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Towards adaptive and transparent tourism recommendations: A survey

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Abstract

Crowdsourced data streams are popular and extremely valuable in several domains, namely in tourism. Tourism crowdsourcing platforms rely on past tourist and business inputs to provide tailored recommendations to current users in real time. The continuous, open, dynamic and non-curated nature of the crowd-originated data demands specific stream mining techniques to support online profiling, recommendation, change detection and adaptation, explanation and evaluation. The sought techniques must, not only, continuously improve and adapt profiles and models; but must also be transparent, overcome biases, prioritize preferences, master huge data volumes and all in real time. This article surveys the state-of-art of adaptive and explainable stream recommendation, extends the taxonomy of explainable recommendations from the offline to the stream-based scenario, and identifies future research opportunities.

KEYWORDS

AutoML, crowdsourced data, data stream mining, recommendation, tourism, transparency

1 | INTRODUCTION

Tourism has changed dramatically with the advent of information and communication technologies, providing an ubiquitous access to tourism-related platforms and applications. In particular, tourism crowdsourcing platforms have revolutionized both the tourist behaviour and the tourism industry. Platforms such as AirBnB, Booking or TripAdvisor are popular online intermediaries between tourism businesses and tourists themselves; and, as a result, continuously accumulate large amounts of data shared by the tourists about their tourism experiences. They adopt a business model where stakeholders play predefined roles: (i) businesses pay to have their services on display; and (ii) tourists search for services of interest at no cost and provide feedback on their customer experience for free. According to Leal et al. (2018), depending on the main type of data shared by the crowd, crowdsourcing tourism services can be classified as evaluation-based, map-based, wiki-based, and social network-based. Tourism-related information refers to data that can help tourists to plan and organize their trips, for example, details about destinations, accommodation options, activities, events, transportation, and other travel-related services. This information can be obtained from various sources, including tourism websites, guidebooks, travel blogs, social media platforms, and online booking platforms. In addition, these platforms encompass crowdsourced/collaborative information about tourism resources, for example, reviews, ratings, images, and so forth, which influence user decisions.

While the processing of crowdsourced data can be performed offline (using data mining) or online (using data stream mining), this survey focuses on the online processing of crowd-generated events.

Abbreviations: AutoML, automated machine learning; BT, blockchain technology; CbF, content-based filters; CF, collaborative filters; HPC, high performance computing.

Data stream mining explores methods and algorithms for extracting knowledge from data streams, which are data sequences occurring continuously and independently. Stream algorithms face three main challenges: (i) to offer lower complexity to keep up with the data rate arrival and good scalability; (ii) to present a manageable memory footprint; and (iii) to adopt incremental techniques in order to build and maintain the model(s) updated (Veloso, Gama, & Malheiro, 2021).

The feedback shared by tourists in tourism crowdsourcing platforms originates data streams which are critical for tourists and tourism businesses alike. While tourists select tourism services based on crowdsourced opinions, tourism businesses mine this crowd feedback to identify problems or anticipate trends (Leal, Malheiro, Veloso, & Burguillo, 2021). Tourism crowdsourced data stream mining predicts the tourist behaviour based on the associated digital footprint through incremental recommendation. The intrinsic dynamic nature of crowdsourced data streams requires on the fly techniques to cope with changes over time, uncurated data and extremely large volumes of data. The openness of crowdsourcing exposes such systems to malicious and erroneous contributions, inevitably resulting in poor data quality. This brings forth the important issue of detecting and filtering false crowdsourced data. Furthermore, data shared by participants normally include considerable amount of missing values, making it harder to accurately detect false data (Calvaresi et al., 2018). As such, it is essential to distinguish between contributors who truly share their experience from those with hidden agendas. The latter can go to great lengths to introduce biases in favour or against specific tourism services. The identification of such contributors will enable purging crowdsourced data from these undesirable biases and provide higher quality recommendations. This means that crowdsourcing applications suffer from heterogeneous data quality since both malevolent (intentionally) and benevolent (unintentionally) users may convey incorrect information. Together, these problems mislead crowdsourcing systems to infer wrong conclusions for all (Tahmasebian et al., 2020).

This review article addresses exclusively the challenge of the online processing of touristsourced data. The application of data stream mining techniques to crowd inputs is more demanding due to the intrinsic adaptation, real time and transparency requirements. It implies the use of stream techniques and technologies that support the online adaptation of recommendation processes and models, together with the generation of explainable recommendations; free from data and algorithmic biases. This can be achieved by integrating emerging research on adaptive recommendation systems, which rely on automated machine learning (AutoML) for adaptation (Al-Ghossein, 2019; Veloso, Gama, Malheiro, & Vinagre, 2019, 2021), and on explainable recommendations, which explore profiling and blockchain to provide the desired transparency (Leal, Malheiro, Veloso, & Burguillo, 2021; Leal, Veloso, Malheiro, & González-Vélez, 2020; Veloso, Leal, Malheiro, & Moreira, 2019). Specifically, AutoML aims to improve the performance of machine learning tasks by automating the selection and tuning of machine learning models and associated hyperparameters (He et al., 2021).

This article significantly expands and refines the previous review on adaptive recommendation systems, reported by Leal, Veloso, Malheiro, and Burguillo (2021), by including AutoML approaches for recommendation systems. Therefore, this survey analyses the most promising techniques and technologies in stream-based adaptive and explainable tourism recommendation and identifies upcoming trends. The rest of this document details the adaptive and explainable data stream recommendation status quo (Section 3), the challenges and support technologies (Section 4), identifies future research trends in the tourism domain (Section 5), and draws the conclusions (Section 6).

2 | METHODOLOGY

Tourism is one of the most dynamic and fastest-growing industries worldwide. In recent years, the emergence of new technologies and widespread Internet access have led to a significant increase in the availability of online tourism-related information. To ensure travel experiences meet tourist expectations, it is essential that the information provided remains reliable and up-to-date. Moreover, given the overwhelming amount of information available, tourists often struggle to find offers matching their preferences and needs. Recommendation systems address this challenge by identifying and proposing the most relevant options for each user. While existing recommender systems have shown promising results, they still face several limitations. Specifically, they often lack transparency and adaptability, making it difficult for users to understand how recommendations are generated and for the system to adapt to contextual factors that may influence user preferences and behaviour over time.

This work proposes a sequential event-driven pipeline comprising preprocessing, profiling, recommendation, with feedback based on evaluation, change detection and adaptation, and, finally, explanation. Moreover, the method relies on blockchain technology (BT), to ensure sensitive data are stored in an immutable distributed database, and high performance computing (HPC) technologies to support seamless scalability. Figure 1 illustrates the reviewed stream-based processing pipeline. The adopted method identifies automated data stream mining techniques and technologies for real-time adaptive prediction, driven by the accountability, responsibility and transparency design principles, and investigates their application to the tourism domain. To this end, this survey covers: (i) preprocessing; (ii) profiling, (iii) recommendation, (iv) evaluation, (v) change detection and adaptation and (vi) explanation. Relevant support technologies, like BT and HPC, are also contemplated. This adaptive and transparent stream recommendation pipeline processes the continuous flow of crowd-originated events to update profiles and prediction models, to adapt to changes in the data over time and to provide personalized self-explainable recommendations.

The incoming crowdsourced events are directed to the feature engineering stage, where relevant features are selected/engineered and used to update user profiles and prediction models. The prediction models cope with data changes over time, ensuring that the personalized

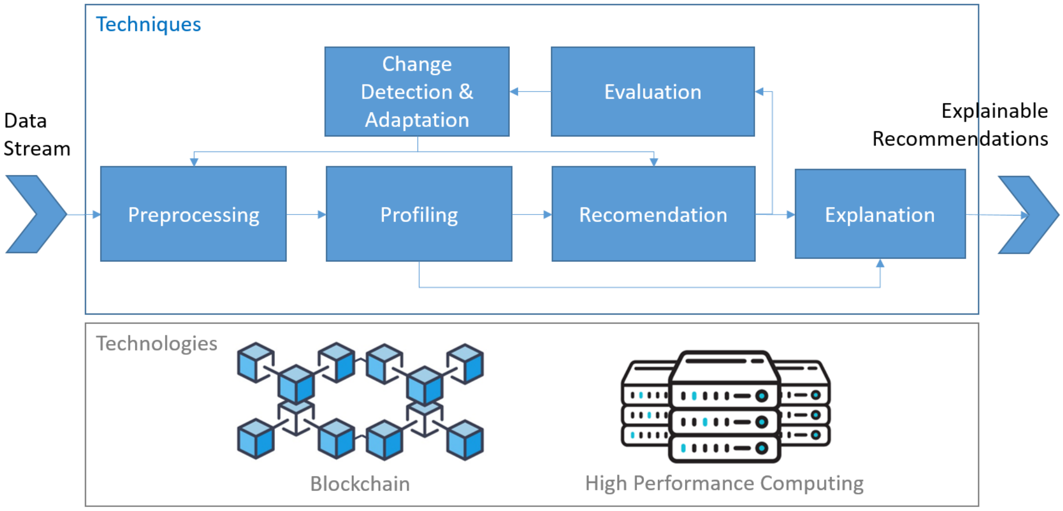


FIGURE 1 Adaptive and transparent stream recommendation.

recommendations remain always up-to-date and relevant to current user needs and preferences. The pipeline also integrates transparency mechanisms, namely outcome explanation and feedback, to ensure that users are able to understand why they received those recommendations and to contribute to the system improvement. Overall, this adaptive and transparent stream recommendation pipeline provides a robust and efficient solution for processing continuous streams of crowd-originated events and generate personalized, self-explainable recommendations.

3 | ADAPTIVE AND TRANSPARENT STREAM RECOMMENDATION

The design of online recommendation systems, capable of automatically adapting to changes over time, falls under the domain of AutoML. The considered AutoML techniques include adaptive preprocessing, profiling and model learning, drift identification and recovery and outlier identification. Nevertheless, according to Al-Ghossein (2019), online adaptive recommendation remains an underexplored topic despite its relevance for real-world applications. Automated model learning refers to the selection of a suitable predictive model (or combination of models), whereas drifts describe unforeseeable changes in the underlying distribution of streaming data over time, which need to be addressed to prevent poor learning results (Lu et al., 2019). By drifts, we encompass both concept and data changes, affecting predicted targets and independent features, respectively. Drifts can occur abruptly or incrementally (Gama et al., 2014), and can be classified according to severity, predictability, and frequency (Kosina et al., 2010). In real time scenarios, it is possible to have a mixture of drifts and outliers, affecting the performance of drift detectors (Chandola et al., 2009). In the case of recommendation, a concept drift occurs when a user, in distinct time windows, rates differently the same feature or item (Abhishek et al., 2011), and a data drift whenever a subset of features becomes, or ceases to be, relevant to the learning task (Barddal et al., 2017). Given this natural evolution of user interests over time, data stream recommendation needs to reflect current rather than outdated interests and, evaluation-wise, requires specialized evaluation protocols and metrics (Gama et al., 2009).

Finally, crowdsourced data are potentially unreliable and accumulate in huge volumes, dictating the adoption of technologies that support parallel processing as well as traceability and authenticity monitoring (Nguyen et al., 2015).

3.1 | Preprocessing

The automated stream recommendation aims to automatically improve the processing pipeline of standard recommendation systems, attempting to minimize the human assistance (Chen et al., 2021; Zöller & Huber, 2021). Therefore, the large amounts of data and their heterogeneity require dedicated techniques (Luengo et al., 2020) to overcome data inconsistencies and redundancies and prepare the data for the following processing steps. Typically, this preprocessing comprises: (i) data cleansing and data transformation; (ii) information fusion; (iii) data balancing; and (iv) feature selection.

Data stream cleansing intends to identify and remove noisy data to improve the accuracy of the systems (Zhu et al., 2008). Data preparation involves multiple transformations such as the conversion of categorical into numerical features, data normalization, re-scaling and standardization. The goal is to obtain a consistent feature space and facilitate the compatibility with the target application (Shehab et al., 2021). In addition, multi-source information can be used to build richer user profiles and improve personalisation. This leads to information fusion, which refers to the integration of data from multiple sources.

Imbalanced data distributions, where the number of observations are not equally distributed, lead to unequal item recommendation opportunities. This is specially relevant since recommendation is affected by data underrepresentation such as population imbalance and observation bias (Yao & Huang, 2017). Population imbalance arises when different types of users occur with distinct frequencies, whereas observation bias when certain types of users display different tendencies when rating disparate kinds of items. In this scenario, the literature provides a set of techniques, which allow to balance the data set, and guarantee that all targets have the same number of samples (Branco et al., 2019). Preprocessing maps data into a format that can be more effectively used by predictors (Zliobaite & Gabrys, 2014). Evolving data streams comprise not only large, sparse, high dimensional data, but also drifting and new incoming features (Wang & Barbu, 2022), requiring adaptive preprocessing. As changes in data happen, both preprocessing and predictor are expected to adapt and to maintain a good accuracy over time (Zliobaite & Gabrys, 2014). Adaptive preprocessing of data streams involves tasks such as feature selection, instance reduction or feature space simplification. These tasks have strict algorithmic requirements: real time, single pass and incremental operation (Nziga, 2015).

Feature selection has been explored in several domains to minimize the search space dimension (John et al., 1994). In this context, Li et al. (2017) state that feature selection is an effective strategy for machine learning problems, especially with high-dimensional data (Cai et al., 2018). Feature selection can be classified into supervised (considers the targets) and unsupervised (ignores the targets). Supervised techniques include filter (statistical and feature importance), embedded (recursive feature elimination) and wrapper (shrinkage) methods, whereas unsupervised techniques comprise principal component or correlation heat map analyses. Filters act before and are independent of the learning process; wrappers use the specified learning algorithm to evaluate subgroups of features; and embedded techniques perform the search as part of the learning process itself. Wrappers methods tend to be more accurate than filters, but also more complex. Embedded methods are less costly than wrappers, but require direct modifications of the learning procedure (Ramírez-Gallego et al., 2017). In summary, the main difference between filters, wrappers, and embedded methods is when the selection is performed: before and independently of the learning algorithm, or tightly coupled with the learning algorithm (Ramírez-Gallego et al., 2017).

The preprocessing of data streams is a time consuming task for knowledge discovery. With this regard, Ramírez-Gallego et al. (2017) analyse preprocessing techniques for stream-based applications contemplating aspects as concept drifts, sliding windows, ensemble learning, and data reduction. Al Nuaimi and Masud (2020) present an embedded stream feature grouping to assemble similar features together, assigning new incoming features to an existing or a new group. Moraes and Gradvhl (2020) contribute with the Massive Online Analysis Feature Selection open-source library for stream-based classification, which is based on the Massive Online Analysis data reduction extension by Ramírez-Gallego et al. (2017). It implements information-based filter algorithms (information gain and gain ratio), symmetrical uncertainty (fast correlation-based filter), statistical tests (chi-squared and Cramers V-test), and wrapper algorithms (online feature selection and extremal feature selection). To handle the arrival of new features, Liu et al. (2020) describe a multi-label feature selection method which chooses the most relevant discriminating current set of features. It attributes label-specific features for each newly arrived label, using inter-class discrimination and intra-class neighbour recognition, to fuse the generated label-specific sets of features into a new feature. Zhou et al. (2019) propose a streaming feature selection method based on the adaptive density neighbourhood relation. The adaptive density neighbourhood relation uses the density information of the surrounding instances and the fuzzy equal constraint to select features with low redundancy.

Considering feature drifting scenarios, where features become or cease to be relevant to the learning task with time, Barddal et al. (2019a) propose a merit-guided and classifier-independent dynamic feature selection algorithm, and an adaptive boosting method for dynamic feature selection (Barddal et al., 2019b). Both techniques rely on scoring operators based on information theory, such as conditional entropy and symmetrical uncertainty, to track the relevance of features during the processing of data streams (Barddal, 2019). Gomes et al. (2019) assign scores to individual features, estimating the relevance of the features in a supervised learning scenario (ensemble of incremental decision trees). They propose two score metrics——the mean decrease in impurity and the number of instances covered by each node——to track how the importance of the features to the ensemble model changes over time. This technique can also explain how features influence a given decision, contributing to the interpretability of the model. Rahmaninia and Moradi (2018) describe and apply two feature selection methods to identify the most informative subset of online streaming features based on the mutual information concept. These filter-based methods evaluate incrementally the correlation between features, and assess the relevancy and redundancy of features in complex classification tasks. Li et al. (2015) conduct unsupervised streaming feature selection for social media data by linking information from external sources.

3.2 | Profiling

Entity profiling, that is, the creation and maintenance of entity models, is central to generate personalized tourism recommendations. Using touristsourced data, it is possible to model the stakeholders according to the corresponding digital footprint stored in tourism crowdsourcing platforms. Resource (item) profiling can be based on intrinsic characteristics, crowdsourced information and semantic enrichment. Tourist (user) profiles are mainly based on crowdsourced data, which can be classified as entity-based or feature-based. While entity-based profiles are directly associated to tourism resources; feature-based rely on intrinsic characteristics, for example, category, location, theme, and so forth. Based on the contents of crowdsourced data, the literature identifies further types of profiles.

Rating-based profiles rely on ratings to express, quantitatively, opinions concerning multiple service aspects. In evaluation-based crowdsourcing platforms, users can classify tourism resources using multiple service dimensions (e.g., comfort, cleanliness, value for money, overall, etc.). Rating-based profiling approaches can be classified as single or multiple criteria, that is, using a single rating or a rating combination through statistical mechanisms. Leal, Malheiro, and Burguillo (2019a) provide a survey of single and multiple criteria rating-based profiles approaches, whereas Nilashi et al. (2015, 2017) present a stream-based multi-criteria approach together with ensemble techniques. Recently, Veloso et al. (2018) and Veloso, Leal, Malheiro, and Burguillo (2019) have used hotel and restaurant evaluations to create stream-based incremental profiles.

Review-based profiles are created from textual reviews. These written texts embody a detailed description regarding the tourist experience, which affects the behaviour of others potential tourists. These reviews generally include qualitative comments and descriptions. In this context, a collection of reviews, rather than being perceived as static, constitutes an ongoing stream (Spiliopoulou et al., 2017), leading to opinion stream mining. However, to the best of our knowledge, there are no research studies of opinion stream mining in crowdsourced tourism applications.

Context-based profiles use context information, which can be personal context data, social context data, and context-aware information data (Leal et al., 2018a). Gomes et al. (2010) propose a context-aware system with data stream learning to improve existing drift detection methods (DDMs) by exploiting available context information. Similarly, Akbar et al. (2015) explore context-aware stream processing to detect traffic in near real-time.

Quality profiles model tourism entities using quality related parameters. It has been used mainly to model tourism wiki pages and corresponding publishers. Wiki publishers originate continuous data streams in the form of content revisions. However, scant research has been conducted to construct quality-based profiles employing wiki-based information as data streams. Leal, Veloso, et al. (2019) use this approach to model the quality of publishers and pages, using wiki streams of publisher-page-review triplets.

Popularity profiles use views, clicks and related-data to model the popularity of tourists and tourism resources. These profiles are frequently used to avoid the cold start problem in collaborative filtering. Leal, Veloso, et al. (2019) rely on a page view data stream to model wiki publishers and pages in terms of popularity.

Trust and reputation profiles model reliability. Trust defines the reliability of stakeholders based on direct one-to-one relationships. Reputation is based on third party experiences, that is, many-to-one relationships. Trust and reputation profiles increase the reliability of the models, and, consequently, the accuracy of the corresponding recommendations. Leal et al. (2018b) propose trust and reputation modelling for stream-based hotel recommendation, and Leal, Malheiro, and Burguillo (2019c) employ incremental trust and reputation models for post-filtering, improving the accuracy of recommendations in both cases. Recently, Leal, Veloso, Malheiro, and González-Vélez (2020) recommended chaining[1] trust and reputation models for reliability and explainability purposes. This work stores pairwise trust models as smart contracts in a private Ethereum blockchain network, and uses the chained trust models to derive system-wide reputation models and explain recommendations.

Hybrid profiles combine multiple types, leading to richer and more refined profiles and, in principle, to higher quality recommendations. Hybrid-based profiles are indicated for heterogeneous data environments, which have been explored using ensembles (Rijn et al., 2018). However, building hybrid-based profiles from touristsourced data streams remains unexplored.

Regardless of the contents or the type of profiling used, crowdsourced data streams allow the continuous updating of tourism stakeholder profiles.

3.3 | Stream-based recommendation

Data stream recommendation enables the continuous updating of the user and item models and contributes to improve the quality of real-time recommendations. This is achieved through incremental modelling. Every time a new user event arrives, the model is updated, and new personalized recommendations are provided (Veloso, Gama, & Malheiro, 2021). These recommendation engines rely mostly on data filtering techniques, ranging from pre-recommendation, recommendation and post-recommendation filters (Figure 2). The standard filtering techniques include:

Content-based filters (CbF) match tourists with tourism resources. They create tourist profiles based on past interactions with the system, and make recommendations based on the similarity between the content of the tourist and resource profiles, that is, regardless of other tourist profiles. According to Lops et al. (2019), content-based filtering is a promising technique since it supports the generation of explainable recommendations and allows the parallel combination of various types of side information.

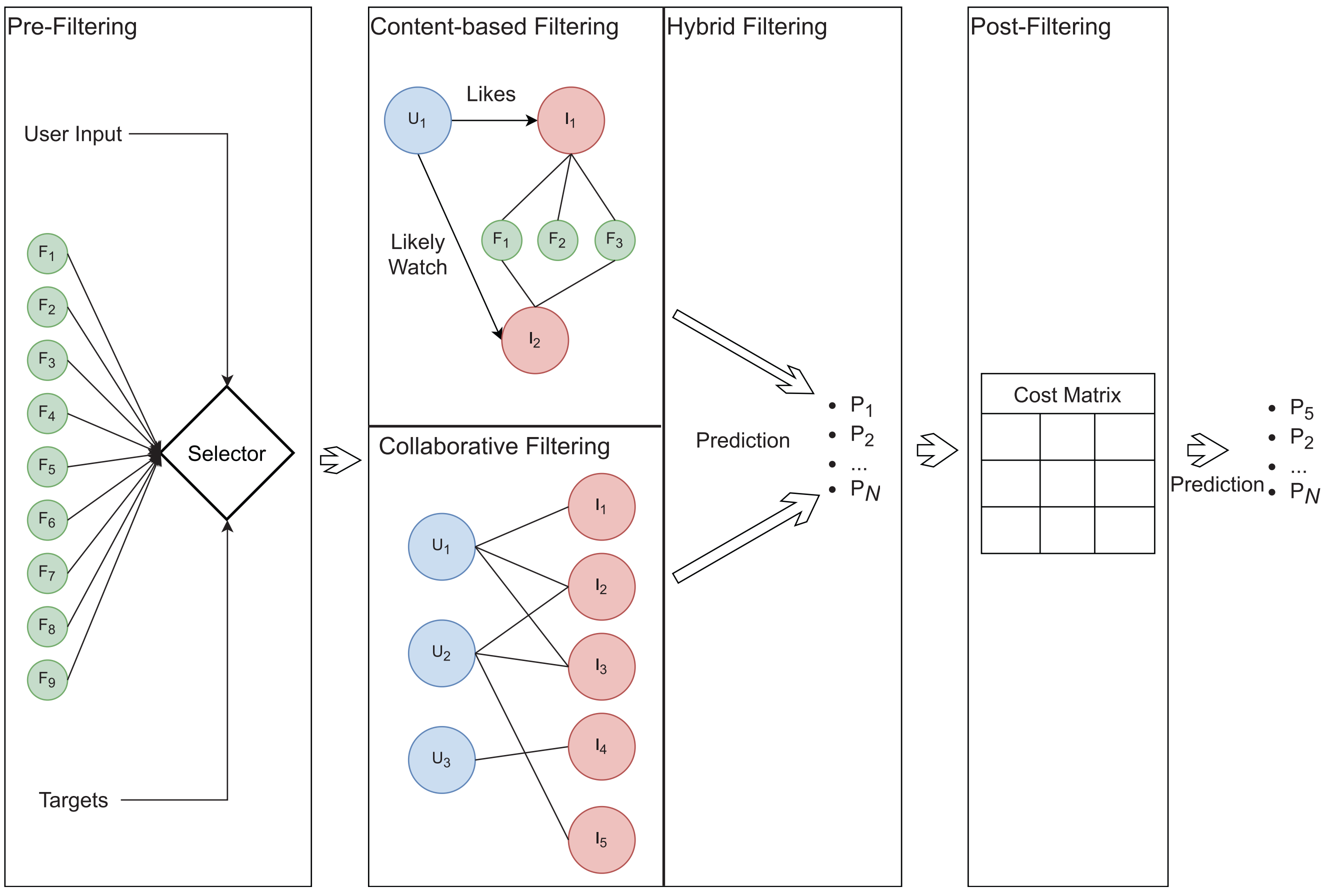


FIGURE 2 Stream-based recommendation.

Collaborative filters (CF) recommend unknown resources to tourists based on other like-minded tourists, using memory or model based algorithms, and building profiles based on the crowdsourced data. While memory-based approaches combine the preferences of neighbours with identical profiles to generate recommendations, model-based algorithms build models based on the tourist profile to make predictions. Collaborative filters may implement tourist-based or resource-based variants by computing the similarity between tourists or between resources. These techniques have been adapted with success to data stream recommendation (Leal et al., 2018b; Leal, Malheiro, & Burguillo, 2019c; Nilashi et al., 2015; Veloso et al., 2018; Veloso, Leal, Malheiro, & Burguillo, 2019). Considering memory-based collaborative filters, Bedi et al. (2014) and Leal et al. (2017, 2018b) employ the Pearson correlation coefficient to calculate similarities between rating-based profiles. Regarding model-based collaborative filters, Leal, Malheiro, and Burguillo (2019c), Veloso et al. (2018), Veloso, Leal, Malheiro, and Burguillo (2019) adopt support vector decomposition with stochastic gradient descent, whereas Nilashi et al. (2015) couple clustering and regression models.

Hybrid filters combine content-based and collaborative counterparts to eliminate frailties and reinforce qualities and, thus, improve the quality of recommendations. Hybrid filters, aggregating multiple mechanisms in parallel, have been explored by session-based recommendation systems (Guo et al., 2019; Souza Pereira Moreira et al., 2019; Sun et al., 2019).

A priori and a posteriori filtering aims to refine the recommendations reducing the search space. Pre-recommendation and post-recommendation filters have been explored mainly using context-based profiles.

Pre-recommendation filters are applied beforehand to select appropriate tourist data (Zheng et al., 2012), for example, weekdays recommendations, business or leisure travels. They increase recommendation relevance by analysing context-aware data.

Post-recommendation filters select or reorder the recommendations generated by the recommendation filter. In tourism domain, the value-for-money, the sentiment-value and the pairwise trust have been used, among others, as post-recommendation filters. Value-for-money confronts the price, the crowd overall rating and the resource official star rating to establish the crowdsourced value for money. The sentiment-value of textual reviews is computed using sentiment analysis (Veloso et al., 2018; Veloso, Leal, Malheiro, & Burguillo, 2019). Finally, the pairwise trust and similarity have been used to reorder the generated predictions (Leal, Malheiro, & Burguillo, 2019c).

Ensemble learning is an alternative to filtering. It explores and combines multiple models to enhance the accuracy of the predictions. Gaber et al. (2014) combine the knowledge of different crowd models, using an incremental ensemble approach. Matuszyk and Spiliopoulou (2017) present a semi-supervised learning algorithm for stream-based recommendation systems with self-training, using one incremental learner, and co-training, with several ensemble learners specialized on user variance, item variance, average rating, and dimension preservation. Vinagre et al. (2018) adapt Stochastic Gradient Boosting for recommendation using ensemble learners and incremental matrix factorisation for implicit feedback. In the tourism domain, Nilashi et al. (2017) explores automatic model learning by proposing a hybrid ensemble. The ensemble recommends personalized tourist routes supported by preferences extracted from location-based social networks. Al-Ghossein (2019) propose dynamic learning model methods to generate stream-based context-aware recommendations.

3.4 | Evaluation

Stream-based evaluation has two main components: the evaluation protocol and the evaluation metrics. An online evaluation protocol has three main constraints: (i) space, where the available memory is limited; (ii) learning time, when the time required to learn is equal that the rate of incoming events; and (iii) accuracy or the capacity of the model capture the data variations. The most used online evaluation protocol is the prequential protocol by Gama et al. (2009). This protocol follows the prequential statistics proposed by Dawi (1984), and adopts sliding windows or fading factors to forget less relevant examples. It has three steps: (i) produce a prediction for an unlabelled instance in the stream; (ii) assess the prediction error; and (iii) update the model with the most recently observed error.

In terms of evaluation metrics, there are predictive, classification, and statistical metrics. Prediction metrics describe the accuracy in the accumulation of predictive errors (Takács et al., 2009). In terms of classification metrics, Cremonesi et al. (2010) present a three-step methodology: (i) Generate the predictions of all items not yet classified by the active user; (ii) select randomly 1000 of these predictions plus the active user real value; and (iii) sort this list of 1001 item values using the post-filter. Finally, concerning statistical metrics, Souza et al. (2018) have recently suggested a new evaluation measure (Kappa-latency), which takes into account the arrival delay of actual instances. Alternatively, Vinagre et al. (2019) propose, for recommendation algorithms, the adoption of the *k*-fold validation framework together with McNemar and Wilcoxon signed-rank statistical tests applied to adaptive-size sliding windows.

3.5 | Change detection and adaptation

While data stream tourism recommendation has been able to adapt standard recommendation techniques, mainly collaborative filters, to real-time processing, it still needs to detect and adapt to novelties and anomalies. Adaptive learning algorithms are advanced incremental learning algorithms able to adapt to the evolution of the data-generating process over time. Novelty corresponds to unforeseeable relevant changes, whereas anomaly to sparse abnormal occurrences. On the fly novelty and anomaly detection is essential to identify and adapt models to changes that may occur over time in the underlying distribution of streaming data. Ignoring these unexpected occurrences deteriorates the quality of the learning results (Lu et al., 2019).

3.5.1 | Change detection

The detection of novelty and anomaly in data streams relies on the identification of drifts and outliers (Faria et al., 2016). In both cases, it is crucial to distinguish between natural and significant changes in the data distribution. Drifts can occur with time (e.g., when interests change), may arise from different situations (e.g., changes in the properties of the data or inappropriate hyperparameter tuning), and are identifiable by alterations in the statistical properties of the data (Veloso, Gama, & Malheiro, 2021). Outliers correspond to data spatially distant from the trend of most of the observations (Veloso, Gama, & Malheiro, 2021), such as rare events or noise.

Concept drifts are related with changes over time in the predicted target. In the case of recommendation, concept drifts represent the evolution of the user preferences. There are several detection methods like the Page–Hinckley test by Page (1954), the DDM by Gama et al. (2004), the Early DDM (EDDM) by Baena-Garcıa et al. (2006), adaptive windowing (ADWIN) by Bifet and Gavalda (2007), the linear four rates (LFR) by Wang and Abraham (2015) or hierarchical hypothesis testing by Yu et al. (2019). Typically, they rely on window-based monitoring, accuracy-based model monitoring, and ensemble-based methods. Collaborative filters recognize concept drift by focusing on the recency, temporal dynamics or time period partitioning. Other recommendation algorithms, like those supported by incremental adaptive unsupervised learning, use *k*-means clustering to detect drifts (Wanas et al., 2019). In the case of stream-based recommendation, concept drifts has been explored by monitoring accuracy metrics (Al-Ghossein, 2019; Veloso, Gama, Malheiro, & Vinagre, 2019). Ferreira José et al. (2020) propose a dynamic mechanism composed of two moving windows with different sizes to capture the long- and short-term preferences of the users. Whenever the average of each window is higher than the double of the SD it indicates a possible concept drift and, consequently, the need to accelerate the learning rate. Viniski et al. (2021) study the impact of concept drifts and cold start on recommendation systems to conclude that window-based evaluation detects concept drifts better than standard evaluation techniques. Mehmood et al. (2021) compare four different concept DDMs, namely, Page–Hinkley test, ADWIN, DDM, and EDDM, with synthetic and real datasets. Page–Hinckley was able to detect with more accuracy the interval where a concept drift occurred within a time series. The detection of concept drifts allows recommendation systems to swiftly adapt to meaningful changes in touristsourced data streams.

Data drifts are related with changes in the input features, namely feature evolution. It occurs whenever a subset of features becomes, or ceases to be, relevant to the learning task (Barddal et al., 2017). Again, these drifts can be detected by monitoring statistical change in the data, that is, their statistical properties. This is the case of the adaptive windowing technique propose by Bifet and Gavaldà (2007), that detects drifts over a stream of data. Data drifts indicate the need to reassess input data.

Outliers in data streams are rare events recognizable with distance (Angiulli & Fassetti, 2007; Kontaki et al., 2011; Tran et al., 2016), density (Pokrajac et al., 2007) and cluster (Elahi et al., 2008) based algorithms or one-class learners (Clark et al., 2018). Angiulli and Fasseti (2007) calculate the Euclidean distance between an object and its neighbours to detect outliers. Pokrajac et al. (2007) describe a local outlier detection scheme based on the distance between observations and their density; Kontaki et al. (2011) propose algorithms based on sliding windows for continuous outlier monitoring; Tran et al. (2016) survey distance-based outlier detection; Salehi et al. (2016) design a memory efficient incremental local outlier detection for data streams in environments with limited memory; Clark et al. (2018) couple an adaptive window and threshold method with a one-class learner; Manzoor et al. (2018) implement a density-based ensemble outlier detector for feature-evolving streams. These outlier detection methods can be applied to touristsourced data streams to identify noise or rare events.

3.5.2 | Adaptation

Adaptation attempts to identify the algorithm or configuration of the current algorithm that optimizes the adopted performance evaluation metrics.

Algorithm selection has been intensely studied over the past 15 years and it is known as the task of automatically selecting an algorithm from a given set of techniques (Kerschke et al., 2019). The selection and deployment of the optimal algorithm is fundamental to develop a high performance application (Pfaffe et al., 2017). Gupta and Katarya (2021) propose the use of hierarchical models to generate ensembles and particle swarm optimisation to find the optimal ensemble of models. This way, it intelligently optimizes the recommendations for the data at hand. Auto-CaseRec provides an automated algorithm selection and parameter tuning for recommendation algorithms (Gupta & Beel, 2020).

Feature selection is triggered by the detection of data drifts. The adaptation to this type of change employs online feature selection methods, which are typically adaptations of their offline counterparts. According to Ramírez-Gallego et al. (2017), most online selection strategies are based on information filtering or on the use of classifier weights (wrapper). These dynamic feature selection strategies enable algorithms to discard irrelevant features and work only with the most relevant subset.

Forgetting is triggered by user preference evolution (concept drifts). The problem of the evolution of preferences over time, optimisation, and evaluation of stream-based recommendations has been addressed by Chang et al. (2017), Lommatzsch and Albayrak (2015), Ludmann (2015), Vinagre et al. (2014), Matuszyk et al. (2018) and Wang et al. (2018). Matuszyk et al. (2018) identify SD-based user factor fading as the best forgetting strategy to improve the results of the biased regularized incremental simultaneous matrix factorization algorithm. Wang et al. (2018) describe a probabilistic matrix factorisation model based on Bayesian personalized ranking to keep relevant long-term user interests with the help of a fixed-sized reservoir.

Hyperparameter tuning is the process of choosing the optimal parameters for the corresponding machine learning algorithms. Typically, it is performed manually or offline, using Bayesian optimization or brute force algorithms such as grid or random search. Recently, Veloso, Gama, Malheiro, and Vinagre (2021) proposed an online adaptation of the Nelder–Mead optimisation algorithm to automatically readjust model hyperparameters when concept drift occurs. When a concept drift occurs, the algorithm explores a set of candidate models until they converge to a local minimum and, then, selects and uses the best model till the next concept drift. A recent extension of this work (Veloso, Caroprese, König, Teixeira, et al., 2021) was applied to latent embedding models.

AutoML tools like Auto-Sklearn (Feurer et al., 2019), Auto-Weka (Kotthoff et al., 2019), H_2O (LeDell & Poirier, 2020) or TPOT (Olson & Moore, 2019) perform automated algorithm selection, feature selection and hyperparameter tuning only in batch mode, which indicates a research gap concerning stream-based AutoML solutions.

3.6 | Explanations

Crowdsourcing platforms apply artificial intelligence (AI) algorithms, specifically data stream mining techniques, to generate personalized recommendations for tourists based on the incoming flow of events. Given the highly influential nature of recommendations, there are growing concerns about the principles behind recommendation algorithms. In this regard, Dignum (2019) recommends that the development of such algorithms should be guided by the following design principles: accountability (to explain and justify decisions), responsibility (to incorporate human values into technical requirements) and transparency (to describe the decision-making process and how data is used, collected, and governed). This means that data stream recommendation must explain and justify the rationale behind all recommendations, increasing the confidence of the users and the transparency of the system.

An explanation is any additional information which clarifies why a system arrived at a particular decision. Specifically, in the case of recommendations, explanations justify why an item has been recommended, adding transparency and supporting decision making. An explainable and transparent system helps the user understand whether the output is based on his/her preferences rather than third party interests. Zhang and Chen (2020) already provide a classification of offline explainable recommendation methods. They contemplate the information source together with the display style, and the type of model used to generate the explanations. While the information source identifies the type of information used for explanations, the model represents the technique employed to make recommendations. Similarly, this work proposes a bi-dimensional taxonomy, for stream-based explanations, based on the source of information and modelling technique. Therefore, the surveyed literature concerning stream-based explainable recommendation models covers:

Explainable model-based collaborative filtering identifies relationships between input features and recommendations. The results are challenging to explain since user/item dimensions are latent, and hide the exact meaning of each factor. The literature presents the following complementary techniques to explain model-based recommendations:

1. *Trust-based* approaches quantify the one-to-one reliability of the participants, as well as their many-to-one reputation, establishing relationships among users, items, or features based on the number of co-raters and their mutual relevance (Leal, Veloso, Malheiro, Burguillo, Chis, & González-Vélez, 2021).
2. *Tag-based* methods which rely on a tag/word cloud to illustrate the explanations. To generate those explanations, typically each latent dimension is aligned with an explicit feature (Liang et al., 2021).
3. *Drift-based* mechanisms identify changes in the data distribution, which make models inaccurate or obsolete. Consequently, these mechanisms have been explored to generate explanations, contributing to a transparent stream-based system.

Explainable memory-based collaborative filtering explores the user rating history to identify relationships among users or items. This technique is applied to neighbourhood-based collaborative filters. This is the case of explanations based on trust which quantify the reliability of the participants based on the neighbourhood.

Explainable hybrid filtering integrates or combines multiple techniques to generate explanations, namely the ones presented above for collaborative and content-based filtering.

To complement the taxonomy, there is also the case of *graph-based* explanations. While a knowledge representation technique, graphs are a transverse technique where relationships between entities are embedded in the graph structure and can be used to explain the outcomes. Thus, graph-based methods hold the information required to generate explanations, becoming self-explainable. All of these models, which rely on information related to the users or items, provide explanations based on drifts, tags, trust or any other relationships. Table 1 illustrates the surveyed explanation techniques for stream recommendations.

Explanations have been explored in online scenarios to enhance the trustworthiness of incremental learning solutions (Wang et al., 2016). Furthermore, explanations enable the transparency of the models, and help users to make appropriate decisions. Bosnic et al. (2014) propose methodologies to improve not only the prediction accuracy, but also the explainability of the models. These explanations can be based on the individual attribute-value contributions to the incremental predictions. This is the case of the detection of concept drifts, which reflect changes in the data distribution. Demšar and Bosnić (2018) explore also explanation-based change detection algorithms by comparing explanations over time. Considering online recommendations, Rago et al. (2021) propose argumentative explanations, using sub-graphs, which illustrate positive and negative relationships among features. The method incorporates explanation-driven feedback, which allows the user to interact with the generated explanation, further enriching the recommendation system. Liang et al. (2021) and Zhang et al. (2014) generate online explanations, via a tag cloud interface, using latent factors of users, items, and tags. Veloso, Leal, Malheiro, and Moreira (2019) suggest exploring trust and reputation profiles to explain recommendations in tourism crowdsourcing platforms while, at the same time, storing these profiles in a blockchain to ensure authenticity and integrity. This proposal, implemented by Leal, Veloso, Malheiro, González-Vélez, and Burguillo (2020), incrementally updates and stores trust models of the crowd contributors in the blockchain as smart contracts and, then, uses them to derive reputation models and generate stream-based explainable recommendations (Leal, Veloso, Malheiro, Burguillo, Chis, & González-Vélez, 2021).

TABLE 1 Drift, graph, tag and trust based explanations.

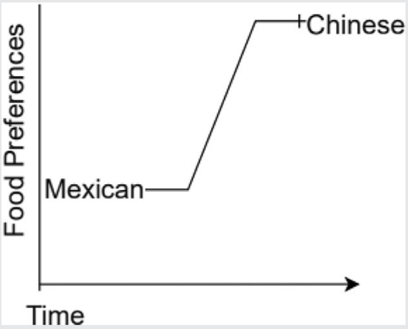
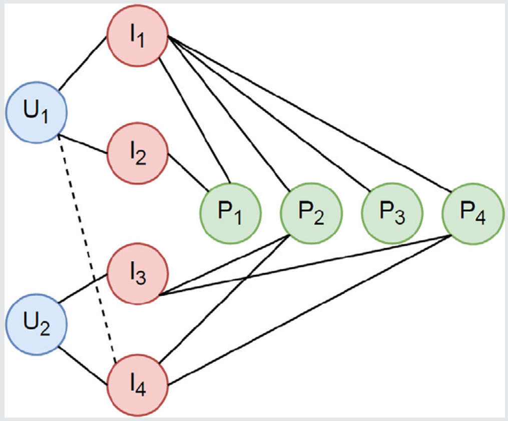
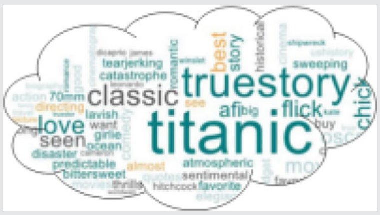
Drift	Graph
‘The recommendation is Chinese food because your food tastes changed since last September’.	‘The recommendation for U_2 is I_1 because it shares two properties (P_3 and P_4) with I_4, which U_2 has previously selected’. (Liang et al., 2021)
	
Tag	**Trust**
‘Titanic has been recommended because U_1 likes classic, love, and true story films’. (Liang et al., 2021)	‘Hotel Porto was recommended because it was rated 4.8 by a group of seven co-raters with a system-wide reputation of 13%, and in whom you trust 13%’. (Leal, Veloso, Malheiro, Burguillo, Chis, & González-Vélez, 2021)
	$\mathbf{T} = \begin{array}{c} U_1 \ \dots \ U_n \\ \begin{bmatrix} T_{1,1} & \dots & T_{1,n} \\ \vdots & \ddots & \vdots \\ T_{n,1} & \dots & T_{n,n} \end{bmatrix} \end{array} \begin{array}{c} U_1 \\ \vdots \\ U_n \end{array}$ $\mathbf{R} = \begin{array}{c} U_1 \ \dots \ U_n \\ [R_1 \dots R_n] \end{array}$

TABLE 2 Surveyed online explainable collaborative filters.

Rely on	Memory-based	Model-based	Hybrid-based
Drift detection		Demšar and Bosnić (2018)	
		Bosnić et al. (2014)	
		Zhang et al. (2014)	
Graph representation			Rago et al. (2021)
User tags		Liang et al. (2021)	
Inter-user trust	Leal, Veloso, Malheiro, Burguillo, Chis, and González-Vélez (2021)	Leal, Veloso, Malheiro, Burguillo, Chis, and González-Vélez (2021)	
	Leal, Veloso, Malheiro, and González-Vélez (2020)	Leal, Veloso, Malheiro, and González-Vélez (2020)	

In principle, tourism crowdsourcing platforms should be able to explore the available sources to provide explanations. However, there is scant research on explainable stream-based recommendations in tourism domain. The exceptions are the works of Veloso, Leal, Malheiro, and Moreira (2019) and Leal, Veloso, Malheiro, González-Vélez, and Burguillo (2020). Table 2 applies the extended taxonomy for explainable stream-based recommendation methods to the surveyed approaches.

4 | SUPPORT TECHNOLOGIES

In the era of big data and massive use of machine learning, data transparency is not only critical but has become a data quality dimension. Improper use of data and algorithms may lead to discrimination, wrong decisions, and other adverse effects. Real time processing requirements of stream-based recommendation, and the uncurated nature of crowdsourced data, poses infrastructural challenges. This review highlights two key technologies to address them: BT and HPC.

Blockchain is a distributed ledger technology maintained by a peer-to-peer network of nodes where blocks, containing validated transactions, are sequentially chained through cryptographic hashes. The network validates new transactions concurrently, using consensus mechanisms. Once validated, they are committed to a block granting security, authenticity, immutability, and transparency. Moreover, it ensures end-to-end verification, which can be used to record data and track sources over time in a trusted manner. BT contributes with an infrastructure for transparency and trust between decentralized untrusted parties, where the policies and queries are implemented as smart contracts. The ledgers are fully replicated among network peers and support query transparency as well as auditable integrity-preserving operation provenance. As stakeholders of data transparency, peers act as data sources, authorized owners, custodians of data and transparency auditors (Bertino et al., 2019). In stream-based environments, BT has been explored to audit IoT data management (Shafagh et al., 2017), store tourism smart contracts and transact cryptocurrencies (Calvaresi, Leis, et al., 2019; Ozdemir et al., 2019) and to explain recommendations (Leal, Veloso, Malheiro, González-Vélez, & Burguillo, 2020; Veloso, Leal, Malheiro, & Moreira, 2019). In the latter case, Leal et al. (2020) propose a transparent data stream recommendation solution, which builds and stores tourist pairwise trust models as blockchain smart contracts to support trustworthy explanations. BT also allows the identification and removal of ill-intended contributions by comparing the present with the past (stored in the blockchain) activity patterns. To this end, blockchain has been adopted to support data anomaly detection in mobile crowd sensing (Arafeh et al., 2019; Huang et al., 2020), which is vulnerable to malicious attacks. According to Abedin (2021), blockchain scaffolds data transparency and traceability as well as the development and application of unified ethical policies and smart contracts between parties.

HPC and, in particular, cloud computing infrastructures, underpin the processing of large amounts of data, becoming a de facto pillar of scalable data analytics (Talia, 2013). HPC and data stream mining have been addressed by several researchers. Assuno et al. (2018) suggest that distributed algorithms for data streams can employ different parallelisation strategies, specifically horizontal and vertical, to build separate models. Horizontal parallelism (data parallel) partitions data sources into multiple subsets, whereas vertical parallelism (task parallel) divides complex tasks into several sub-tasks. HPC architectures, using parallel computing and MapReduce frameworks, meet the performance requirements of data stream mining (Liang et al., 2010; Meng et al., 2014; Riyaz & Varghese, 2016; Shrote & Deorankar, 2016; Zhao & Shang, 2010). Another possible arrangement is to complement Apache Hadoop, that processes large data volumes based on a file storage system, with Apache Spark, which implements fast memory-based processing (Zaharia et al., 2016). The combination of both platforms seems promising for scalable data analytics scenarios. In this regard, Narayanan and Cherukuri (2016) concluded that recommendation systems must work in parallel to support efficiently the final user; Gao et al. (2015) explored data parallel clustering for data streams; and Campa et al. (2014) investigated the on-demand scaling of computationally intensive task parallel streams from a local to a public cloud infrastructure using FastFlow, a parallel pattern environment. In the tourism domain, Veloso et al. (2018) explores the scalability of crowdsourced data stream recommendation using HPC.

On the one hand, blockchain and smart contracts can enhance transparency. Specifically, BT provides quality control for data authenticity and traceability (Leal, Veloso, Malheiro, & González-Vélez, 2020; Veloso, Leal, Malheiro, & Moreira, 2019). As crowdsourced data is prone to manipulation, the blockchain ledger can guarantee that data are not modified, a posteriori, to satisfy third party interests. The integration of BT with recommendation systems enables transparent recommendations (Yeh & Kashef, 2020), and also eliminates the need for centralized authorities (Lisi et al., 2019). In addition, by integrating AI and BT, decentralized AI applications and algorithms can be developed, with access to an identical view of a secure, trusted, shared platform of data, logs, knowledge, and decisions. Such platform can also be used to host a trusted trail of all records taken by AI algorithms before, during, and after the learning and decision making processes (Salah et al., 2019). While BT suffers from weaknesses such as scalability and efficiency, AI has its share of issues with trustworthiness, explainability, and privacy. The marriage of these two technologies, which complement each other, can revolutionize the next digital generation. BT brings trustworthiness, privacy, and explainability to AI; in turn, AI can help build a machine learning system for better security, scalability, and more effective personalisation and governance (Dinh & Thai, 2018). Smart contracts, trusted oracles and decentralized storage has been proposed to model explainability decisions subject to a consensus between distributed agents, with the assumption that the majority of agents involved are truthful. Blockchain-enabled explainability can offer transparency and visibility, immutability, traceability and nonrepudiation, and smart contracts (Nassar et al., 2020).

On the other hand, smart tourism produces crowdsourced data at a high rate and volume, demanding agile mechanisms to profile and filter information in real time and, consequently, efficient computational infrastructures and Big Data techniques. In particular, cloud computing infrastructures have powerful computing and storage capabilities, which can be used to improve the performance of systems to handle Big Data (Zhang, 2021). Since data streams environments demand high computing performance, HPC infrastructures are a key technology for data stream processing. As demonstrated by Veloso et al. (2018), there are clear benefits in exploring HPC for the scalability of crowdsourced data stream recommendations in the tourism domain.

5 | RESEARCH TRENDS

The most challenging research topics associated with crowdsourcing platforms for online tourism recommendation are reliable profiling, change detection & adaptation, and fairness & transparency.

Reliable profiling——Crowdsourced data streams are unfiltered and uncurated by default, meaning that they are exposed to malicious manipulation. This suggests the need to build reliable models of data contributors, and to trace data contributions back to contributors. To this end, trust and reputation profiling approaches have been explored together with BT (Leal, Veloso, Malheiro, González-Vélez, & Burguillo, 2020; Veloso, Leal, Malheiro, & Moreira, 2019).

Change detection & adaptation——The detection of concept drifts (novelty) and outliers (anomaly) is crucial to continue generating meaningful recommendations over time. Stream-based tourism recommendation becomes more robust and accurate with the identification of outliers and the adaptation to drifts. The detection of these changes relies on constant monitoring of relevant metrics. The adaptation to drifts may trigger model learning (Al-Ghossein, 2019; Nilashi et al., 2017; Veloso, Gama, Malheiro, & Vinagre, 2019), forgetting (Matuszyk & Spiliopoulou, 2017; Wang et al., 2018) or feature selection (Ramírez-Gallego et al., 2017).

Fairness & transparency——Fairness addresses the practical implications of deploying a model in a real-world situation. It embraces the principle of equal opportunity against discriminatory algorithms or data to avoid prejudicial or unethical results (Elahi et al., 2021; Shin & Park, 2019). Fair recommendation means that there is no direct relation between sensitive features and predictions (Edizel et al., 2020). Transparent personalized recommendations require the explanation of the underlying reasoning and data, particularly when they are based on crowdsourced data. According to Nilashi et al. (2016), the explanations raise transparency, which directly influences the recommendation quality. Moreover, it increases the trust in the recommendations (Leal, Veloso, Malheiro, González-Vélez, & Burguillo, 2020; Veloso, Leal, Malheiro, & Moreira, 2019) and provides a human-understandable interface. Therefore, recommendation systems require transparency (through explainability) and fairness (Giannopoulos et al., 2021).

The technologies best positioned to provide data authenticity & traceability and seamless scalability to stream-based tourism recommendation are BT and HPC (Leal, Malheiro, Veloso, & Burguillo, 2021).

Blockchain & smart contracts——These technologies are a pillar in domains where transparency is of paramount importance. Specifically, BT provides quality control for data authenticity and traceability (Leal, Veloso, Malheiro, González-Vélez, & Burguillo, 2020; Veloso, Leal, Malheiro, & Moreira, 2019) and smart contracts to automatically launch processes when predetermined conditions are met. As crowdsourced data is prone to manipulation, the blockchain ledger can guarantee that data are not manipulated to satisfy third parties interests. The integration of BT with recommendation systems enables transparent recommendations (Yeh & Kashef, 2020) and eliminates the need for centralized authorities (Lisi et al., 2019). Moreover, its decentralized architecture, supported by consensus mechanisms, is highly suitable for detecting malicious users, which is a problem in crowdsourcing platforms. Building, maintaining and updating the profiles of data contributors (crowd) as smart contracts supports the explanation of the reasons behind collaborative recommendations, contributing to the transparency of recommendations (Calvaresi, Mualla, et al., 2019; Leal, Malheiro, Veloso, & Burguillo, 2021; Nassar et al., 2020). Moreover, the comparison of recent behaviours with those stored in the blockchain, allows the identification and isolation of ill-intended contributions, improving the quality of the generated recommendations.

HPC——Smart tourism produces crowdsourced data at a high rate and volume, demanding agile mechanisms to profile and filter information in real time and, consequently, efficient computational infrastructures (Veloso et al., 2018). In particular, cloud computing infrastructures have powerful computing and storage capabilities, which can be used to improve the performance of systems which handle large amounts of data (Zhang, 2021). Since data streams environments demand a high computing performance, HPC infrastructures are a key technology for seamless data stream processing scalability.

The majority of online tourism platforms employ opaque techniques without explanations or the ability to adapt the model according to the data changes. Furthermore, the absence of such techniques hinder the detection and the traceability of malicious behaviours which can damage the final recommendations. To promote fairness, authenticity, and transparency in stream-based tourism recommendations using crowdsourced data it is imperative to adopt: (i) reliable profiling; (ii) on the fly change detection and model adaptation; and (iii) fair and transparent methods. Together, BT and HPC can provide transparency, authenticity, explainability, traceability, and improve the accuracy of recommendations. In a recent contribution aligned with this vision, Leal, Veloso, Malheiro, Burguillo, Chis, and González-Vélez (2021) adopt blockchain profiling to provide explainable and reliable stream-based recommendations.

6 | CONCLUSION

The research on crowdsourcing platforms for online tourism recommendation presents multiple algorithmic and technological challenges, that are starting to be tackled by the research community. The continuous, open, dynamic and non-curated nature of the crowd-originated data demands for specific data stream mining techniques to support online profiling, recommendation, change detection and adaptation, explanation and evaluation. This article has surveyed the state-of-art of adaptive and explainable stream recommendation, extended an existing taxonomy of explainable offline recommendation methods to the stream-based scenario, and identified future research opportunities.

On the one hand, the algorithmic design needs to address further crowd reliability, change detection and adaptation, fairness and transparency. As shown in this survey, these research directions are beginning to be explored, but there is still a long way to go. On the other hand, the data reliability, pace and volume and the near real time operation impose extremely demanding requirements for supporting technologies. Nevertheless, BT and HPC appear as two promising pillars. The adoption of BT grants data traceability, authenticity and, when integrated with trust and reputation modelling, provides algorithmic transparency, whereas HPC contributes with a computational infrastructure solution for the real time performance requirements.

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DATA AVAILABILITY STATEMENT

Data sharing not applicable to this article as no datasets were generated or analysed during the current study.

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ENDNOTE

[1] Storage in a blockchain.

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