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RESEARCH ARTICLE

Recommender Systems for Outdoor Adventure Tourism Sports: Hiking, Running and Climbing

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Abstract
Adventure tourism is a popular and growing segment within the tourism industry that involves, but is not limited to, hiking, running, and climbing activities. These activities attract investment from foreign travelers interested in practicing sports while exploring other countries. As a result, many software companies started developing Artificial Intelligence solutions to enhance tourists' outdoor adventure experience. One of the leading technologies in this field is recommender systems, which provide personalized recommendations to tourists based on their preferences. While this topic is actively being researched in some sports (running and hiking), other adventure sports disciplines have yet to be fully explored. To standardize the development of intelligence-based recommender systems, we conducted a systematic literature review on more than a thousand scientific papers published in decision support system applications in three outdoor adventure sports, such as running, hiking, and sport climbing. Hence, the main focus of this work is, firstly, to summarize the state-of-the-art methods and techniques being researched and developed by scientists in recommender systems in adventure tourism, secondly, to provide a unified methodology for software solutions designed in this domain, and thirdly, to give further insights into open possibilities in this topic. This literature survey serves as a unified framework for the future development of technologies in adventure tourism. Moreover, this paper seeks to guide the development of more effective and personalized recommendation systems.

Keywords Adventure tourism · Recommender systems · Artificial intelligence · Sports

Abbreviations

ACM	Association for Computing Machinery
AI	Artificial Intelligence
AT	Adventure Tourism
CA	Context-Aware
CAI	Club Alpine Italiano
CARs	Context-Aware Recommender System
CB	Content-Based
CF	Collaborative Filtering
FFM	Five-Factor Model
GUI	Graphical User Interface
H	Hybrid
i-CF	Item-based Collaborative Filtering
IEEE	Institute of Electrical and Electronics Engineers
KB	Knowledge-Based
POIs	Points of Interests
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
RQ	Research Question
RQs	Research Questions
RS	Recommender System
RSs	Recommender Systems
S	Social
SAC	Swiss Alpine Club
SUS	System Usability Score
the 3 M	Meta-theoretic Model of Motivation and personality
TV	Television
u-CF	User-based Collaborative Filtering
UB	Utility-Based
UIAA	International Climbing and Mountaineering Federation
UK	United Kingdom

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1 Introduction

Active living has become a crucial aspect of people's life: those who practice sports live at their full potential and have more strength to fulfill their dreams [1]. Consequently, sportive and hyperactive people prefer active tourism, referred to as **adventure tourism** (AT). AT is characterized by practicing physical activities within a tourist destination in natural environments. The most affordable types of AT are terrestrial activities such as running, climbing, and hiking [2]. The increased popularity of these outdoor sports led to the development of automatic tools supporting people practicing sports. One of the most impactful tools of such support is a recommender system (RS), which aims to help users to make their decisions [3]. Although abundant research has been undertaken on different sports recommender systems (RSs), no literature survey has been conducted specifically for outdoor sports as part of adventure tourism. One recent survey reviewed RSs for attending different sports events as part of the sport tourism aspect based on events' descriptions in [4]: the main idea of this survey was focused on tourists' willingness to visit a particular event. At the same time, there are more complex scenarios in the outdoor sports domain, including training and mental preparation, staying motivated and dealing with emotions, risky environment, diet, and equipment. Those aspects should be considered by the researchers who aim to develop RSs in the outdoor sports domain.

In addition, in recent times, many RSs have employed Artificial Intelligence (AI) in their technology, including mathematical computations applied for modeling real-time systems from different data sources, such as images, text, speech, and time-series data. Such rapid growth of research creates difficulties in advancing state-of-the-art technology without the prior analysis of previous work. This paper, therefore, surveys outdoor sports recommender systems and describes common approaches of AI employed for them, including methods for user profiling, item modeling, item-user interaction, and evaluation, from a series of novel techniques that have been found. This analysis benefits researchers who aim to develop and deploy sports-related RSs using AI.

The high-level research question (RQ) of this literature review is:

RQ: 'How to recommend items related to the land-based adventure tourism domain: hiking, running, and climbing?'

From the high-level research question, several specific research questions have been raised from conducting this survey. The research questions (RQs) addressed with this literature survey are outlined in Table 1.

The flow of this literature survey is organized as follows: Sect. 2 describes basic terminology used in the adventure tourism domain and explains the main concepts defined in hiking, running, and climbing. Section 3 outlines the search procedure to find articles about RSs in adventure tourism and presents the search outcome results and preliminary analysis of the articles' information. Furthermore, Sect. 4 answers seven research questions posed in Sect. 1 and relates the studies found to the descriptive answers. Moreover, Sect. 5 provides a statistical analysis of the studies included in the survey and discusses the main contribution of this outcome. Last but not least, Sect. 6 focuses on the limitations of state-the-art technologies and discusses future work.

2 Background: Adventure Tourism

Since the 1970s, tourism-related sports activities have become increasingly popular, especially in places where the major investments are coming from tourists. This has led to sport-associated travel - a leisure phenomenon where the critical feature lies in AT [5]. AT has different meanings, generally associated with adventure in the natural environment, where specific emotions, but more importantly, experiences have an economic value [6]. To clarify the distinction between AT and nature tourism, ecotourism, adventure travel, commercial expeditions, outdoor recreation, and outdoor education, we adopt the definition of AT as (self)-guided tours where the objective attraction is an

Table 1 Research questions posed in this work

RQ #	RQ Definition
RQ1	What items related to land-based adventure tourism (such as hiking, running, climbing) have been recommended?
RQ2	Which RSs algorithms or methods have been used to provide relevant content in the adventure tourism domain?
RQ3	How are users profiled in adventure tourism, and what data type is employed for this purpose?
RQ4	How are items profiled in adventure tourism, and what type of data is employed for this purpose?
RQ5	How was interaction modeled between users and items in adventure tourism?
RQ6	Which devices have been used to deliver user recommendations?
RQ7	What evaluation techniques are used to measure the quality of RSs?

Table 2 Sports and activities related to soft and hard adventure tourism

Place	Soft adventure activities	Hard adventure activities
Land-based	Camping	Backpacking across rugged terrain
	Hiking	Via Ferrata, Rock/mountain climbing
	Running short/middle distance	Running long distance/ Orienteering
	Bicycle touring	Off-road biking/mountain biking
	Bird/ animal watching	Jungle exploring
	Horse riding	Motorcycling
	Wilderness tour in off-road vehicles	Spelunking/ Cave exploring
	Snowshoeing	Skiing/ Snowboarding
Water-based	Canoeing	Canyoning
	Sailing	White-water rafting/ Kayaking
	Water skiing	Snorkelling/ Scuba diving
	Sailing	Wakeboarding
	SUP Yoga	Flyboard Flying
Air-based	Hot Air Ballooning	Skydiving
	Zip-Lining	Base/ Bungee jumping
	Helicopter tours	Paragliding
	Scenic Airplane Rides	Parachuting

outdoor activity based on features of natural terrain bringing excitement for people [7]. It was underlined that AT is characterized by a person's engagement via intensive sensory stimulation (typically outdoors) while challenging oneself in physical skills [8]. One unique subdivision of AT is mountain AT, where mountaineering and tourism are merged with two ideas: practical engagement of tourists based on outdoor physical effort and a business enterprise [9]. There is a particular risk associated with this type of tourism, and several researchers classified AT into two classes of adventure activities based on the amount of risk involved, nature present, or level of activity, namely, the soft and the hard adventure [10, 11]. 'Soft' refers to a low level of actual risk with minimal commitment and preparation required, whereas 'hard' is related to high levels of risk; therefore, serious commitment and preparation are mandatory [12]. Sports related to soft and hard adventure activities are summarized in Table 2 (adopted and extended from [10–12]).

Furthermore, different motivation factors lead to practicing certain sports: in hard adventure activities, the risk is the primary driving strategy for satisfaction, whereas, in soft adventure activities, the essential focus is not around experiencing risk but instead developing and improving the new skills as well as experiencing different settings [13]. At the same time, some general vital factors make a person spend vast sums and undergo fear to perform adventure in an unknown area: motivation received from their family, needing to challenge and express oneself, going exploring, inspiration from books or films [14]. Furthermore, recommendations for outdoor adventures are directly related to the user's personality, and the psychological framework of tourists is essential to consider for recommendations [15]. Several frameworks have been used for this purpose; the earliest work was the Five-Factor Model (FFM) of personality traits, which consists of people's characteristic patterns of thoughts, feelings, and behaviors [16]. According to the FFM model, there are four reference levels of a person's behavior: elemental, compound, situational, and category-specific surface traits. The more sophisticated model to predict how personality interacts with situations is the Meta-Theoretic Model of Motivation and Personality (the 3 M), which evolved from the mentioned FFM, and combines control theory, evolutionary psychology, and hierarchical personality models with FFM [17]. Extending the 3 M, seven personality traits associated with adventure tourist profiles are provided for soft and hard adventure tourism: *need for arousal*, *agreeableness*, *competitiveness*, *altruism*, *need for learning*, *interest in cultural experiences*, and *need for uniqueness* [18]. Interestingly, a significant reason for adventure travel was not a risk but rather *interest in culture experience*. The traits are summarized according to soft and hard adventure tourism in Table 3.

Unfortunately, current recommender systems have addressed only a limited amount of sports associated with adventure tourism. This survey included three land-based activities: hiking, running, and climbing (including alpine mountaineering). The sports are chosen based on their accessibility and a few tools required, as well as the difficulty level flexibility related to a person's physical abilities. We briefly describe each of these sports below.

Table 3 Personality traits defined in adventure tourism [18]

Reference level	Personality trait	Description
Elemental Traits	Need for arousal	The desire for stimulation and excitement
	Agreeableness	The need to express kindness and sympathy to others
Compound Traits	Competitiveness	The enjoyment of interpersonal competition and the desire to win and be better than others
	Altruism	General predisposition to selflessly seek to help others
	Need for learning	An enduring disposition to seek information resources
Situational Traits	Interest in cultural experiences	Activities that take place on the mosaic of places, traditions, art forms, celebrations, and experiences portraying the beauty of a country and its people, reflecting the diversity and character of the country
	Need for uniqueness	Individual's pursuit of differences relative to others that are achieved through the acquisition, utilization, and disposition of consumer goods to develop and enhance one's personal and social identity

2.1 Hiking

Hiking is defined as the activity of walking for some distance outdoors while negotiating natural barriers like rocks and tree roots and carrying own supplies and equipment [19]. In [20], hiking was also defined as wilderness travel, with outlined skills to successfully achieve a summit: orientation, navigation, and the ability to interpret trails, rocks, and weather conditions before and during the hike. Furthermore, hiking is practiced along way-marked trails unsuitable for motor vehicles [21]. In addition, this sport is associated with other definitions, such as bush-walking, tramping, trekking, jogging, or simply walking; it can last several hours or days, or even weeks, on or off trails [7]. Moreover, this activity has become the most important recreational activity in the mountains-based regions due to the natural landscape view [22].

In the late 90-s, it was shown that the significant effect of landscape encountered and experienced during the hike affects the decisions of hikers. As such, the sequence of views and objects a person observes during hiking influences her feelings and thoughts associated with activity [23]. Thus, the landscape is an essential factor for a human, resulting in a perceived perception of everyday visited surroundings, and represents an element of identity for a hiker [21]. Therefore, hiking RS should consider landscape as one of the main objectives of a user.

Regarding the categorization of this sport, hiking can be practiced either on foot, by mountain bike, or by riding a horse, with the planning of localization according to the defined requirements [24]. Moreover, some important aspects should be considered during the localization of the most suitable path: limitations on soil erosion and growth, the path's difficulty, beautiful view, and functionality for hikers. In addition, hiking is subdivided based on the distance: into Long Distance Walking or Long Trails (more than one day) and Short Distance Walking (one day) [25]. Another categorization is based on different levels of difficulty, which are defined according to specified standards in various countries. The unified notions of hiking grades are provided by Club Alpino Italiano (CAI) and Swiss Alpine Club (SAC) in [26]. The difference between the two notions is that CAI introduced four groups of hiking difficulties, and the Swiss scale instead has six groups .[1] Swiss hiking scales defined by the SAC are provided in Appendix (Table 10). Other countries and/or continents have their own scale: in Australia, for instance, trails were described as a function of their length, gradient, and terrain and classified as 'easy', 'moderate', and 'hard'. As such, 'easy' trails were defined as broad tracks with few ascents/descents, on average not more than 5 km, and in general, well maintained and accessible with prams and wheelchairs, therefore, suitable for elderly people and young children. Furthermore, 'moderate' trails are named as tracks of moderate length or difficulty. And the narrow paths typically present 'hard' trails with steep ascents/descents, tended to be less maintained, and be up to 26.8 km in length [27].

In addition, hiking as an adventurer tourism asset is considered one of the most affordable domains due to the low level of equipment. Several criteria are defined in [28] for providing hiking as a tourism product: 1) determining target audience; 2) expectation from hiking activity: sport or culture; 3) understanding hiking level, the physical ability of a person; 4) providing appropriate level accommodation; 5) price estimation for the trip. Moreover, the motivation of the hiker is an essential part of proper recommendations, and it has been found from the study that the four main reasons for hiking activity were enjoying nature, physical exercise, relaxation, and fun [29].

[1] https://www.bergfreunde.eu/alpine-grades-calculator/

Table 4 Running categorization based on surface type, distance, and elevation gain

		Categories names			
Based on	Surface	Road running		Trail running	
	Distance	Short-distance	Middle-distance	Long-distance	Ultra-endurance
		< 800 m	800 m - 3000 m	5000 m - 42,000 m	> 42,000 m
	Elevation Gain	Rolling terrain	Hilly	Very hilly	Mountainous
		< 200 m	200 m - 500 m	500 m - 1000 m	> 1000 m

2.2 Running

Running, along with walking, was identified as the top three sport and leisure-time physical activities among 40 countries in the following regions: Africa, America, Europe, Eastern Mediterranean, Southeast Asia, and Western Pacific [30]. Running is commonly considered to be a sporting activity, but recently, due to organized running events, such as parkrun and running races, along with social media promotion, running has become an attractive leisure activity for active sportspeople who would like to travel to new destinations for participation in some running events [31].

Classification of running as a sport is made based on the surface where it is performed: 1) road running (practiced on a hard surface, e.g., asphalt road), 2) trail running, including cross-country running, orienteering, and fell running (mainly practiced on a natural terrain). Trail running races consist of semi-autonomous running along marked trails in natural environments and impose considerable constraints that the runners must adapt to [32].

Categorization of this sport is also based on the distance of running paths and elevation gain (can be referred to as steepness). The overall categorization schema for running is outlined in Table 4 (adopted from [33]).

The difficulty of running routes is similar to hiking difficulty categorization; thus, some researchers adopt a similar structure for running difficulty definitions as for hiking [27]. Hence, we embrace a similar schema for running as for hiking in this paper.

2.3 Climbing and Mountaineering

Climbing and mountaineering have become popular as adventure tourism assets despite the price of equipment. Several reasons made mountaineering more affordable in recent years [7]: 1) the democratization of leisure opportunities and availability of cheap flights; 2) improvements in technology and equipment; 3) organized clubs and communities promoting climbing and mountaineering; 4) embodiment of leisure in personal identity and psychological aspect of searching for self-identity, provided by reaching a summit. While 'mountaineering refers to human climbing activity in high mountains' [34], climbing is related to the activities practiced on natural rocks and can be performed on the low land as well as in the mountains. Different categorization for disciplines was used in mountaineering: for instance, five disciplines, such as ice climbing, rock climbing, combined climbing, Himalaism, and ski mountaineering, were employed in [35]. In this literature survey, we included several disciplines of this sport: alpine climbing (also referred to as trad climbing), sport climbing, and bouldering (adopted and modified from [36]). *Trad climbing* is a climbing activity performed within unprepared natural relief while employing special climbing gear (e.g., friends or camelots, knots, and quickdraws). *Sport climbing* represents moving in the mountains or rocks on the route, which is already equipped by the others with metallic bolts. An ascending person uses only a few additional elements (quickdraws) for the ascent. *Bouldering* is a climbing activity performed on natural rocks without any extra equipment, but only crash-pads (special mats) for safety [37]. Depending on the height and skills required from the person, disciplines of trad and sport climbing can be sub-divided into single-pitch and multi-pitch climbing styles. In a single-pitch manner, the paths' height is around 50 ms with one fixed point (station) on the path's end; one person ascends while the other performs a belaying activity for safety purposes. Moreover, when the ascending individual reaches the summit/top, she is lowered to the ground. In multi-pitches, the paths' height is higher than 50 ms, and there are several fixed points within it, that the climber uses for belaying the other partner(-s) [38]. Two or more persons ascend the route one by one: the first climbs, and when he reaches the station, he belays the other partners who follow him. All participants require knowledge of large-distance mountaineering. In addition, all individuals should reach the summit [39]. A single-pitch is commonly associated with less danger than a multi-pitch.

Depending on the requirements and technical difficulties, climbing difficulty is categorized variously in different countries. As such, a unified approach for classifying climbing grades has been proposed in [40]. Describing a route as the highest skills and effort required for successful ascent is common. For every climbing discipline, a unique system was adopted for grade classification. For instance, in the alpine/mountaineering domain, two scales commonly used in Europe are *UIAA Scale* (defined by International Climbing and Mountaineering Federation) and *French scale*. Climbing grades of those two systems and their difficulty

Table 5 Criteria for literature search

Source name	Search string
Scopus	TITLE (("climb*" OR "run*" OR "hiking" OR "trekking" OR "jogging") AND (("recommender system*") OR ("decision support") OR ("recommendation*"))) AND PUBYEAR > 2007 AND PUBYEAR < 2023
IEEE Xplore	(("Document Title":recommender system* OR "Document Title":decision support OR "Document Title":recommendation*) AND ("Document Title":hiking OR "Document Title":climb* OR "Document Title":run* OR "Document Title":trekking OR "Document Title":jogging)) 2008–2022
ACM Guide	[[Publication Title: recommender system*] OR [Publication Title: decision support] OR [Publication Title: recommendation*]] AND [[Publication Title: climb*] OR [Publication Title: hiking] OR [Publication Title: jogging] OR [Publication Title: trekking] OR [Publication Title: run*]] AND [E-Publication Date: (01/01/2008 TO 31/12/2022)]
PubMed	(recommender system*[Title] OR decision support[Title] OR recommendation*[Title]) AND (climb*[Title] OR hiking[Title] OR trekking[Title] OR run*[Title] OR jogging[Title]) 2008–2022
lens.org	title:(recommender system* OR decision support OR recommendation*) AND title:(climb* OR hiking OR run* OR jogging OR trekking) 2008–2022
Springer	(recommendation* OR recommender AND system* OR decision AND support) where title contains (climb* OR hiking OR run* OR jogging OR trekking) within Computer Science 2008–2022

description are provided in the Appendix (Table 11). Plus, climbing grades are subjective values, and this aspect should be considered when recommending climbing routes to sportsmen [41].

3 Search Procedure

To answer the research questions posed in Sect. 1, we used a systematic literature review technique following the Preferred Reporting Items for Systematic reviews and Meta-Analyses (PRISMA) guidelines [42]. Below, the steps for this search procedure are described.

3.1 Search Query

Papers were searched in several databases: Scopus ,[2] IEEE Explore ,[3] ACM Guide ,[4] PubMed ,[5] lens.org ,[6] and Springer .[7] The search was performed on November 23, 2022, using relevant search terms formed by two groups related to (i) recommender system and (ii) hiking, running, and climbing. The search strategy included the query on document title: (‘recommender system*’ or ‘decision support’ or ‘recommendation*’) and (‘climb*’ or ‘run*’ or ‘hiking’ or ‘trekking’ or ‘jogging’). Wildcard (*) was used where supported to broaden the search for words starting or ending with the keyword. The interval when the papers were published was limited to 2008 and 2022. The search strings for each source used are given in Table 5.

3.2 Inclusion and Exclusion Criteria

To be included in this survey, the study needed to satisfy several requirements:

1. *The paper covered a recommender system.*
2. *The recommender system was applied in such sports as hiking, climbing, running.*
3. *The paper was published in the computer science domain.*
4. *The paper was published in peer-reviewed conferences, book chapters, lecture notes, books, and workshops.*
5. *The paper was published after 2008.*

The following criteria have excluded papers:

1. *The paper did not cover a recommender system.*
2. *The paper was not published in the computer science domain.*
3. *The recommender system is applied to other domain than land-based adventure sports (hiking, running, climbing).*
4. *The work is not written in English.*
5. *The paper was published before 2008.*
6. *The paper was not published in peer reviewed conferences, book chapters, lecture notes, books, or workshops.*

3.3 Quality Assessment

The quality of papers was assessed based on the quality checklist: for each statement below, we calculated the paper’s score as the sum of answers (for ‘yes’ score is 1;

[2] https://www.scopus.com/search/form.uri?display=advanced
[3] https://ieeexplore.ieee.org/search/advanced
[4] https://dl.acm.org/search/advanced
[5] https://pubmed.ncbi.nlm.nih.gov/advanced/
[6] https://www.lens.org/
[7] https://link.springer.com/advanced-search

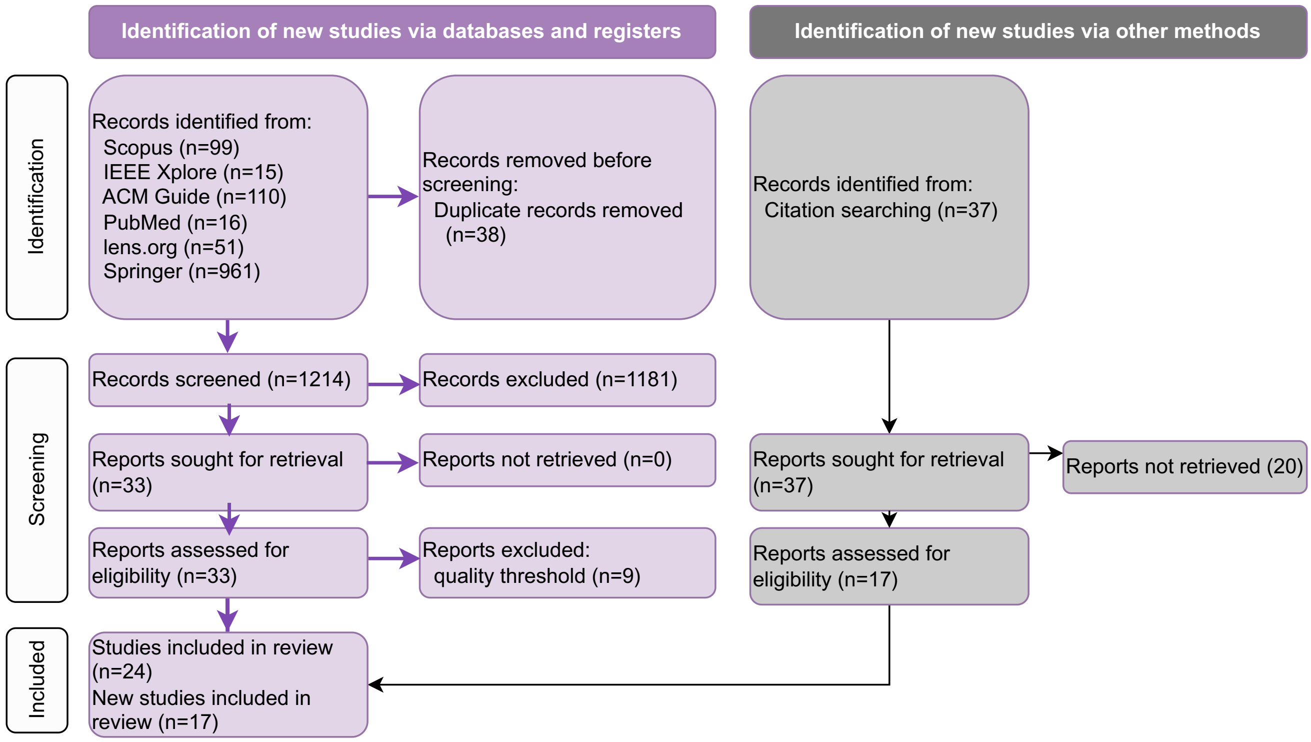


Fig. 1 Flowchart of the study screening procedure according to PRISMA [42]

for 'partly' = 0.5; for 'no' = 0). The cutoff score to reject the paper was chosen to be 1. The statements used for this purpose are as follows:

1. *The purpose of the work is the development of a recommender system in running, hiking, or climbing.*
2. *The paper applies the recommendation algorithm.*
3. *The paper evaluates a proposed recommender system.*
4. *The paper describes how a user profile is built.*
5. *The paper describes how contextual user information is obtained and the technology used.*

3.4 Search Outcome

The literature search resulted in 99 papers in Scopus, 15 publications in IEEE Xplore, 110 studies in ACM Guide, 16 articles in PubMed, 51 papers in lens.org, and 961 studies in Springer Link. After removing 38 duplicated papers, 1214 studies remained for screening. After screening the title and abstract, we excluded 1181 papers from the review. The full text of the remaining 33 studies has been read and checked for eligibility by quality assessment procedure: 9 articles were excluded based on the cutoff threshold, and the remaining 24 papers were included in this survey. In addition, we added 17 reports via screening the references list. In total, we had 41 documents eligible to be included in this survey. The selection procedure according to PRISMA is provided as a flow chart in Fig. 1.

3.5 Preliminary Finding

As a preliminary step, we analyzed the sources from which most papers were coming (studies' sources and amount of studies per source are shown in Table 6). We can see that the primary publishing source was ACM Conference on Recommender Systems with four papers published. The second-main source was International Conference on Case-Base Reasoning. The third was Information and Communication Technologies in Tourism. Moreover, most reports were published in conference proceedings, and fewer were published in journals and workshops. Interestingly, some of the articles have been published not in Artificial Intelligence venues: for instance, one of them [43] was presented in Journal of Geographical Systems.

The number of publications about recommender systems in the adventure tourism domain has increased substantially over the years, as shown in Fig. 2 (left): we can see that the majority of papers about running have been published in recent years (2018–2021), while the most publications about hiking were written in 2018. The number of published papers about climbing has grown since 2020. On the right of Fig. 2, papers distribution per sport is shown: around 2/3 of the papers were published about running activity, while the

Table 6 Studies sources and amount of studies per source

Source description	Venue	#
ACM Conference on Recommender Systems	Conference	4
International Conference on Case-Based Reasoning	Conference	3
Information and Communication Technologies in Tourism	Conference	2
International Conference on Intelligent User Interfaces	Conference	1
Journal of Geographical Systems	Journal	1
International Conference on Web Information Systems and Technologies	Conference	1
International Conference on Web Intelligence and Intelligent Agent Technology	Conference	1
International Symposium on Symbolic and Numeric Algorithms for Scientific Computing	Conference	1
International Workshop on Database and Expert Systems Applications	Workshop	1
Pacific Asia Conference on Information Systems	conference	1
International Conference on Sport Sciences Research and Technology Support	Conference	1
Personal and Ubiquitous Computing	Journal	1
Pervasive and Mobile Computing	Journal	1
Proceedings of The Web Conference	Conference	1
ACM International Conference on Hypertext and Social Media	Conference	1
Thirty-First AAAI Conference on Artificial Intelligence	Conference	1
User Modeling and User-Adapted Interaction	Journal	1
Workshop on Information Semantics	Workshop	1
International Conference on Web Engineering	Conference	1
International Conference on Entertainment Computing	Conference	1
International Conference on Human-Computer Interaction	Conference	1
International Conference on Computers for Handicapped Persons	Conference	1
International Conference on Advances in Computer Entertainment Technology	Conference	1
IOP Conference Series: Materials Science and Engineering	Conference	1
IEICE Transactions on Information and Systems	Journal	1
IEEE International Conference on Big Data	Conference	1
IEEE Access	Journal	1
IEEE International Conference on Wearable and Implantable Body Sensor Networks	Conference	1
Conference on Designing interactive systems	Conference	1
CHI Conference on Human Factors in Computing Systems	Conference	1
CEUR Workshop Proceedings	Workshop	1
Advances in Science, Technology and Engineering Systems Journal	Journal	1
ACM Conference on User Modeling, Adaptation and Personalization	Journal	1
ACM Conference on User Modeling, Adaptation and Personalization	Conference	1
Workshop on Recommendation in Complex Scenarios	Workshop	1
Total		41

amount of articles about climbing and hiking is distributed in between: 20% of papers were about climbing, and 17% were about hiking.

4 Literature Review Results

Papers selected with the above-described search procedure are analyzed to answer the research questions posed in Sect. 1. Related information answering posed questions is summarized below. We classify each research question into particular aspects of RSs adventure sports tourism. Moreover, we provide terminology used in the previous works according to the related elements.

4.1 Recommended Items

The first research question is connected to the recommended items in AT domain:

RQ1: What items related to land-based adventure tourism (such as hiking, running, climbing) have been recommended?

One can see that most RSs in the adventure tourism domain recommend items in the form of routes and paths

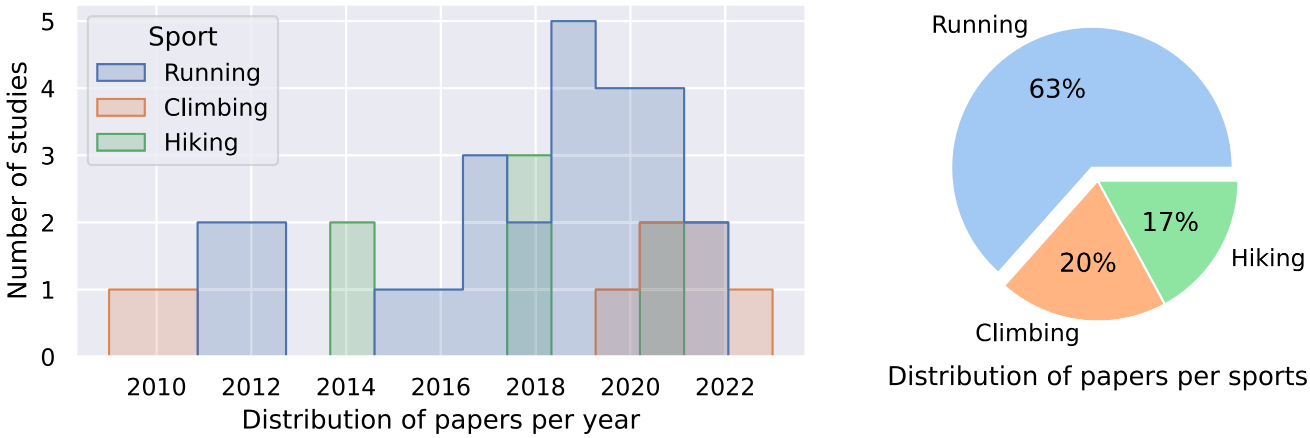


Fig. 2 Preliminary results. Left - distribution of studies per year (2008–2022); right - distribution per sport

to interested users; however, the recommendations are not limited to hiking/running/climbing paths. As such, AT includes other aspects, for instance, health promotion, enjoyable views, natural parks advertisement, people flow organization across touristic places, etc. Therefore, we identified several items which are considered by the corresponding RSs:

1. *Routes:* the most intuitive and frequently referenced items by RSs in the land-based AT are different types of routes and paths. Based on the motivation of an interested user, RS can recommend routes for different types of experiences, for instance, to feel quietness while practicing sports [29], to increase health [44, 45], to see a beautiful view [46], etc.
2. *Sequence:* instead of recommending routes to the user, this system suggests a sequence of paths as a unique item as part of the user trip planning. This approach was applicable for training purposes in marathon preparation [47, 48], but also for the scenario when the user plans a long adventure trip that involves several paths along the journey [49].
3. *Destination:* in climbing, mountain areas, for instance, mountains or climbing crags with several routes, are considered as a separate item for recommendations [46, 50].
4. *Training:* this type of recommendation is relevant for those who would like to achieve some specific goals in their performance, such as desired time while preparing for a marathon in trail running [51–55], or a specified height in climbing (e.g., a mountain with a selected difficulty and height) [56]. These recommendations are related to the physical level of a person and his physical preparation for the activity (including the user's predicted racing time and personal best performance that could be achieved).
5. *Management:* one of the focuses of such RS is to promote remote, rarely visited places of interest to ensure equal distribution of tourists flow across the outdoor facilities [29, 43]. Risk prevention is included in this recommendation, as adventure trips are associated with a particular kind of risk that should be minimized and managed accordingly [57].
6. *Diet:* this category consists of food suggestions for athletes to achieve their goals and increase their performance [58]. A sportsmen's diet is essential to attain a specific time in a race or perform an intensive activity.
7. *Health:* these RSs are focused on health promotion of sports activities, for instance, nudges towards walking when a person is not active for a certain amount of time [44, 45].
8. *Injury:* recommendations to prevent possibly occurring sportsmen's injuries. In marathon running preparation, the injury can be tracked automatically from sensor data when the athlete stops training [59].
9. *Shoes:* novel running RSs consider shoes recommendations based on the users' physical parameters [60, 61].
10. *Music:* music significantly affects human emotion, and recent RS recommends certain audio tracks to change the mood and to increase sportspeople's motivation for sports [62–64].
11. *Virtual coach:* system imitates the behavior of a sports coach to increase athletes' motivation to continue practicing sports. This type of suggestion includes decision support systems that imitate partners competing at the same level [65]. In addition, we included a study where coach feedback is given in the form of video projection on the wall in climbing [66].

4.2 Recommender System Methods

Different recommendation techniques developed in the adventure tourism domain are summarized below in an attempt to answer the following research question:

RQ2: Which RSs algorithms or methods have been used to provide relevant content in the adventure tourism domain?

RS techniques are classified into several categories based on the methods defined in [3].

1. *Content-Based (CB) RS:* recommends items similar to those that the target user liked in the past. The system aligns the attributes of the items and a user's preferences for these attributes [67]. CB systems calculate the degree of similarity between the users and the items based on a defined similarity function. Sports content is normally learned from different data sources, e.g., training logs from mobile or web applications, sensor data logs, comments, and feedback. This content can include the goal a user (such as finishing time planned to achieve in marathon running [68] or a daily number of steps in the health promotion system [69]), current physical level of a user (e.g., how often the user performs a certain type of training [70]), routes characteristics [56].
2. *Collaborative Filtering (CF) RS:* ignores content and exploits collective preferences of the crowd, i.e., generates recommendations using different users' profiles based on the similarity between users or between items. Consequently, CF is sub-divided into user- and item-based CF. The user-based CF (u-CF) measures similarity between users from their history, e.g., their previous likes or ratings. The item-based CF (i-CF) relies on the items similarities based on their ratings given by the users in the past.
3. *Knowledge-Based (KB) RS:* recommends items based on specific domain knowledge about how certain item features meet users' needs and preferences and targets to suggest the items based on the similarities defined from this match [3, 71]. The similarity between the users and items is estimated based on how much the user's needs (problem description) match the recommendations (solution of the problem). Case-Based Reasoning (CBR) is one example of knowledge-based RS: commonly applied in the running domain, where users' profiles are presented as a 'case' derived from sensor data collected during preparation for a marathon race [48, 52].
4. *Community-Based or Social (S) RS:* model preferences of users from their interaction with their friends or acquaintances [72].
5. *Utility-based (UB) RS:* suggests items based on a computation of the utility (value) of each item per user. Different functions are employed to model user behavior, e.g. reinforcement learning and utility score estimation from agents actions [73].
6. *Hybrid (H) RS:* combines the techniques mentioned above, addressing the disadvantages of the methods via introducing mixed techniques that solve particular limitations of the system [74]. For instance, music recommender system in running employs i-CF with KB (rules-based filtering) approaches to be able to provide songs aligned with a person emotional current state [63].

In addition to all the above mentioned methods, introducing user context enhances the quality of RS. As such, *Context-Aware (CA) RS* offers a new perspective to incorporate context information (e.g., location, season, time, companion) targeting to increase the recommendation accuracy and user satisfaction [75]. As such, the context in adventure tourism includes: geo-location for planned activity (hiking paths recommendations should be aligned with the current location of a person [76]), a time when the sport is planned to be performed (e.g., the season is an essential aspect for outdoor sports), with whom the user intends to practice this activity (family with children or friends) [50]. In running, real-time contextual factors are explicitly defined: weather, season, hour of the day, etc. [77]. Those contextual factors can be static (the context is the same over a specific time) or dynamic (change over time). Paradigm for modeling context include three general techniques: 1) pre-filtering: the recommendations are computed based only on the items that match context of a user, 2) post-filtering: the algorithm itself ignores context while calculates suggestions, and after computation removes items that are not relevant to context of a user, 3) contextual modeling: the model considers context information in computing suggested items.

4.3 User Profiling

An adventure tourism recommender system needs to meet users' various requirements, whereas understanding their preferences demands human research and investigating factors affecting human choices. This problem is not easy to solve, and it leads to answering the third research question:

RQ3: How are users profiled in adventure tourism, and what data type is employed for this purpose?

We distinguish user profiling approaches into several categories based on the input data used for this purpose as follows (adopted from [78, 79]):

1. *Explicit*: the user specifies their preferences in different ways, such as 1) via dialog or interface, 2) asking for an alternation, 3) rating items, 4) giving the user's opinion about recommended items, 5) mixed interaction interface [80]. For explicit profiling, scientists typically developed different interfaces where users should fill

in their preferences via standard questionnaires [81] or other methods.
2. *Implicit*: systems attempt to infer preferences unobtrusively (without asking for user references, but instead, learning preferences from a user's behavior). This unobtrusive learning could be done by browsing or recording visits actions. In AT, the implicit information was employed from wearable sensors in running: for this purpose, Strava company [8] is the most significant source of data input. Furthermore, researchers considered user feedback in the form of their training logs recorded in web or mobile applications for learning preferences implicitly in climbing. The primary source of such feedback is Vertical-Life company .[9]

Besides the methods used for user profiling, there are several vital characteristics to be considered for a full user profile in AT:

1. *Users' physical capacities and limits:* tourists have different physical levels, which allow them to perform an activity with certain limitations. For instance, a hiker can only hike routes of a specific difficulty level [81]. Similarly, a climber can only climb certain grades [56].
2. *Training goals:* what are the current plans aimed by the user, e.g., running time [64].
3. *Training accomplishments:* athletes' progress towards accomplishing their goals, including planned workout exercises and diet [58]. The speed at which they move to achieve their aims.
4. *Physical characteristics while performing particular activity:* this feature is related to the personalized information typically measured with wearable sensors: heart rate, cadence, pace [64].
5. *Nutrition:* food preferences, diet restrictions of a user [58].
6. *Risk perception*: tourists in AT are targeting to experience a defined level of risk, e.g., some users prefer to lower this level, while others are targeting a high level. In hiking, the risk was defined by participants via manual feedback [76].
7. *Motivation and expected perceived gains:* the reason behind pursuing the AT activity [82].
8. *Emotional state at certain point:* feelings of a person when they perform their running activity [62].
9. *Asocial concept preferences:* appropriate amount of people on the track to satisfy user experience [29].
10. *Elevation gain and steepness:* related to a person's physical capacities, and describes her preferences for the angle of a path [62].

Moreover, in Context-Aware recommender systems, contextual factors for a person are defined according to the following criteria:

1. *Weather information:* predicted weather in the recommended location [77]. This information includes the temperature, the humidity, prediction of precipitations (their intensity), wind [62].
2. *Season of the year:* season when the activity is planned: summer, autumn, winter, spring [50, 77].
3. *Hour of the day:* visiting some places also depends on the hour of the day; hence, sometimes, timing when the activity is planned (morning, midday, evening) affects the choice of the user [77].
4. *Location of the user:* landscape affects users' choice of activity and mood, and a person's physical location such as home, office, store, library, or gym is relevant to certain physical activity [62].

4.4 Item Profiling

To provide good recommendations to the user in the first place, one should properly describe and present the items. As such, items have major features that affect the user's choice, which can be measured on a certain designated scale. A summary of those features is outlined below, aiming to answer the fourth research question:

RQ4: How are items profiled in adventure tourism, and what type of data is employed for this purpose?

Recommended items in AT have several characteristics that can be divided into personalized and non-personalized. As such, personalized (or subjective) characteristics are defined subjectively for individual users, and they include:

1. *Diversity:* whether the route is different from what the user has already experienced before [83];
2. *Individualized time estimation:* related to the effort and physical energy required from a particular user to finish the path/training successfully. For instance, personalized time estimation models have been developed for hiking activity in [84, 85]. Also referred to as running activity *duration* [86].
3. *Risk:* how likely is the potential accident to happen [76, 81].
4. *Distinctiveness and attractiveness of the item:* whether the item has potential interest to a specific user.
5. *Difficulty points:* risk and technical evaluation scores [76].
6. *Beauty:* how much the path or location is beautiful [46].

8 https://www.strava.com

9 https://www.vertical-life.info

7. *Pleasant level:* whether the path is pleasant to a person. It can be measured as a sum of people's perceptions along three dimensions: beautiful, quiet, and happy levels [87].

Non-personalized characteristics are defined in a standard way and consist of the following definitions:

1. *Distance:* measured in meters;
2. *Height:* measured in meters;
3. *Natural landscape:* and its relation to the emotional state of mind of a person [88];
4. *Solitary level:* estimating the chance of meeting other people within the target hiking path in a specified time [29]. This level was measured from the points of interest (POIs) and pictures uploaded in Flickr data near the routes.
5. *Elevation gain/steepness:* steepness of the path predefined according to specific rules. For instance, three classes were used in running (flat, hilly, and alpine) [89, 90]. This parameter is determined in climbing from a set of rock formations (arete, crack, overhang, wall, slab) [49].
6. *Presence of light:* whether the path is lighted and therefore safe for activity at night; or whether the trail is located in an unlit forest path, making it impossible for activity practicing due to darkness and possible safety problems [86].
7. *Proximity to nature:* the segment's close location to a nature area, such as a park, forest, beach, lake or river border [90, 91].
8. *Distance to traffic roads:* the path's distance to high traffic roads (main road, motorway) [77, 90].
9. *Nature of Route:* in running, whether the route is a track, an on-road/off-road, and whether it ends at the starting point [91].
10. *Air quality:* the overall air condition of the routes' location, and the possible presence of health-damaging particles in the air [62].
11. *Noise pollution:* the level of traffic and other types of noise within the routes [62].

The typical path presentation approach in hiking is via a graph, divided into segments [29]. Weighted multigraph was employed in [92] to model the relationship between users and items, where hiking trails were described through the set of weights expressed as a function of different parameters of the tracks, which include estimated average duration of the path, length of the route in kilometers, cumulative elevation gain in meters, cumulative elevation loss in meters, seasonality (in which season it is safer to hike), other additional information.

4.5 Functionality and Interaction Design

The next research question posed in this work aims to model the interaction between users and items:

RQ5: How was interaction modeled between users and items in adventure tourism?

The typical scenario of the RS for routes recommendations follows several steps: 1) the target user inserts constraints for items and search parameters; 2) the RS engine searches for the items and then ranks them according to some heuristics; 3) the user receives recommendations in the GUI of the output device. These steps are accompanied by specific components contributing to the user experience with the system. For instance, the vital components of the hiking app are presented as a questionnaire in [93] and summarized below:

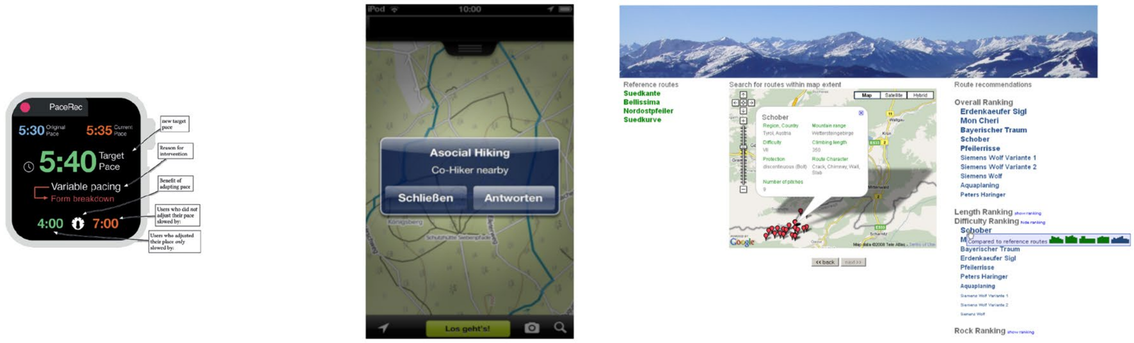
1. *Satisfaction level:* is related to overall satisfaction with the system functionalities and includes several aspects such as the installation process, creating a profile, and overall app performance affecting users' feeling of comfort.

    (a) *Installation process:* whether the app installation went smoothly and produced any issues.
    (b) *Creation of user's profiles:* users provide their details such as name, date of birth, gender, email, etc.
    (c) *Map function:* comprises some detailed information about the location of the hike on the map. It includes starting point of the route, parking spots, and POIs. POIs consist of interesting places, such as ponds, spoil tips, water reserves, etc.
    (d) *Selection of qualifier:* interface for user's preferences selection, including the route's starting point, distance desired to hike, pathway preferences, and selection of POIs.
    (e) *Time to propose route:* how long it takes to receive recommendations in the app.
    (f) *Convenience to use smartphone:* whether the application is comfortable for users.
    (g) *Accurate navigation:* whether the app considers navigation along the way an important aspect.
    (h) *High battery consumption:* whether the app consumes too much battery energy, thus, affecting smartphone work.

(i) *Parallel usage of other applications:* whether the current app affects the quality of other running apps.

    (j) *Enhanced the hikers' experience:* whether the app positively affects the experience of hiking activity.

2. *Users' requirements:* additional functions accessible for target users.



(a) (b) (c)

Fig. 3 Examples of output devices employed for recommendations: (**a**) smartwatch app [53]; (**b**) mobile app [29]; (**c**) website [49]

   (a) *Saving a route:* possibility to save the route by the user for further investigation/comparison with other items.
   (b) *Points of interests:* possibility to express preferences for POIs.
   (c) *Meeting all the requested criteria:* whether the system allows users to express their full preferences.

3. *App functionality:*

   (a) *Registering/saving the route:* possibility to include the new route by the user in the app's database.
   (b) *Find the registered route:* possibility to search for the desired item.
   (c) *Sending/receiving a message:* possibility of communicating with other hikers on the same platform. For example, social interaction was a key factor in motivating runners to exercise [94].
   (d) *Detailed contact information:* possibility to contact the managers of the hiking area.
   (e) *Info about fauna and flora:* information provided by the app about animals, plants, trees, and flowers present within the area. There is a certain probability of meeting menacing animals or plants in a specified location, and this option is an important aspect for outdoor dangerous event prevention.
   (f) *Taking pictures of species:* possibility to upload users' pictures of flora and fauna in the application.
   (g) *Sharing pictures:* possibility to share pictures with other app members.

4. *Statistics:* useful information presented to a user about his activity performed.

   (a) *Display of statistics:* user's location on the map (latitude and longitude), positioning of nearby POIs, distance made, average speed, time.
   (b) *Comparison of statistics:* possibility of comparing routes from other months.

5. *Added value:* whether the app contributes positively/negatively to a user experience and nature.

   (a) *Added value:* whether the app contributed positively to the experience of visiting a hiking place.
   (b) *Connection to nature:* how much the app disturbs user connection to nature.
   (c) *Enhances the hikers' mobility:* whether the app enhances the mobility within the hiking area.
   (d) *Recommendation to friends:* whether the users would recommend this app to their friends.

In addition, some running system is based on sound feedback to indicate the type of landscape where the runner currently is [77]. The workflow of such a system is similar to the previously described one: 2) the user selects starting and ending points, 2) the system computes route recommendations, and 3) the system shows the information on a page and simulates the sounds while the person runs. Similarly, in the hiking app, a sound alert is used to indicate whether another hiker is near the current location of a target user [29].

4.6 Output Devices for Recommendations

Another important aspect of the adventure tourism RS is the device where a target user can receive recommendations. Historically, tourists used navigators to search for tourist paths in a specified region. Nowadays, with the development of smartphones, using them for navigation is more common.

Different output devices are summarized to address the sixth posed research question:

RQ6: Which devices have been used to deliver user recommendations?

The output devices are classified into four main groups.

1. *Smartwatch:* wrist-worn sensors are considered in RSs for runners, as athletes usually wear them to track their activities and analyze their performance. An example of a smartwatch app interface for running RS is shown in Fig. 3(a).
2. *Smartphone*: mobile applications are easy to use as the cost for smartphones and the internet has decreased significantly in the last ten years, and it has become affordable to use smartphones instead of real navigators. The hiking app RS interface is given in Fig. 3(b).
3. *Web*: any internet browser is considered to fall into this class, where the device can be either mobile phones, laptops, or other devices allowing to use browsers. An instance of website RS for climbers is presented in Fig. 3(c).
4. *Other Communication Device:* other types of devices used for recommendations (an example of such is described in [95]).

4.7 Evaluation

To measure the quality of RS, one should perform specific evaluation procedures. We describe the main approaches of AT RSs evaluation below to answer the seventh research question:

RQ7: What evaluation techniques are used to measure the quality of RSs?

Commonly, for RS evaluation, either offline or online evaluation should be performed according to [96]:

1. *Offline evaluation:* it typically calculates the error of RS accuracy prediction and does not require interaction with users [96]. This type of evaluation is performed on the existing data set and is measured as an error (root mean squared, absolute) made by model predictions on the test set. As large data sets became available, more than a thousand participants could be involved in this type of analysis.
2. *Online evaluation:* it consists of conducting a user experiment where the goal is to measure the personal user experience of a system usage [97]. This evaluation is typically performed with fewer participants (around 50). Several types of online scenarios are considered:

   (a) *Formative Study:* comprises questions about user's needs and is aimed to find the necessary attributes to be developed in the application prototype. Typically, at this stage, the prototype of RS is not required.

   (b) *Usability Study:* is performed as a preliminary step in application deployment and typically requires a working prototype of an RS. The goal of this study is, firstly, to understand the users' needs. Secondly, to collect target users' feedback about the system with the idea of system further improvement. Thirdly, to evaluate the prototype based on a usability evaluation framework (for instance, based on the standard protocol for software product evaluation System Usability Scale or SUS [98]).

   (c) *User Study:* this evaluation is generally done in the form of collected user feedback after users tried and tested out the system. After this trial step, the participants are asked questions about different system aspects. This stage requires a fully-working and deployed system.

   (d) *Field study:* recommendations should be tested in a real scenario, where a user tries recommended items and provides feedback after performing the activity. Like the user study evaluation, field study is performed on a fully working and deployed system.

To unify the information from all papers, we summarized RSs' aspects in Tables 7, 8, and 9, where each column represents related RQs: column 'Items' answers RQ1, column 'Method' addresses RQ2, columns 'Profiling' and 'Input data' describe RQ3 and the data source for user profiling accordingly, column 'Output device' targets RQ6, column 'Evaluation' shows how the evaluation was performed and answers RQ7. Moreover, the 'Users' column also relates to RQ7, and shows how many users were involved in the evaluation procedure.

5 Discussion

This literature review intended to classify, synthesize, and present papers according to different perspectives of recommender systems in the adventure tourism domain. Through the standard PRISMA procedure, we have selected 41 articles eligible for inclusion in this survey. After preliminary analysis of the papers, we reported recent trends according to several research questions in Sect. 1. Those questions are related to vital aspects of RSs, such as recommended item types, recommender systems approaches, user profiling and input data source, item profiling, critical application functionalities, and evaluation procedures.

Furthermore, the overall results presented in this paper have several significant implications:

Table 7 Papers summary. 1st page

#	Sport	Year	Recommended Items	Method	User Profiling	User profile Data	Output Device	Evaluation	# Users
[59]	Running	2021	Injury	CBR	Implicit	Strava	–	Offline	5000
[48]		2022	Training, Sequence	CBR	Implicit	Strava	Mobile app	Offline	85,883
[54]		2020	Training	u-CF	Implicit	Strava	Mobile app	Offline	8730
[52]		2019	Training	CBR	implicit	Strava	–	Offline	1266
[55]		2021	Training, Injury	KB	Implicit	Strava	Mobile app	Offline	20,000
[47]		2020	Training, Sequence	CBR	Implicit	Strava	Mobile app	Offline	19,930
[51]		2017	Training	CBR	Implicit	Strava	–	Offline	5390
[53]		2019	Training	KB	Implicit	Strava	Smartwatch	Offline	7931
[86]		2012	Routes	CB, CA	Explicit	–	Mobile app	–	–
[90]		2021	Routes	CB	Explicit	–	Mobile app	Field study	11
[99]		2011	Training	CB, CA	Explicit	–	Mobile app	–	–
[91]		2016	Routes	i-CF	Explicit	–	Web app	Field study	14
[89]		2019	Routes	CB, CA	Explicit	–	–	Formative study	7
[100]		2018	Routes	CB	Explicit	–	Mobile app	Field study	11
[58]		2012	Training, Diet	u-CF	Explicit	–	Web app	User study	5
[77]		2017	Routes	CB, CA	Explicit	-	Mobile app	User study	30
								Field study	8

Table 8 Papers summary. 2nd page

#	Sport	Year	Recommended Items	Method	User Profiling	User profile Data	Output Device	Evaluation	# Users
[63]	Running	2020	Music	H, CA	Both	Sensors Spotify	Mobile app	Usability study	1080
[64]		2022	Music	KB, CA	Both	Sensors	–	Field study	12
[62]		2019	Music	i-CF, CA	Both	Sensors, spotify	Mobile app	–	–
[44]		2015	Health	CB	–	Explicit	–	Agent simulation	–
[45]		2017	Health	CB, CA	Explicit	–	Web app	Agent simulation	–
[61]		2020	Clothes	KB	Implicit	Sensors	–	Offline	203
[65]		2021	Virtual Coach	u-CF, S	Implicit	Sensors	Mobile app, Smartwatch	Formative study	16
[60]		2018	Clothes	KB	Implicit	Sensors	–	Offline	27
[94]		2011	Virtual Coach	–	Explicit	–	Mobile app	Formative study	5
								Field study	10
[101]		2019	Health	CB	Explicit	–	Web app	Agent simulation	–
[102]	Climbing	2021	Routes, Destination	KB	Both	Vertical-life	Web app	Offline	–
[103]		2021	Routes	KB	Implicit	Vertical-life	Web app	Offline	2624
[46]		2020	Routes, Destination	CB	Explicit	–	Web app	User study	3
[104]		2022	Routes, Destination, Training	CB	Explicit	–	Web app	Usability study	48

1. *Adventure tourism activities:* recommender systems in the adventure tourism domain are still unexplored, and only three sports as part of land-based AT are currently being developed. The distribution of papers is unequal: in running, the number of published documents increases yearly, while climbing and hiking are still early-stage domains. At the same time, more sports activities require attention from the scientific community since a larger amount of people are involved in practicing those (for instance, paragliding is a well-developed

Table 9 Papers summary. 3d page

#	Sport	Year	Recommended Items	Method	User Profiling	User profile Data	Output Device	Evaluation	# Users
[49]	Climbing	2009	Routes	i-CF	Explicit	–	Web app	–	
[66]		2010	Virtual Coach	–	–	–	Other	–	–
[56]		2022	Routes, Training	CB	Implicit	Vertical-life	Web app	–	
[50]		2023	Destination	KB, CA	Explicit	Vertical-life	Web app	User study	40
[43]	Hiking	2018	Routes, Management	CB	Explicit	–	Web app	–	–
[81]		2018	Routes	CB	Explicit	–	Web app	–	–
[29]		2014	Routes, Management	KB, CA	Explicit	–	Mobile app	Formative study	171
								Field study	8
[83]		2018	Routes	i-CF	Explicit	–	Web app	–	–
[76]		2021	Routes	CB	Explicit	–	Web app	–	–
[93]		2021	Management	CB	Explicit	–	Mobile app	Formative study	20
								User study	68
[87]		2014	Routes	CB	Explicit	–	Web app	User study	84

Table 10 Swiss hiking scales defined by SAC (Schweizer Alpen Club)

Level	Path, marking, terrain	Requirements
T1 Hiking	Path: well developed and marked. Marking: yellow. Terrain: flat or slightly inclined, no danger of falling	No special footing is necessary, can be walked in trainers, navigation without a map is possible
T2 Mountain hiking	Path: continuous route. Marking: white-red-white. Terrain: steep in parts, danger of falling not excluded	Some steady footing, trekking shoes recommended, basic navigation skills
T3 Challenging mountain hiking	Path: not always visible. Exposed places are secured with ropes and chains or hikers need to use hands for balance. Marking: white-red-white. Terrain: some areas can be exposed with a danger of falling, gravel plains, steep and pathless terrain	Good steady footing, good trekking shoes, average navigation skills, basic alpine experience
T4 ± Alpine hiking	Path: not always available. Sometimes hikers need to use hands to keep going. Marking: white-blue-white. Terrain: mostly exposed, tricky grass heaps, rocky slopes, simple firn fields, glacier passages	Familiarity with exposed terrain, stable trekking shoes are necessary, terrain assessment, good navigation skills, alpine experience, in a bad weather the way back can be difficult to find
T5 ± Challenging Alpine hiking	Path: often pathless, individual simple climbing sections. Marking: white-blue-white. Terrain: exposed, challenging terrain, steep shoes, glaciers and firn field with danger of slipping	Mountaineering boots, very good navigation skills, good alpine experience, secure terrain assessment, basic knowledge in handling a pickaxe and rope
T6 ± Difficult Alpine hiking	Path: mostly without a path, climbing sections up to II UIAA. Marking: usually unmarked. Terrain: exposed, challenging terrain, steep slopes, glaciers and firn field with danger of slipping	Excellent navigation skills needed. Proven alpine experience and familiarity with alpine equipment and technique

sport in the Dolomites, sailing is popular in the UK, skiing is an Olympic games sport, etc.). From this analysis of papers, we can conclude that a considerable research gap exists in this domain.

2. *Limited recommended items:* most studies presented in this review are concerned with suggesting routes and paths (35% overall) and training (21%). In contrast, only a few of them deal with other aspects such as diet (2%), injury (4%), sequential recommendations (4%), or clothes (4%). The main reason for this situation is the lack of RSs developed in other similar scenarios and the lack of promotion and investments from the government and industry. At the same time, the RS for clothes promotion can significantly increase the industry selling [105].
3. *Limited amount of RS methods* recommendation methods are restricted to a few techniques. Many studies employed the CB approach (39% of the papers). The second most mentioned method was KB (19% of documents). Contextual information was considered in less than one-fifth of the articles; hence, the novel systems should address this issue. The least used methods were S and H (2% of documents per each); therefore, more research should be done utilizing those methods in the future. None of the articles has proposed UB yet; this is partly due to difficulties associated with the method implementation and deployment.
4. *User Profiling:* more than half of the papers profiled users based on explicit feedback, whereas only around 30% of them employed implicit information. Moreover, only 10% of the reports profiled users on combining explicit and implicit feedback, although it is a more reliable source of information than others.
5. *User profile data:* several companies are involved in user profiling: Strava, Vertical-Life, and Spotify. Herefore, a considerable number of companies still need to be included and can contribute to this research.
6. *Evaluation:* more than half of the articles evaluated the proposed RS with the online scenario, while offline evaluation is considered in 34% of them. Moreover, the preliminary formative study was described in less than one-fifth of the RSs. Interestingly, 20% of the RSs considered a real scenario of testing the system with a field study.
7. *Output devices:* most of the research articles either developed a web application (48% of overall presented papers), or a mobile application (45%); only 6% of them considered a smartwatch application. The large-scale evaluation (more than 5000 users) was done offline for running sports only, while missing for climbing and hiking sports.

The overall findings of this research provide scientists with some generic insights into how recommender systems for adventure tourism should be developed in the future. As shown, there is a high need for the development of RSs in adventure tourism sports activities since the popularity of sports activities is increasing. The research questions above investigate the methodology and data employed in RSs in AT. Meanwhile, more questions could be posed and answered. For instance, 'What is the impact of RS applied in AT?', 'What is the significant attribute of AT offered to RS development?', 'What are the benefits of RSs in AT for tourists?', 'How should the interface be developed for RS app in AT?', 'How to prevent risky activities in AT with an RS?'.

6 Conclusion

In this work, we summarize 41 papers describing RSs in AT domain. To introduce the reader with the topic, we provide helpful terminology related to adventure tourism and it's subdivision into land-, water - and air-based sports activities. Moreover, three land-based sports are described thoroughly: running, hiking, and climbing. For those sports, we outline essential characteristics defined in the literature and vital information for further RS development. To find related papers in this domain, we employed the standard procedure of PRISMA, and showed in details how articles are searched in the scientific sources. After that, we posed seven research questions, and for each of them, we provided detailed answers based on the analysis of the papers. Last, we give the main insights from those posed questions. The main contribution of this paper is, firstly, the detailed description of land-based sports, such as running, hiking, climbing; secondly, a descriptive analysis of recent scientific articles published in recommender systems applied in these sports; and thirdly, a unified framework for future development of recommender systems in AT.

RSs in AT are the least advanced systems among the other non-sports domains, such as TV, music, or books. At the same time, increased Artificial Intelligence technologies and big data availability made it possible to research this topic. Although many exciting systems and their advantages/limitations are elaborated on in this work, many challenges still need to be tackled, such as:

1. Unobtrusive tracking technology and how it can be employed for user profiling.
2. The interface of the RSs has yet to be considered due to the lack of research presented. An advanced interface should be the first target in the new tools due to the none being found in other papers.
3. There is a need to combine implicit and explicit feedback for user profiling because there is no clearly defined methodology for this purpose.

Table 11 Details of International Union of Alpine Associations (UIAA) difficulty in rock climbing and related grades in French system (adopted from [106])

UIAA	French scale	Description
I	1	It is the easiest kind of scramble. Frequent use of hands is required to support balance and hand and foot-holds must be trusted
II	2	Here real climbing begins, that requires the movement of a limb at a time and a proper setting of the movements. Holds and supports are still abundant
III, III+	3a, 3b	The rock structure, already more steep or even vertical, offers holds and supports the rarest and can already require the use of force. Typically the passages are not solved yet in an obliged manner
IV-, IV, IV+	3c, 4a, 4b	Holds and supports become more rare and / or small. It requires a good climbing technique applied to the various rock structures (chimneys, crevices, corners, etc.) as well as a certain degree of specific training
V-, V, V+	4c, 5a, 5b	Holds and supports are very rare and small. The climbing becomes delicate (slabs, etc..) or hard (by opposition or interlocking in slits and chimneys). Usually requires the prior examination of the passage
VI-, VI, VI+	5c, 6a, 6a+	Handholds and/or supports are small and arranged so as to require a particular combination of movements well studied. The rocky structure may force you to climb very delicate or very hard where overhanging. Requires special training and considerable strength in the arms and hands
VII-, VII, VII+	6a+, 6b, 6b+, 6c	There are handholds and / or supports very small and widely spaced. It requires a sophisticated training with particular development of finger strength, skill in balancing and grip techniques
VIII-, VIII, IX, X, XI,.	6c+, 7a, 7a+, 7b, 7b+, 7c, 7c+, 8a, 8a+, 8b, 8b+, 8c, 8c+, 9a, 9a+, 9b, 9b+, 9c	From VIII the difficulties increase to the current extreme level (XI c / a)

The set of tables and visualizations that we proposed in this paper serves as a starting point for the future development of new ideas in this field. We hope this will increase interest among the research community in sports activity RSs development and contribute to overall community health, well-being, and living time.

Appendix A Tables

Author Contributions II made substantial contributions to conceptualisation, investigation, and methodology, analysis and interpretation of data. MW helped in the revision and gave final approval of the version to be published.

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Data availability The data that support the findings of this study are openly available at https://docs.google.com/spreadsheets/d/1bOy8Mxz7PU9MdIRBsivNAWFQH17LbTt4Rw_k2jlX4A4/edit?usp=sharing.

Declarations

Conflict of interest The authors declare they have no financial interests.

Employment Author II was a PhD student in the University of Bolzano until October 2022 working on a relevant topic.

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