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Recommender systems applied to the tourism industry: a literature review

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ABSTRACT
Recommender systems -RS- have experienced exponential growth in various fields, especially in the tourism sector, improving tourism activities' accuracy, personalization, and experience, thus strengthening indicators such as promotion. However, some challenges and opportunities exist to overcome, such as the lack of data on emerging destinations wishing to adopt these solutions. This manuscript presents a literature review of the current trends in RS applied to the tourism industry, including categories associated with their use and emerging techniques. Likewise, it presents a pathway for implementing an RS when insufficient data are available for a destination. The SLR followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines and used the WoS, Science Direct, and Scopus databases. The results show that the hybrid RS integrates deep learning algorithms, data analytics, and optimisation techniques with collaborative tourism features to provide innovative solutions in terms of performance, accuracy, and personalisation of recommendations, thus achieving the management of tourist destinations or tourism-oriented services. Emerging destinations that lack RS data in tourism should use various data sources generated by tourists on social media, tourism portals, and through their interaction with tour operators. New tourism recommender system solutions can emerge following trends integrating new technologies based on user experience, collaboration, and the integration of multiple data sources.

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1. Introduction

The tourism industry generates essential contributions to the world economy and is a valuable resource for developing nations that need to address the industry's requirements by enhancing product diversification and competitiveness in the services they provide (Gof et al., 2019; Kontogianni & Alepis, 2020; Solano-Barliza et al., 2023). Tourism, as an economic sector, is vital because it is an essential source of income for many countries and communities, as tourists spend money on accommodation, transport, food, activities, and shopping. It can also help boost the local economy and create jobs in the tourism industry and related sectors, such as hospitality, transport, and commerce. It can also help preserve and promote the culture and heritage of a region as tourists can visit historical sites, museums, and local festivals (Ovallos & Zamora-musa, 2020).

The tourism industry is an integral organisation that produces the products of a tourist destination, made up of companies that develop activities such as transport, cuisine, hotels, and those that create

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infrastructure to promote cultural exchange (Florido-Benítez, 2022; Yu, 2022). This industry is currently developed and carried out within the different typologies of tourism presented by the author (P. Zhang et al., 2023), such as mass tourism, social tourism, elite tourism, study tourism, honeymoon tourism, voluntary tourism, backpacker tourism, package tourism, halal tourism, pilgrimage tourism, romantic tourism, family adventure tourism, friendship tourism.

According to Kontogianni and Alepis (2020).) the term 'smart tourism' refers to the application of intelligent technologies and innovative solutions in the tourism industry to improve the tourist experience and the efficiency of tourism services (Lu et al., 2022). This includes the use of technologies such as artificial intelligence (Li et al., 2022), the Internet of Things (Makoondlall-chadee, 2021), augmented reality (Psefti et al., 2021), blockchain, big data (Chen et al., 2021), and immersive environments (Zamora-musa, 2017), among others, to offer personalised services tailored to the needs of tourists, as well as to improve the management and promotion of tourism destinations (Bigi et al., 2022), such as the use of social media in destination marketing organisations (DMOs) (Florido-Benítez, 2022). Leveraging Information and Communication Technologies (ICT) is the foremost approach to enhancing the competitiveness of tourist destinations (Ghorbani et al., 2020; Nadeem et al., 2022).

Today, the tourism industry uses technology to improve the efficiency and quality of tourism services, enhance tourist experience, and increase customer satisfaction. For example, technology can help book accommodation (Xu & Gursoy, 2021), transport, and tourist activities more quickly and easily, save time and reduce stress for tourists, and help promote and market tourist destinations more effectively, which can increase the number of tourists visiting a region. Another example is that social media and digital marketing platforms can reach a wider audience and promote regional tourist attractions (Feng et al., 2022). Likewise, technology enhances tourism services' efficiency, quality, promotion, and safety, benefiting tourists and tourism businesses and destinations.

Although the tourism sector uses a wide range of technologies, there is currently a growing use of Recomender Systems-RS in this sector, contributing to the development, accessibility and innovation of destinations and improving competitiveness indicators such as strengthening the supply and management of destinations (Hanafiah & Zulkifly, 2019; Solano-Barliza et al., 2023). According to Isinkaye et al. (2015), RS are algorithms for data analysis and information gathering through user criteria to make predictions, represented as recommendations, promoting the tourist's interaction with the environment and with other users.

Tourism RSs were first implemented in the 1990s. One of the first tourism RS was the 'Ringo' system developed by the University of Minnesota in 1995, which recommended restaurants and bars in Minneapolis. Since then, RS have been developed for streaming, social networking, e-commerce, healthcare, education, scientific information, and tourism (Almomani et al. 2023). In tourism, various areas, such as recommending hotels (Alrehili et al., 2018), tourist attractions (Herzog et al., 2018), tourist mobility (Senefonte et al., 2022), points of interest (Massimo & Ricci, 2021), and RS. With the advancement of technology and increasing availability of data, tourism RS is more sophisticated and accurate and is expected to continue to evolve in the future.

Therefore, researchers need to further explore the development of recommender systems that tackle the associated challenges to enhance their performance and aspects related to tourism competitiveness in a destination. However, designing such technology becomes more intricate when attempting to implement it in tourist destinations with limited data to train and prepare models. Despite the successful implementation of RS in tourism destinations, challenges and opportunities remain, such as the lack of data on emerging destinations wishing to adopt these solutions.

This manuscript presents a systematic literature review (SLR) of current trends in SR applied to the tourism industry, including categories associated with their use and emerging techniques, and contributes to improving the construction of recommender systems in emerging tourism destinations for the management of tourism destinations and tourism-oriented services. It also presents a pathway for implementing an RS when insufficient data are available for a destination. Section 2 discusses the related work on implementing RS in the tourism industry. Section 3 presents the methodology used in this study. Section 4 presents the results and discussions. Finally, the section relates to the concluding aspects, summarises the identified gaps, and suggests approaches for future research.

2. Related works

As technology, RS is increasingly used in different areas of knowledge. Some use cases have been found in mathematics (Wu et al., 2021; Xu et al., 2022), Social Sciences (Laštovi et al., 2022; Rodpysh et al., 2022), Business, Management and Accounting (Kang et al., 2022), economic sciences (tourism) (Hassannia et al., 2019; Logesh et al., 2018; Shafqat & Byun, 2020; Suanpang et al., 2022), and Smart Tourism (Torabi et al., 2023; Ur et al., 2021; Yuan et al., 2014).

In the context of tourism, reviews such as that proposed by Borràs et al. (2014) presented a review of intelligent recommender systems in tourism, highlighting the use of ontologies, planning, and clustering as key elements in these systems. The methodology used includes the analysis of previous work and the evaluation of different approaches based on web or mobile interfaces for tourism recommendations. The data sources vary according to the specific system but range from location data and user preferences to contextual information such as weather. It was found that some systems go beyond providing a list of recommended tourist attractions, using automatic planners to organise these recommendations into a route that may span several days. The review highlights areas for improvement, including the adaptation of web applications for use during the tourist's stay, as many are not currently designed to be easily accessible.

Ko et al. (2022) presented the trends of using RS between 2013 and 2020 in different fields and identified the most used models and techniques. The methodology employed included the selection of more than 135 high-ranking articles and analysis of Google Scholar data from 2010 to identify trends in the research and application of recommender systems in various service fields. The main findings revealed that recommender systems have expanded and been used in various service fields, such as streaming services, social networks, tourism, e-commerce, healthcare, education, and academic information. In the field of tourism, interest in tourism service recommendation research increased slightly at first and then gained momentum in 2019, coinciding with an increase in the number of Airbnb users. This study found that the most commonly employed models were content-based filtering, collaborative filtering, and hybrid systems. These techniques include text mining, K-nearest neighbours (KNN), clustering, matrix factoring, and neural networks. This also indicates that 17.9% of RS applications have been in the tourism sector. However, this article does not present a more in-depth review of the specific techniques and algorithms used in each service field, especially in tourism, where the article indicates a significant increase in interest.

A study developed by Hamid et al. (2021) presents a systematic literature review of smart tourism RS applying data management in a time window from 2013 to 2020. The authors analysed some studies to highlight the benefits, challenges, and recommendations of smart e-tourism. The methodology used in this review included a Boolean search using several keywords related to intelligent recommendation approaches and e-tourism systems. Inclusion and exclusion criteria were defined to select relevant studies. Finally, 65 articles were selected and classified into two main categories: recommendation systems based on intelligent tourism, and tourism marketing. The main findings showed that the content model-based approach has a profound impact on intelligent e-tourism, while the collaborative filtering approach has the worst impact. Several techniques and algorithms have been identified in the field of tourism and recommender systems, including collaborative filtering, content models, context models, and hybrid models. These approaches were classified according to their application in smart tourism and tourism marketing, highlighting the importance of context awareness, recommender systems, social networks, the Internet of Things (IoT), real-time user experience, and user modelling. However, this review lacks an in-depth exploration of existing studies, as it is described as a superficial systematic review.

Kulkarni and Rodd (2020) review the Context-Aware RS applied in tourism. This study classified the techniques for these types of recommender systems into the categories of bio-inspired computing techniques and statistical computing techniques. The study also shows the ability of these systems to cope with cold start, data sparsity, and scalability. The methodology employed includes the analysis of different techniques and algorithms to improve the accuracy and efficiency of recommender systems, such as the inclusion of frame keywords and movie mood similarity in the matrix factorization (MF) model, and the use of parallel programming frameworks to address the scalability problem. The main findings indicate that incorporating contextual information, such as plot keywords and specific movie mood similarities, improves the performance of recommender systems compared to popularity-based methods and other MF approaches. Furthermore, it highlights the importance of developing integrative models that use more than one technique together with the appropriate use of context and feedback mechanisms, without compromising privacy. However, this review did not address the inclusion of specific and in-depth aspects of recommender systems in the tourism context, such as the exploration of machine learning techniques, inclusion of contextual information features, and user- and item-specific information, which could further improve the accuracy of the system.

Although the aforementioned studies have reviewed recommender systems, they have not gone in depth and detailed these technologies in the tourism industry. Currently, these systems have a significant impact on industries that continue to grow owing to digitalisation. Therefore, it is crucial to develop methods of personalising services to improve the competitiveness of the sector. This review considers the technical aspects of recommender system technology and presents solutions that offer useful insights into the management of emerging tourism destinations or tourism-oriented services.

3. Materials and methods

This systematic review combines and synthesises multiple research studies to answer two research questions using the preferred reporting items for systematic reviews and meta-analyses (PRISMA) methodology (Chaudhari & Thakkar, 2019; Ferretti et al., 2021; Jacob et al., 2023).

The questions that guided the review were as follows: (RQ1) What are the current trends in techniques, models, or algorithms for recommender systems in the context of tourism? (RQ2) What are some alternative solutions for developing systems for tourist destinations with limited data availability?

3.1. Eligibility criteria

The literature review encompassed research on 'recommender systems', 'tourism', 'algorithms', 'machine learning', 'multi-objective', and Selection criteria for the literature included articles, books or book chapters written in English, published between 2010 and 2023. Records were excluded if they did not meet inclusion criteria.

3.2. Information sources and search strategy

During the identification phase of the PRISMA process, bibliographic searches were performed using the Web of Science (WoS), Science Direct, and Scopus databases. The keywords used for the review were selected from a previous study of articles that only had the keywords 'Recommender system' and 'tourism'. As a result of this first search, the keywords that were repeated the most in the articles consulted emerged, and from these, the words that guided the search were defined. For the database query process, the Boolean operators 'AND' and 'OR' were used.

3.3. Study selection and exclusion criteria

To ensure consistency and accuracy, we conducted individual reviews of the downloaded results and eliminated duplicates by cross-referencing the DOI identifiers and document titles. Initially, the search yielded 2745 records, searching abstracts, titles, and keywords from the databases. In the database search, only open-access articles were considered for the review. This process removed 213 duplicate records. We then created a comprehensive database containing various details, such as record type, language, authors, title, abstract, keywords, number of citations, and year of publication.

Subsequently, 117 non-English documents were excluded from the study. Relevance checks were then carried out on the remaining documents, with a focus on excluding publications that did not meet the criteria for peer-reviewed academic articles, books, or book chapters. This additional screening resulted in the removal of 22 retracted papers, 53 papers related to health, 60 papers related to education, and 1,924 records related to other topics. This left 336 retrieved records for the eligibility assessment.

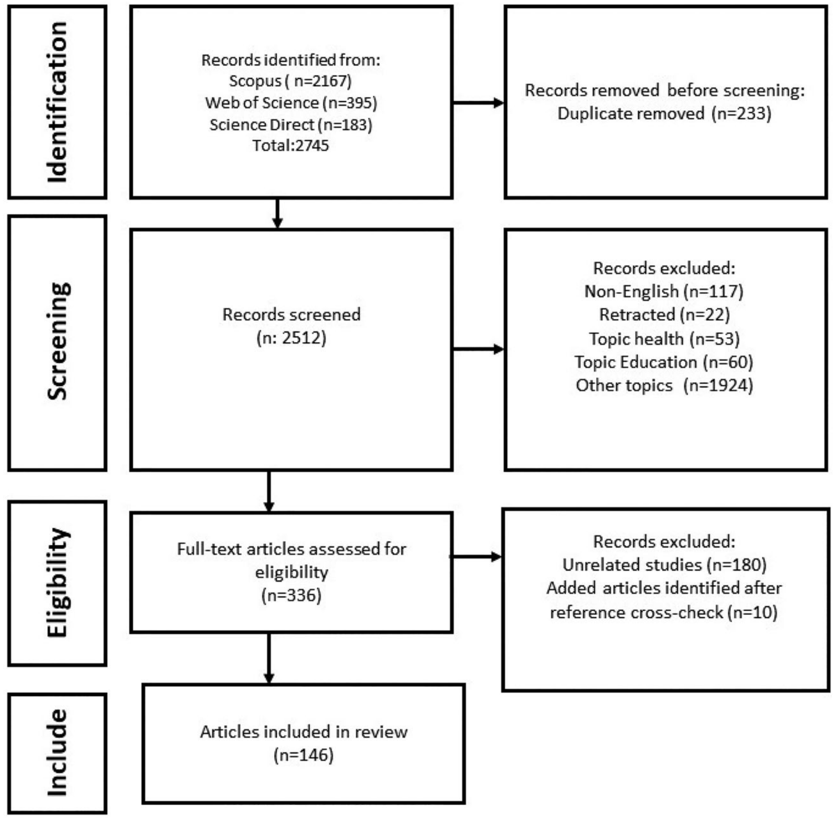

Figure 1. PRISMA diagram of data 'identification, screening, eligibility, and inclusion process'.

After thorough discussion and resolution of any disagreements among the research teams, it was unanimously agreed that 180 publications met the eligibility criteria. However, during the subsequent full-text reading, 10 papers were excluded despite their potential to provide contextual information for the review. A visual representation of the data identification, selection, eligibility, and inclusion processes is provided in Figure 1, which shows the PRISMA diagram.

4. Results

This section presents the results and discussions of the systematic literature review process through a scientometric analysis of the reviewed documents, which can be divided into three categories to identify the current trends in techniques, models, and algorithms for recommender systems applied in tourism. The last section describes alternative solutions for developing recommender systems for tourist destinations with limited data availability.

4.1. Descriptive scientometric analysis

This scientometric section presents descriptive statistics, analysing the distribution of publications by year, journals, authors, type of scientific papers, and countries of publication on the research topic addressed in recommender systems. Figure 2 shows the distribution of publications from 2010 to 2023, revealing a notable surge over the last eight years.

Figure 2 shows that around 80% of the papers included in the SLR were published within the last eight years, while the remaining 20% were published before this period, indicating a growing interest among researchers in the utilisation and application of recommender systems in the tourism sector.

For this SLR, 100 journals had articles related to RS, and seven featured multiple articles about interest. The journals with the highest number of publications were Advances in Intelligent Systems and

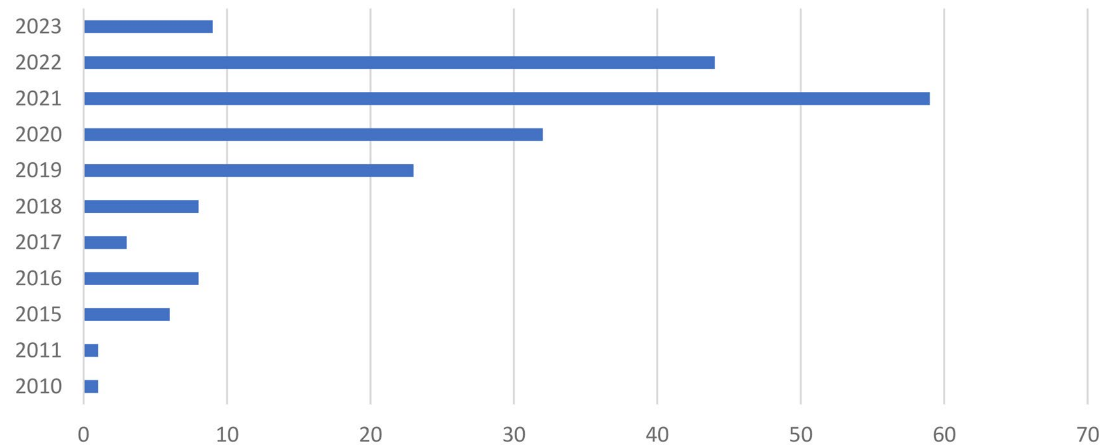

Figure 2. Distribution of publications from 2010 to 2023.

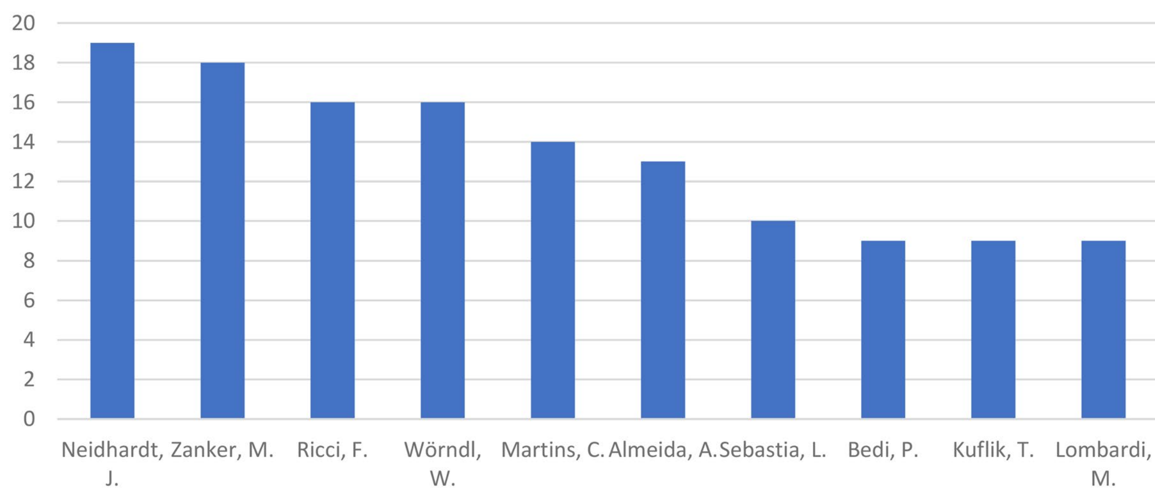

Figure 3. Authors of publications topic research.

Computing (19), ACM International Conference Proceeding Series (14), Tourism Management (13), Expert Systems with Applications (10), Sustainability (Switzerland) (9), the International Journal of Advanced Computer Science and Applications (7), and the International Journal of Contemporary Hospitality Management (7).

The authors who contributed the most papers on the topic addressed in this systematic review are presented in Figure 3.

The authors are Neidhardt, J. (19), Zanker, M. (18), Ricci, F. (16), Wörndl, W. (16), Martins C. (14), Almeida, A. (13), Sebastia, L. (10), Bedi, P. (9), Kuflik, T. (9), and Lombardi, M. (9). Figure 4 presents the types of scientific documents consulted to conduct the review.

From Figure 4, the results show that 89% are equivalent to scientific articles, most of which developed prototypes, designs, and implementations of recommender systems. Regarding the origin of country publications, Figure 5 presents the country publication origin of the research.

Figure 5 shows that China had the most significant number of publications in this area, corresponding to 24% of the articles consulted, followed by India and Italy, with 11% and 8%, respectively. The most significant percentage of the graph is represented by other countries, including the United States, Indonesia, United Kingdom, Malaysia, Spain, Brazil, Iran, Greece, Saudi Arabia, Ukraine, Canada, Iraq, Iran, Morocco, Russia, New Zealand, Germany, and Argentina. China has the highest number of publications in this area because it has significant technological development. The countries with the most publications correspond to Asia and Europe. In Latin America, research has only been conducted in Brazil and Argentina.

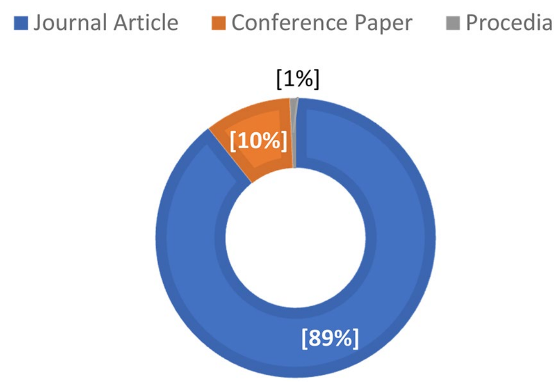

Figure 4. Publications according to the type of scientific documents.

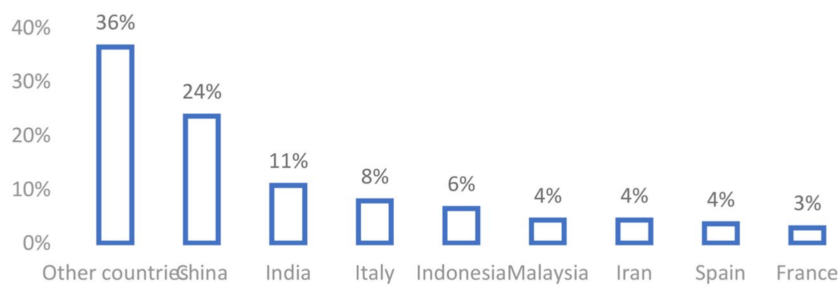

Figure 5. Publications according to the countries of origin of the research.

Table 1. Categories emerging from a review of tourism recommendation systems.

Category	References
Recommender system and tourist management: Use of recommender systems in tourism businesses	(Bi et al., 2021; X. Li et al., 2021; Rodriguez-Sanchez & Martinez-Romo, 2017)
Recommender system and typology and Techniques: It refers to the technical and technological aspects of recommender systems applied in the tourism context.	(Alhijawi & Kilani, 2020; Fararni et al., 2021; Ko et al., 2022; Kolahkaj et al., 2020; Maru'ao, 2021; Nan et al., 2022; Saeid Hosseini, et al., 2019; Shambour et al., 2022; Wayan et al., 2022; Wayan & Yuni, 2021)
Recommender system and learning systems: Refers to the algorithms used for learning recommender systems used in the tourism sector and emerging trends within recommender systems	(Avval & Harounabadi, n.d.; Forouzandeh et al., 2021; Halkiopoulos et al., 2021; Nilashi et al., 2021; Qiao et al., 2022; Ranga & Nagpal, 2023) (Baker et al., 2021; Baker & Yuan, 2021; Bellodi et al., 2022; Luo et al., 2021; Malthouse et al., 2019; Raffe et al., 2015; Sinha & Dhanalakshmi, 2020; Wenan et al., 2022; C. Zhang et al., 2023)

4.2. Categorization technical analysis

In a study using the R tool in the Biblioshiny environment, three main categories emerged within tourism recommender systems. For this analysis, data were exported from Bibliometrix databases in the BibTex format, which is compatible with imports into Biblioshiny for use with Bibliometrix tools. The most recent version of this R package includes Biblioshiny, a web interface application designed specifically to facilitate bibliometric analysis. This tool allows the data to be filtered directly within Biblioshiny. In our article, we took advantage of these capabilities to present the results obtained from such analyses. Table 1 presents the categories that emerged, their significance within the review, and some references supporting these categories within the tourism recommender systems.

The first category, 'Recommender Systems and Tourism Management' refers to the Use of recommender systems in tourism businesses. The second category, 'Recommender system and typology and Techniques' refers to the technical and technological aspects of recommender systems applied in the tourism context and 'Recommender Systems and Learning Systems', refers to the algorithms used for learning recommender systems used in the tourism sector and emerging trends within recommender systems. Each category that emerged from the analysis of recommender systems is explained below.

Table 2. Types of uses of recommender systems in tourism.

Uses of recommender systems in tourism	Purpose	References
Lodging	These RS can help travellers find the best accommodation that suits their needs and preferences, based on location, price, amenities and other users' opinions.	(Guizzardi et al., 2021; Ramli et al., 2019; Shambour et al., 2022; X. Zheng et al., 2018)
Restaurants	These RS can help tourists find the best restaurants based on their gastronomic preferences, the type of food they want to try, the location and the opinions of other users.	(Al-Nafjan et al., 2022; Amirat & Fournier-viger, 2018; Baizal et al., 2021; Hong & Jung, 2021)
Transportation	This type of recommender system helps tourists find the best transportation options to move from one place to another, such as trains, buses, and rental cars.	(Arif et al., 2022; Baizal et al., 2021; Fararni et al., 2021; Gamidullaeva et al., 2023; Hsu et al., 2012; Huiling & Jing, 2022; Missaoui et al., 2019; W. Zheng et al., 2017; X Zheng et al., 2018)
Tourist activities	These RS help travellers find the best tourist activities for their interests and preferences, such as guided tours, excursions, and adventure sports.	(Al-Ghobari et al., 2021; Esmaeili et al., 2020; Fararni et al., 2021; Lin, 2021; Richa & Bedi, 2019; Urdaneta-Ponte et al., 2021) (Casillo, et al., 2021).

4.2.1. Recommender system and tourism management

Recommender systems applied to tourism management are one of the primary uses of this technology in this economic sector since generates an increment of user satisfaction and revenue for businesses. These systems have strengthened indicators related to food (Almomani et al., 2023; Hong & Jung, 2021), improving the overall tourist experience (Huda et al., 2022; Richa & Bedi, 2019).

According to Liu et al. (2023), recommender systems enable tourism companies to collect behavioural data and predict user preferences to conduct targeted planning and work organisations to improve economic benefits and promote the construction of smart destinations (Huda et al., 2021; Mishra et al., 2023).

From the analysed documents, in tourism management, the main activities using the recommender system are gastronomic, natural, and cultural. Table 2 presents a breakdown of the classified tourism activities, purposes, and specific activities for which recommender systems have been used.

In the realm of tourist activities, recommender systems employ various features including location, temperature, week, season, weather, time of day, traffic conditions, nearby resources, and the company of fellow travellers. Such features prove beneficial in the context of tourism (Al-Ghobari et al, 2023; Solano et al., 2021; Zhao et al., 2020). Consequently, the interaction between users, system, and context contributes to the configuration of preferences, resulting in the creation of a set of contextual data.

4.2.2. Recommender system and typology and techniques

The recommender system-RS algorithm optimises data analysis and information collection through user criteria to make predictions, represented as recommendations (Isinkaye et al., 2015), promoting the tourist's interaction with the environment and other users (Solano-Barliza, 2021). Collaborative filtering (CF) has been the most widely used model for recommender systems since the early stages of its development (Li et al., 2019).

To better understand the diverse types of recommender systems used in the tourism industry, Figure 6 summarises the classification of the recommender systems most used in different areas.

Based on a literature review, Table 3 displays the prevalent models of recommender systems employed within the tourism domain. These include collaborative filtering, location-based recommendations, content-based filtering, context-aware systems, and hybrid models, each accompanied by a brief description.

Collaborative filtering, location-based filtering, content-based filtering, context-awareness, and hybrid models are the most commonly used. The hybrid model is the most popular, with collaborative filtering being the most frequently used hybridised technique.

The review found that location-based recommender systems can be considered a subset of context-aware systems because location can be understood as an attribute or characteristic that is integral to the context in which users find themselves. Context-aware systems consider information that characterizes a situation related to the interaction between people and their environment. In this sense,

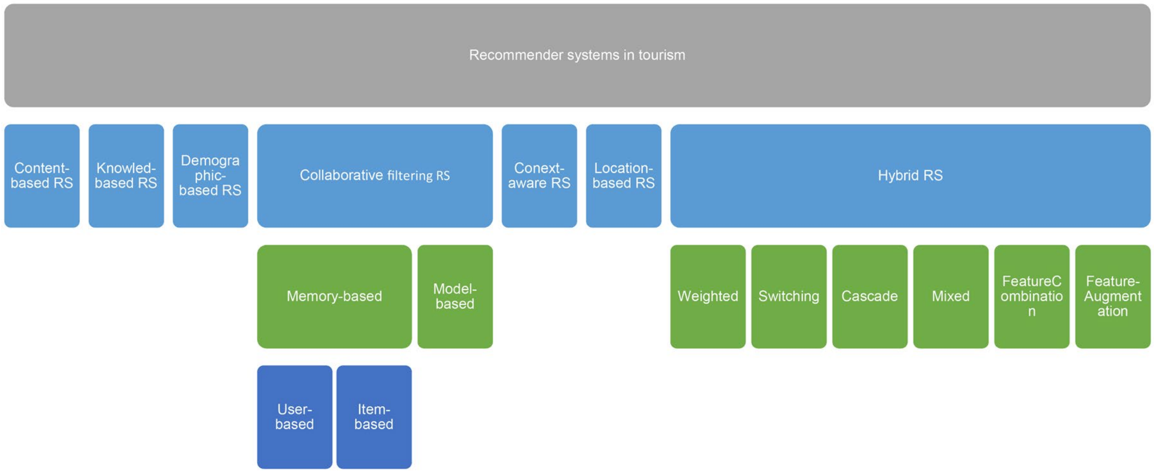

Figure 6. Classification of recommender systems (*Source:* Ko et al., 2022; Stitini et al., 2022; Yochum et al., 2020).

Table 3. Types of recommender systems applied to tourism.

Types of recommender systems	Description	References
Collaborative filtering	This typology recommends personalized items by effectively using the information stored in the system to identify similarities between different domains. This model works by comparing each user's rating data on the same item to determine their similarities, generating a list of the N items that best match their tastes based on the ratings provided by a group of similar users. The main drawbacks or limitations of Collaborative Filtering (CF), which can affect its accuracy and effectiveness in providing relevant recommendations to users. Cold start problem: The system has difficulty making recommendations for new users or items with limited data. Data size management difficulty: The large amount of data required can be difficult to manage, affecting system performance.	(Alhijawi & Kilani, 2020; Alhijawi, & Kilani, 2020; Choi et al., 2021; Fararni et al., 2021; Hasan, 2019; Lin, 2021; Nan et al., 2022; Renjith et al., 2022; Shambour et al., 2022)
Content-based filtering	Content-based filtering is another model in recommender systems, where items are suggested based on their inherent information or content. However, this model has limitations as it cannot recommend items that are not directly related to existing content. It has mainly been used in services that recommend articles or textual data, leaving out items that are added later.	(Fararni et al., 2021; Isinkaye et al., 2015; Lavanya et al., 2021; Ojagh et al., 2020; Wayan et al., 2022)
Location-based	Location-based recommender systems use geographic location to improve recommendations for places or activities that a user may be interested in. There are two types of location-based systems: autonomous place recommender systems and sequential place recommender systems. Autonomous place recommender systems match the user's preferences for restaurants, hotels, or cities, while sequential place recommender systems provide popular routes, time budgets, and costs.	(Amirat & Fournier-viger, 2018; Artemenko et al., 2019; Bahulikar et al., 2017; Baral et al., 2019; Gao et al., 2020; Huang et al., 2020; Ojagh et al., 2020; Shafqat & Byun, 2020; Suguna et al., 2020)
Context-aware	Context-aware recommender systems aim to provide more personalized and relevant recommendations by considering contextual variables in the user's activity. These systems can be classified into collaborative filtering, content-based filtering, graphical, and hybrid models. The context information is categorized into individual, activity, time, space, and communication categories, and includes elements such as location, time of day, and network connectivity.	(Abbasi-moud et al., 2022; Abu-issa et al., 2017; Boppana & Sandhya, 2021; Huo & Jing, 2018; Kolahkaj et al., 2020; Naser, 2019; Richa & Bedi, 2019; M. del C. Rodríguez-Hernández et al., 2017; M. Rodríguez-Hernández & Ilarri, 2021; Syed et al., 2022)
Hybrid	Hybrid recommender systems combine two or more techniques to improve recommendation accuracy by complementing the limitations of each individual technique.	(Alhijawi & Kilani, 2020; Fararni et al., 2021; Forouzandeh et al., 2022; Ko et al., 2022; Kolahkaj et al., 2020; Maru'ao, 2021; Ravi et al., 2019; Sabet et al., 2022; Saeid Hosseini, et al, 2019; Wayan et al., 2022; Wayan & Yuni, 2021)

Table 4. Classification of recommender systems applied in tourism.

Type of recommender systems	Use of learning algorithms	References
Location-based RS	Clustering, K-means, K Nearest Neighbor (KNN), Support vector machine, Neural networks Neural network, recurrent neural networks, Deep Learning	(R. Ding & Chen, 2018; Duan et al., 2018; Suguna et al., 2020; Xing et al., 2018)
Context-aware RS	Clustering, Deep neural networks, Recurrent Neural Network	(Baral et al., 2019; M. Rodríguez-Hernández & Ilarri, 2021; L. Wu et al., 2022)
Collaborative filtering	Clustering, K-Nearest Neighbors	(Kolahkaj et al., 2020; Wayan & Yuni, 2021)
Hybrid RS	Clustering, associative rules, Deep neural network, Support vector machine, Forecasting	(Bhaskaran & Marappan, n.d.; Forouzandeh et al., 2022; Wang et al., 2020)

location is a key contextual attribute that influences the recommendations offered to users. Therefore, location-based systems can be considered a specific application of context-aware systems, where location acts as a critical component of the context used to improve the relevance and personalisation of recommendations for products and services in the tourism industry.

4.2.3. Recommender system and learning systems

This category highlights the strong correlation between recommender and learning systems, such as the use of machine learning algorithms to generate personalised recommendations (Acharya et al., 2023). These algorithms scrutinise user behaviour and preferences to identify patterns and similarities that can be employed to suggest items that would appeal to or interest users. In this regard, learning systems are critical in enhancing the precision and efficacy of RS.

By training on extensive datasets, machine learning algorithms can boost recommendation accuracy and adjust user preferences and behaviour shifts over time. Additionally, they can tackle the typical challenges of recommender systems, including data sparsity and cold-start problems. Furthermore, RS can utilise deep learning techniques to examine significant data volumes and provide more precise and personalised recommendations. Table 4 lists the learning system algorithms used by diverse types of recommender systems.

Recommender systems utilize a variety of techniques and algorithms for data processing. The algorithms implemented within machine learning are supervised and unsupervised. The prevalence of algorithms employed in every model is clustering (Orama et al., 2022; X. Zheng et al., 2016), sentiment analysis (Santamaria-granados & Mendoza-moreno, 2021; Srivastava et al., 2022), ontology (Baizal et al., 2021), semantics (Ferraro & Lo Re, 2014), KNN, Deep neural networks, and fuzzy (Baizal et al., 2021; Roy et al., 2016). The most popular machine-learning technique in this review is clustering. In contrast, KNN uses a proximity-based classification approach that evaluates datasets by measuring the similarity between individual data points using distance-weighted metrics. It primarily uses the Euclidean distance, cosine similarity, and Pearson correlation to measure similarity (Ko et al., 2022).

The review found that 70% of recommender systems applied to tourism were hybrid systems, with collaborative filtering being the most commonly used algorithm. The features and qualities of these systems play a crucial role in promoting innovation, progress, and accessibility of destinations. They have the potential to improve competitiveness metrics, including strengthening the supply chain and improving destination management (Esmaeili et al., 2020; Solano-Barliza et al., 2023). In addition, the review highlighted the hybridisation of collaborative filtering with multi-criteria approaches used in the field of multi-criteria decision aid-MCDA, such as the study by Shambour et al. (2022), which uses a technological solution to provide more effective and personalised hotel recommendations.

In contrast, recommender systems use optimisation algorithms to improve the effectiveness and efficiency of their algorithms and recommendation techniques, resulting in more accurate and relevant recommendations. In the field of tourism, it has been applied in various areas such as tourist route planning, personalised itineraries, point of interest (POI) recommendations, and tours in urban environments, among others (Zaizi et al., 2023). Optimisation algorithms can improve recommendations by (1) balancing criteria such as accuracy, diversity, and novelty, resulting in more accurate and personalised recommendations; (2) facilitating the exploration of a large solution space, identifying optimal combinations of recommendations that maximise accuracy; (3) adjusting the parameters of the recommendation model to improve the accuracy of predictions; and (4) addressing multi-objective recommendation problems, resulting in a significant improvement in the accuracy of recommendations.

By addressing scalability and accuracy issues, optimisation algorithms can help overcome the challenges and limitations faced by these systems. Therefore, optimisation algorithms are crucial for improving the quality of recommender systems and providing better user experience. Some examples of these optimisation techniques are addressed by Cai et al. (2020), who presented a hybrid recommendation model that combines multi-objective optimisation techniques (MaOEA) to improve recommendation accuracy, diversity, novelty, and coverage.

Similarly, the study developed by Xiaoyao Zheng et al. (2023), a tourist route RS is presented by a multi-objective evolutionary algorithm using a two-stage decomposition structure and Pareto layers to improve the diversity and distribution of the proposed solution. This method decomposes the multi-objective problem into several sub-problems and improves the solution distribution using a two-stage method. Evaluating it on real data from Beijing tourist sites and comparing it with other methods demonstrated the effectiveness and efficiency of the algorithm.

Ding and Chen (2018) propose a Tourism RS (TRS) using the Fireworks Algorithm (FWA) as a meta-heuristic method. At the same time, TTDP is a multi-constraint discrete optimisation problem whose main difference lies in the definition of distance. The experimental results demonstrated the effectiveness of the proposed FWA.

Forouzandeh et al. (2022) proposed a hybrid tourist destination RS using an artificial bee-colony algorithm and Fuzzy TOPSIS. It reviewed the literature on recommender systems and methods in the tourism sector and analysed the effectiveness of the ABC algorithm and TOPSIS model. The proposed system was evaluated through online surveys and compared with other algorithms, demonstrating high accuracy and highlighting the relevance of this solution for personalisation in the tourism sector. Multi-objective genetic algorithms used in tourism recommender systems include NSGA-II, MOEA/D, and MOGA. These algorithms optimise different objectives in tourism recommender systems, such as accuracy, recommendation diversity, and user satisfaction.

4.3. Main limitations of tourism recommender systems

The main difficulties encountered in recommender systems in the scope of the reviewed articles were cold start, accuracy, efficiency, data sparsity. An explanation of each constraint is presented below.

Cold start refers to the difficulty faced by these systems in making accurate recommendations when little or no information is available regarding a new user or item. This is the type of limitation faced by most recommender systems (Cui et al., 2018; Renjith et al., 2020).

Accuracy refers to the calibration and balancing of the diversity of recommendations. This is related to ensuring that the recommendations given by the system match the tastes and preferences of users (Aliannejadi & Crestani, 2017).

Efficiency is related to the scalability of the systems, as the volume of data and the number of users increases, the recalculation of large intermediate matrices can become computationally expensive, which affects the efficiency of the system (Jinpeng Chen et al., 2018; Zaizi et al., 2023).

Data sparsity in recommender systems refers to insufficient information regarding users and recommended items (Gamidullaeva et al., 2023). This phenomenon occurs when few users interact with articles, making it difficult for the system to identify patterns and provide accurate recommendations. In addition, data sparsity can occur when there are many items but few users, making it difficult to identify similar users and create reliable neighbourhoods. Overcoming data sparsity is a common challenge in recommender systems, often requiring the application of machine learning techniques and strategic approaches to improve the accuracy of recommendations and expand coverage (Cui et al., 2018; Jinpeng Chen et al., 2018; G. Li et al., 2020; Ravi et al., 2019; Saeid Hosseini, et al., 2019).

Although technical in nature, the problems associated with recommender systems can have a significant impact on the user experience of various products and services in tourism destinations. These issues require careful attention because the solutions provided by recommender systems are crucial for tourists. If not properly addressed or if recommender systems do not work optimally, they may generate inaccurate or irrelevant recommendations. This scenario could result in an unsatisfactory experience for tourists, undermining trust in the tourism sector. It is important to proactively address the challenges associated with recommender systems to ensure that tourists receive accurate and relevant recommendations. This approach not only improves user experience but also increases the efficiency and profitability of tourism businesses.

4.4. Emerging tourist destinations with lack of data

The main challenge for emerging destinations lies in the collection of data for the operation of intelligent systems, such as recommender systems (Acharya et al., 2023). Consequently, the lack of data is an obstacle for these destinations when implementing smart systems, such as recommender systems. Data is one of the challenges in implementing recommender systems. collection (Muneer and Basheer, 2022). Despite their involvement in tourism activities, especially in developing countries, destinations often lack adequate data management practices, hindering the development of sufficient datasets. Table 5 presents the different proposed actions for data collection in recommender systems based on different data sources.

The data sources outlined in Table 5 indicate that the resulting data can be structured, semi-structured, or unstructured, which presents challenges in creating high-quality datasets and integrating these data types to generate inputs for recommender system implementation. Consequently, there is a responsibility to collect and store accurate and relevant data for use in recommender systems. These data must be continually updated and maintained to ensure the accuracy and value of recommendation algorithms. Efficient and reliable data collection and storage processes are critical for ensuring data quality, as only complete, accurate, and unbiased data can lead to useful recommendations (Kushwaha & Pant, 2021).

Although the amount of tourism data is increasing through social media and tourism portals, many emerging destinations still lack sufficient data to build effective recommender systems (Acharya et al., 2023; Kolahkaj et al., 2020). This limitation is more pronounced for lesser-known destinations or less-popular tourist attractions, where less data are likely to be available.

To address these limitations, innovative methods for collecting and analysing tourism data need to be developed. Strategies can be explored to collect data from a variety of sources and types, including actively engaging tourists through mobile applications and digital platforms to collect information on their experiences and preferences. Government agencies, destination marketing organisations, and service providers should collaborate in these data-collection efforts to generate data for tourism recommendation systems. Table 5 details practical and accessible actions, many of which may require manual data collection for recording in simple databases, such as Microsoft Excel. This initial process can be an essential starting point for integrating solutions to optimise the management and customisation of tourism products in emerging destinations. Currently, online portals such as TripAdvisor or Booking.com are valuable sources of data, collecting information on a wide range of destinations, including those that are considered smart and others that are in the process of being promoted. Using data from these portals can be key to developing smart solutions. However, data collection and extraction followed by classification and analysis are often required to identify the most relevant information for recommender system development.

5. Discussions

Recommender systems have become crucial in tourism management. According to Hamid et al. (2021), the main objectives of these tourism systems range from identifying the most attractive destinations to improving the accuracy and efficiency of recommendations. They also focus on integrating different transport options, considering multi-criteria and capturing changing user preferences (Jabreel et al., 2020). The review also found that various multi-criteria decision aid (MCDA) methods have been used in tourism to build recommender systems. This field of research is dedicated to the development of methods that consider different evaluation criteria to analyse a set of alternatives and thus rank recommendations according to their overall suitability, thus facilitating user decision-making (Arif et al., 2022; Hong & Jung, 2021; Maru'ao & Suharjito, 2021; Shambour et al., 2022). These systems play an essential role in

Table 5. Specific actions for building a collection of data for recommender systems.

Data sources	Type data	Specific actions	Tools for recollection
Data generated by tourists themselves, such as opinions and ratings of products and services consumed.	Structured data Semi-structured data Unstructured data	Surveys (questionnaires focused on finding out the interests and preferences of the destination visited by the tourist).	Survey monkey Google forms
Data generated by tourist feedback	Semi-structured data Unstructured data	Interviews (direct questioning of users to find out their interests regarding the destination)	Videos Audio
Data from social networks and social media.	Semi-structured data	User opinions (Selection of comments on social media to evaluate positive and negative aspects of the destination) Location of users (Identify the most visited points of interest in the destination) (Collection of distances from strategic points in the city to others, using google maps. This can be used to make recommendations by proximity to points of interest)	Twitter (X. Zheng et al., 2018) Facebook (Forouzandeh et al., 2022) Instagram (Egger & Yu, 2021; Silaa et al., 2022)
Data from destination tourism managers	Unstructured data	User feedback (Collection of ratings and comments from customers in hotels and restaurants) Costs (Collection of historical prices of products in the establishments)	Hotels data (Patel et al., 2023) Restaurants data (Fararni et al., 2021)
Data from tourism portals	Structured data Semi-structured data Unstructured data	Ratings (Collection of data related to ratings, analysis of reviews, and ratings of products and services offered by hotels) Market trends based on tourism behaviour (Recording and storage of purchases made by users in the establishment).	TripAdvisor (Rinaldi et al., 2022) Booking (Bennawy & el-Kafrawy, 2022) Trivago (Bennawy & el-Kafrawy, 2022; Srivastava et al., 2022) Blogs of travels
Data on collaboration with other organizations.	Structured data Semi-structured data	Historical data on tourism behaviour (Registration and storage of studies carried out by governmental organisations, universities and researchers on the interests and areas of improvement in the destination).	Technology companies, Universities Research organizations

improving tourism services, increasing destination awareness, and facilitating tourism tracking and segmentation. The adoption of technologies, such as recommender systems, represents a significant opportunity to personalise and enrich tourism products and services.

Destinations, therefore, need to focus on implementing strategies to attract new visitors and better understand tourists' needs and preferences. This will lead to more accurate and personalised recommendations, which, in turn, will improve customer satisfaction. Technological developments in the tourism sector are reinforced by the inclusion of contextual information, such as the tourist's current location and specific situation, which allows recommender systems to provide more relevant suggestions tailored to tourists' immediate needs. All these developments contribute significantly to strengthening the branding and promotion of tourism destinations and to the benefit of both destinations and tourism service providers.

However, in relation to recommender systems and their typology and techniques, the study found that there are limitations and areas for improvement. Several limitations were identified in the reviewed studies, including the scarcity of research evaluating the effectiveness of recommender systems in terms of user satisfaction and improved travel experiences. In addition, there is a need for research on how recommender systems can be integrated with other emerging technologies, such as augmented reality and artificial intelligence, to improve user experience. Other limitations include the need to explore how recommender systems can address specific challenges in the tourism industry, such as seasonality and variability in the quality of tourism services, and a lack of studies evaluating the effectiveness of these systems in different cultural and geographical contexts.

From the review, several common trends and patterns were identified, including: (1) the use of data mining and machine learning techniques to analyse large amounts of user data and generate personalised recommendations; (2) the integration of RS into mobile applications and online platforms to improve user experience and increase customer satisfaction. At this point, it is essential to note that new proposals for tourism RS must balance the personalisation and privacy of the data provided by tourists, particularly their interests, preferences, GPS data, and opinions (Srisawatsakul & Boontarig, 2020).

Another trend identified in this review is the growth of existing Group Travel Recommendation Systems (GTRS), which focus on individual user preferences and make group recommendations by aggregating profiles Kargar and Lin (2021). Ceh-Varela et al. (2022) reviewed studies on group recommender systems (GRecSys) and presented commonly used aggregation strategies and functions to combine the preferences of group members. The results show that GRecSys evaluation should use both data types and that singular value decomposition or neural collaborative filtering methods perform better than the others. W. Liu and Liu (2019) introduce Travel RS (TRS) and Group Travel RS (GTRS). Current GTRSs exploit users' individual preferences and make group recommendations by aggregating their profiles or recommendations. This study proposes a conceptual framework for a hybrid group travel recommendation system that considers the interactions between tourists and their influence on group travel preferences.

Hybrid model solutions with optimisation algorithms such as NSGA-II would allow the generation of recommendations based not only on geographical proximity, but also on other important characteristics such as quality of service, price, and accessibility. Allows a more comprehensive and personalised approach to the user, which can increase satisfaction and trust in recommendations. The application of multi-objective optimisation in recommender systems has shown promising results in improving the diversity, novelty, and coverage of recommendations (Gamidullaeva et al., 2023). New recommender system solutions can be significantly improved by integrating optimisation techniques and algorithms as they help find more efficient and accurate solutions, thus improving the quality of recommendations offered to users (Cai et al., 2020).

In addition, there are opportunities to develop metrics to assess the effectiveness of recommendations received by tourists, and to use these metrics to improve the quality of recommendations and measure their impact on businesses or activities. Analyzing tourist behavior in smart destinations can help define key predictors of tourist intentions, enabling governments and tourism managers to implement more comprehensive and specific tourism plans to promote better perceptions among potential tourists (Kontogianni et al., 2022; Liao et al., 2022; Xia, 2022).

The challenges facing the tourism industry and the use of recommender systems in the coming years need to address the gaps identified in the review, which include: (1) Lack of consideration of social influence: Some recommender systems do not consider social influence when recommending points of interest. (2) Adaptation to dynamic changes in external factors and formulation of personalised recommendations for tourists in changing situations. (3) Bias and lack of diversity: Some recommender systems may be affected by bias and lack of diversity in recommendations, limiting the exploration of new destinations and tourism experiences. (4) Limited choice of places to visit: recommender systems tend to recommend the most popular and well-known places, leaving out lesser-known, but potentially relevant and interesting places. (5) The lack of data for designing and developing sustainable tourism infrastructure is the main challenge for the tourism sector. Many emerging destinations require the adoption of technologies based on artificial intelligence; however, the culture and practice of data collection have not yet been established in this area, which significantly hinders progress in the implementation of these technological solutions.

6. Conclusions and future work

The review found that the recommender systems most commonly used in tourism are collaborative filtering, content-based, location-based, contextual, and hybrid. These recommender systems have impacted the tourism industry by improving competitive indicators, such as supply, promotion, security, and user satisfaction. These technological solutions have enabled destinations and tourism companies to collect and analyse data on tourist behaviour, anticipate their preferences, and plan and organise their work efficiently.

The development of recommender systems in tourism involves the application of advanced data analysis and machine learning techniques to increase accuracy and efficiency. Today, new recommender system solutions can be built following trends such as personalisation, integration of new technologies, focus on user experience, collaboration, and the integration of multiple data sources.

Recommender systems in tourism currently face several challenges, such as adaptation to dynamic and temporal context, and the quality, reliability, and sparsity of data on user preferences and behaviour, especially in lesser-known tourist destinations.

Lack of data is one of the main limitations of building recommendation systems, especially for less known destinations or less popular tourist attractions. The main actions to address these limitations are the collection and processing of data from surveys, interviews, user opinions, user location, observations, tourist images, destination images, user opinions, rating data, costs, comments, tourism behaviour, market trends, and historical tourism behaviour data. These are the primary sources for the collection and implementation of recommendation systems.

Future work on the use of recommender systems should consider the user context, such as geographical location, travel history, and personal preferences, to generate relevant and accurate recommendations. Multiple data sources, such as social media, user reviews, and booking data, are used to improve the quality of recommendations. There is a need to continuously evaluate and improve recommender systems to ensure their effectiveness and relevance in a constantly evolving tourism environment. Use of recommender systems for accessible tourism for people with disabilities. Explore how recommender systems can contribute to indicators such as tourism safety and destination sustainability. In addition, we propose to develop tourism recommendation systems using multi-objective optimisation algorithm techniques and to further investigate different multi-criteria methods, which will allow the development of more personalised systems that are more responsive to users' interests and preferences.

Author contributions

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Data availability statement

Data are available on request from the authors.

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