (2021); Pessemier et al. (2017); Ravi et al. (2019); Ravi and Vairavasundaram (2016); Wang et al. (2016)

4.2 Discussion on Tourism Recommendation System Effectiveness in Different Scenario

Each TRS type has distinct strengths that make it suitable for particular travel scenarios. A collaborative filtering-based TRS recommends travel destinations based on previous travel history, ratings, and reviews. It is best suited for active travellers with diverse preferences and frequent platform engagements. This can effectively address the challenges of providing safe and budget-friendly recommendations based on user ratings, profiles, item information, and contextual data.

A content-filtering-based TRS recommends destinations, accommodations, and activities based on user-generated content and specific content attributes. It is ideal for frequent travellers who value detailed information about specific travel options based on demographic data and activity preferences for family-friendly activities and accommodations. This can overcome the challenge of providing personalised recommendations to meet the diverse needs of frequent travellers based on detailed item information and contextual data.

A context-aware filtering-based TRS provides dynamic, real-time, and personalised recommendations based on user preferences and various contextual factors. It is suitable for frequent travellers who actively share their preferences and feedback and context-aware users who consider current location, time, and environmental conditions. This can ensure a contextually timely, relevant, and highly personalised recommendation, taking into account user profiles, current context, feedback, geospatial and temporal data, social context, environmental context, and travel routes.

A hybrid TRS combines multiple techniques, such as collaborative filtering, content-based filtering, and context-aware approaches, to recommend destinations, accommodations, and activities based on user preferences, social trust, and contextual factors. It is well suited for adventure travellers because it provides more comprehensive activity choices. The integration of user preferences and profiles, user ratings and feedback, contextual information, trust and social network data, geospatial data, temporal data, item attributes and content features, and crowdsourced and review data ensures that the recommendations are relevant.

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A knowledge graph-based TRS uses user preferences, historical travel data, social relationships, and contextual information to provide personalised and timely travel recommendations. The system is best suited for frequent travellers who provide ratings and reviews. It efficiently recommends destinations preferred by similar travellers using a comprehensive knowledge graph to capture high-level semantic relationships and contextual factors. This approach ensures that recommendations are explainable, accurate, and highly personalised.

A social network-based TRS generates relevant and accurate personalised travel recommendations based on user interactions, social relationships, and contextual data. The system is particularly suitable for socially connected travellers. Based on social network data, the system can recommend destinations that other travellers prefer. Social connections, user feedback, and real-time interactions can influence recommendations through this method.

A group-based TRS uses user profiles, ratings, preferences, and contextual information to provide personalised travel recommendations for groups. Group-based TRS is ideal for groups of travellers because it considers all group members' preferences and constraints in order to provide harmonious travel recommendations. This approach ensures that recommendations meet the diverse needs and budget constraints of group members.

5. FUTURE DIRECTIONS AND RESEARCH OPPORTUNITIES

The field of travel recommendation systems is ripe for innovation and advancement due to technological advancements and changing user preferences. Researchers and practitioners can explore new directions and address unresolved challenges. This section identifies open research questions and areas that require further investigation in the future. By exploring these areas, researchers and practitioners can create more effective, engaging, and trustworthy recommendations for users.

5.1 Context-Aware Recommendation

One promising avenue for future research is the development of context-aware recommendation systems that can dynamically adapt recommendations based on the user's context and situational factors. By incorporating contextual information such as time, location, weather, and user activity, TRS can deliver more relevant and timely recommendations that meet the user's immediate needs and preferences. Future research in this area could focus on developing novel algorithms and techniques for context-aware recommendation, as well as exploring the impact of contextual factors on user engagement and satisfaction.

5.2 Personalization at Scale

With the proliferation of data and the increasing complexity of user preferences, there is a growing need for scaled personalization in TRS. Future research could focus on developing scalable algorithms and techniques that can handle large volumes of data and deliver personalized recommendations to a diverse range of users. Additionally, research could explore methods for incorporating implicit and explicit user feedback into the recommendation process to enhance personalization and recommendation accuracy.

5.3 Explainable AI and Transparency

As recommendation systems become increasingly sophisticated, there is a growing need for transparency and explainability to build trust and confidence among users. Future research could focus on developing explainable AI techniques that provide users with insights into how recommendations are generated and why specific recommendations are made. By making recommendation systems more transparent and interpretable, users can better understand and trust the recommendations they receive, leading to increased user satisfaction and engagement.

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5.4 Multimodal Recommendation

With the rise of multimedia content on travel platforms, there is an opportunity to explore multimodal recommendation systems that can leverage diverse data sources, such as text, images, and videos. Future research could focus on developing algorithms and techniques for integrating and analysing multimodal data to generate more comprehensive and engaging recommendations. Additionally, research could explore methods for incorporating user-generated content, such as reviews and social media posts, into the recommendation process to enrich the recommendation experience.

5.5 Ethical and Fair Recommendation

As recommendation systems increasingly shape user experiences and decision making, there is a growing need to address ethical and fairness considerations in the design and implementation of these systems. Future research could focus on developing ethical guidelines and frameworks for designing recommendation systems that prioritize user privacy, autonomy, and wellbeing. Additionally, research could explore methods for mitigating algorithmic bias and discrimination in recommendation systems to ensure fair and equitable treatment of all users.

6. CONCLUSION

This study aimed to improve TRS to provide more personalised travel recommendations by addressing key issues and challenges identified in the literature. This review summarised the existing data collection, feature representation, and recommendation algorithm. Additionally, this review has delved into the development, types, current SWOT analysis, and potential future paths of diverse TRS systems. The strengths, weaknesses, opportunities, and threats of different TRS types, such as collaborative filtering, content-based filtering, hybrid systems, context-aware TRS, knowledge graph-based TRS, social network-based TRS, and group-based TRS, are identified. This result demonstrated that collaborative filtering is most suitable for active travellers with a variety of preferences, whereas content-based filtering is excellent for content-rich travel planning. Hybrid systems offer safe and adventurous travel planning, while context-aware TRS provide real-time and personalized travel recommendations. Knowledge graph-based TRS, social network-based TRS, and group-based TRS are ideal for explainable recommendation, socially influenced recommendation, and group-oriented travel planning. In addition, this review highlights key findings and implications for the future of travel recommendation systems, including context-aware recommendation, personalisation at scale, explainable AI, multimodal recommendation, and ethical and fair recommendation while mitigating algorithmic bias and discrimination. Researchers should explore new directions and prioritize user-centric design principles, transparency, and user engagement in TRS development and implementation. Collaboration between academia and industry can foster innovation and accelerate the development of next-generation systems that meet the evolving needs and preferences of travellers. In conclusion, travel recommendation systems are crucial in shaping how travellers discover, plan, and experience their journeys. By continuing to innovate and address key challenges, researchers and practitioners can create more effective, engaging, and trustworthy recommendation experiences that enhance the travel planning process for users around the world.

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8. CONFLICT OF INTEREST STATEMENT

The authors declare that this research was carried out without any self-benefits, commercial or financial conflicts of interest.

9. AUTHORS' CONTRIBUTIONS

Aderline Song Ke Xin: Writing- original draft, Writing- reviewing and editing; **Ting Huong Yong**: Validation, Supervision, Writing- reviewing and editing; **Abdulwahab Funsho Atanda**: Co-Supervision, Validation, Writing- reviewing and editing.

10. REFERENCES

Achmad, K. A., Nugroho, L. E., Diunaedi, A., & Widyawan. (2018). Context based- tourism recommender system: Towards tourists' context-sensitive preference conceptual model. In *2018 4th International Conference on Science and Technology (ICST)* (pp. 1–6). IEEE Xplore. https://doi.org/10.1109/ICSTC.2018.8528676

Adomavičius, G., & Tuzhilin, A. (2005). Toward the next generation of recommender systems: A survey of the state-of-the-art and possible extensions. *IEEE Transactions on Knowledge and Data Engineering, 17*(6), 734–749. https://doi.org/10.1109/tkde.2005.99

Adomavičius, G., & Tuzhilin, A. (2010). Context-Aware recommender systems. *Springer eBooks* (pp. 217–253). https://doi.org/10.1007/978-0-387-85820-3_7

Aivazoglou, M., Roussos, A. O., Margaris, D., Vassilakis, C., Ioannidis, S., Polakis, J., & Spiliotopoulos, D. (2020). A fine-grained social network recommender system. *Social Network Analysis and Mining*, *10*(1), 8. https://doi.org/10.1007/s13278-019-0621-7

Aliannejadi, M., & Crestani, F. (2018). Personalized context-aware point of interest recommendation. *ACM Transactions on Information Systems*, *36*(4), 1–28. https://doi.org/10.1145/3231933

Amaral, F., Tiago, T., & Tiago, F. (2014). User-generated content: Tourists' profiles on TripAdvisor. *International Journal of Strategic Innovative Marketing*, *1*(3), 137-145. https://doi.org/10.15556/ijsim.01.03.002

Ambarwati, L., & Baizal, Z. K. A. (2019). Group recommenders system using hybrid filtering for tourism domain. *4*(2), 21–30. https://doi.org/10.21108/indojc.2019.4.2.258

Andrade, M. T., & Almeida, F. (2013). Novel hybrid approach to content recommendation based on predicted profiles. In *2013 IEEE 10th International Conference on Ubiquitous Intelligence and Computing and 2013 IEEE 10th International Conference on Autonomic and Trusted Computing* (pp. 507–514). IEEE. https://doi.org/10.1109/uic-atc.2013.49

Arinez, J., Chang, Q., Gao, R. X., Xu, C., & Zhang, J. (2020). Artificial intelligence in advanced manufacturing: Current status and future outlook. *Journal of Manufacturing Science and Engineering*, *142*(11). https://doi.org/10.1115/1.4047855

Bahramian, Z., Ali Abbaspour, R., & Claramunt, C. (2017). A context-aware tourism recommender system based on a spreading activation method. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, *XLII-4/W4*, 333–339. https://doi.org/10.5194/isprs-archives-XLII-4-W4-333-2017

https://dx.doi.org/10.24191/jcrinn.v9i2.438

Bakarov, A. (2018). A survey of word embeddings evaluation methods. *arXiv preprint arXiv:1801.09536*. https://doi.org/10.48550/arXiv.1801.09536

Baltrunas, L., Church, K., Karatzoglou, A., & Oliver, N. (2015). Frappe: Understanding the usage and perception of mobile app recommendations In-The-Wild (arXiv:1505.03014). *arXiv*. http://arxiv.org/abs/1505.03014

Banerjee, A., Banik, P., & Wörndl, W. (2023). A review on individual and multistakeholder fairness in tourism recommender systems. *Frontiers in Big Data*, *6*, 1168692. https://doi.org/10.3389/fdata.2023.1168692

Bao, J., Zheng, Y., Wilkie, D. A., & Mokbel, M. F. (2015). Recommendations in location-based social networks: a survey. *GeoInformatica/Geoinformatica*, *19*(3), 525–565. https://doi.org/10.1007/s10707-014-0220-8

Bargeman, B., & Richards, G. (2020). A new approach to understanding tourism practices. *Annals of Tourism Research*, *84*, 102988. https://doi.org/10.1016/j.annals.2020.102988

Barranco, M. J., Noguera, J. M., Castro, J., & Martínez, L. (2012). A context-aware mobile recommender system based on location and trajectory. In J. Casillas, F. J. Martínez-López, & J. M. Corchado Rodríguez (Eds.), *Management Intelligent Systems* (Vol. 171, pp. 153–162). Springer Berlin Heidelberg. https://doi.org/10.1007/978-3-642-30864-2_15

Belaidan, S. L. M., Yee, L. Y., Rahman, N. a. A., & Harun, K. S. (2019). Implementing k-means clustering algorithm in collaborative trip advisory and planning system. *Periodicals of Engineering and Natural Sciences*, *7*(2), 723-740. https://doi.org/10.1016/j.annals.2020.102988

Ben-Shimon, D., Tsikinovsky, A., Rokach, L., Meisles, A., Shani, G., & Naamani, L. (2007). Recommender system from personal social networks. *Springer eBooks* (pp. 47–55). https://doi.org/10.1007/978-3-540-72575-6_8

Benzaghta, M. A., Elwalda, A., Mousa, M., Erkan, I., & Rahman, M. (2021). SWOT analysis applications: An integrative literature review. *Journal of Global Business Insights*, *6*(1), 55–73. https://doi.org/10.5038/2640-6489.6.1.1148

Borràs, J., Moreno, A., & Valls, A. (2014). Intelligent tourism recommender systems: A survey. *Expert Systems with Applications*, *41*(16), 7370–7389. https://doi.org/10.1016/j.eswa.2014.06.007

Burke, R. (2002). Hybrid recommender systems: Survey and experiments. *User Modeling and User-Adapted Interaction*, *12*(4), 331-370. https://doi.org/10.1023/A:1021240730564

Burke, R., Hammond, K. J., & Young, B. C. (1996). Knowledge-based navigation of complex information spaces. In the *National Conference on Artificial Intelligence*, 462–468. https://www.aaai.org/Papers/AAAI/1996/AAAI96-069.pdf

Cai, Y., Li, G., Wen, L., & Chang, L. (2024). Intellectual landscape and emerging trends of big data research in hospitality and tourism: A scientometric analysis. *International Journal of Hospitality Management*, *117*, 103633. https://doi.org/10.1016/j.ijhm.2023.103633

Çano, E., & Morisio, M. (2017). Hybrid recommender systems: A systematic literature review. *Intelligent Data Analysis*, *21*(6), 1487–1524. https://doi.org/10.3233/ida-163209

Chaudhari, K., & Thakkar, A. (2019). A comprehensive survey on travel recommender systems. *Archives of Computational Methods in Engineering*, *27*(5), 1545–1571. https://doi.org/10.1007/s11831-019-09363-7

https://dx.doi.org/10.24191/jcrinn.v9i2.438

Choi, I. Y., Ryu, Y. U., & Kim, J. K. (2021). A recommender system based on personal constraints for smart tourism city. *Asia Pacific Journal of Tourism Research*, *26*(4), 440–453. https://doi.org/10.1080/10941665.2019.1592765

Chouiref, Z., & Hayi, M. Y. (2022). Toward preference and context-aware hybrid tourist recommender system based on machine learning techniques. *Revue d'Intelligence Artificielle*, *36*(2), 195–208. https://doi.org/10.18280/ria.360203

Cibilić, I., Poslončec-Petrić, V., & Tominić, K. (2021). Implementing augmented reality in tourism. In the *Proceedings of the ICA*, *4*, 1–5. https://doi.org/10.5194/ica-proc-4-21-2021

Dara, S., Chowdary, C. R., & Kumar, C. (2019). A survey on group recommender systems. *Journal of Intelligent Information Systems*, *54*(2), 271–295. https://doi.org/10.1007/s10844-018-0542-3

De Pessemier, T., Dhondt, J., Vanhecke, K., & Martens, L. (2015). Travelwithfriends: A hybrid group recommender system for travel destinations. In *Workshop on Tourism Recommender Systems (Tours15), In Conjunction with the 9th ACM Conference on Recommender Systems (RECSYS 2015)* (pp. 51-60).

El Yebdri, Z., Benslimane, S. M., Lahfa, F., Barhamgi, M., & Benslimane, D. (2021). Context-aware recommender system using trust network. *Computing*, *103*(9), 1919–1937. https://doi.org/10.1007/s00607-020-00876-9

Esmaeili, L., Mardani, S., Golpayegani, S. A. H., & Madar, Z. Z. (2020). A novel tourism recommender system in the context of social commerce. *Expert Systems with Applications*, *149*, 113301. https://doi.org/10.1016/j.eswa.2020.113301

Fayyaz, Z., Ebrahimian, M., Nawara, D., Ibrahim, A., & Kashef, R. (2020). Recommendation systems: Algorithms, challenges, metrics, and business opportunities. *Applied Sciences*, *10*(21), 7748. https://doi.org/10.3390/app10217748

Filieri, R. (2015). What makes online reviews helpful? A diagnosticity-adoption framework to explain informational and normative influences in e-WOM. *Journal of Business Research*, *68*(6), 1261–1270. https://doi.org/10.1016/j.jbusres.2014.11.006

Filieri, R., Açikgöz, F., Ndou, V., & Dwivedi, Y. K. (2020). Is TripAdvisor still relevant? The influence of review credibility, review usefulness, and ease of use on consumers' continuance intention. *International Journal of Contemporary Hospitality Management*, *33*(1), 199–223. https://doi.org/10.1108/ijchm-05-2020-0402

Font, X., Torres-Delgado, A., Crabolu, G., Palomo Martinez, J., Kantenbacher, J., & Miller, G. (2021). The impact of sustainable tourism indicators on Destination Competitiveness: The European Tourism Indicator System. *Journal of Sustainable Tourism*, *31*(7), 1608–1630. https://doi.org/10.1080/09669582.2021.1910281

Fu, C. Y., Hu, M. C., Lai, J. H., Wang, H., & Wu, J. L. (2014). Travelbuddy: interactive travel route recommendation with a visual scene interface. In *MultiMedia Modeling: 20th Anniversary International Conference, MMM 2014, Dublin, Ireland, January 6-10, 2014, Proceedings, Part I 20* (pp. 219-230). Springer International Publishing. https://doi.org/10.1007/978-3-319-04114-8_19

Gaggi, O. (2013). Discovering local attractions from geo-tagged photos. In *Proceedings of the 28th Annual ACM Symposium on Applied Computing* (pp. 730-735). https://doi.org/10.1145/2480362.2480502

https://dx.doi.org/10.24191/jcrinn.v9i2.438

Garcia, A., Torre, I., & Linaza, M. T. (2013). Mobile Social Travel Recommender System. In Z. Xiang & I. Tussyadiah (Eds.), *Information and Communication Technologies in Tourism 2014* (pp. 3–16). Springer International Publishing. https://doi.org/10.1007/978-3-319-03973-2_1

Garcia, I., Sebastia, L., & Onaindia, E. (2011). On the design of individual and group recommender systems for tourism. *Expert Systems with Applications*, *38*(6), 7683–7692. https://doi.org/10.1016/j.eswa.2010.12.143

Gavalas, D., & Kenteris, M. (2011). A web-based pervasive recommendation system for mobile tourist guides. *Personal and Ubiquitous Computing*, *15*(7), 759–770. https://doi.org/10.1007/s00779-011-0389-x

Gemmell, J., Schimoler, T., Mobasher, B., & Burke, R. (2012). Resource recommendation in social annotation systems: A linear-weighted hybrid approach. *Journal of Computer and System Sciences*, *78*(4), 1160–1174. https://doi.org/10.1016/j.jcss.2011.10.006

Goldberg, D. T., Nichols, D. M., Oki, B. M., & Terry, D. B. (1992). Using collaborative filtering to weave an information tapestry. *Communications of the ACM*, *35*(12), 61–70. https://doi.org/10.1145/138859.138867

Gonzalo-Alonso, J., De Juan, P., Garcí-A-Hortelano, E., & Iglesias, C. Á. (2009). A hybrid collaborative filtering system for contextual recommendations in social networks. In *Lecture notes in computer science* (pp. 393–400). https://doi.org/10.1007/978-3-642-04747-3_31

Gretzel, U. (2011). Intelligent systems in tourism: A social science perspective. *Annals of tourism research*, *38*(3), 757-779. https://doi.org/10.1016/j.annals.2011.04.014

Guo, Q., Zhuang, F., Qin, C., Zhu, H., Xie, X., Xiong, H., & He, Q. (2020). A Survey on Knowledge Graph-Based Recommender Systems (arXiv:2003.00911). *arXiv*. http://arxiv.org/abs/2003.00911

Gupta, G., & Katarya, R. (2020). Research on understanding the effect of deep learning on user preferences. Arabian Journal for Science and Engineering, 46(4), 3247–3286. https://doi.org/10.1007/s13369-020-05112-2

Gürel, E. (2017). Swot analysis: A theoretical review. *Journal of International Social Research*, *10*(51), 994–1006. https://doi.org/10.17719/jisr.2017.1832

Hall, C. M., Gößling, S., & Scott, D. (2015). The evolution of sustainable development and sustainable tourism. In *The Routledge handbook of tourism and sustainability* (pp. 16–35). Routledge. https://doi.org/10.4324/9780203072332.ch2

Hamid, R. A., Albahri, A. S., Alwan, J. K., Al-Qaysi, Z., Albahri, O. S., Zaidan, A. A., Alnoor, A., Alamoodi, A. H., & Zaidan, B. B. (2021). How smart is e-tourism? A systematic review of smart tourism recommendation system applying data management. *Computer Science Review*, *39*, 100337. https://doi.org/10.1016/j.cosrev.2020.100337

He, J., & Chu, W. W. (2010). A social network-based Recommender System (SNRS). *Data Mining for Social Network Data*, 47–74. https://doi.org/10.1007/978-1-4419-6287-4_4

Huang, S., Wu, X., Wu, X., & Wang, K. (2023). Sentiment analysis algorithm using contrastive learning and adversarial training for poi recommendation. *Social Network Analysis and Mining*, *13*(1), 75. https://doi.org/10.1007/s13278-023-01076-x

https://dx.doi.org/10.24191/jcrinn.v9i2.438

Jain, D., Mistry, G., Inchanalkar, T., Dholakia, R., Dalal, J., & Rote, U. (2021). Travel buddy: Travel companion using knowledge graph attention networks. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3867158

Javed, U., Shaukat, K., A. Hameed, I., Iqbal, F., Mahboob Alam, T., & Luo, S. (2021). A Review of Content-Based and Context-Based Recommendation Systems. *International Journal of Emerging Technologies in Learning (iJET)*, *16*(03), 274. https://doi.org/10.3991/ijet.v16i03.18851

Kbaier, M. E. B. H., Masri, H., & Krichen, S. (2017). A Personalized Hybrid Tourism Recommender System. *2017 IEEE/ACS 14th International Conference on Computer Systems and Applications (AICCSA)*, 244–250. https://doi.org/10.1109/AICCSA.2017.12

Kontogianni, A., & Alepis, E. (2020). Smart tourism: State of the art and literature review for the last six years. *Array*, *6*, 100020. https://doi.org/10.1016/j.array.2020.100020

Lathia, N., Hailes, S., & Capra, L. (2009). Temporal collaborative filtering with adaptive neighbourhoods. In *Proceedings of the 32nd International ACM SIGIR Conference on Research and Development in Information Retrieval*, 796–797. https://doi.org/10.1145/1571941.1572133

Li, L., Chu, W., Langford, J., & Schapire, R. E. (2010). A contextual-bandit approach to personalized news article recommendation. In *Proceedings of the 19th international conference on World wide web* (pp. 661-670). https://doi.org/10.1145/1772690.1772758

Liang, T., He, L., Lu, C.-T., Chen, L., Yu, P. S., & Wu, J. (2017). A broad learning approach for context-aware mobile application recommendation. In *2017 IEEE International Conference on Data Mining (ICDM)*. https://doi.org/10.1109/icdm.2017.121

Lin, K., Yang, S., & Na, S.-G. (2022). Collaborative Filtering Algorithm-Based Destination Recommendation and Marketing Model for Tourism Scenic Spots. *Computational Intelligence and Neuroscience*, *2022*, 1–7. https://doi.org/10.1155/2022/7115627

Logesh, R., & Subramaniyaswamy, V. (2019). Exploring Hybrid Recommender Systems for Personalized Travel Applications. In P. K. Mallick, V. E. Balas, A. K. Bhoi, & A. F. Zobaa (Eds.), *Cognitive Informatics and Soft Computing* (Vol. 768, pp. 535–544). Springer Singapore. https://doi.org/10.1007/978-981-13-0617-4_52

Logesh, R., Subramaniyaswamy, V., & Vijayakumar, V. (2018). A personalised travel recommender system utilising social network profile and accurate GPS data. *Electronic Government*, *14*(1), 90. https://doi.org/10.1504/eg.2018.089538

Lorenzi, F., Loh, S., & Abel, M. (2011). PersonalTour: A recommender system for travel packages. In *2011 IEEE/WIC/ACM International Conferences on Web Intelligence and Intelligent Agent Technology* (Vol. 2, pp. 333-336). IEEE. https://doi.org/10.1109/WI-IAT.2011.69

Mahdi, A. J., & Esztergár-Kiss, D. (2023). Supporting scheduling decisions by using genetic algorithm based on tourists' preferences. *Applied Soft Computing*, *148*, 110857. https://doi.org/10.1016/j.asoc.2023.110857

Manggopa, H. K., Komansilan, T., Kumajas, S., & Batmetan, J. R. (2022). Augmented Reality for Geospatial in E-Tourism: Current status, research trends, and future directions. *International Journal of Information Technology and Education*, *1*(3), 38–55. https://doi.org/10.62711/ijite.v1i3.58

Masthoff, J. (2005). The pursuit of satisfaction: affective state in group recommender systems. In *International Conference on User Modeling* (pp. 297-306). Berlin, Heidelberg: Springer Berlin Heidelberg. https://doi.org/10.1007/11527886_39

https://dx.doi.org/10.24191/jcrinn.v9i2.438

Mathew, P. V. (2022). Sustainable tourism development: discerning the impact of responsible tourism on community well-being. *Journal of Hospitality and Tourism Insights*, *5*(5), 987-1001. https://doi.org/10.1108/JHTI-02-2021-0052

Menk, A., Sebastia, L., & Ferreira, R. (2019). Recommendation systems for tourism based on social networks: A survey. *arXiv preprint arXiv:1903.12099*. https://doi.org/10.48550/arXiv.1903.12099

Namugenyi, C., Nimmagadda, S. L., & Reiners, T. (2019). Design of a SWOT Analysis Model and its Evaluation in Diverse Digital Business Ecosystem Contexts. *Procedia Computer Science*, *159*, 1145–1154. https://doi.org/10.1016/j.procs.2019.09.283

Noshad, Z., Bouyer, A., & Noshad, M. (2021). Mutual information-based recommender system using autoencoder. *Applied Soft Computing*, *109*, 107547. https://doi.org/10.1016/j.asoc.2021.107547

Öğüt, H., & Onur Taş, B. K. (2012). The influence of internet customer reviews on the online sales and prices in hotel industry. *The Service Industries Journal*, *32*(2), 197–214. https://doi.org/10.1080/02642069.2010.529436

Ojagh, S., Malek, M. R., Saeedi, S., & Liang, S. (2020). A location-based orientation-aware recommender system using IOT smart devices and social networks. *Future Generation Computer Systems*, *108*, 97–118. https://doi.org/10.1016/j.future.2020.02.041

Olshannikova, E., Olsson, T., Huhtamäki, J., & Kärkkäinen, H. (2017). Conceptualizing big social data. *Journal of Big Data*, *4*(1), 1-19. https://doi.org/10.1186/s40537-017-0063-x

Partridge, M., & Calvo, R. A. (1998). Fast dimensionality reduction and simple PCA. *Intelligent Data Analysis*, *2*(3), 203–214. https://doi.org/10.1016/s1088-467x(98)00024-9

Pazzani, M. J., & Billsus, D. (2007). Content-based recommendation systems. In *The adaptive web: methods and strategies of web personalization* (pp. 325-341). Berlin, Heidelberg: Springer Berlin Heidelberg. https://doi.org/10.1007/978-3-540-72079-9_10

Pérez-Almaguer, Y., Yera, R., Alzahrani, A. A., & Martínez, L. (2021). Content-based group recommender systems: A general taxonomy and further improvements. *Expert Systems with Applications*, *184*, 115444. https://doi.org/10.1016/j.eswa.2021.115444

Pérez-Núñez, P., Luaces, O., Bahamonde, A., & Díez, J. (2019). Improving recommender systems by encoding items and user profiles considering the order in their consumption history. *Progress in Artificial Intelligence (Zeitschrift. Print)*, *9*(1), 67–75. https://doi.org/10.1007/s13748-019-00199-7

Pessemier, T. D., Dhondt, J., & Martens, L. (2017). Hybrid group recommendations for a travel service. *Multimedia Tools and Applications*, *76*(2), 2787–2811. https://doi.org/10.1007/s11042-016-3265-x

Ravi, L., & Vairavasundaram, S. (2016). A Collaborative Location Based Travel Recommendation System through Enhanced Rating Prediction for the Group of Users. *Computational Intelligence and Neuroscience*, *2016*, 1–28. https://doi.org/10.1155/2016/1291358

Ravi, L., Subramaniyaswamy, V., Vijayakumar, V., Chen, S., Karmel, A., & Devarajan, M. (2019). Hybrid Location-based Recommender System for Mobility and Travel Planning. *Mobile Networks and Applications*, *24*(4), 1226–1239. https://doi.org/10.1007/s11036-019-01260-4

Ren, X., Song, M., Haihong, E., & Song, J. (2017). Context-aware probabilistic matrix factorization modeling for point-of-interest recommendation. *Neurocomputing*, *241*, 38–55. https://doi.org/10.1016/j.neucom.2017.02.005

https://dx.doi.org/10.24191/jcrinn.v9i2.438

Resnick, P., & Varian, H. R. (1997). Recommender systems. *Communications of the ACM*, *40*(3), 56-58. https://doi.org/10.1145/245108.245121

Richa, N., & Bedi, P. (2019). Parallel context-aware multi-agent tourism recommender system. *International Journal of Computational Science and Engineering*, *20*(4), 536. https://doi.org/10.1504/ijcse.2019.104440

Sarkar, J. L., & Majumder, A. (2022). gTour: Multiple itinerary recommendation engine for group of tourists. *Expert Systems with Applications*, *191*, 116190. https://doi.org/10.1016/j.eswa.2021.116190

Sarkar, J. L., Majumder, A., Panigrahi, C. R., Roy, S., & Pati, B. (2022). Tourism recommendation system: a survey and future research directions. *Multimedia Tools and Applications*, *82*(6), 8983–9027. https://doi.org/10.1007/s11042-022-12167-w

Sarwar, B., Karypis, G., Konstan, J., & Riedl, J. (2001). Item-based collaborative filtering recommendation algorithms. *Proceedings of the 10th International Conference on World Wide Web*, 285–295. https://doi.org/10.1145/371920.372071

Sharma, K., Lee, Y.-C., Nambi, S., Salian, A., Shah, S., Kim, S.-W., & Kumar, S. (2024). *A Survey of Graph Neural Networks for Social Recommender Systems*. https://doi.org/10.1145/3661821

Sharpley, R. (2020). Tourism, Sustainable Development and the theoretical divide: 20 Years on. *Journal of Sustainable Tourism*, *28*(11), 1932–1946. https://doi.org/10.1080/09669582.2020.1779732

Su, X., Sperli, G., Moscato, V., Picariello, A., Esposito, C., & Choi, C. (2019). An edge intelligence empowered recommender system enabling cultural heritage applications. *IEEE Transactions on Industrial Informatics*, *15*(7), 4266–4275. https://doi.org/10.1109/tii.2019.2908056

Sun, Y.-Y., Lin, P.-C., & Higham, J. (2020). Managing tourism emissions through optimizing the Tourism Demand Mix: Concept and analysis. *Tourism Management*, *81*, 104161. https://doi.org/10.1016/j.tourman.2020.104161

Takács, G., & Tikk, D. (2012). Alternating least squares for personalized ranking. In *Proceedings of the Sixth ACM conference on Recommender systems* (pp. 83-90). https://doi.org/10.1145/2365952.2365972

Tarek, I. H., Munna, F. U., Mojumder, A. T., Rahman, M. M., Hossain, M. S., & Andersson, K. (2022). A Hybrid Hotel recommendation using collaborative, content based and knowledge based approach. *Intelligent Computing & Optimization*, 1049–1057. https://doi.org/10.1007/978-3-031-19958-5_98

Valdivia, A., Hrabova, E., Chaturvedi, I., Luzón, M. V., Troiano, L., Wang, Z., & Herrera, F. (2019). Inconsistencies on TripAdvisor reviews: A unified index between users and sentiment analysis methods. *Neurocomputing*, *353*, 3–16. https://doi.org/10.1016/j.neucom.2018.09.096

Vargas, S., & Castells, P. (2013). Exploiting the diversity of user preferences for recommendation. In *Proceedings of the 10th conference on open research areas in information retrieval* (pp. 129-136). https://citeseerx.ist.psu.edu/document?repid=rep1&type=pdf&doi=3ecc3ee0517907a0882f066502f734433720c39e

Vekariya, V., & Kulkarni, G. R. (2012). Notice of violation of IEEE publication principles - Hybrid recommender systems: Survey and experiments. In *2012 Second International Conference on Digital Information and Communication Technology and It's Applications (DICTAP)*, 469–473. https://doi.org/10.1109/DICTAP.2012.6215409

https://dx.doi.org/10.24191/jcrinn.v9i2.438

Wang, J., Wu, N., & Zhao, X. (2022). Personalized route recommendation with neural network enhanced search algorithm. *IEEE Transactions on Knowledge and Data Engineering (Print)*, *34*(12), 5910–5924. https://doi.org/10.1109/tkde.2021.3068479

Wang, W., Zhang, G., & Lu, J. (2016). Member contribution-based group recommender system. *Decision Support Systems*, *87*, 80–93. https://doi.org/10.1016/j.dss.2016.05.002

Wilcox, J. (2022). How can we get more accurate: Recommendations about human judgment. *SpringerBriefs in Psychology*, 113–133. https://doi.org/10.1007/978-3-031-19205-0_8

Xiang, Z., Du, Q., Ma, Y., & Fan, W. (2017). A comparative analysis of major online review platforms: Implications for social media analytics in hospitality and tourism. *Tourism Management*, *58*, 51–65. https://doi.org/10.1016/j.tourman.2016.10.001

Xiao, L., Sun, L., Ling, M., & Peng, Y. (2023). A survey of graph neural network based recommendation in social networks. *Neurocomputing*, *549*, 126441. https://doi.org/10.1016/j.neucom.2023.126441

Yang, X., Guo, Y., Liu, Y., & Steck, H. (2014). A survey of collaborative filtering based social recommender systems. *Computer Communications*, *41*, 1–10. https://doi.org/10.1016/j.comcom.2013.06.009

Yin, H., Lu, X., Wang, C., Yu, N., & Zhang, L. (2010). Photo2trip: an interactive trip planning system based on geo-tagged photos. In *Proceedings of the 18th ACM international conference on Multimedia* (pp. 1579-1582). https://doi.org/10.1145/1873951.1874291

Yochum, P., Chang, L., Gu, T., & Zhu, M. (2020). Linked open data in location-based recommendation system on tourism domain: A survey. *IEEE Access*, *8*, 16409–16439. https://doi.org/10.1109/access.2020.2967120

Yuan, Y., & Zheng, W. (2024). Your trip, your way: An adaptive tourism recommendation system. *Applied Soft Computing*, *154*, 111330. https://doi.org/10.1016/j.asoc.2024.111330

Zeng, L., Guan, J., & Chen, B. (2023). MSBPR: A multi-pairwise preference and similarity based Bayesian personalized ranking method for recommendation. *Knowledge-Based Systems*, *260*, 110165. https://doi.org/10.1016/j.knosys.2022.110165

Zhang, S., Liu, W., Deng, X., Xu, Z., & Choo, K. R. (2018). Micro-blog topic recommendation based on knowledge flow and user selection. *Journal of Computational Science*, *26*, 512–521. https://doi.org/10.1016/j.jocs.2017.10.021

Zhang, S., Yao, L., Sun, A., & Tay, Y. (2020). Deep learning based recommender system: A survey and new perspectives. *ACM Computing Surveys*, *52*(1), 1–38. https://doi.org/10.1145/3285029

Zhou, X., Wang, M., & Li, D. (2017). From stay to play – A travel planning tool based on crowdsourcing user-generated contents. *Applied Geography*, *78*, 1–11. https://doi.org/10.1016/j.apgeog.2016.10.002

https://dx.doi.org/10.24191/jcrinn.v9i2.438