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Group recommender systems for tourism: current state and future directions

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Abstract

Recommender systems, as sucessful personalization tools, are focused on helping potential clients to obtain the information that best corresponds to their needs and preferences, in a search space overloaded with options. Properly, group recommender systems (GRSs) focus on suggesting certain types of item (products or services) that tend to be consumed in groups. This paper analyzes the use of GRSs in the tourism domain. It considers the most representative works in this area, highlighting the type of study and evaluation, the application scenario, its purpose, and the methodology used for the generation of recommendations. With this goal, the PRISMA methodology is used, being 1115 works initially identified in the Web of Science and Scopus, which are reduced into a set of 79 articles after the application of several inclusion and exclusion criteria. A comprehensive study of such works identifies three main working domains: 1) GRSs for restaurants, 2) GRSs for itineraries and points of interest (POIs), and 3) GRSs for destination and travel. An overview of the main methodologies and evaluation approaches in these works is also discussed. The analysis performed also identifies relevant research lines for future work.

KEYWORDS
tourism, personalization, group recommender systems, research trends

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1 | INTRODUCTION

In recent decades, the impact of tourism innovation on tourism development has grown significantly (Cao et al. 2022), not only due to the generation of new products, but also due to its impact on the implementation of new and/or improved processes, marketing and organizational methods (Pikkemaat et al. 2019). This fact leads to the growing personalization of travel and leisure offers, marked by the need to satisfy the varied needs and preferences of groups of consumers. Furthermore, tourism is one of the most important sectors of e-commerce today, and it is expected that within 4 to 5 years, the proportion of tourism e-commerce in the overall e-commerce scenarios will reach 20%-25% (Tang and Zeng 2021). In this context, the role of the smart tourism is currently receiving a key attention as a way of filling a set of incoming requirements and expectations (Kontogianni et al. 2024c).

In contrast to the established role of personalization in improving user/customer satisfaction (Fan and Poole 2006), several recent surveys have suggested the need to improve personalization in the tourism sector (Chaudhari and Thakkar 2020, Renjith et al. 2020), and mainly in the wide definition of e-tourism (Xiang et al. 2022), which involves the analysis, design, implementation and application of IT/e-commerce solutions in the travel and tourism industry, as well as the analysis (of the impact) of the respective technical/economic processes and market structures. It has been pointed out that 96% of the tourism marketing specialists believe that personalization improves customer relationships [♯]. However, despite these data, only 31% believe that the travel and tourism industry is implementing personalization mechanisms effectively; this shows that there is still much room for improvement in such a dynamic and ever-growing sector of tourism.

[♯] https://komarketing.com/industry-news/96-marketers-agree-personalization-improves-customer-relationships-3435/

In the last two decades, the development of recommender systems has been considered a successful alternative to the development of personalized services (Salonen and Karjaluoto 2016, Ricci et al. 2022), focused on providing customized content to individual users in e-commerce environments and beyond. Recommender systems dynamize marketing processes and are focused on helping potential customers to obtain information on products or consumption options that best meet their needs and preferences, in a search space increasingly overloaded with several offers (Adomavicius and Tuzhilin 2005). Recommendation methods are usually divided into content-based filtering methods, collaborative filtering methods, demographic filtering methods, and hybrid methods (Bobadilla et al. 2013).

While a typical search engine focuses on finding what the user is looking for, whether it is data or information, a recommender system helps the potential customer to make a decision based on the information that best matches his/her interests and preferences (Adomavicius and Tuzhilin 2005). This decision may be associated with the purchase of a product through e-commerce, the reading of a book, the review of a scientific article, the choice of a movie, or the access to a particular web page. Overall, the application of recommender systems has been primarily focused on e-commerce (Huang et al. 2007) and e- learning (Yera and Martínez 2017), although they have been extended to more and more diverse scenarios such as food, music, fashion, multimedia and tourism (Ricci et al. 2022). In particular, contributions related to the development of recommender systems for tourism have increased and gained importance in recent years (Renjith et al. 2020, Hamid et al. 2021, Ricci 2022), motivated by the increasing need for personalization services in this domain, as was pointed out above.

The literature features recommender systems for suggesting items to individual users or customers, which is the most common recommendation scenario, but also focused on groups of users (Dara et al. 2020). Group recommender systems are designed to better suggest certain types of item that tend to be consumed in groups and not by individual users, such as TV programs and tour packages (Castro et al. 2017). The group recommender systems personalize then the recommendations to be consumed in a group. In this new context, each group's member could have different needs and interests, and then the development of new recommendation approaches that cope with these issues for delivering group recommendations would be necessary.

More specifically, several scenarios can evidence the relevancy of group recommendation in e-tourism, from simpler to more sophisticated contexts:

- In the selection of a touristic travel by a family for spending holidays, it is necessary to take into account the different preferences of the group.
- In a group of friends visiting a new city, it is necessary to consider group recommendation techniques to choose the sequence of places to visit.
- In a critiquing-based scenario, group recommendation methods and related interfaces can be used to process initial feedback elicited from group interactions, to suggest the definitive points of interest to visit (Nguyen and Ricci 2018).
- In the composition of a tourist package composed of several items with touristic interests, where group recommendation and optimization-based techniques can be combined (He et al. 2020).

However, while research work on recommender systems in tourism has been covered in recent survey papers and books (Borràs et al. 2014, Felfernig et al. 2018b, Renjith et al. 2020, Chaudhari and Thakkar 2020, Hamid et al. 2021, Ricci 2022), the absence of review work focused on group recommendation in tourism is remarkable. Similarly, several authors have developed reviews on general group recommender systems (Kompan and Bielikova 2014, De Pessemier et al. 2014, Dara et al. 2020, Pérez-Almaguer et al. 2021, Alvarado et al. 2022), but with very little emphasis in the tourism domain. Therefore, the aim of the current work is to offer a comprehensive analysis of group recommender systems in tourism.

As far as we know, a similar survey is conducted by Delic et al. (Delic et al. 2022) as part of the Handbook of e-tourism, where the authors provide an overview of the research done in the field of group decision making, group recommender systems, and group personalization in the travel and tourism domain. However, while Delic et al. (Delic et al. 2022) are primarily focused on exploring how group decision making and group recommender systems can be used to support the tourism domain, our current survey complements this work by presenting a comprehensive analysis of the literature on group recommendation in tourism, using a systematic review methodology.

Therefore, the main contributions of the present work are the following:

- The development of a detailed review of the state-of-the-art in group recommender systems in the tourism area.
- The comparison of the identified works, highlighting the strengths and weaknesses in each case, as well as grouping them according to their main features and goals.

- An overview of the main methodologies and evaluation protocols used in the identified works.
- An analysis of future lines of work that could be followed in this research area.

The remainder of the paper is structured as follows. Section 2 presents a brief reference to previous literature reviews in this area. Section 3 presents the methodology used to develop the review. Section 4 presents an analysis of the identified works based on their application domain. Section 5 performs an analysis of the research methods used in the proposal, including novel interfaces and user modeling approaches, the underlying recommendation techniques, the evaluation procedure, and group modeling. Section 6 points out future work. Finally, Section 7 concludes the contribution.

2 | PREVIOUS LITERATURE REVIEWS ON RECOMMENDER SYSTEMS IN TOURISM

This section illustrates the necessity of building group recommender systems in tourism.

In recent years, there have been numerous applications in the area of recommender systems. Lu et al. (2015) have carried out a review of the main application areas, identifying eight major groups of works, which are e-government, e-business, e-commerce, e-library, e-learning, e-tourism, e-resources and e-group activity.

In the particular case of e-tourism, several authors have been centered on performing a systematic review of the available works in this area. Previously, Borràs et al. (2014) presented a survey on tourism recommender systems, discussing the functionalities and interfaces of modern e-tourism recommendation tools, as well as the artificial intelligence techniques used throughout their development.

In parallel, Gavalas et al. (2014) provide an analysis of the state-of-the-art in the use of mobile recommender systems in tourism, proposing a classification of mobile tourism RS and providing information on their offered services. Specifically, the authors scan new developments in mobile computing, wireless networking, web technologies and social networking, that leverage massive opportunities to provide highly accurate and effective tourist recommendations.

Chaudhari and Thakkar (2020) and Renjith et al. (2020) have recently prepared reviews of the available work on the state of the art in this research area. Among the categories identified regarding group recommendation, there are hotel recommender systems, restaurant recommender systems, tour package recommender systems that include route planning and travel packages, and recommender systems for points of interest and museums.

Hamid et al. (2021) presents a multi-field systematic review that exposes new research opportunities, motivations, recommendations, and challenges and limitations, around tourism recommender systems and tourism marketing. It also provides a state-of-the-art e-tourism data management classification taxonomy by reviewing works in different research fields.

Ricci (2022) has also discussed the most important key dimensions for recommender systems especially considering the travel and tourism domains. Here, several stages related to an RS workflow in tourism are discussed, such as preference elicitation, scoring and ranking recommendations, recommendation refinement, and context-awareness.

Finally, Delic et al. (2022) also recently provided an overview of research done in the field of group decision making, group recommender systems, and group personalization in travel and tourism. The main aim of this work is to explore how group decision-making and group recommender systems can be exploited to support the tourism domain, providing a baseline for our additional analysis.

Recently, Kontogianni et al. (2024c) have identified recommender systems as key concepts in the definition of smart tourism. Herein, AI Smart Tourism Recommender Systems are established as one of the two pillars of the use of artificial intelligence in smart tourism (Kontogianni et al. 2024a), discussing different contributions that include POI recommendation, deep learning models, and fuzzy logic. Specifically, the authors also discussed how deep learning approaches can be used to implement a smart crowdsourcing tourism application based on moments of interest (Kontogianni and Alepis 2019, Kontogianni et al. 2022 2024b).

In general, although a significant group of works are identified in these recent literature reviews, it should be noted that most of them are focused on the development of individual recommender systems. In both these recent reviews and the general literature, there is a very limited analysis of works focused on group recommender systems. This is in contrast to the nature of many touristic products, which are usually consumed in groups.

In view of this shortcoming, this paper undertakes a literature analysis of the most recent works focused on the task of group recommendation in the tourism domain.

3 | DEVELOPMENT OF THE REVIEW

In recent years, there has been a consensus in the research community on group recommender systems, around modeling group recommendation as a complex approach that goes beyond simple preference aggregations (Masthoff and Delic´ 2022). Specifically, Delic and Neidhardt (Delic and Neidhardt 2017) pointed out that in the tourism domain there are additional challenges regarding that packages of products and services are interconnected, that tourism is mainly an emotional experience and therefore preference elicitation is not a trivial task, and that user-item rating matrix is very sparse. To overcome these types of challenges in GRS, several authors have recently focused on aspects such as personality (Felfernig et al. 2018a), user relationships (Tran et al. 2021), and conflict resolution (Nguyen et al. 2019). The current literature review also works to characterize the GRS in tourism in this novel and relevant aspects.

This section then develops the review on group recommender systems as a personalization tool in the tourism area. Ini- tially, the methodology used in the review process is presented. Secondly, an analysis of the identified works is made. Further discussions on methods, evaluation protocols, and the modeling of the group concept are also developed.

3.1 | Methodology

This section shows the methodology which has been followed for the review of recent works on group recommender systems applied to tourism. A systematic bibliographic analysis was performed, similar to previous reviews on other research branches on recommender systems (Yera and Martínez 2017, Yera et al. 2023). The methodology selected for this analysis was the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) (Page et al. 2021), and the procedure for the literature analysis went through the following process.

1. Identification of the initial list of articles: Obtain the initial list of possible papers to be analyzed, taking as literature sources the Web of Science and Scopus, widely used in other previous reviews in this area of knowledge (Yera and Martínez 2017, Yera et al. 2023).
2. Eligibility criteria (Inclusion/Exclusion): The exclusion of papers for the bibliographic analysis was performed, based on the following criteria:

   - Articles excluded for not belonging to the areas of study, especially papers that do not address group recommendation in tourism despite being obtained with the used search string.
   - Articles excluded during the content analysis, by eliminating duplicates associated with the same result. In this scenario, the paper presenting the more complete results was considered. In addition, duplicates that appeared as a result of obtaining the same work through different databases were also eliminated.

3. Information sources and search strategies: For the identification of the proper articles, the Web of Science and Scopus databases were used, as they were the most widely used in previous systematic reviews in this area of knowledge, as already referred.

   To this end, the following search queries were used, considering articles in English:

   - group (recommendation OR recommender) systems AND (tourism OR travel)
   - group (recommendation OR recommender) systems AND (restaurant OR restaurants)
   - group (recommendation OR recommender) systems AND (point-of-interest OR point of interest OR POI)
   - group (recommendation OR recommender) systems AND (itinerary OR itineraries)
   - group (recommendation OR recommender) systems AND (destination OR destinations)
   - group (recommender OR recommendation) systems AND (hotel OR hotels)

   For the generation of these queries, several keywords associated with the domain of tourism recommendation were used, such as travel, restaurant, points of interest, itinerary, destination, and hotel. Such keywords have been used in previous surveys such as Chaudhari and Thakkar (Chaudhari and Thakkar 2020), Renjith et al. (Renjith et al. 2020) or Hamid et al. (Hamid et al. 2021), focused on characterizing individual recommendation and personalized services in tourism.

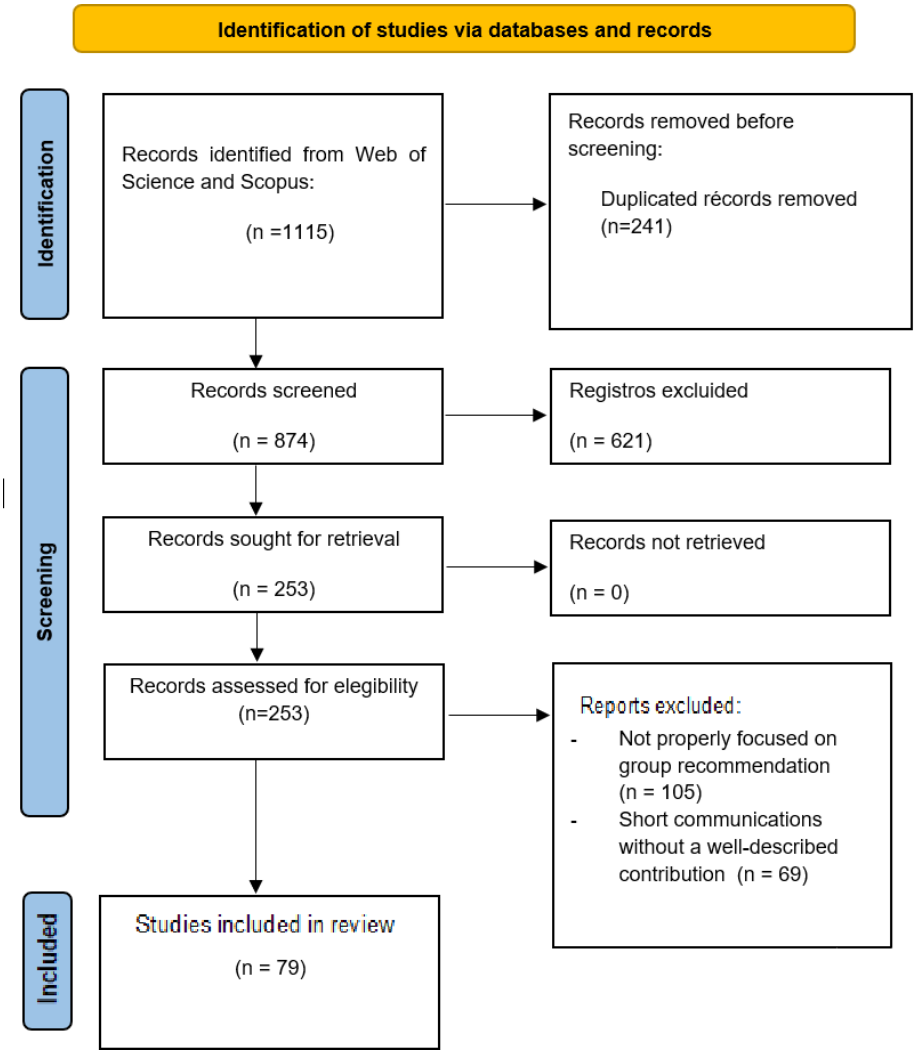

FIGURE 1 PRISMA 2020 flow diagram for the current review.

4. Selection of the studies: The aforementioned query was used to obtain the initial set of papers, which was filtered by taking into account the title, abstract and keywords of each of the articles and based on the exclusion criteria.
5. Data extraction: To refine the inclusion criteria, a set of information items was extracted for each paper, including type of study, type of evaluation, application scenario/main goal, and overall methodology; all in line with the initially proposed research objective. This information was synthesized and a summary table was constructed to identify several characteristics and scopes of group recommender systems in tourism.
6. Quality evaluation of the performed search: This is usually done using checklists of various areas of application. In this work, the checklist proposed by Ataei and Litchfield (Ataei and Litchfield 2022), of general purpose and composed of four groups and seven items, is used.
7. Obtaining the final list of items for the study.

3.2 | Analysis of the results

The results obtained were organized using the PRISMA methodology according to the description presented in the previous section (Figure 1).

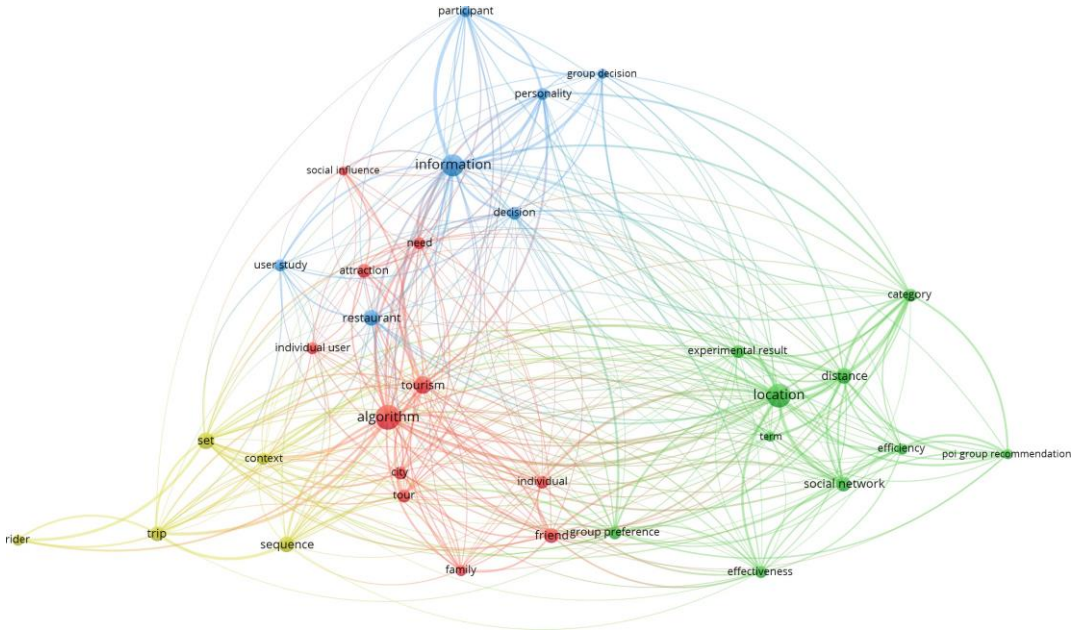

FIGURE 2 Term co-occurrence in the 79 identified works

Figure 1 shows the application of the PRISMA methodology on the results of the search performed. The queries retrieved 1115 records from the Web of Science and Scopus, with the particularity that a significant number of papers were obtained through both databases. As a result, the duplicate elimination stage removed 241 papers from the subsequent analysis, leaving a total of 874 for a more detailed study through their title and abstract.

This more detailed study excluded 331 papers that were not focused on personalization or recommendation systems, as well as 290 papers that, although they refer to the term "group", were actually focused exclusively on individual recommendation. The remaining 253 papers were reviewed in greater depth, detecting that in 105 of them, despite incorporating references to group recommendation, the objective of the proposals and the evaluations performed were centered on individual recommendation. In these cases, they were not included in the current review. Finally, 69 short communications were identified as position papers or contributions to doctoral symposiums, which were also excluded from this review.

Finally, the present review includes a total of 79 papers. In order to achieve a direct characterization of these papers, a graph of terms co-occurrences used in their abstracts was constructed. The VOSViewer tool [§] was used for this purpose. Since its initial presentation in 2010 (van Eck and Waltman 2010), VOSViewer has become a widely used software for bibliometric mapping. It is supported by a well-defined approach centered on a unified mapping and clustering of bibliometric networks that guarantees robustness and reproducibility (Waltman et al. 2010). Today, the term “vosviewer" leads to the retrieval of 4500+ results only from the Web of Science Core Collection, illustrating the current acceptance level of this tool by the research community.

In the graph of co-occurrence terms associated with the abstracts of the retrieved works, terms with a minimum level of co-occurrence of seven were visualized, identifying more than 30 terms (Figure 2). This figure included generic terms such as group recommender systems, framework, tourist, data, item, system, etc; with large co-occurrence values but meaningless in the identification of key characteristics of the identified works.

The figure shows the presence of four term clusters that would suggest large-scale working areas:

[§] https://www.vosviewer.com/

- The green color shows a group of works mainly represented by the words *location*, *distance*, *poi group recommendation*, *social network*, etc; that would indicate the presence of several focused on the POI recommendation domain in the social network framework, which has been regarded as a key scenario in tourism recommender systems (Massimo and Ricci 2021).
- The blue color reflects works represented by terms such as *group decision*, *user study*, *participant*, *personality*, *decision*, etc; which have been common in recent user studies in group recommendation (Delic et al. 2018, Barile et al. 2024). In this group, the term *restaurant* also appears.
- The red color incorporates a heterogeneous set of words such as *city*, *attraction*, *social influence*, *family*, etc; all of them connected to the term *algorithm* which appears highlighted in this set.
- Finally, the smaller term cluster represents with the yellow color some terms such as *context* and *sequence*, that could also have some connection with the red cluster.

This one-shot analysis through term cooccurrences suggests the following conclusions: 1) POI recommendations is currently a relevant research area in GRS, 2) Several research works on tourism group recommendation have incorporated some kind of user study, 3) There is a set of group of works developing GRS approaches for tourism, not necessarily connected with user studies evaluation methodologies.

The next sections will verify these overall findings, by analyzing the identified works from the viewpoints of the application domain, as well as the methodology, group modeling, data, and evaluation.

4 | ANALYSIS OF THE IDENTIFIED WORKS BASED ON THEIR APPLICATION DOMAIN

This section will analyze the identified works across their application domains. Beyond the general findings previously discussed, we have identified three major domains: 1) Restaurant recommendations for groups, 2) Points of interest and itineraries recommendations, and 3) Destinations and travel recommendation.

4.1 | Restaurant recommendations for groups

The works centered on group restaurant recommendation systems emphasize the need to balance individual preferences within groups (Zhang et al. 2018), incorporate contextual factors (Zhu and Wang 2020), and use decision making models (Park et al. 2015, Marques et al. 2016) that can handle real-time and mobile scenarios. These approaches generally aim to optimize recommendations by understanding both the personal tastes of group members and their collective dynamics. Context-aware systems, for example, adapt recommendations based on situational factors such as time, location, or social settings, making the process more responsive and personalized (Zhu and Wang 2020).

In mobile environments, advanced techniques such as multicriteria decision-making (MCDM) and Bayesian networks (Park et al. 2008 2015) are employed to weigh various attributes of restaurants (e.g., food quality, price) and manage uncertainty in group preferences. These probabilistic and decision-making models ensure that, even when group preferences are incomplete or uncertain, the system can still provide reliable suggestions.

In addition, content-based filtering is commonly used to analyze group preferences and recommend restaurants that align with collective interests (Pérez-Almaguer et al. 2024). The focus is often on improving group satisfaction by combining individual preferences with strategies that promote consensus and collaboration in decision-making processes. In general, the identified group of works solves the complexities of group restaurant recommendations by using a combination of advanced algorithms, contextual data, and collaborative decision-making techniques to ensure more accurate and satisfactory results.

4.2 | Point-of-interest and itinerary recommendations for groups

Research on Group Recommendation Systems for points of interest (POIs) has evolved to address the complexity of recommending suitable locations for groups with diverse preferences. The core challenge is to balance individual preferences within a group while considering factors such as spatial proximity, social relations, and group dynamics, as illustrated in Figure 3, which illustrates the main trends in POI recommendations for groups; discussed in this section.

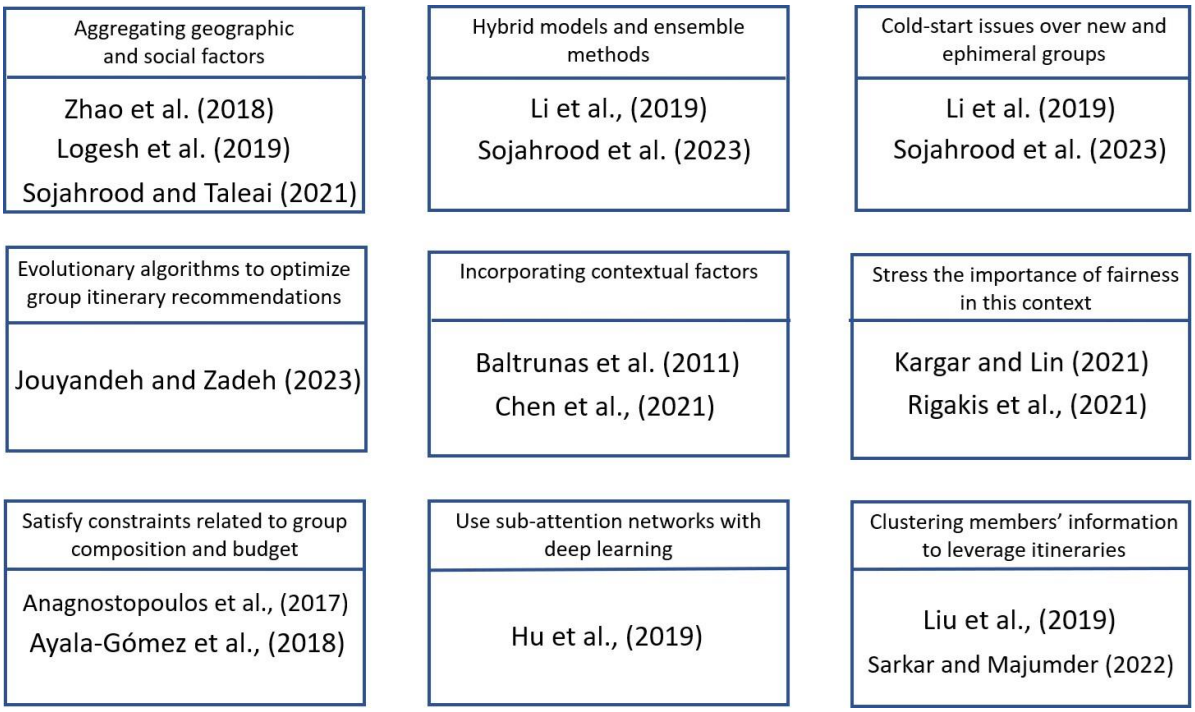

FIGURE 3 Main research trends in POI recommendation

Several studies, such as Herzog and Wörndl (2019) and Zhao et al. (2018), explore the issue of generating recommendations for groups. The study of Herzog introduces the concept of splitting groups into subgroups to enhance satisfaction, which is a novel method to address individual differences within a group. Similarly, Zhao et al. introduce the Geo-Social Group Recommendation (GSGR) model which leverages personal preferences influenced by geographic and social factors to aggregate group preferences, thereby enhancing POI accuracy.

Researchers including Sojahrood et al. (2023) and Li et al. (2019) have introduced hybrid models and ensemble methods to improve recommendation accuracy. Sojahrood et al. present a hybrid method that dynamically switches between strategies depending on group homogeneity and type, significantly improving precision and recall. Li et al. present a multi-layer ensemble framework that combines multiple personalized recommendation methods for individuals, followed by aggregation at the group level, resulting in higher recommendation quality.

Collaborative filtering techniques are also applied to group POI recommendations, as highlighted in Liu et al. (2021), specifically addressing intragroup divergence, varying preferences within a group. This divergence is measured based on POI preferences between group members and their social networks, leading to more personalized and precise group recommendations.

Many studies emphasize the importance of spatial proximity and social factors in making POI recommendations. For example, Sojahrood and Taleai (2021) integrates spatial features such as distance and uses a fuzzy approach to model how user preferences change when in a group, focusing on the impact of distance, time, and category preferences.

Cold-start issues, where new or ephemeral groups lack sufficient historical data, remain a significant challenge. Sojahrood et al. (2023) and Liu et al. (2024) propose models that address this using graph neural networks and data from similar users to overcome cold-start problems. Lius cooperative graph neural network (CGNN-PRRG) specifically targets random groups and achieves superior performance by learning from similar user interactions.

Some studies, such as Jouyandeh and Moradian Zadeh (2023), propose evolutionary algorithms such as cultural algorithms to optimize group itinerary recommendations. These models consider both individual satisfaction and overall group goals, ensuring that group itineraries minimize travel time and cost while maximizing the group's collective enjoyment.

Contextual factors such as time, season, and group composition play a crucial role in recommendation accuracy. Baltrunas et al. (2011) and Chen et al. (2021) focus on context-aware systems, where user context, such as motivation and real-time

conditions, is integrated into the recommendation process. These systems outperform traditional models by adapting to users' immediate circumstances, resulting in more relevant POIs.

Finally, several studies stress the importance of fairness in group decision-making. Kargar and Lin (2021) and Rigakis et al. (2021) propose frameworks that balance conflicting preferences among group members by maximizing fairness and ensuring that no group member feels left out. This fosters higher group participation and satisfaction, especially in multi-day group tours.

Anagnostopoulos et al. (2017) and Ayala-Gómez et al. (2018) use information from geolocation services to generate recommendations of points of interest that satisfy constraints related to the composition of the available group and budget.

Meanwhile, Vallejos et al. (2019) presents a methodology focused on automatically identifying the level of interest of users on previously visited attractions (points of interest), to find compatible groups of tourists. Herzog et al. (2018), on the other hand, represent the problem as a sequential scenario in which sequences are modeled as a succession of points of interest, being a "pleasant" route obtained for the user by collecting points of interest at origins and destinations. In addition, Logesh et al. (2019) also uses information from heterogeneous sources to recommend tourist points of interest.

A similar approach was carried out by Hu et al. (2019) for several European cities, with the particularity of using sub-attention networks with deep learning to identify the most influential attributes within a list of points of interest.

Alves et al. (2019) introduce an architecture focused on integrating a POI-related service, the social network-related service, and a gamification module.

More recently, Xu et al. (2021) used a database of relevant places in the city of Beijing to recommend points of interest based on confidence levels over the preferences of other users or groups similar to the current one.

Furthermore, Streviniotis and Chalkiadakis (2022) has proposed the recommendation of points of interest located in the city of Agios Nikolaos, in Crete, Greece, using several aggregation mechanisms of users' individual preferences, based on the social choice theory. As part of the work, he obtains a real database of that location with several points of interest. Abbas et al. (2022), on the other hand, enables dynamic recommendation of points of interest, allowing dynamic readjustment of the same depending on the real-time preferences of users during their journey; also using deep learning for this purpose.

Liao et al. (2022) have proposed a "joining and forking" strategy, in which group members are allowed to have a "time apart" to consume their recommendations individually, and a "time together", for the co-creation of shared experiences; all within a POI recommendation framework.

Finally, Telonis et al. (2023) have recently brought the Cooperative Location Set Cover Problem to the context of POI group recommendation, formulating it as a constraint-based scenario.

In general, the field of POI group recommendation systems is shifting towards hybrid, context-aware, and fairness-focused models. By integrating individual preferences, social and spatial factors, and addressing cold-start challenges, researchers are pushing the boundaries to provide more personalized and satisfying group recommendations.

Beyond direct management of points of interest, recent advances in group recommender systems for travel itineraries address the complexities of aggregating diverse preferences within groups of travelers. Liu et al. (2019) introduces the Comprehensive Group Similarity Preference Aggregation (CGSPA) algorithm, which enhances group satisfaction by considering multiple aspects of user preferences, demonstrating higher average scores compared to traditional methods. Building on this, Sarkar and Majumder (2022) present the gTour algorithm, capable of generating customized itineraries even in unfamiliar locations, achieving superior performance on a Flickr dataset. Yin et al. (2019) emphasizes the role of temporary mobile social networks in optimizing travel experiences for groups formed around common interests, facilitating cost-effective travel through shared itineraries. Yu and Yang (2023) advocates for customized tourism by clustering similar visitors and combining their needs with online resources to create efficient itineraries, although further validation across diverse datasets is required. Ezin et al. (2019) address the challenge of consensus in group decision-making by utilizing collaborative filtering based on YouTube viewing histories to aggregate preferences and enhance trust within groups. Lastly, Ruiz-Meza et al. (2021) adresses the Tourist Trip Design Problem through an extension of the Team Orienteering Problem with Time windows, optimizing itineraries to maximize group preferences while accommodating real-world constraints. Collectively, these studies reflect a significant shift towards personalized and efficient group travel solutions, leveraging advanced algorithms to enhance the travel experience.

4.3 | Destinations and travel recommendations for groups

Research on group recommender systems for travel and destination planning focuses on addressing the complexities of providing personalized recommendations for groups of users with diverse preferences. While classical recommender systems focus on individual users in domains such as movies and books, group travel planning introduces unique challenges related to group

dynamics, preference aggregation, and contextual constraints. The following synthesis explores key themes and innovations in research.

A common challenge in group travel recommendation systems is balancing individual preferences with the collective decision-making needs of the group. Pessemier et al. (2017) and Garcia et al. (2011) focus on aggregating individual preferences into a coherent group recommendation, using mechanisms such as content-based, collaborative filtering, and demographic classification. Both emphasize the importance of ensuring that the group's preferences are reflected in the final recommendation, with the model of Garcia et al. further incorporating demographic factors to personalize suggestions. Xu et al. (2021) highlight the role of trust and social influence in shaping group recommendations, proposing a model that integrates user trust relationships into the decision-making process. This approach ensures that social dynamics, such as trust and interaction history, are considered when generating recommendations, leading to more accurate and satisfactory group outcomes. In Liao et al. (2022), an innovative solution addresses the challenge of conflicting preferences within groups by allowing members to temporarily split and rejoin the group. This "joining and forking" strategy balances individual preferences with shared group experiences, promoting both personal satisfaction and group cohesion.

Several studies underscore the importance of interactivity in group decision making for travel. Zhang and Sun (2018) designed a system that allows members of the group to interact with and influence the recommendation process, enhancing user engagement. The system relies on an ontology that structures tourism-related information and incorporates an aggregation strategy to generate recommendations. Similarly, Vallejos et al. (2019) introduced TourWithMe, a peer recommendation system that helps users form groups based on shared interests and explore attractions together. This highlights the social aspect of group travel, where tourists may seek new companions to enhance their travel experiences.

Context is a very important component in many travel recommender systems, as user preferences can change based on situational factors. Ayala-Gómez et al. (2018) presents a context-aware solution that adapts recommendations based on group preferences and itinerary constraints. This approach tailors recommendations to the context of the groups visit and time constraints, optimizing the travel experience through a Monte Carlo Tree Search method. Pitakaso et al. (2023) takes a multi-objective approach, incorporating safety as a criterion in the planning of tourist routes, addressing an important but often overlooked factor. Their solution balances tourist safety with group preferences and fairness, ensuring a secure and enjoyable travel experience for all members of the group.

Many systems leverage hybrid algorithms to improve the quality of recommendation by combining various techniques. Christensen et al. (2016) presents Hermes, a system that combines collaborative, content-based, and demographic filtering to generate individual and group recommendations. This hybrid approach minimizes the disadvantages of individual techniques while maximizing recommendation accuracy, particularly when social relationships among group members are taken into account. Similarly,He et al. (2020) propose a modified collaborative filtering (CF) approach that incorporates individual and group constraints to recommend comprehensive travel packages. This approach ensures that individual preferences and group dynamics are taken into account when selecting destinations, hotels, and attractions, thus improving user satisfaction.

The impact of social relationships on group travel decisions is a recurring theme in several studies. Delic et al. (2018) explore the role of social centrality and its influence on group satisfaction, revealing that groups with socially close members are happier with their decisions. This insight reinforces the need for group recommender systems to account for social factors in decision-making processes. Tang et al. (2019) focuses on the psychological factors that influence the formation of a ride-sharing group, introducing social links and the acceptance of the rider into the equation. By optimizing group recommendations based on both spatial and social context, this approach enhances group satisfaction and reduces travel time.

In general, the synthesis of these studies demonstrates that group travel recommender systems must account for various factors, including individual and group preferences, contextual information, social dynamics, and safety. The most effective systems leverage hybrid algorithms and incorporate interactive features that engage users in the decision-making process. In addition, consideration of social relationships and trust among group members can significantly improve the accuracy and satisfaction of group recommendations. These advances highlight the evolving complexity of group recommender systems in the domain of tourism and travel.

The next subsection will analyze in depth the methodologies employed in the proposals associated with the discussed papers.

5 | ANALYSIS OF THE RESEARCH METHODS USED ACROSS THE IDENTIFIED WORKS

This section presents a traversal analysis of several key works identified in this review in relation to relevant topics in group recommender systems research, such as novel interfaces and user modeling approaches, the underlying recommendation approaches, the evaluation procedures, and the evolution of the concept of group.

5.1 | Novel interfaces and user modeling approaches

The first family of research approaches includes some pioneering works in group recommendation. For example, Ardissono et al. (2003) present the INTRIGUE system, which recommends sightseeing destinations and itineraries taking into account the preferences of heterogeneous user groups, such as families with children and the elderly. It exploits a structured group modeling, where subgroups are represented by different entities composed of homogeneous people. Subgroup-specific rankings are aggregated to generate an overall ranking according to the preferences of the entire group.

Jameson et al. (2004) have proposed a system that facilitates asynchronous communication between group members in the tourism domain, by incorporating a novel application of animated characters, where each character serves as a representation of a group member who is not currently available for communication. Another representative work from the methodological point of view is the development of the CATS system by McCarthy et al. (2006), based on the incremental critiquing technique (Reilly et al. 2005) where a group preference model is also maintained by combining the individual user models and associating each unit critique.

TABLE 1 Key works in novel interfaces and user modeling approaches

Paper	Goal
Ardissono et al. (2003)	Interface with structured user modeling managing preference aggregation.
Jameson et al. (2004)	Asynchronous communication in the group, with animated characters.
McCarthy et al. (2006)	Use incremental critiquing for building the user profile.
Álvarez Márquez and Ziegler (2015)	Interface supporting preference elicitation and negotiation.
Nguyen and Ricci (2018)	Member utility and group utility are built over a chat-based interfaces.
Delic et al. (2018)	Observational study using questionnaire and discussion phases.
Alves et al. (2023)	Identify how personality is related to the choice of tourist attractions.
Najafian et al. (2024)	Explore how individuals balance privacy concerns in group travel decision-making.

More recent work has followed some of these paradigms. Álvarez Márquez and Ziegler (2015) designed an interface concept that provides discussion support in a collaborative preference elicitation and negotiation process. This proposal allows negotiation already in the preference elicitation stage through an (adding features-get recommendation-negotiate)-cycle that can be repeated several times, until the reaching of the final agreement in the group. This concept is implemented in the prototype hotel recommender Hootle.

Nguyen and Ricci (2018) present a mobile chat-based group recommender system for tourism, that allows group members to participate in a group conversation by exchanging messages in a chat. The system observes the users actions during group discussion to infer novel information about the current users preferences in the corresponding group context. In contrast to critiquing approaches, this proposal does not ask users to provide explicit feedback about the item features. Instead, this kind of information is automatically extracted from the feedback given at the item level and represented through a utility vector for each group member, which is updated taking into account the discussions developed in the group. Afterwards, a group utility function is calculated on the basis of these individual vectors, using an average aggregation approach. Finally, when some member asks for group recommendation, the set of available items is obtained according to a group utility function that receives as input the group utility vector.

Beyond properly introducing software, Delic et al. (2018) develop an observational study of group recommendation in the tourism domain. As far as we have identified, this work is the unique observational study in GRS, introducing a methodology composed of a pre-questionnaire phase, group meetings/discussions phase, and a post-questionnaire phase. As relevant findings, this novel methodology suggests that the application of aggregation strategies over the members' prediscussion preferences does not overall lead to predicting the final group choice, that the choice satisfaction of the members is linked to their personality,

that the satisfaction of the group in relation to the selected choice is related to the difficulty of the decision making process, personality, travel patterns, and level of agreement among group members; as well as other relevant finding relating personality and recommendation output.

Alves et al. (2023) developed an extensive user study focused on identifying how personality is related to the choice of a wide range of tourist attractions, travel motivations, and travel-related preferences and concerns; also considering the frame of the group context. The main purpose of this research was to provide a solid base for GRS tourism researchers to automatically model more accurate tourist profiles and create groups with similar preferences. In this direction, the authors also proposed different models for automatic group recommendations.

Recently, Najafian et al. (2024) explored how people balance privacy concerns and the benefits of disclosing personal information in group travel decision making. Factors such as personality, trust, and task design influence this trade-off. Through a chatbot-based user experiment, findings reveal that privacy risks affect disclosure more in competitive tasks than in cooperative ones, highlighting the role of task framing.

The performed analysis on research approaches where the main innovations are driving by the user interfaces and user studies, evidences a clear evolution of the employed methodology. Although the former approaches focused mainly on optimizing information gathering through novel user interfaces (Jameson et al. 2004, McCarthy et al. 2006), more recent works have focused, in addition, on bringing relevant concepts related to group recommendation, such as personality (Delic et al. 2018, Alves et al. 2023).

5.2 | Underlying recommendation approaches

Several approaches have introduced new algorithms related to novel methodologies in this domain, to a larger or lesser extent.

Garcia et al. (2011) present one of the first contributions in this direction, using a generalist recommender system kernel based on basic concepts of RS and GRS, such as demographic filtering and content-based filtering modules, a group preference manager incorporating aggregation and overlapping detection methods among users' preferences, an item selector, and a hybrid recommendation module for combining output of different algorithms. Subsequently, Pessemier et al. (2017) developed a similar approach, in which they propose a recommender system that offers personalized recommendations for travel destinations to individuals and groups, based on a hybrid approach that integrates content-based, collaborative filtering, and knowledge-based methods. This proposal manages the user rating profile, personal interests, and specific demands for their next destination.

As was pointed out in previous sections, the use of information from social relationships represents an important milestone in RS and GRS. As discussed, one of the first research works that incorporates this kind of information in touristic GRS was developed by Christensen et al. (2016). Here, the authors built a hybrid user profile that combined three different profiles: collaborative, content-based, and demographic profiles. As the main novelty, the group profile is created by taking into account different types of social relationships among members of a group. Therefore, for the rating aggregation stage, these influences are considered by incorporating them as weights in the final rating calculation. More recently, Xu et al. (2021) also proposed a travel group recommendation approach supported by user trust and social influences. This model calculates the direct and indirect trust of a user. This information is incorporated into a group consensus model that also contains the social influence of users, integrated with a neighborhood recommendation approach through a weighting scheme.

Another dimension of the research in GRS for tourism, identified previously in Section 4.2, was the application to points of interest recommendation. Although points of interest recommendations have attracted the interest of researchers to a greater extent (Werneck et al. 2021), there is a smaller amount of work specifically focused on concepts closely focused on the tourism domain in the group case, as detected by our survey.

Anagnostopoulos et al. (2017) focus this task as the orienteering problem, where the goal is to nd a path in a graph within a time budget that has the best value for the group. Here, the group value is represented as an objective function that aggregates the individual preferences of POIs on the path. The proposed approach is composed of two steps: 1) the calculation of the individual preferences of the group members over the available POIs using a content-based approach, and 2) the itineraries building for groups through the use of several objective functions supported by preference aggregation schemes. Herzog et al. (2018) present a mobile recommender system for tourist trips, focusing on recommending sequences of points of interest across pleasant routes. In this application, a user first rates some POIs, using this information to build their profiles. The user then requests a new tourist trip recommendation by specifying the origin, destination, starting time, and maximum duration of the trip. Group recommendations are generated by aggregating user models or individual recommendations. Ayala-Gómez et al. (2018) present a solution based on a similar scheme, which enhances the POI recommendation stage through POI temporal

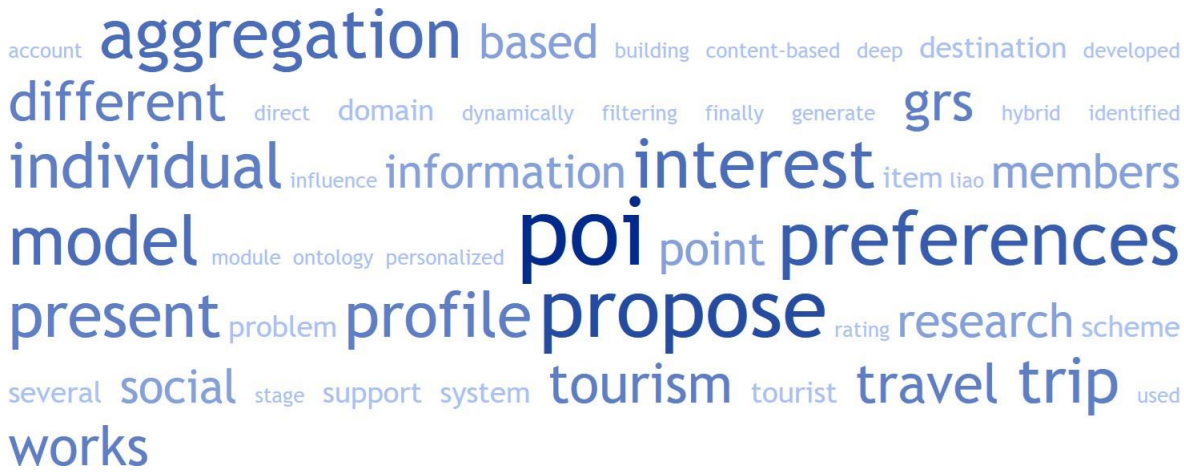

FIGURE 4 Word cloud illustrating the main approaches across the underlying algorithms

and transitional features. Alves et al. (2019) have presented a conceptual architecture of a mobile GRS for tourism based on agents, using a recommendation service, a POI service, a social network-based module, and a gamification module. The overall objective of the architecture is to present an argumentation-based dialogue model between several agents that will accompany the group during the tour. Logesh et al. (2019) present a hybrid architecture for personalized travel applications, which includes an activity and behavior-induced personalized recommender system for POI recommendation, and a novel user-based social relationship-induced group recommendation model that takes into account the relationships between group members. Vallejos et al. (2019) also propose an approach focused on suggesting groups of people to visit different attractions together. At first, the proposal infers the users interests from the user's geolocation data. Afterwards, under request, the approach proposes forming a group with nearby users, using the information of individual profiles to compose a cohesive group. Finally, the top-k POIs are delivered to the group. Streviniotis and Chalkiadakis (2022) propose the use, in the tourism GRS framework, of the reweighted approval voting scheme for recommendation aggregation, not considered before in the GRS literature (Faliszewski et al. 2017); and have tested their approach in a POI dataset.

In the same domain of POI recommendation to groups in tourism, a more sophisticated approach empowered with deep learning technologies was developed by Hu et al. (2019). They proposed a new approach named AGREE, which uses an attention mechanism to dynamically adjust the influence of group members, through aggregating their historical preferences using attention sub-networks that depend on the group and the previous group item and user item interactions. A bidirectional recurrent unit is used to generate the recommended POIs. Abbas et al. (2022) is focused on sequential POI recommendations, proposing a model entitled Recommending Reforming Trip. Here, the travel plan is presented dynamically (i.e. taking into account the change of users' plans in the middle of the trip), with the support of deep neural networks for solving the formulated sequence-to-sequence problem. The proposed deep learning-based transformer model follows an encoderdecoder structure but does not depend on repetition and convolution to produce an output. Finally, Telonis et al. (2023) have recently presented a different modeling of the trip recommendation problem for a group of tourists, by reducing it to the cooperative location set cover problem, formulated as integer linear programming. This problem is focused on finding a group of facilities that can satisfy all the aggregated and demanded points. Here, the restrictions are focused on satisfying all the preferences of the group members as much as possible and as evenly as possible.

In a different research direction, Zhang and Sun (2018) illustrate a touristic group recommendation approach based on ontologies. At first, here an ontology is developed based on knowledge provided by senior travelers at Nanjing, China. Furthermore, the user profile is built using the preference degree over the different classes in the ontology. The recommendation mechanism is then focused on selecting the items, represented as instances in the ontology, that satisfy the group preferences. He et al. (2020) introduce a modified collaborative filtering procedure to suggest a destination for a group travel planning service. Herein, individual users requirements are modeled by constraints, which are also used to build group-level constraints. A two-stage process drives the recommendation generation: 1) at first, a neighborhood-based recommendation approach generates an initial list of top-k destinations, 2) at second, the best items that meet the predefined constraints for each group are finally recommended.

An interesting approach to group recommendation has been pointed out by (Liao et al. 2022) related to dynamic group formation in travel recommendation. It suggests the implementation of a joining and forking strategy in the system design, allowing members to have time apart to enjoy the trip separately and time together to gather shared experiences and memories. This strategy is implemented by assuming that a trip is composed of several stages according to discrete visits to vertices (which could be considered as POIs). The utility of a certain stage for a tourist depends on the individual preference over the vertex, and the time spent there. These individual utility values are aggregated to achieve the overall experience of the group. In addition to this information, the proportion of shared experiences is also taken into account in the joining and forking strategy.

In general, the analysis performed identified several works focused on proposing new algorithms and approaches for group recommendation in the tourism domain, synthesized in a word cloud (Figure 4). However, in contrast to the work mainly focused on user studies and interfaces, here it is not clear a well-defined research line across the last few years. It is interesting that an important group of works analyzed in this section adopted the POIs recommendation for group as default framework for building GRSs in the referred domain, also with the support of well-known approaches such as deep learning, or location and orientation-based mathematical formulations. However, some recent works were also identified to focus only on the direct use of preference or recommendation aggregation schemes to support the group dimension, which could be insufficient to manage this dimension in a proper way. We also identified some works that attempted to model the dynamics of the group throughout the recommendation process (e.g., the joining and forking strategy at Liao et al. (2022)), which could also be an interesting research area to explore in the future.

5.3 | Evaluation procedures

Most of the RS and GRS evaluation procedures have focused on offline protocols and user studies (Gunawardana et al. 2022). In this section, a brief overview of the evaluation protocols employed in the identified research works on GRS in tourism will be provided, taking into account the two paradigms of research works considered in the previously presented methodology-related section.

In the case of the evaluation approaches linked to the works supported by user studies and novel interfaces, several of the have effectively completed studies with real users. McCarthy et al. (2006), as a first stage of the evaluation of their system CATS, developed a trial with graduated students in computer science with varying degrees of interest and experience. The composition of the group and the satisfaction of the users were also evaluated. Álvarez Márquez and Ziegler (2015) performed a user study focused on testing their interface concept, comprising several groups with sizes between three and five users, including a total of 48 students. Two group decision making scenarios are presented to users, respectively related to selecting a hotel with some attributes, and to finding a place to stay during summer vacations. Using role cards, the authors expected to generate conflicts and discussion among group members. Nguyen and Ricci (2018) conducted a user study to evaluate the usability of their proposed system, the perceived quality of group recommendations, and the satisfaction of the group choice. The study involves 15 participants, divided into groups of size 2 and 3. After registering on the system and loading personal preference data, users were invited to meet physically and at the beginning each received a mobile device with the system. After using the system's features for discussing and deciding which place to visit together in the frame of a tentative travel to the South Tyrol region, participants are asked to fill out a questionnaire composed of four parts evaluating the system usability scale, the perceived recommendation quality, the choice satisfaction, and group identification.

Delic et al. (2018) develop a large-scale user study, more detailed in the previous section, focused on observing and measuring the evolution of user preferences and interaction in the task of finding a destination to visit together as a group. The study comprises 200 decision-makers in 55 groups of 2-5 group members, and is driven by three stages: a pre-questionnaire phase, groups meetings/discussions phase, and a post-questionnaire phase. Recently, Alves et al. (2023) develop a user study focused on finding the relationship between personality and user choices in the frame of the group context, also more detailed in the previous methodology section. This user study with a questionnaire applied on 1000+ participants.

Other works such as (Jameson et al. 2004, Ardissono et al. 2003), even though they accomplish the exploration of some user interaction with the systems, do not have this issue as the main objective.

In the case of the work mainly centered on the underlying algorithm in the tourism domain, a high diversity of evaluation protocols can be identified, the offline analysis being predominant with a larger or smaller scale.

Garcia et al. (2011) use a questionnaire with questions about general preferences, demographic data, visited places, and degree of preferences, over 60 users. The results are used to build a dataset for offline evaluation of the recommendation output, through metrics such as Precision/Recall/F1. In Pessemier et al. (2017), the proposed system was explored by 16 users,

which also made up four groups, who experience the recommendations provided by the various approaches included in the proposal. Users are asked about their opinion about the different recommendation algorithms, according to match interest, novelty, diversity, and usefulness. An additional questionnaire was used to assess the group recommendation, focused on the balance and satisfaction of the recommendations. Zhang and Sun (2018) evaluate their approach based on questionnaire surveys and interviews, as well as EEG signals.

Christensen et al. (2016), in one of the first works focused on social relationships and group recommendation, tested their proposal through an artificial dataset composed of 1300 tours and 800 users obtained through a simulation procedure, and used metrics such as MAE and Precision.

In a different direction, Anagnostopoulos et al. (2017), in one of the pioneering works in POI recommendation to groups, created a set of own datasets starting from location and trajectories data taken from sources such as Wikipedia and Flickr. The user profiles are based on the number of photos taken at each point of the trajectories. Ayala-Gómez et al. (2018), on their hand, collected a dataset with check-ins from Swarm by FourSquare, a popular location-based social network, and used traditional evaluation metrics such as Precision, Recall, and NDCG. Logesh et al. (2019) use for the evaluation the two large-scale real-time datasets of Yelp and TripAdvisor, and consider Precision, MAE, and Hit-Rate as criteria. Hu et al. (2019) based their offline experiments on a set of individual trajectories taken from a previous work (Muntean et al. 2015), in three European cities; and used as metrics the average score and precision. (Xu et al. 2021) collect the evaluation data of 200 scenic spots from 37000 tourist at Beijing city; and also consider the Yelp Restaurant dataset to evaluate their approach. They use the Precision and NDCG metrics. Abbas et al. (2022), also in the POI domain, use a dataset gathered from Weeplace, a site that plans user check-in exercises in location-based social networks. The authors use traditional and sequence-oriented metrics, such as Adjust Precision and Sequence-mindful precision.

Streviniotis and Chalkiadakis (2022) use a real world dataset including 430 POIs located in the city of Agios Nikolaos, Crete, Greece, and is focused on measuring some fairness-related metrics such as m-proportionality and m-envy-freeness. Liao et al. (2022) collect information from real tourists groups about POIs to visit, and use the inverted generational distance as a criterion to assess their model performance, in contrast to other basic approaches centered on path recommendation. Telonis et al. (2023) in their POI recommendation approach based on the cooperative location set cover problem, evaluate their proposal using the same dataset previously used by Anagnostopoulos et al. (2017), and propose novel metrics to evaluate group recommendation in the POI context, named the Initial average preference per tourist, Recommended average preference per tourist, Initial variation of preference per user, Recommended variation of preference per tourist, Average precision per tourist, and Average recall per tourist, which extend the traditional Precision and Recall metrics and are also built over the basic group preference aggregation approaches.

In this group of works centered on the underlying algorithm for group recommendation as the main goal, we also identified several works where the evaluation stage was out of their scope (Herzog et al. 2018, Alves et al. 2019, Vallejos et al. 2019, He et al. 2020).

TABLE 2 Key works regarding evaluation procedures

Evaluation goal
User studies for measuring group comprising, user satisfaction, choice satisfaction, etc.
McCarthy et al. (2006), Álvarez Márquez and Ziegler (2015), Nguyen and Ricci (2018), Delic et al. (2018) Alves et al. (2023), Najafian et al. (2024)
Offline studies using typical metrics such as MAE/Precision/Recall/NDCG and simulating real groups.
Garcia et al. (2011), Pessemier et al. (2017), Christensen et al. (2016), Anagnostopoulos et al. (2017) Xu et al. (2021), Logesh et al. (2019), Abbas et al. (2022)
Specific metrics such as fairness-related, invert generation distance, POI oriented, etc
Anagnostopoulos et al. (2017), Streviniotis and Chalkiadakis (2022), Liao et al. (2022)

In general, this section has illustrated that an important number of analyzed works incorporate some kind of evaluation protocol to measure performance in some dimension (Table 2). However, it is important to note that despite some works mainly focused on this goal, most evaluation protocols are not aligned with research trends such as personality, emotions, or conflict resolution; as mentioned above. In addition, it is not clear whether the evaluation protocols in the tourism domain can take

advantage of the information coming from social relationships, which is a central concept in GRS. These shortcomings suggest that further work is needed to become evaluation methods in this scenario more realistic and in line with the tourism context.

5.4 | Evolution of the concept of group

In addition to the analysis of the methodology and the evaluation procedures used in group recommendation in tourism, an interesting topic to explore is the evolution of the concept of group in this context. As mentioned by Delic et al. (Delic et al. 2018), the application domain is an important factor considered in the design of a GRS. The characterization of the group modeling could then be relevant in the tourism scenario. Here, in those works, mainly focused on user studies, the group representation issue has been covered through various ways. In contrast, in the works based on offline experiments, groups are usually built through a predetermined criteria, or sometimes appear predeterminately in the used dataset. From the analysis developed in this section, we have excluded some works identified in this survey, which lack details regarding the considered view of the group concept inside their GRS proposal.

In this way, Ardissono et al. (Ardissono et al. 2003) considers in their proposal heterogeneous user groups, such as families. McCarthy et al. (McCarthy et al. 2006) develop their system with an initial base of European skiing holidays, the trialists being three groups of four computer science graduate students. Alvarez and Ziegler (Álvarez Márquez and Ziegler 2015) considers a proposal where the group of users can communicate with each other presentially or remotely. Furthermore, the evaluation of the proposal is also done by students who simulated the group behavior. Delic et al. (Delic et al. 2018), in their observational study on the evolution of user preferences, characterize groups as a casual joining of users associated with some kind of previous relationship, in their case the study was conducted by students from different European universities. Nguyen and Ricci (Nguyen and Ricci 2018), who evaluated their chat-based group recommendation approach with groups of students and colleagues, explored a similar view.

Anagnostopoulos et al. (Anagnostopoulos et al. 2017) and Telonis et al. (Telonis et al. 2023) identify users and groups based on information available on platforms such as Flickr, being groups of users built taking into account the matching level regarding common POI trajectories. Christensen et al. (Christensen et al. 2016) define groups as a set of interdependent people, with relationships among them and capable of interaction with each other. In their social relationship-based approach, they think of relationships between users in a similar way to the social network-based view. De Pessemier et al. (Pessemier et al. 2017) use the group concept in the frame of the travel destination selection task, usually performed by family or friends. Therefore, in the evaluation, they worked with real users and real groups, such as real-life family groups or a group of friends. Ayala et al. (Ayala-Gómez et al. 2018) composed groups with up to 12 participants, taking into account common check-in information posted on location-based social networks. Logesh et al. (Logesh et al. 2019) also present a group recommendation approach where the group is driven by social relationships. Herzog et al. (Herzog et al. 2018) point out the use of location-related services, such as Google Nearby Connections, to facilitate group composition. The same direction was followed by Hu et al. (Hu et al. 2019) using a set of trajectories from three European cities as the basis for group modeling, and by Vallejos et al. (Vallejos et al. 2019), where groups are built on request, based on nearby users, also in the POI recommendation context. Beyond the definition of the concept of the group, Alves et al. (Alves et al. 2019) have also highlighted the collaborative decision-making dimension among group members as an indispensable factor for the success of GRS, and also pointed out the ability to explain as a relevant attribute. Finally, Liao et al. (Liao et al. 2022) conceive an GRS scenario where groups can be dynamically joined and forked across the performed travel, this issue being innovative in group recommendation.

In summary, the analysis performed in the current section leads to the following findings:

- The literature has reported several works centered on user studies, that are based on the modeling of casual groups for the proposal and evaluation stages. Specifically, in the evaluation, these groups are simulated through the participation of volunteer users, which are usually university students and colleagues.
- A group of works were found based both on user studies and on the proposal of new algorithms, where groups are composed and modeled by exploiting social relationships between users, such as friendship or family relationships.
- There are several works, mainly those focused on recommending POIs, that are based on trajectories and proximity values between users, for composing groups.
- We also identified a research work focused on dynamic joining and forking of user members in the group, during the travel route.

- Overall, we think that it is necessary to unify and formalize how the concept of group inside GRS can be modeled and managed.

6 | FUTURE WORKS

The analysis performed in previous sections, leads to the identification of the following research opportunities in the next few years, for boosting the research around group recommender systems for the tourism domain.

- **The development of a generalizable research framework for group recommendation in tourism.** The analysis carried out throughout this work detected that in recent years there has been an increase in the development of user studies, without regard to the development of full-cycle research that includes the construction of new algorithms and methodologies that conclude with an extensive experimental study, tailored to the specific domain of group recommendation for tourism. Despite the increasing number of identified works globally focused on POIs, it is necessary to develop new proposals focused on the tourism domain as a central goal, which can be directly reused by other developers of computer systems in this area (Renjith et al. 2020).
- **The exploitation of the nature of the group, beyond the simple sum of its members.**In this direction, the construction of new proposals is also necessary focusing on the development of new techniques to aggregate individual preferences at the group level, how to distinguish between satisfied and unsatisfied groups, how to correlate and compare individual preferences with group preferences, and how to relate personal preferences as the personality of users, as recently reflected by Delic et al. (2018). Other computational methods intrinsically related to groups, such as the application of minimum cost consensus models (Yera et al. 2018) for improving group's preferences agreement, can be also considered here.
- **A better characterization of the concept of the group within GRS models.** Although group recommendation in tourism has been mostly studied through a common framework in relation to the group concept, the analysis of the works identified different types of groups, e.g., a family, friends, travelers that have been joined together in some touristic space, casual groups, etc. It is necessary to identify whether the same research approaches are applicable to all the cases, or whether specific approaches are needed in some scenarios.
- **The exploitation of alternative recommendation goals**. It is also necessary to make a more active use of traditional recommendation paradigms, such as content-based recommendation and collaborative filtering (Adomavicius and Tuzhilin 2005), to consider other criteria for the quality of recommendations, such as diversity (Javari and Jalili 2015) and coverage (Gunawardana and Shani 2009) of the list of generated group recommendations. These criteria would be very relevant in the tourism domain.
- **The generation of explainable recommendations.** The generation of post-hoc explanation for adding trustworthiness in the recommendation generation process, is currently a hot topic in the research community (Zhang et al. 2020). Furthermore, the use of explainable recommendations in tourism GRS would be a necessary area to explore (Yera et al. 2022, Yera and Martínez 2024), including the development of tailored evaluation protocols. In the context of human-centered explainable artificial intelligence (Rong et al. 2024), other measures of explanatory methods such as trust, understanding, usability, and human-AI collaboration performance, would be interesting to explore in this domain.
- **The exploration of new application domains.** Finally, it is necessary to study new recommendation domains within the area of e-tourism itself and related to the group recommendation problem, such as the recommendation of sequences of innovation activities, recently referred by Carballo-Cruz et al. (2019). It is also necessary to work on specific evaluation protocols for such scenarios.

7 | CONCLUSIONS

This paper focused on a review of the role of group recommender systems in the tourism domain. To this end, an analysis of the most relevant recent work identified in the literature was developed, focused on the problem of group recommendation of items associated with the tourism domain.

The analysis yielded as main results the presence of a convergence of application domains of group recommender systems in the area of tourism, to consider domains such as tourist routes or points of interest. However, the extensive use of offline evaluation as an initial step of the evaluation process, customized to the specific tourism GRS domain was not identified as

suggested by established protocols in the area of recommender systems (Shani and Gunawardana 2013). As a result, research development focused on the proposal of new methods and algorithms focused on this particular problem was considered insufficient.

These conclusions therefore give rise to the proposal of future lines to be explored, among which are mentioned the development of new proposals focused on new algorithms and methodologies that conclude with an extensive experimental study, which can be directly reused by other developers of computer systems focused on the tourism domain. In addition, it is necessary to consider the creation of new proposals that take into account other criteria of quality of recommendations, such as diversity (Javari and Jalili 2015) and coverage (Gunawardana and Shani 2009).

We hope that the present work will be useful to the scientific community, with a view to further developing the still incipient research line on group recommender systems for tourism.

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