 DOI: 10.22616/RRD.31.2025.042

RECOMMENDER SYSTEMS IN TOURISM: A COMPREHENSIVE SCIENTIFIC REVIEW

***Pradeep Sharma, Tatjana Rubina**
Latvia University of Life Sciences and Technologies, Latvia
*Corresponding author's email: pradeepchobe@gmail.com

Abstract
The rapid development within the tourism sector, coupled with the widespread accessibility of digital information, has necessitated the development and use of advanced tools to aid in navigating and managing the vast amounts of data within the industry. One of the main tools that have emerged as a solution to this issue is recommender systems, which can offer customized suggestions, enhancing the user experience by matching personal preferences with services, accommodations, activities, and destinations. This paper examines the integration of recommender systems into the tourism industry to support data analysis and enhance user experience through personalized recommendations. To achieve that, the paper presents a study that utilizes the mixed method approach to research with both quantitative and qualitative research methods to analyze existing literature on the application of recommender systems within tourism, highlighting their potential to transform user experience. In this, various algorithms related to recommender systems are reviewed. In addition, the paper also analyzes the challenges associated with tourism, like the need for real-time updates, seasonal variations, and the dynamic nature of tourist preferences, among others. The paper presents conclusions that include recommendations on the most suitable algorithms and approaches to augment the accuracy, robustness, and user-friendliness of recommender systems in tourism as well as a discussion of future directions.
Keywords: recommender systems, tourism, information filtering, collaborative filtering.

Introduction

Recommender systems (or recommendation systems) represent a subclass of machine learning (ML), specifically within the domain of information filtering which utilizes data to predict user preferences, narrow choices, and identify desired options from a large set of alternatives. They work by employing complex algorithms to deliver personalized recommendations based on user's preferences, past behavior, and historical data (Bulchand-Gidumal, 2022). They are especially helpful in scenarios where users have to decide on something from a potentially overwhelming list of things (Fararni et al., 2021). Today, recommender systems are used in multiple domains, with key examples including playlist generators for music and video services, service/product recommenders for online service providers and e-commerce shops, open web content recommenders, and content recommenders for social media networks. The systems can operate using single inputs, such as music, or multiple across and within platforms like search queries, books, and news, among others. Recommender systems can also be used for particular topics like online dating, restaurants, and financial services to provide tailored suggestions to users (Chaudhari & Thakkar, 2019).

In recent years, other sectors such as tourism have also started employing the capabilities of these systems (Fararni et al., 2021). In fact, recommender systems have grown to become a cornerstone in modern travel planning. This has resulted in a complete revolution of how users explore destinations, accommodations, and activities within different travel companies (Fararni et al., 2021). Within this sector, recommender systems have streamlined decision-making processes by providing tailored suggestions and options (Felfernig et al., 2018). For instance, the application of recommender systems in areas of tourism, such as customer service, has significantly simplified the planning phase for travelers. These systems analyze user interactions together with their preferences and historical patterns and use this data to offer personalized travel itineraries and suggestions with the aim of enhancing user experiences (Bulchand-Gidumal, 2022). However, these systems are not without limitations. For instance, concerns persist regarding the accuracy of recommendations as well as potential biases in interpreting user preferences. Likewise, there are also other concerns regarding the critical aspect of safeguarding user data and privacy (Chang et al., 2019).

As such, it is essential to understand the key concepts and aspects related to recommender systems before embarking on any attempt to develop or implement such a system. This research aims to explore the existing literature on recommender systems within the tourism domain to provide a comprehensive understanding of such concepts through an in-depth analysis of existing publications and a review of current state of art recommender systems. The focus lies in comprehending their underlying mechanisms, strengths, and limitations to identify potential areas of improvement. Therefore, the research ultimately seeks to unveil opportunities for enhancement and innovation by evaluating the successes and challenges faced by current systems.

Literature review

Systems use information registered on their database or from user profiles to determine travellers' preferences (Bulchand-Gidumal, 2022). Such an approach makes predictions based on the travel patterns and the visitors' history (Felfernig et al., 2018; Kontogianni & Alepis, 2020). However, Deldjoo et al. (2020) state that the dynamic nature of travel preferences would require more robust systems that would be able to predict based on real-time information obtained from the user. Having real-time predictions ensures that the system can advise travellers based on the current information as a method of complementing the information registered in the past. This enhances the prediction accuracy and ultimately improves the ability to correctly provide customers with better travel choices (Chang et al., 2019). Also, there is a need to capture and analyse different forms of information such as graphics and videos. Graphics and video content can contain more detailed information compared to text content. Systems that can process this information are likely to have more data for reference when making predictions (Kontogianni & Alepis, 2020), thus higher accuracy may be achieved.

One of the main challenges with the recommender system is the availability of sufficient data (Niu et al., 2022). Prediction models rely heavily on availability of data to make more accurate and precise decisions. Availability of huge amounts of data ensures that there is enough information to make a prediction (Berkani, 2018). It is therefore important to have a recommender system that will capture and analyse information in a more efficient way to improve the accuracy of predictions (Logesh et al., 2018). Correcting different formats of information and including this data in predictions will increase the performance of the recommender system predictions (Massimo & Ricci, 2022). A review of the literature, reveals that recommender systems have become integral to modern travel planning, providing users with personalized recommendations based on their preferences, behaviours, and historical data (Beheshti et al., 2020). These systems have significantly impacted the tourism sector by streamlining decision-making processes and simplifying the planning phase for travellers (Niu et al., 2022). The application of complex algorithms allows these systems to analyse user interactions, providing tailored suggestions for accommodations, activities, and destinations, ultimately enhancing user experiences (Gillingham, 2019).

However, despite their widespread use and positive impacts, recommender systems in the tourism domain are not without challenges (Doborjeh et al., 2021). Accuracy of recommendations and potential biases in interpreting user preferences remain concerning, along with the critical issue of safeguarding user data and privacy (Chang et al., 2019). This research explores the existing literature on recommender systems in tourism, delving into their mechanisms, strengths, and limitations to identify areas for improvement and innovation.

The majority of existing travel recommendation systems rely on data from their databases and user profiles to predict travellers' preferences based on historical patterns and travel history (Bulchand-Gidumal, 2022). However, the dynamic nature of travel preferences necessitates more robust systems capable of real-time predictions, supplementing past information with current data for enhanced accuracy (Pantano et al., 2019). Real-time predictions ensure that users receive advice based on the most recent information, contributing to more accurate and up-to-date recommendations (Hamid et al., 2021).

In addition to real-time considerations, the need to capture and analyse diverse forms of information, such as graphics and videos, poses another challenge and opportunity for improvement in recommender systems (Pantano et al., 2019; Massimo & Ricci, 2022). While processing power requirements may be higher for analysing graphics and video content (Kontogianni & Alepis, 2020; Li et al., 2021), the potential for more detailed information could lead to higher prediction accuracy. As suggested by Roy & Dutta (2022), systems capable of effectively processing and integrating this type of information can enhance their reference data, ultimately improving prediction accuracy.

A critical challenge faced by recommender systems is the availability of sufficient data (Bulchand-Gidumal, 2022). Prediction models heavily rely on large datasets to make accurate decisions (Missaoui et al., 2019). The availability of extensive data ensures that recommender systems have enough information to generate precise predictions (Sánchez, 2019). It is imperative to develop recommender systems that efficiently capture and analyse information, correcting for different formats, and incorporating diverse data types to boost prediction accuracy (Renjith et al., 2020).

Following an in-depth review of the literature, several key trends and findings have emerged. Firstly, the importance of real-time information for accurate predictions has been highlighted as a key factor in enhancing recommender systems (Missaoui et al., 2019). Secondly, the capability to process and analyse diverse forms of information, such as graphics and videos, is seen as a potential avenue for improving recommendation accuracy (Doborjeh et al., 2021). Finally, addressing the challenge of sufficient data availability is identified as crucial for the performance of recommender systems.

Thus, the existing literature on recommender systems in the tourism domain emphasizes their significant impact on travel planning while acknowledging challenges related to accuracy, biases, and data privacy. This research contributes to the field by exploring opportunities for improvement and innovation, particularly focusing on real-time predictions, diverse information types, and efficient data capture and analysis. The identified trends and findings lay the groundwork for the development of robust and user-friendly recommender systems in the tourism industry.

The efficiency of recommender systems relies on the availability of information from the customer and the ability of the existing system to process the data and derive insights from it (Walek & Fojtik, 2020). Also, the accuracy of the recommender system when making predictions requires accurate and up-to-date information (Kontogianni & Alepis, 2020). While many of the existing systems used records stored in their databases over time, using real-time information can be more effective (Silveira et al., 2017). Focusing on the trends and research that has been carried out on recommender systems, the study presented in this paper shows the attempts being made to enhance their performance through collected information.

In addition to the challenges aforementioned, another significant aspect influencing the effectiveness of recommender systems is user engagement and feedback mechanisms (Li et al., 2021). Engaging users in the recommendation process enhances the overall user experience and provides valuable data to be used in the improvement of recommendation algorithms (Renjith et al., 2020), which can be done by implementing interactive features such as rating systems, reviews, and personalized feedback loops (Wang, 2023). This potentially fosters a sense of involvement and ownership among users, leading to higher satisfaction levels and increased trust in the recommendations provided (Silveira et al., 2017).

Integration of social media data and collaborative filtering techniques additionally presents an opportunity for enhancing recommendation accuracy (Pradhan & Pal, 2020). By analysing users' social connections, shared interests, and past behaviours within social networks, systems can efficiently generate more personalized recommendations (Missaoui et al., 2019). Insights gained from such social media data ensure that users are given contextually relevant recommendations that are relevant to their planning and decision-making process (Pantano et al., 2019). Leveraging the data insights from social networks enriches the recommendation process and helps to mitigate issues of data sparsity and cold starts (Gao et al., 2022).

Additionally, adoption of hybrid recommendation approaches that combine content-based, collaborative, and knowledge-based filtering methods is theorized to overcome the limitations of individual techniques (Suryawanshi & Narnaware, 2020). By leveraging the strengths of different recommendation paradigms, hybrid systems promise more comprehensive and accurate recommendations that cater to the diverse user preferences in the tourism and travel field (Zhang et al., 2019).

The objective of this paper is to propose effective methods for collecting quality data required by prediction models by analyzing the current trends and efforts made through research to enhance the performance of the current recommender systems. Also, the study includes a survey that collects and analyzes different features of the existing systems that enable them to collect relevant information for efficient recommendations. Ultimately, the report will bring together facts about current research and existing systems in the travel industry. It will also include recommendations of the best approaches that can be applied and tested for enhancing the accuracy and precision of a recommender system.

Materials and Methods

A mixed-method approach was adopted in this study to enable a more comprehensive understanding of diverse perspectives on the topic and to support a thorough analysis and discussion of the results. The method integrates a systematic review and a qualitative survey to comprehensively investigate the landscape of recommender systems in the tourism sector.

Systematic Review

The significance of this method to the study is that it helps to extensively and intensively examine existing literature on recommender systems within the tourism domain. As such, the study heavily follows the guidelines provided by Gridach (2020) and draws insights from the application of this method by Zou et al. (2019). Relevant databases such as ACM Digital Library, IEEE Xplore, Scopus, and Google Scholar were searched following the established protocols for systematic reviews. A well-developed search strategy is necessary for effective use of this method. The strategy includes a well-framed search query containing keywords such as 'recommender systems', 'tourism', 'travel recommendations', and related terms to identify peer-reviewed articles, conference papers, and relevant publications.

On the other hand, the inclusion/exclusion criteria were defined to ensure the selection of studies that meet specific quality standards and relevance to the research objectives. Data extraction includes identifying key themes, mechanisms, strengths, limitations, and emerging trends related to recommender systems in the tourism industry.

Findings and Discussion

The required resources for the study were obtained by following the guidelines outlined in PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) (Kontogianni & Alepis, 2020). At the start, a total of 144 publications were identified as being pertinent to the study based on a selection of keywords detailed in Table 1 below. These articles were further reviewed by applying various filtering criteria, including the presence of an abstract, the relevance of the title and discussion to the study topic, clarity of results, the inclusion of a conclusion and references, publication information, and compliance with ethical standards. These measures were taken to ensure the articles' relevance and quality for the study. Figure 1 below depicts the process followed in selecting the article to be used in the study:

Table 1 below shows the inclusion and exclusion criteria included in PRISMA, showing the guidelines used to assess the articles for exclusion or inclusion.

Table 2 below summarizes the main contributions of the scientific publications identified for the study. The publications are grouped in 6 categories based on their discussion in relation to the impact and accuracy of recommender systems.

Analysis

Recommender systems are valuable tools for the tourism sector due to their capabilities of enhancing the user experience by suggesting destinations, activities, accommodations, and travel packages tailored to individual preferences.

This repository of historical data acts as the raw materials for refining recommendations and optimizing system performance over time.

Figure 1
A PRISMA diagram depicting the so selection process of articles for the study

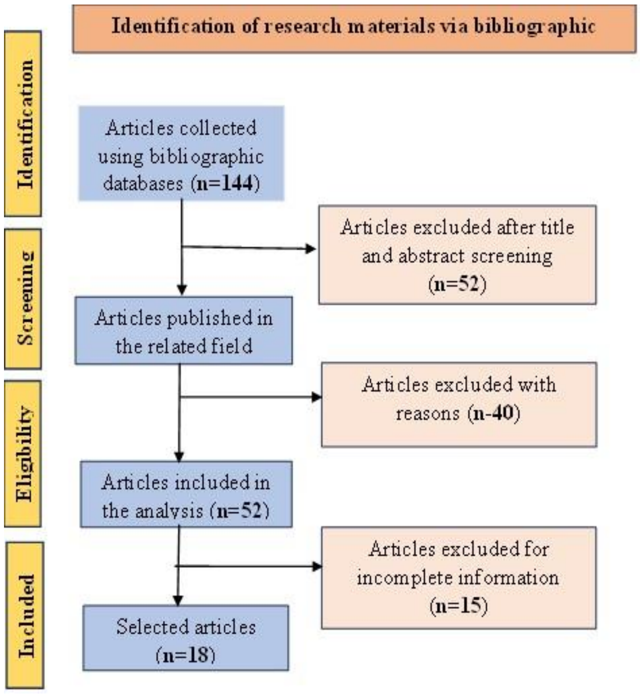


Table 1
Exclusion and inclusion for selection of articles for the research

Criteria	*Inclusion Criteria*	*Exclusion criteria*
Kinds of study	Peer-reviewed original publications	Editorials, reports, communication letters, white papers, and theses
Language	Publications written in English	Non-English and duplicate publications
Year of publication	Scientific articles and papers published between 2020 and 2024 (for the analysis of results)	Not relevant to the time range specified
Source	Papers and articles published only in conferences and academic journals	Publications that are missing key relevant information and review articles
Intervention	Recommender systems in tourism, information filtering	Basic and traditional methods
Region	Not limited to specific regions	–
Settings	Recommender systems	Not germane to recommender systems

The model Figure 2 depicts a recommendation system for tours and travel business, comprising four major components: the client, the application, a database server, and a recommendation computing system. It includes the following processes:

1. Acquisition of user data: The system initiates by gathering useful data from the user such as their preferences, past activities, location, and demographics.
2. Initial recommendation: The system then leverages the acquired user data to offer recommendations even before engaging the recommendation system. This initial step swiftly provides the users with custom suggestions, enhancing their overall experience from the outset.
3. Processing and storage of data: The application renders these recommendations to the users, and while they browse and use it, more data is obtained and stored in a robust database alongside the initial user data. This ensures accessibility for future reference and analysis.

Table 2
Systematic research findings

Category	***Authors***	***Main Contribution***
Pivotal Role in Travel Planning	Huang et al. (2022)	Acknowledged the transformative impact of recommender systems, streamlining decision-making processes and enhancing the planning phase for travellers.
	Kontogianni & Alepis (2020)	Highlighted the significant impact of recommender systems in the tourism sector, simplifying decision-making processes through tailored suggestions.
Accuracy and Biases	Al Fararniet al. (2021)	Raised concerns regarding the accuracy of recommendations and potential biases in interpreting user preferences within recommender systems.
Reliance on Historical Data	Zhang Mu et al. (2010)	Identified concerns related to safeguarding user data and privacy, addressing critical issues in the ethical implementation of recommender systems.
Reliance on Historical Data	Yoon & Choi (2023)	Explored existing travel recommendation systems' reliance on historical data and user profiles, emphasizing the dynamic nature of travel preferences.
Importance of Real-Time Information	Suryawanshi & Narnaware (2020)	Recognized the crucial role of real-time information in enhancing recommender systems, ensuring accurate predictions based on current data and historical patterns.
Diverse Information Types	Berkani (2021)	Explored the challenge and opportunity of diverse information types, such as graphics and videos, in improving prediction accuracy within recommender systems.
Enhancing Prediction Accuracy	Wang (2023)	Emphasized the potential for systems capable of processing graphics and video content to achieve higher prediction accuracy and reference data.
Data Availability Challenge	Massimo & Ricci (2022)	Highlighted the critical challenge of data availability, emphasizing the importance of extensive and efficient data capture and analysis for accurate predictions.

4. Preprocessing and data frame preparation: Prior to analysis, historical user data undergoes preprocessing to cleanse, transform, and data is organize it into a structured format conducive to identifying intricate patterns and associations within the data.

5. Algorithm selection and integration (R): The recommendation system selects and integrates suitable recommendation algorithms, such as **Apriori or FP Growth.** These sophisticated algorithms play a pivotal role in identifying.

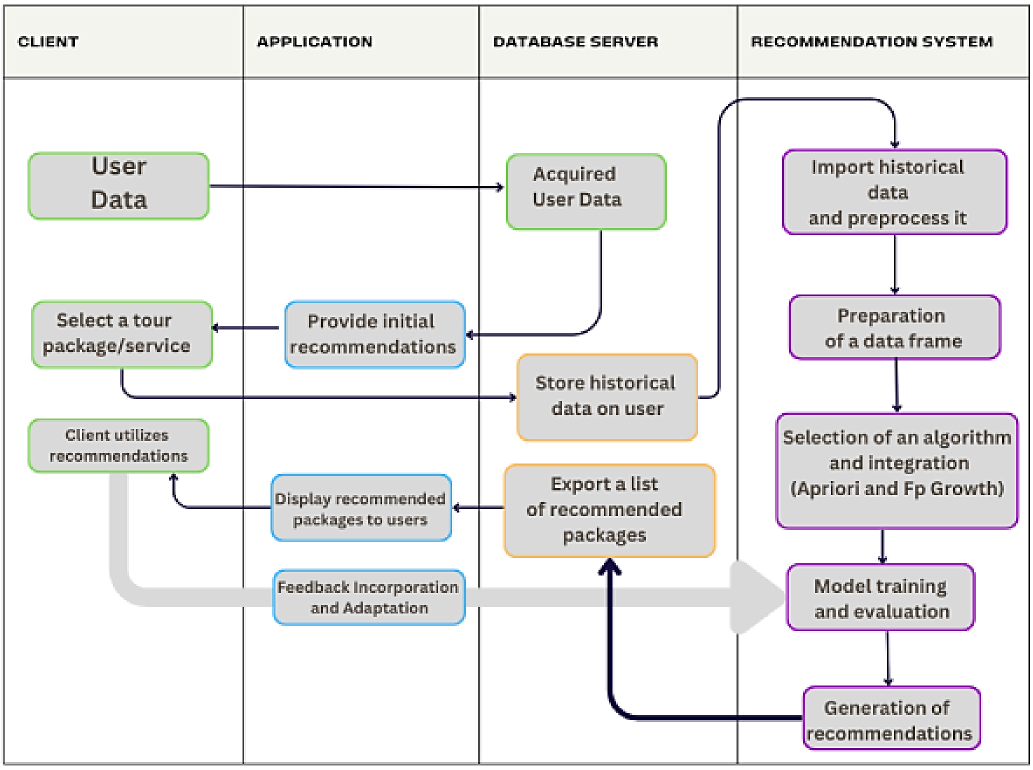
- Apriori Algorithm: This algorithm operates by identifying the frequency of item sets in transactional databases. Using prior data of the frequency of item sets, the algorithm discovers associations between different items. In the context of tour and travel, recommendations, Apriori can aid in the identification of common combinations of destinations, activities, and preferences, thereby facilitating the generation of personalized recommendations based on users past interactions.
- FP Growth Algorithm: FP Growth algorithm, on the other hand, utilizes a frequent pattern tree structure to mine frequent item sets directly without explicitly generating candidate sets. It can efficiently handle large datasets and is particularly effective for dense databases. In this context, FP Growth can identify frequent patterns of user preferences and activities, thus assisting in the generation of personalized recommendations tailored to individual preferences.

6. Model training and evaluation: The selected algorithms undergo a series of training using pre-processed data, followed by a thorough evaluation to guarantee efficacy in generating accurate recommendations. This iterative process ensures that the recommendation models are continuously refined and optimized.

7. Generation and export of recommendations: The recommendation system then generates personalized recommendations using the trained models. These are tailored to individual user preferences and past interactions. The recommendations are then exported for further utilization, ensuring seamless integration into the user experience.

8. Feedback and improvement: For the system to suffice, it must actively solicit feedback from users regarding the recommendations provided. The feedback is then analysed in an iterative process to refine the recommendation algorithms and adjust parameters, ultimately enhancing the quality and relevance of recommendations over time.

Figure 2
Recommender system flowchart



Source: taken from Hang Lei et al., 2018 and adopted by author.

Results and Discussion

The working hypothesis of the study posits that recommender systems play a vital role in the tourism sector. The results of the analysis consistently support the hypothesis by confirming the significance of recommender systems in the tourism sector. Manifold literature reviewed in this study confirms that these systems considerably boost user experience, which leads to higher engagement and conversion rates. For instance, research by Massimo & Ricci (2022), Berkani (2021) and Yoon & Choi (2023) revealed that tailored recommendations resulted in more booking conversions by up to 15 percent, accentuating the significance of recommender systems in this sector. Some of the key observed benefits of recommender systems in tourism include:

1. *Pivotal Role in Travel Planning*

Recommender systems have been conclusively determined as performing a crucial function in travel planning and changing the decision-making process through personalized recommendations based on user preferences and historical data (Missaoui et al., 2019). This result highlights the change that these systems have on user experience among tourism companies.

2. *Accuracy Concerns and Potential Biases*

The persistence of reservations for recommendation accuracy and prejudices in interpreting user preferences have been identified as significant challenges faced by recommender systems associated with the tourism sector (Roy & Dutta, 2022). Addressing these concerns is of utmost importance, as it ensures the dependability and credibility of recommendations, thereby enhancing user satisfaction.

3. *Historical Data and User Profiles*

One obvious result is that existing travel recommendation systems are inescapably dependent on historical data and user profiles to predict the preferences of travellers based on travel history and patterns (Gillingham, 2019). This underscores the dynamic shift of travel preferences and stresses for further development of more flexible systems that can afford predictions in real-time.

4. *Importance of Real-Time Information*

Real-time data has been unambiguously deemed to be essential for the improvement of recommender systems, providing timely information and historical data (Suryawanshi & Narnaware, 2020). This result emphasizes the need to develop adaptive recommender systems that respond in real time based on users' evolving preferences, which improves suggestions for relevance and timeliness.

5. *Diverse Information Types: a Challenge and an Opportunity*

Notably, diverse forms of information including images and videos in travel advice have been identified as a very practical finding that has to be addressed (Berkani, 2021; Wang, 2023). While taking note of the increased processing power needs, this assumes a possibility for providing more detailed information that can represent an opportunity to upgrade recommender systems.

6. *Critical Challenge of Data Availability*

The fundamental challenge of data scarcity has been identified, as many predictive models rely heavily on large datasets to generate accurate results (Massimo & Ricci, 2022). This highlights the urgent necessity to resolve data availability problems by creating appropriate development of effective strategies for data capture and analysis in order to provide successful functionality recommender systems.

Besides these specific results, the qualitative insights resulting from data gathered through a mixed-method approach add useful information about users' experiences and preferences that make an ideal complement to trends found in the systematic review. These aggregated findings serve as a solid basis for future research and development initiatives, helping design improved advisors that are more flexible, and reflective of the evolving nature of travel planning.

Conclusions

1. This study offers a detailed examination of recommender systems in the tourism sector, presenting key observations that illustrate the current state and indicate potential future developments. The study provides concrete evidence of the significance of recommender systems through a qualitative analysis that provides a strong basis for recommender systems' ground-breaking ability in the tourism sector. First of all, it cannot be overstated that these systems play a decisive role in travel planning; they completely revolutionize the principles and procedures for decision-making by offering adaptive suggestions based on user preferences and historical data. While consistent reservations as well as accuracy and possible biases underscore the need for continuous work on refining these systems, it is vital that they are able to present reliable suggestions, improving user satisfaction and trust.

2. While this approach is effective, it highlights the need for more adaptive systems to manage real-time predictions. Given the dynamic nature of travel preferences, the industry shall strive to provide recommendations that reflect evolving user behaviour, with an emphasis on integrating real-time information into system functionalities. In addition, the incorporation of diverse information types, such as charts and video highlights that enhance the processing capacities of recommender systems, may lead to improved prediction accuracy and the provision of more detailed recommendations.

3. A major priority concerning the future of recommender systems is to address the issues related to data accessibility i.e. Data privacy and regulations (GDPR, CCEA), Siloed data across platform, Limited access data to third party and Data format & quality issue. In the future, recommender systems in tourism will likely face an impasse between revolution and further advancement. In this regard, future research should focus on enhancing accuracy, eliminating biases and data imperfections, and developing more adaptable user-friendly, and highly reliable recommender systems.

References

Beheshti, A., Yakhchi, S., Mousaeirad, S., Ghafari S. M., Goluguri, S. R., & Edrisi, M. A. (2020). Towards Cognitive Recommender Systems, *Algorithms, 13*(8), 176. https://doi.org/10.3390/a13080176

Berkani, L. (2018). Using a Social-Based Collaborative Filtering with Classification Techniques. *IFIP advances in information and communication technology,* 522, 267–278. https://doi.org/10.1007/978-3-319-89743-1_24

Berkani, L. (2021). Recommendation of items using a social-based collaborative filtering approach and classification techniques, *International Journal of Data Mining, Modelling and Management*, *13*(1/2), 137. https://doi.org/10.1504/ijdmmm.2021.10035118

Bulchand-Giduma, J. (2022). Impact of Artificial Intelligence in Travel, Tourism, and Hospitality. *Handbook of e-Tourism*, 1943–1962. https://doi.org/10.1007/978-3-030-48652-5_110

Chang, Y. C., Ku, C. H., & Chen, C. H. (2019). Social media analytics: Extracting and visualizing Hilton hotel ratings and reviews from TripAdvisor. *International Journal of Information Management*, *48*(2), 263–279. https://doi.org/10.1016/j.ijinfomgt.2017.11.001

Chaudhari, K. & Thakkar, A. (2019). A Comprehensive Survey on Travel Recommender Systems. *Archives of Computational Methods in Engineering*, 27, 1545–1571. https://doi.org/10.1007/s11831-019-09363-7

Deldjoo, Y., Schedl, M., Cremonesi, P., & Pasi, G. (2020). Recommender Systems Leveraging Multimedia Content. *ACM Computing Surveys, 53*(5), 1-38. https://doi.org/10.1145/3407190

Doborjeh, Z., Hemmington, N., Doborjeh, M., & Kasabov, N. (2021). Artificial intelligence: a systematic review of methods and applications in hospitality and tourism. *International Journal of Contemporary Hospitality Management, 34*(3), 1154-1176. https://doi.org/10.1108/ijchm-06-2021-0767

Fararni, K. A., Nafis, F., Aghoutane, B., Yahyaouy, A., Riffi, J., & Sabri, A. (2021). Hybrid recommender system for tourism based on big data and AI: A conceptual framework. *Big Data Mining and Analytics, 4*(1), 47–55. https://doi.org/10.26599/bdma.2020.9020015

Felfernig, A., Polat-Erdeniz, S., Uran, C., Reiterer, S., Atas, M., Tran, T. N. T., …, & Dolui, K. (2018). An overview of recommender systems in the internet of things. *Journal of Intelligent Information Systems, 52*(2), 285–309. https://doi.org/10.1007/s10844-018-0530-7

Gao, C., Wang, X., He, X., & Li, Y. (2022). Graph Neural Networks for Recommender System. *Proceedings of the Fifteenth ACM International Conference on Web Search and Data Mining,* 1623 – 1625. https://doi.org/10.1145/3488560.3501396

Gillingham, P. (2019). Can Predictive Algorithms Assist Decision-Making in Social Work with Children and Families? *Child Abuse Review, 28*(2), 114–126. https://doi.org/10.1002/car.2547

Gridach, M. (2020). Hybrid deep neural networks for recommender systems. *Neurocomputing*, 413, 23–30. https://doi.org/10.1016/j.neucom.2020.06.025

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

Hang, L., Sang-Hun., K., Wenquan, J., & Do-Hyeun, K. (2018). Design and Implementation of an Optimal Travel Route Recommender System on Big Data for Tourists in Jeju. *Application Research to Small and Medium-Sized Enterprises (SMEs), 6*(8), 133. https://doi.org/10.3390/pr6080133

Huang, A., Chao, Y., Mora, Velasco, E. de la, Bilgihan, A., & Wei, W. (2021). When artificial intelligence meets the hospitality and tourism industry: an assessment framework to inform theory and management. *Journal of Hospitality and Tourism Insights, 5*(5), 1080-1100. https://doi.org/10.1108/jhti-01-2021-0021

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

Li, X., Law, R., Xie, G., & Wang, S. (2021). Review of tourism forecasting research with internet data. *Tourism Management,* 83, Article 104245. https://doi.org/10.1016/j.tourman.2020.104245

Liu, H., Wang, Y., Peng, O., Wu, F., Gan, L., Pan, L., & Jiao, P. (2020). Hybrid neural recommendation with joint deep representation learning of ratings and reviews. *Neurocomputing*, 374, 77–85. https://doi.org/10.1016/j.neucom.2019.09.052

Logesh, R., Subramaniyaswamy, V., Vijayakumar, V., & Li, X. (2018). Efficient User Profiling Based Intelligent Travel Recommender System for Individual and Group of Users. *Mobile Networks and Applications, 24*(3), 1018–1033. https://doi.org/10.1007/s11036-018-1059-2

Massimo, D. & Ricci, F. (2022). Building effective recommender systems for tourists. *AI Magazine, 43*(2), 209–224. https://doi.org/10.1002/aaai.12057

Missaoui, S., Kassem, F., Viviani, M., Agostini, A., Faiz, R., & Pasi, G. (2019). LOOKER: a mobile, personalized recommender system in the tourism domain based on social media user-generated content. *Personal and Ubiquitous Computing, 23*(2), 181–197. https://doi.org/10.1007/s00779-018-01194-w

Mu, Z., Shan, C., Jing, L., & Lei, F. (2010). Design of the tourism-information-service-oriented collaborative filtering recommendation algorithm. *2010 International Conference on Computer Application and System Modeling (ICCASM 2010),* Taiyuan, V13-361-V13-365. https://doi.org/10.1109/iccasm.2010.5622799

Niu, T., Song, M., Wang, X., & Wang, L. (2022). Tourism Destination Recommendation and Marketing Model Analysis Based on Collaborative Filtering Algorithm. *Mobile Information Systems*, 2022, Article 5905490, 1–10. https://doi.org/10.1155/2022/5905490

Pantano, E., Priporas, C.-V., Stylos, N., & Dennis, C. (2019). Facilitating tourists' decision making through open data analyses: A novel recommender system. *Tourism Management Perspectives*, 31, 323–331. https://doi.org/10.1016/j.tmp.2019.06.003

Pradhan, T. & Pal, S. (2020). A hybrid personalized scholarly venue recommender system integrating social network analysis and contextual similarity. *Future Generation Computer Systems,* 110, 1139 (1166). https://doi.org/10.1016/j.future.2019.11.017.

Renjith, S., Sreekumar, A., & Jathavedan, M. (2020). An extensive study on the evolution of context-aware personalized travel recommender systems. *Information Processing & Management, 57*(1). https://doi.org/10.1016/j.ipm.2019.102078

Roy, D. & Dutta, M. (2022). A systematic review and research perspective on recommender systems. *Journal of Big Data, 9*(1). https://doi.org/10.1186/s40537-022-00592-5

Sánchez, P. (2019). Exploiting contextual information for recommender systems oriented to tourism. *Proceedings of the 13th ACM Conference on Recommender Systems*, 601-605. https://doi.org/10.1145/3298689.3347062

Silveira, T., Zhang, M., Lin, X., Liu, Y., & Ma, S. (2017). How good your recommender system is? A survey on evaluations in recommendation. *International Journal of Machine Learning and Cybernetics, 10*(5), 813–831. https://doi.org/10.1007/s13042-017-0762-9

Suryawanshi, S. & Narnaware, M. (2020). Design and analysis of collaborative filtering based recommendation system. *International Journal of Engineering Applied Sciences and Technology*, *5*(4), 223–226. https://doi.org/10.33564/ijeast.2020.v05i04.031

Walek, B., & Fojtik, V. (2020). A hybrid recommender system for recommending relevant movies using an expert system. *Expert Systems with Applications,* 158, Article 113452. https://doi.org/10.1016/j.eswa.2020.113452

Wang, Z. (2023). Intelligent recommendation model of tourist places based on collaborative filtering and user preferences, *Applied Artificial Intelligence*, *37*(1). https://doi.org/10.1080/08839514.2023.2203574

Yoon, J. & Choi, C. (2023). Real-Time Context-Aware Recommendation System for Tourism. *Sensors*, *23*(7), Article 3679. https://doi.org/10.3390/s23073679

Zhang, Q., Sun, H., Wu, X., & Zhong, H. (2019). Edge Video Analytics for Public Safety: A Review. *Proceedings of the IEEE*, *107*(8), 1675-1696. https://doi.org/10.1109/jproc.2019.2925910

Zou, L., Xia, L., Ding, Z., Song, J., Liu, W., & Yin, D. (2019). Reinforcement Learning to Optimize Long-term User Engagement in Recommender Systems. *arXiv:1902.05570v4 [cs.IR]*. https://arxiv.org/abs/1902.05570