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Design and Implementation of a Tourism Experimentation Platform for Context-Aware and Sustainable Recommendations

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Abstract

The digitization of tourism has made numerous platforms available, but there remains a significant shortage of tools capable of promoting local events and activities. This study hypothesizes that a decentralized digital interface can mitigate over-tourism. We conducted an experiment by deploying a digital platform to assess the synergy between local providers and visitors through the Tourism Open-ended Experimentation Platform (TOEP), a multi-interface solution designed to directly connect tourism activity providers with residents and visitors. The platform integrates a web portal for providers and a mobile app for users, supported by a recommendation system based on individual profiles and preferences. TOEP stands out for its focus on local and sustainable tourism, facilitating the promotion of smaller events and helping to reduce the concentration of tourist flows in already saturated destinations. Initial validation, conducted with a panel of industry experts, highlighted the ease of use and good organization of the interfaces, with scores above average. Preliminary results confirm the relevance of TOEP as a tool for the sustainable and digitized promotion of local tourism, opening prospects for development towards a smart, participatory tourism ecosystem that can be replicated in different territorial contexts.

Keywords: smart tourism; smart tourism business; smart tourism region; digital humanism; cultural heritage; recommendation systems; mobile applications; user-centric designs

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1. Introduction

This project was conceived within the broader framework of contemporary transformations in the tourism sector, where digital technologies are increasingly recognized as essential enablers of both business innovation and sustainable territorial development. The ongoing digitization of tourism involves the creation, growth, and management of enterprises, but also opens new opportunities for the enhancement of local heritage, the valorization of cultural and natural resources, and the diffusion of sustainable practices across destinations. In this sense, technological infrastructures are functional to operational efficiency or market competitiveness, and to the redefinition of the relationship between tourism supply and demand, supporting more balanced and territorially integrated models of development.

At the policy level, these processes resonate with global and regional strategies aimed at fostering innovation and sustainability. The United Nations 2030 Agenda for Sustainable Development [1] emphasizes the role of digital transformation in achieving Sustainable Development Goals (SDGs) such as SDG 8 (Decent Work and Economic Growth), SDG 11 (Sustainable Cities and Communities), and SDG 12 (Responsible Consumption and Production). Relatedly, the European Union's Digital Strategy [2] and the European Agenda for Tourism 2030 [3] underline the importance of smart, sustainable, and resilient tourism, explicitly recognizing the capacity of digital tools to promote competitiveness while also supporting sustainability and inclusion. In this broader context, digital platforms are becoming crucial tools for market development, social innovation and territorial cohesion.

Against this backdrop, the project aimed to establish a comprehensive Software-as-a-Service (SaaS) [4] infrastructure designed to address multiple strategic objectives. These included advanced data analysis of tourism flows, optimization of online tourism offerings, and the integration of different applications into a collaborative ecosystem. The overarching goal was to support digital transformation while fostering sustainability and enhancing the symbolic and experiential value of Made in Italy tourism. The adoption of a crowdsourcing approach was particularly significant, as it enabled the aggregation of proposals for integrated sustainable tourism, thereby strengthening the visibility of local excellence and promoting innovative forms of collaboration between stakeholders.

Within this larger vision, the Tourism Open-ended Experimentation Platform (TOEP) was developed as a specialized response to a persistent gap in the digital tourism market. Despite the proliferation of tourism applications and platforms, most existing solutions were primarily oriented towards broad travel services, booking functionalities, and general information provision. Far fewer addressed the need for specialized tools capable of providing timely, detailed, and context-specific information on local events and regional activities. This limitation was particularly significant in the context of cultural and community-based tourism, where the attractiveness of destinations depends increasingly on the richness and accessibility of unique, place-based experiences.

TOEP was designed precisely to fill this gap. Conceived as a multi-interface system, it directly connects local providers of activities with both residents and visitors, establishing a more dynamic and interactive tourism ecosystem. Distinct user interfaces were developed to accommodate the specific needs of providers—who can easily add, manage, and update their offerings—and of end-users, who are enabled to explore, register for, and engage with local experiences. In doing so, TOEP illustrates how digital technologies can serve a dual purpose: on the one hand, they enhance the competitiveness and visibility of enterprises; on the other, they contribute to sustainable territorial valorization by diversifying tourism flows, reducing concentration in traditional hotspots, and encouraging encounters with cultural and natural heritage in a more responsible way.

To the best of the authors' knowledge, this work represents an original contribution by designing and validating a multi-interface platform specifically for overtourism mitigation. While its technological components are well-established, their integration into a cohesive system is novel. This system simultaneously boosts provider visibility and balances tourism flows, a dual approach that has seen limited attention at the system-design level.

The initial validation of TOEP focused primarily on the provider interface. Results highlighted a generally high level of satisfaction, with participants reporting no significant usability issues and overall scores consistently exceeding the mean. Nonetheless, limitations were identified, particularly about user-facing functionalities, which were tested using AI-generated event data. While this restricted the extent of the evaluation, the findings nonetheless provide a valuable foundation for future refinements and for the gradual extension of validation to real users and real data.

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2. Background

An investigation of the scientific literature and an analysis of some of the existing platforms (mobile and web) were conducted to support the development of TOEP. The results of this research, highlighting the challenges and opportunities, are presented below, along with a specific subsection detailing the application's perspective from a tourism standpoint.

2.1. Literature Review

The scientific literature review on the development of applications/platforms for the promotion of tourism activities was conducted in 5 databases: Springer, ScienceDirect, Taylor and Francis, ACM, and IEEE. The search was performed using the word "Tourism" in the title field and "mobile" and "application" in any other field of the article. The inclusion of "Tourism" specifically in the title field was a deliberate methodological choice to ensure that the identified studies focused on tourism as the primary research domain rather than as a secondary application of a specific technology. This allowed for a more robust analysis of platforms and frameworks designed to address the intrinsic challenges of the tourism sector, such as regional development and stakeholder participation. Additionally, the following filters were applied (depending on what the database allowed): scientific articles, open access, in the area of computer science, published between 2019 and early 2025. We only considered the last five years, bearing in mind that the COVID-19 pandemic changed the way tourism is perceived [5]. Finally, articles that focused on the creation of routes, tours, or virtual reality were excluded, as these topics are outside the scope of TOEP.

From the conducted search, 16 articles were identified that met the established selection criteria. The selected articles were classified into three main categories: Challenges, Recommendation Systems, and Tourism Frameworks.

Table 1 outlines several key insights within the tourism sector, categorized into Challenges, Recommendation Systems, and Frameworks.

Table 1. Literature review summary.

Category	Insights	Articles
Challenges	Technology driving the tourism evolution	[6,7]
	Cultural Preservation and Sustainability	[6,8–10]
	Promotion of rural tourism	[6,10]
	Stakeholder participation (tourists and promoters)	[9,11]
	Impact of COVID-19 (digital tourism)	[5,12]
	Measurement instruments for evaluating digital tourism	[11]
	Personal Services (user modeling)	[13]
Recommendation Systems	Social media for cold starts problems	[14–18]
	Learn about user behaviors	[18]
	User preferences	[14–16]
Tourism Frameworks	Looker: mobile app for personalized tourism suggestions	[5]
	Access@tour: app for accessible tourism interfaces	[19]
	TourismGo: mobile game to incentivize visit to cultural heritage sites	[20]

From an analysis of the articles, the COVID-19 pandemic significantly altered the landscape of tourism [5], positioning technology as the primary driver of its evolution [6,7]. A notable example is the utilization of virtual reality to bridge the gap between tourism activities and individuals [5,12]. However, as post-pandemic travel resumed, a surge in tourist visits to various destinations has prompted a shift in research focus towards cultural site preservation and sustainability [8]. In terms of sustainability, current studies employing data analysis methodologies [6,9,10] demonstrate the potential of technology to broaden the range of tourism activities. Furthermore, the creation of a sense of place and the provision of cultural experiences have been shown to positively influence tourist satisfaction and their inclination to support cultural preservation [9,13]. These factors highlight the importance of robust stakeholder participation, from both tourists and promoters [9,11,13], and underscore the need for effective metrics to evaluate digital tourism [11] in order to ensure the continued growth and sustainability of the industry.

Furthermore, our research identified a substantial body of work concerning the application of recommendation systems to provide tourism activities tailored to individual user profiles. While not the primary focus of our investigation, we selected several articles that support the need for recommendation systems to enhance tourism offerings. In general, the development of effective tourism recommendation systems relies on understanding user behavior, specifically their interests and opinions [18], to provide personalized experiences. The 'cold start' problem, a prominent area of research, is mitigated in many studies by leveraging social media data [14–18]. Accurate user preference modeling [14–16] also plays a fundamental role in the successful implementation of these tourism activity recommendation systems.

Finally, in the last category, we classified articles that present specific tools and frameworks designed to enhance tourism. Among these, Looker is a mobile application that offers personalized tourism suggestions [5], utilizing data from Facebook, Twitter, and TripAdvisor to provide users with tourism offers based on a multilayer user profile. Another application, Access@tour, focuses on accessible tourism interfaces [19], where a study was conducted to create interfaces adapted to individuals with special needs, including services that ensure seamless viewing for those with disabilities. Lastly, TourismGo is a mobile game aimed at incentivizing visits to cultural heritage sites [20], particularly those less frequented, to mitigate tourist overcrowding. These three tools address some of the challenges identified within the research, such as sustainability and personalized tourism activity recommendations.

Based on this literature review, we identified, from the limited number of articles found, a relatively low interest in the creation of new tourism applications at the research level. On the other hand, there is significant interest in the creation and improvement of recommendation algorithms. However, these systems often utilize data from centralized tourism activity points, which are popular destinations where social media data is abundant. We also identified that this centralization of tourism is exposing cultural sites to deterioration. This makes the promotion of rural or more regional tourism (e.g., the "sagre" in Italy) [10] a promising new avenue to explore. Another gap we found is the lack of connection between tourism apps and tourism promoters; apps tend to gather information from external sources, not directly from the activity creator, which can lead to data veracity issues. Lastly, due to the impact of the pandemic, there is considerable research in Virtual Reality, but this could also be detrimental to regional tourism activities.

2.2. Comparative Analysis: Application and Web Sites

Comparative analysis of tourism-related applications and web pages reveals a diverse landscape of functionalities and specializations. The analysis of existing platforms was conducted in late 2024 through a systematic search on the Google Play Store and the open web. This approach ensured that the results reflect the actual experience of an average user. The search employed keywords such as "tourism", "regional events", and "local events". Inclusion criteria for mobile applications were restricted to the Italian market and high user ratings, excluding platforms focused solely on route planning. For web portals, the identification was supported by an initial screening using the Gemini 1.5 Flash AI model (prompted to identify 15 portals specialized in Italian regional events like sagre and festivals), followed by manual verification to ensure data accuracy and relevance.

Table 2 lists the applications and websites analyzed. Platforms categorized as "Mobile/Web" offer a broad spectrum of services, including hotel and restaurant reviews

(TripAdvisor), outdoor route planning (Komoot, AllTrails), travel itineraries (Visit A City), and tour bookings (GetYourGuide, Klook). However, a recurring limitation across these platforms is the focus on general tourist activities, with a lack of detailed information on regional events such as festivals and fairs, as noted in the comments for several applications. In contrast, the "Web" platforms present a different set of characteristics. Webs like TuttiGliEventi.it and "Torino Today" aim to provide information on events, but face challenges such as complex interfaces and outdated information. In contrast, Sagritaly.com offers a more modern web interface for regional events, although detailed activity information is limited to PDF documents. The diversity in functionality and information quality highlights the need for specialized platforms that can provide comprehensive and up-to-date details on regional and local events.

Table 2. Comparison of Tourism Apps and Web Pages.

Name	Platform	Top Download Country	Local Tourist Activities	Recom. System
TripAdvisor	Mobile/Web	Global	No	Yes
AllTrails	Mobile/Web	USA	N/A	Yes
Komoot	Mobile/Web	Europe	N/A	Yes
Visit A City	Mobile/Web	Europe	No	Yes
Maps.me	Mobile/Web	Regions with limited connectivity	No	Yes
Minube	Mobile/Web	Spain & Latin America	No	Yes
GetYourGuide	Mobile/Web	Europe	No	Yes
Klook	Mobile/Web	Asia	No	Yes
Culture Trip	Mobile/Web	Europe & USA	No	Yes
ZonzoFox	Mobile/Web	Italy	No	Yes
SmartGuide	Mobile/Web	Global (with strong focus on Italy)	No	Yes
TabUI	Mobile/Web	Italy	Yes	N/A
Guida Torino	Web	Italy	Yes	No
TuttiGliEventi.it	Web	Italy	Yes	No
Torino Today [a]	Web	Italy	Yes	No
Sagritaly.com	Web	Italy	Yes	No

[a] A dedicated webpage exists for each city (e.g., Turin or Milan).

Among existing tourism applications, TabUI stands out as a conceptually proximate solution. However, its adoption appears limited, as evidenced by its lack of visibility in standard Google Play searches for tourism apps. While TabUI seemingly incorporates a recommendation system, much of the information it presents appears redundant and its sources lack clear reliability, making a comprehensive comparison challenging.

Overall, the analysis indicates a gap in the availability of platforms that effectively cater to specific regional events and activities. While many applications offer general travel information and booking services, there is a need for improvement in providing detailed, current and easily accessible information on local events and cultural activities. This limitation suggests an opportunity for the development of more specialized tools that can enhance the user experience by offering targeted and relevant information on regional tourism.

2.3. Tourism Standpoint

The intersection of digital innovation and sustainable tourism is a critical area of study, driven by the need to address modern tourism challenges. While digital tools have long been seen as mechanisms for enhancing efficiency and competitiveness, a new perspective is emerging where they are also recognized for their capacity to promote social responsibility, cultural preservation, and equitable development. This shift aligns with the

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concept of digital humanism, which advocates for technology to be developed and used in a way that benefits humanity and respects cultural and social values [21].

Traditional tourism studies often focus on the physical dimensions of travel, but the digital age has expanded the concept of tourist space. Contemporary research suggests that tourist experiences are increasingly shaped by relational and digital dimensions, where interaction, participation, and accessibility play a crucial role [22]. This redefinition highlights the importance of digital tools—such as geospatial data, interactive maps, and recommendation systems—not merely as technical features but as strategic instruments for sustainable territorial analysis and planning [23]. These technologies facilitate the understanding and management of visitor flows, enabling a more nuanced approach to tourism development.

The challenges of overtourism and the need to support local economies are central issues in current tourism discourse. Digital platforms offer promising solutions by mitigating visitor concentration in saturated destinations and fostering direct connections between local suppliers and consumers. By dispersing tourist flows, these platforms can help reduce the negative impacts on highly visited areas while simultaneously supporting small-scale providers and entrepreneurship. This model generates economic benefits that are more likely to stay within the local community, contributing to a more resilient and inclusive tourism ecosystem. Recent literature underscores this potential, highlighting how platforms can promote responsible tourism by embedding sustainability and cultural valorization into their operational and recommendation logics [24–26]. This paper will explore how platforms like TOEP can serve as instruments to accompany the transition towards more responsible, inclusive, and sustainable tourism models [27].

The contribution of TOEP also resonates strongly with international frameworks that prioritize sustainability, inclusivity, and digitalization. The UNWTO's One Planet Vision for a Responsible Recovery of Tourism [28] emphasizes digital innovation as a cornerstone of post-pandemic resilience, while the European Commission's Pathway to the Transition for Tourism [29] calls for smarter, greener, and more resilient models that leverage technology to reduce environmental impact, promote cultural heritage, and sustain local economies. In this sense, TOEP illustrates how research and experimentation at the micro level can support macro-level strategies, aligning technological progress with the objectives of Agenda 2030 [1] and the European Green Deal [30].

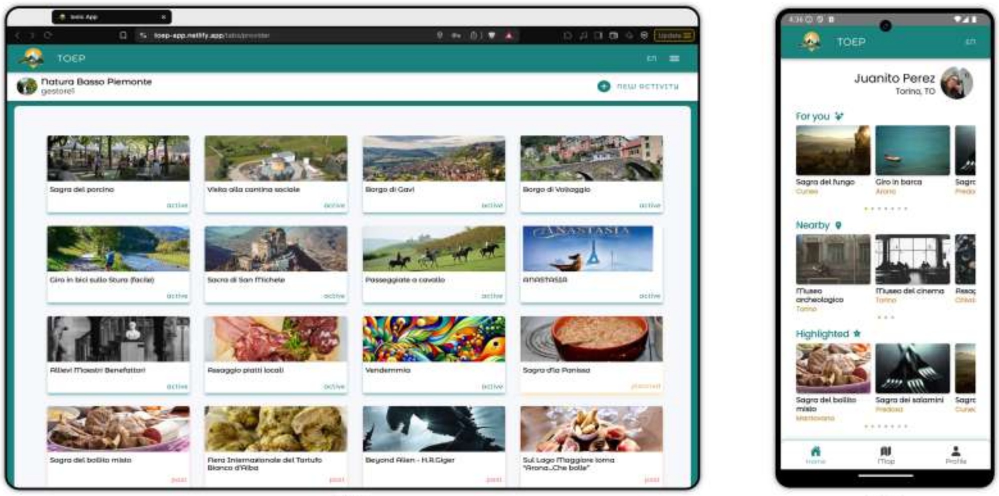
3. Materials and Methods

The experimental framework was built upon a multi-tier architecture designed to facilitate real-time interaction between tourism providers and end-users. The materials utilized in this study consist of a cross-platform software stack and a cloud-based infrastructure. The front-end interfaces (Web Portal and Mobile Application) were developed using the Ionic Framework (version 7.0.0) and Angular (version 17.0.2), ensuring high performance across various operating systems. The backend infrastructure was hosted on a virtual machine provided by the "Chameleon Project" (a large-scale NSF-supported cloud computing testbed), utilizing a Node.js (version 22.11.0) API environment and a MongoDB (version 8.0.3) cloud database for scalable data persistence. Security and user authentication were managed through the Firebase platform integration.

The methods followed a structured experimental protocol divided into three phases: system architecture design, data synthesis, and expert validation. To simulate a high-density tourism environment and address the "cold-start" problem, we implemented a data generation method using the Gemini 1.5 Flash Large Language Model (LLM). This allowed for the creation of a controlled dataset comprising synthetic user profiles, regional activities, and historical reviews. The recommendation logic was executed through a hybrid filtering algorithm (Collaborative and Content-Based), which was tested for its ability to prioritize sustainable "hidden gems" over saturated landmarks. Finally, a qualitative and quantitative validation was performed with a panel of industry experts, using standardized usability metrics to evaluate the platform's efficacy as a tool for sustainable tourism management.

3.1. Experimentation Platform Architecture

TOEP is a multi-interface platform designed to connect regional activity providers with local residents and tourists (see Figure 1). The platform features distinct user interfaces tailored for both providers (see Figure 1a) and users (see Figure 1b). Providers are enabled to add and manage regional activities. Users can browse, register for and provide feedback on these activities. The following section will detail the development process of TOEP, including the architectural design, user interface design, and the recommendation system.



(a) (b)

Figure 1. TOEP platform home pages: (**a**) web interface for Providers and (**b**) mobile app interface for Users.

The TOEP system architecture (see Figure 2) is based on two distinct interfaces, each designed for a different user type. Both interfaces connect to a centralized database that stores all information related to activities created by tourism providers, as well as the profiles of users (potential participants in these activities). Utilizing this data, a recommendation system filters activities that best match the user's profile and geographic location, thereby suggesting relevant and localized experiences.

TOEP utilizes a robust tech stack: a web interface for providers and a mobile app for users. The apps are built using Ionic Framework [31] and Angular [32] for cross-platform development and efficient user interaction. Both integrate with a scalable cloud-based MongoDB database [33] and a Node.js API for efficient server-side operations [34]. The server-side components run on a virtual machine hosted on the Chameleon Project [35], a cloud computing testbed supported by the National Science Foundation. Additionally, Firebase is used for user authentication [36]. These technologies enable efficient handling of user requests, intuitive user interface design, and reliable communication with the database. At the core of TOEP's personalization is its Recommendation System (more details in Section 3.2). This system is powered by machine learning algorithms that analyze user data to generate highly personalized activity recommendations, enhancing the user experience.

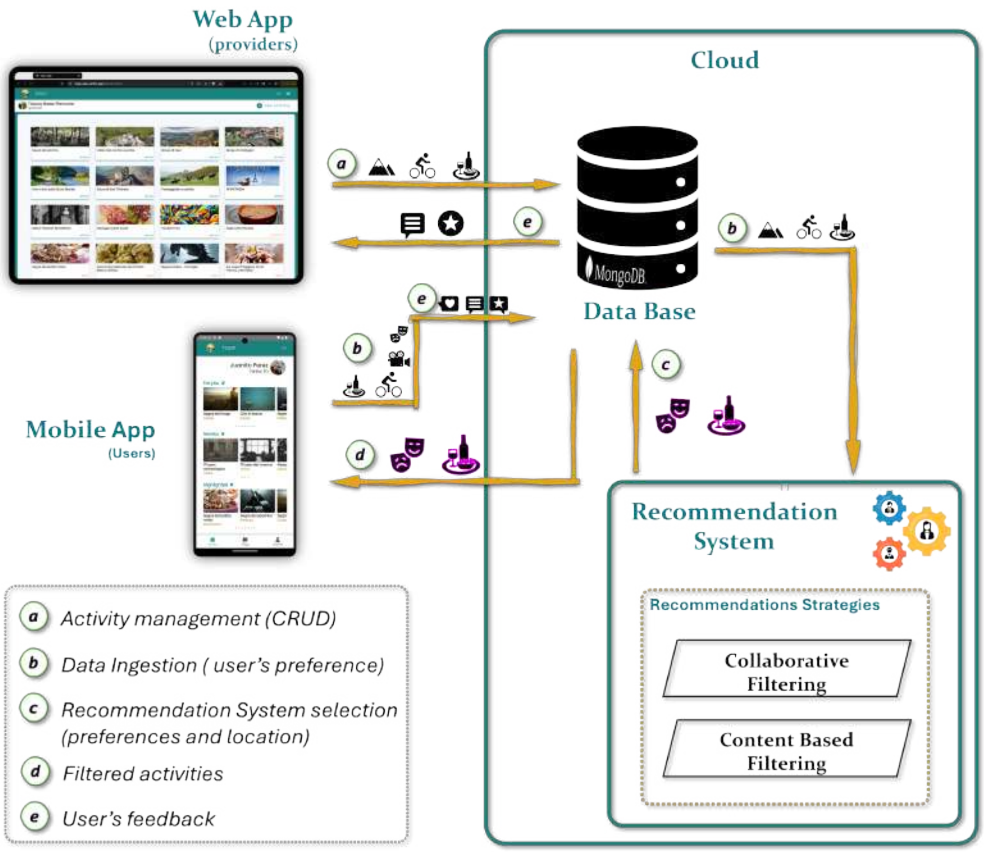
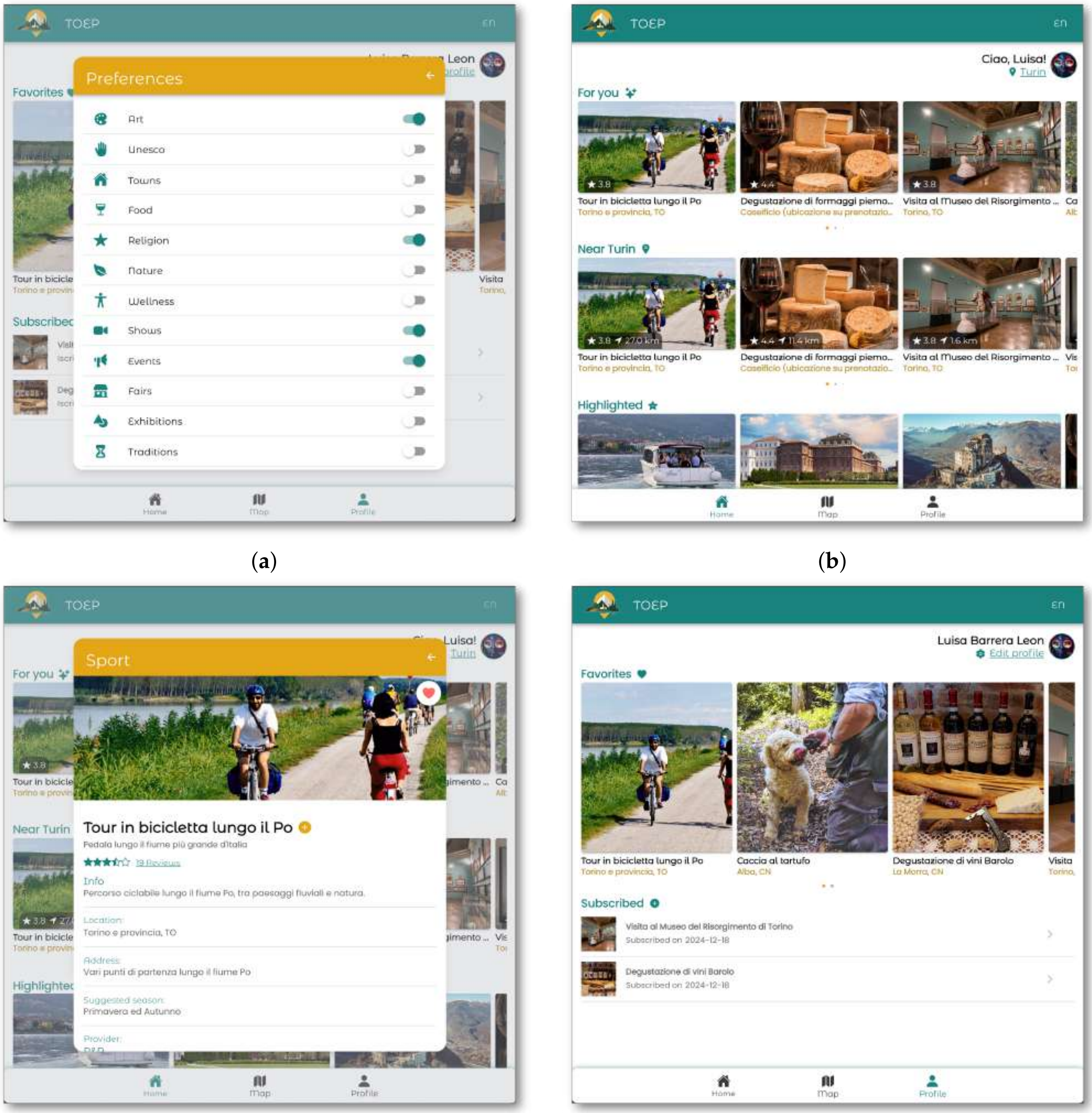


Figure 2. TOEP overall architecture.

3.1.1. User Segments

The two primary TOEP clients are Users and Providers. The Users group employs the platform to discover activities that align with their individual profiles, factoring in interests, current location, and recommendations influenced by similar users. Users may include tourists, travelers, residents, and more. Users have a mobile app that allows them to perform different actions:

- Profile Creation: complete a detailed profile to improve the accuracy of recommendations, save their activity category preferences and add their favorite activities to a list (Figure 3a).
- Personalized Search: conduct a map-based activity search based on their interests, location, and other criteria.
- Intelligent Recommendations: receive personalized activity suggestions thanks to a recommendation system that analyzes their preferences and the behavior of similar users (Figure 3b).
- Online Bookings: make reservations directly from the app and receive instant confirmations (Figure 3c).
- Ratings: Rate and leave comments on completed activities, contributing to the improvement of the information available on the platform (Figure 3d).



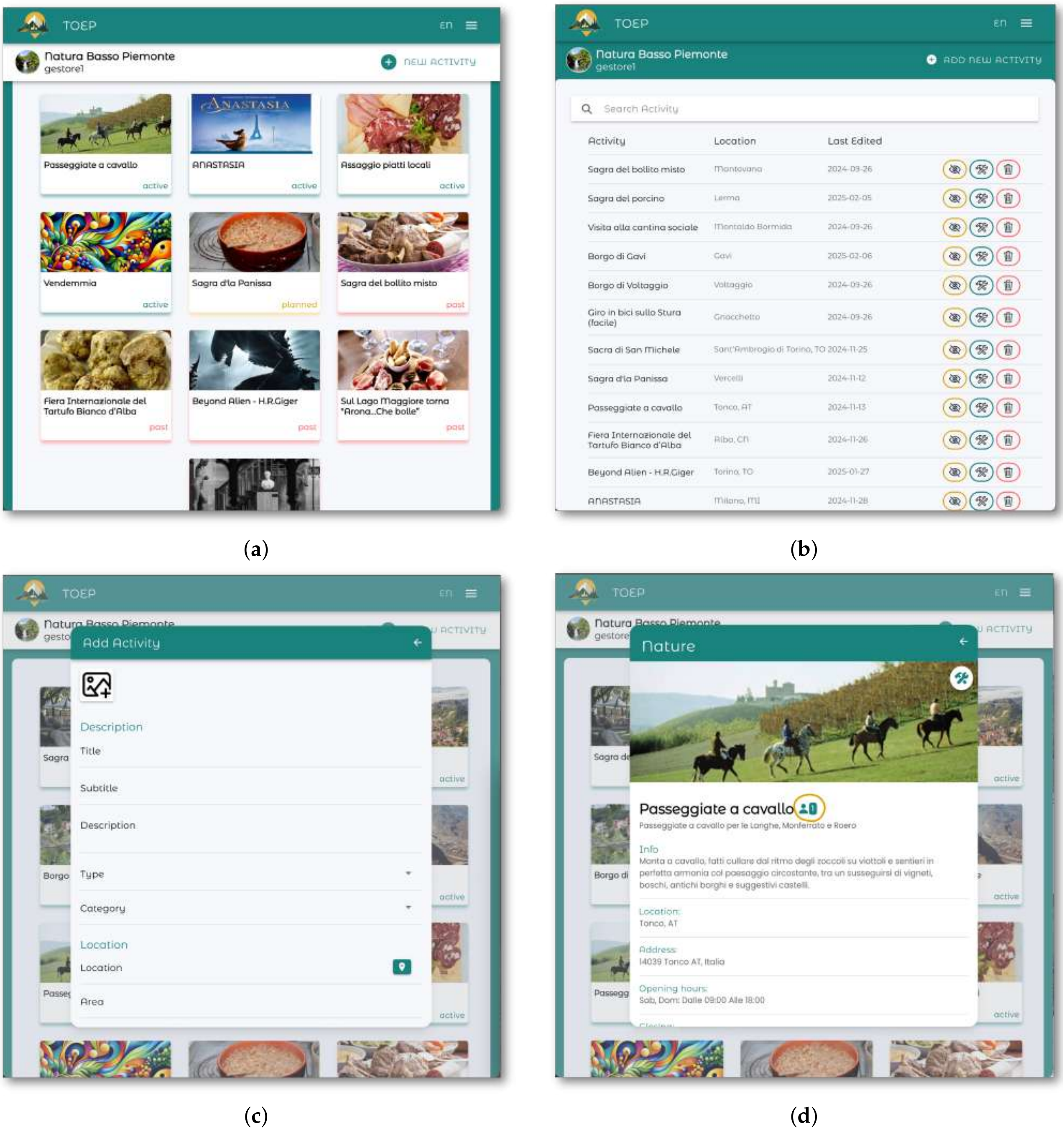
(**a**) (**b**)

(**c**) (**d**)

Figure 3. TOEP user interface examples: (**a**) user preferences list; (**b**) user home page with recommended activities; (**c**) activity detail pop-up; and (**d**) user's saved and booked activities.

Conversely, Provider entities utilize the platform to disseminate, advertise, and assess their tourism initiatives. Providers can encompass enterprises, associations, public agencies, accommodation facilities, and private operators. Providers can access a web-based portal that allows them to:

- Activity management: create, edit, delete and publish new tourism activities (Figure 4a–c).
- Customization: configure details such as schedules, prices, detailed descriptions, and attach images or videos (Figure 4c).
- Performance data: access information on the performance of their activities, including bookings, reviews, and user ratings (Figure 4d).



(a) (b) (c) (d)

Figure 4. TOEP Provider interface examples: (**a**) provider home page with activity status; (**b**) created activities list; (**c**) activity create/edit pop-up; and (**d**) activity detail/booking pop-up.

3.1.2. Activity Categorization

The platform's data collection process is designed for flexibility and adaptability, accommodating the diverse range of activities offered by providers. The specific information required for each activity is dynamically adapted based on its category (e.g., art, towns, food, nature, shows, traditions, etc.) and type (activity, event or itinerary). A key differentiator among these types is temporality. For instance, an Event necessitates specific start and end dates and times, as its nature is inherently time-bound. In contrast, an Attraction (like a museum) or a Destination (like a city park) requires information such as operating hours, seasonal availability, and general accessibility, rather than precise beginning and end times. This tailored approach ensures all necessary data is captured efficiently, optimizing both the user's search experience and the provider's ability to effectively showcase their offerings.

3.1.3. Enhanced User Experience: Categorized Suggestions

To further enhance the user experience, the mobile application categorizes activity suggestions into separate groups, as illustrated in Figure 3b. This intuitive categorization scheme empowers users to quickly identify activities that align with their specific interests and needs, streamlining the discovery process. In particular, the categories for the activity suggestions are:

- Inspired activities are closely aligned with a user's individual preferences, providing highly personalized recommendations.
- Near You suggestions prioritize activities located in proximity to the user's current location.
- Highlighted activities represent the platform's top-rated and most popular options.
- Recent activities show those activities that were created recently. They may be outside the user's profile.

The user profile (Figure 3d) page allows users to adjust their preferences at any time. Here, users can modify their preferences, view a list of favorite activities, and access a history of their past participation, complete with review options

3.2. Recommendation System

In order to improve the user experience, the TOEP platform is provided with a flexible recommendation engine (see Figure 2. Recommendation System). This component reads data from the MongoDB repository and provides two different classical recommendation strategies:

- Collaborative Filtering (CF) [37]: the idea is to make predictions (filtering) about the interests of a user by collecting preferences or interest information from many users (collaborating); the underlying assumption is that if two users have agreed on certain items in the past, they are likely to agree on other items in the future.
- Content-Based (CB) [38]: this approach suggests items to a user based on the characteristics of the items and a profile of the user's preferences; the core idea is to recommend items that are similar in content to items the user has liked in the past, by matching the attributes of the item profiles with the user's profile (to find new items that the user might like).

The recommendation system is designed to run daily, ensuring that recommendations are consistently updated with any new user interactions or activities. The application is deployed within a Docker container and is executed by a cron job set to run at 00:01 Central European Time (CET). This timing was chosen specifically because the platform is focused on the Piedmont region of Italy, and it is assumed that user traffic will be minimal at midnight, allowing the server to dedicate resources to the recommendation engine without impacting client-side performance.

For reproducibility and reliable operation, the recommendation engine is executed as a server-side batch service in a Dockerized Python 3.10 environment (tested with Docker 27.0.3), with MongoDB connectivity for reading user/activity/review data and writing recommendations. A practical minimum deployment is a CPU-only Linux server with 4 vCPUs, 16GB RAM, and 30GB SSD, while a recommended production setup is 8 vCPUs, 32GB RAM, and 80+GB SSD to accommodate NLP/embedding workloads and data growth; no GPU is strictly required, although CUDA-capable hardware can reduce semantic-model inference time.

3.2.1. Synthetic Data Generation Using Gemini

In recommender systems, the *cold-start problem* refers to the lack of sufficient historical interaction data at system launch (or when new users/items are introduced), which makes it difficult to estimate user preferences and item relevance reliably. In our case, because the platform was still under development, no real user–activity interactions were initially available; therefore, synthetic users, activities, and reviews were generated to bootstrap model training and early-stage evaluation.

To overcome this, a synthetic dataset was generated using the Gemini 1.5 Flash API [39]. This process involved creating a set of fictitious users, activities, and user reviews, which served as the foundational data for building and evaluating the recommendation system.

To generate the initial set of activities and users, the script uses a repetitive prompting strategy. It starts with a base prompt that defines the persona of the model, the data to be generated, and the specific output format (a list of JSON objects). The prompt also includes a sample object to ensure strict adherence to the required schema. For reference, Table 3 shows an example of the prompt used to generate users.

Table 3. Prompt for users generation.

<table>
<tr><th colspan="2">Prompt for Users Generation</th></tr>
<tr>
<td>You are in charge of generating data for a tourism website, where users can review the activities they have participated in, your goal is to populate the mongodb database of this website. Let's start to generate users only, they must be resident in the Piedmont region in Italy.

You must use the italian language and you must answer with a list of JSON objects, it is important that the generated list and each object inside it will be perfectly compliant to the JSON standard.

There must be a variety of users, some with preferences for food, some for art, some for shows and some for sports, or a combination of those. Users preferences must be a list of strings with a random combination of values fetched from the following list: <code>{categories}</code>.</td>
<td>You must not generate duplicate users. You must generate exactly 10 users.

Here is an example of an user: {
"_id": "673dff810c27ea6aa626df0e",
"email": "giovanni.rossi@gmail.com",
"name": "Giovanni Rossi",
"username": "Giovanni",
"location": "lat": 45.450001, "lng": 8.616667,
"locationName": "Novaro, NO",
"phone": "3401234567",
"type": "user",
"birthday": 725846400000,
"gender": "male",
"preferences": ["food", "art"],
}

Generated data: """</td>
</tr>
</table>

Note that `{categories}` is a placeholder to be substituted with the actual available preferences, fetched from the appropriate table in MongoDB.

Both the activities prompt and users prompt define the rules for generating data relevant to the Piedmont region of Italy, ensuring a variety of user preferences and unique IDs for each entry. The script then iteratively calls the Gemini API to generate more data, dynamically updating the prompt with the already-generated users and activities to prevent duplicates.

Review generation is handled by a function that creates a dynamic prompt for each user. This function embeds the user's preferences and the full list of activities into the prompt, instructing the model to generate a specific number of reviews for that user. This personalized approach ensures that the content of the reviews aligns with the user's defined preferences and that a variety of review scores and text lengths are generated, simulating authentic user behavior.

The prompt for review generation is presented in Table 4. The following placeholders can be noted in this prompt:

- `{activities}`: this is the list of all the activities previously generated, represented as JSON Objects.
- `{user}`: the user to impersonate as JSON Object.
- `{num_reviews}`: this is an integer that controls the number of reviews to generate; in order to simulate a normal website this number is randomly selected from a normal distribution.

Table 4. Prompt for review generation.

Prompt for Review Generation	

You are in charge of generating data for a tourism website where users can review the activities they have participated in, our goal is to populate the mongodb database of this website. You must use the italian language and you must answer with a list of JSON objects, it is important that the generated list will be perfectly compliant to the JSON standard. You already generated users and activities for this website, now you must generate reviews for the activities.
 	
Considering that you have already generated these activities:`{activities}`. You now have to generate `{num_reviews}` reviews for these activities as if you were the following user: `{nuser}`.
 	
You will generate exactly ***{num_reviews}*** *reviews for this user. User preferences indicate which categories of activities the user is interested in, so the reviews must be mostly related to those categories, remember that the task is to perfectly mime how a normal user would behave on a normal tourism website.*
	Some reviews will be more positive, some more negative, some will be neutral, and some will be very detailed, while others will be very short. Remember, variety is key.
	
	It is important that the activityId field is correctly filled in each review and it must refer to actually existing activities, you can fetch them from the list I gave you above.
	
	Here is an example of a review:
	
	{
	"_id": "789ghg810c27gh6aa626ff08",
	"userId": user["_id"],
	"activityId": "973gfg811f29ge6ab727hf09",
	"mainScore": 4,
	"staffScore": 5,
	"text": "Bellissima esperienza, lo staff è stato molto cordiale e la location ci ha stupito!",
	"editTimestamp": 1727345204000
	}
	
	Generated data: """

To mitigate known risks of LLM-generated data (e.g., hallucinations, invalid fields or formats), we applied a post-generation quality-control pipeline before loading data into MongoDB. First, outputs were accepted only if they were valid JSON and compliant with the expected schema. Second, we enforced semantic constraints and referential integrity (e.g., valid score ranges, coherent timestamps, unique identifiers, and review `activityId/userId` values matching existing entities). Finally, we removed duplicates and near-duplicates, and discarded samples with inconsistent or implausible content. While these safeguards substantially improved data quality for prototyping, we acknowledge that synthetic data may still encode model biases as well as hallucinations and cannot fully replace real user behavior.

3.2.2. Content-Based Recommender

The Content-Based Recommender is designed to suggest activities to a user based on the textual content of activities they have previously reviewed. The process involves vectorizing activity descriptions, building a user profile, and performing a similarity search. We implemented two different vectorization techniques:

- Term Frequency-Inverse Document Frequency (TF-IDF)-based: activities are vectorized by means of their description's TF-IDF representation.

- Semantic-based: activities are vectorized by embedding their description in a dense vector using the Jina sentence embedding model [40].

TF-IDF Recommender

The core of this system relies on the TF-IDF technique to represent each activity's description as a vector [41]. The process can be formalized as follows:

1. First each activity a_j is represented as its TF-IDF vector $v_{a_j} \in \mathbb{R}^d$ where d is the size of the vocabulary, which is the total number of unique tokens (words, n-grams, or characters) identified across the entire dataset and thus defines the dimensionality of the resulting sparse vector. The TF-IDF score for a term t_k in an activity description a_j is given by:
$$\text{TF-IDF}(t_k, a_j) = \text{TF}(t_k, a_j) \cdot \text{IDF}(t_k)$$
where $\text{TF}(t_k, a_j)$ is the term frequency of t_k in a_j and $\text{IDF}(t_k)$ is the inverse document frequency of t_k across all activity descriptions.
2. A user's profile, u_i, is constructed as a centroid vector. This vector is the weighted mean of the TF-IDF vectors of all activities, A_i, that user i has reviewed. The weights, $r_{i,j}$, correspond to the user's review score for activity $j \in A_i$. The centroid is defined as:
$$u_i = \frac{\sum_{j \in A_i} r_{i,j} \cdot v_{a_j}}{\sum_{j \in A_i} r_{i,j}}$$
3. Recommendations for a user i are generated by calculating the cosine similarity between their profile vector, u_i, and the TF-IDF vectors of all activities a_k that they have not yet reviewed. The set of unreviewed activities is denoted as $\hat{A}_i$.
$$\text{similarity}(u_i, v_{a_k}) = \frac{u_i \cdot v_{a_k}}{||u_i|| \, ||v_{a_k}||}$$
4. The final recommendations $\mathcal{L}_{i,N}$ for user i are obtained by ranking all activities in $\hat{A}_i$ in descending order based on their cosine similarity scores. The top N activities from this ranked list are then selected and presented to the user.

Semantic Recommender

The semantic recommender leverages dense vector embeddings to capture the underlying meaning of activity descriptions rather than relying solely on surface-level word statistics. In this approach, each activity description is transformed into a dense numerical representation using the Jina Embeddings model. These embeddings map semantically similar descriptions closer together in the vector space, even if they do not share exact terms. The process can be formalized as follows:

1. Each activity a_j is converted into its embedding vector $v_{a_j} \in \mathcal{R}^m$, where m is the embedding dimension of the pretrained Jina model.
2. The user profile u_i is constructed as the weighted centroid of embeddings of all activities previously reviewed by the user. The same weighting scheme as in the TF-IDF recommender is applied, using the user's review score $r_{i,j}$:
$$u_i = \frac{\sum_{j \in A_i} r_{i,j} \cdot v_{a_j}}{\sum_{j \in A_i} r_{i,j}}$$

3. For generating recommendations, the cosine similarity between the user profile u_i and the embedding vectors of unseen activities v_{a_k}, with $a_k \in \hat{A}_i$, is computed:

$$\text{similarity}(u_i, v_{a_k}) = \frac{u_i \cdot v_{a_k}}{||u_i||||v_{a_k}||}$$

4. The list of recommendations $\mathcal{L}_{i,N}$ then consists of the top N activities ranked by similarity score, with higher values indicating greater semantic alignment with the user's interests.

3.2.3. Collaborative Filtering Recommender

The Collaborative Filtering recommender leverages the collective behavior of users to identify and suggest activities. This system is built upon a matrix factorization approach. The process can be formalized as follows:

1. The foundation is a user–item interaction matrix, $\mathbf{R} \in \mathbb{R}^{m \cdot n}$, where m is the number of users and n is the number of activities. Each entry $\mathbf{R}_{i,j}$ represents the review score given by user i for activity j, with $\mathbf{R}_{i,j} = 0$ if user i has not reviewed activity j.
2. The similarity between any two users i and j is measured using the cosine distance between their rating vectors, r_i and r_j:

$$\text{similarity}(i, j) = cos(\theta) = \frac{r_i \cdot r_j}{\|r_i\|\|r_j\|}$$

3. For a given user i and an unrated activity j, the predicted rating, $\mathbf{R}^{i,j}$, is calculated as the weighted average of the ratings from a set of k similar users, S_i, who have rated activity j. The weights are the similarity scores between user i and each similar user $s \in S_i$.

Figure 5 shows a graphical depiction of both methods.

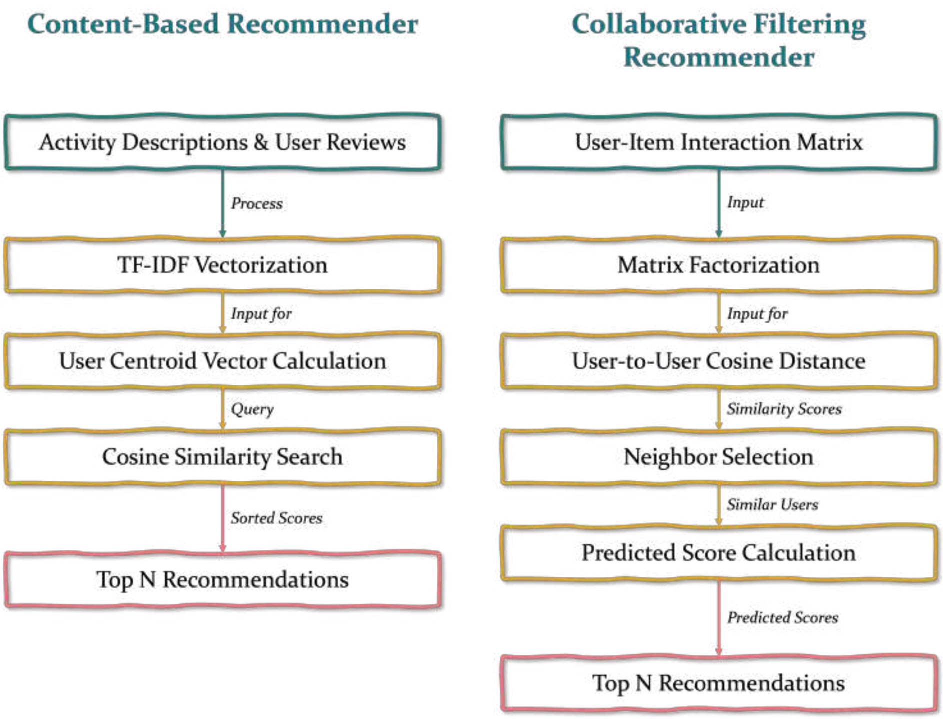


Figure 5. Graphical visualization of both recommendation processes.

4. Results

This section details the experimental results derived from a multi-stage validation of the proposed platform. We first report the findings from a heuristic evaluation conducted to verify the system's logic and architectural integrity. Subsequently, we present the performance outcomes of the recommendation engine, quantified through rigorous technical metrics.

4.1. Heuristic Validation

We employed a heuristic validation methodology to assess the TOEP application. This involved experts critically examining the app to determine its strengths and weaknesses. While a wide range of heuristics exist for subjective evaluation, many are geared towards general interaction and usability. Therefore, we specifically adapted parts of these heuristics to concentrate on aspects most relevant to our applications: perceived usefulness, user satisfaction, overall reactions, and system capabilities. This methodology is often implemented through questionnaires. For the TOEP validation, we incorporated relevant sections from established questionnaires like USE (Usefulness, Satisfaction, and Ease of use) and QUIS (Questionnaire for User Interface Satisfaction). A comprehensive list of questions presented to the expert panel can be found in Table 5.

Table 5. Satisfaction Survey Questions.

Survey Division	Questions
Overall System Satisfaction	Q1—It helps me be more productive Q2—It helps me be more effective Q3—It is useful Q4—It does everything I would expect it to do Q5—It is easy to use
Overall Experience Feeling	Q6—Terrible . . . Wonderful Q7—Difficult . . . Easy Q8—Frustrating . . . Satisfying Q9—Dull . . . Stimulating Q10—Rigid . . . Flexible Q11—Inadequate power . . . Adequate power
Screen Factors	Q12—Reading characters on the screen Q13—Organization of information Q14—Sequence of screens
Terminology and System Feedback	Q15—Use of terms throughout system Q16—Terminology related to task Q17—Position of messages on screen Q18—Prompts for input Q19—Error messages
Learning	Q20—Learning to operate the system Q21—Performing tasks is straightforward
System Capabilities	Q22—System speed Q23—System reliability Q24—Correcting errors in data entry has been (Difficult . . . Easy) Q25—System tends to be (Noisy . . . Quiet) Q26—Designed for all levels of users

The validation involved a panel of seven experts: six tourism consultants operating within the European area and one web designer. Their ages ranged from 35 to 47 years, comprising four women and three men. It is important to note that these participants were engaged with the project as content creators, responsible for generating event information, rather than being part of the development team. Consequently, their interaction with the application was limited exclusively to the validation phase.

The participants' initial reactions to their interaction with the application are presented in Figure 6. Based on these results, participants consistently reported above-average scores. The highest values were observed for the app's ease of use (Q5), while the lowest pertained to whether the app met their expectations (Q4). Overall, the application generated modest impact on the participant group.

Figure 6. Overall system satisfaction results.

Figure 7 presents the results for the more specific aspects of the satisfaction survey. As illustrated in the graphs, the average response per question remained consistent across all inquiries, ranging from 5.67 to 6.67 (on a maximum scale of 9.0). Notably, the highest score was for the perceived organization of information on the screen (Q20), indicating effective information structuring. Conversely, the lowest score pertained to the perceived usefulness of error-support messages.

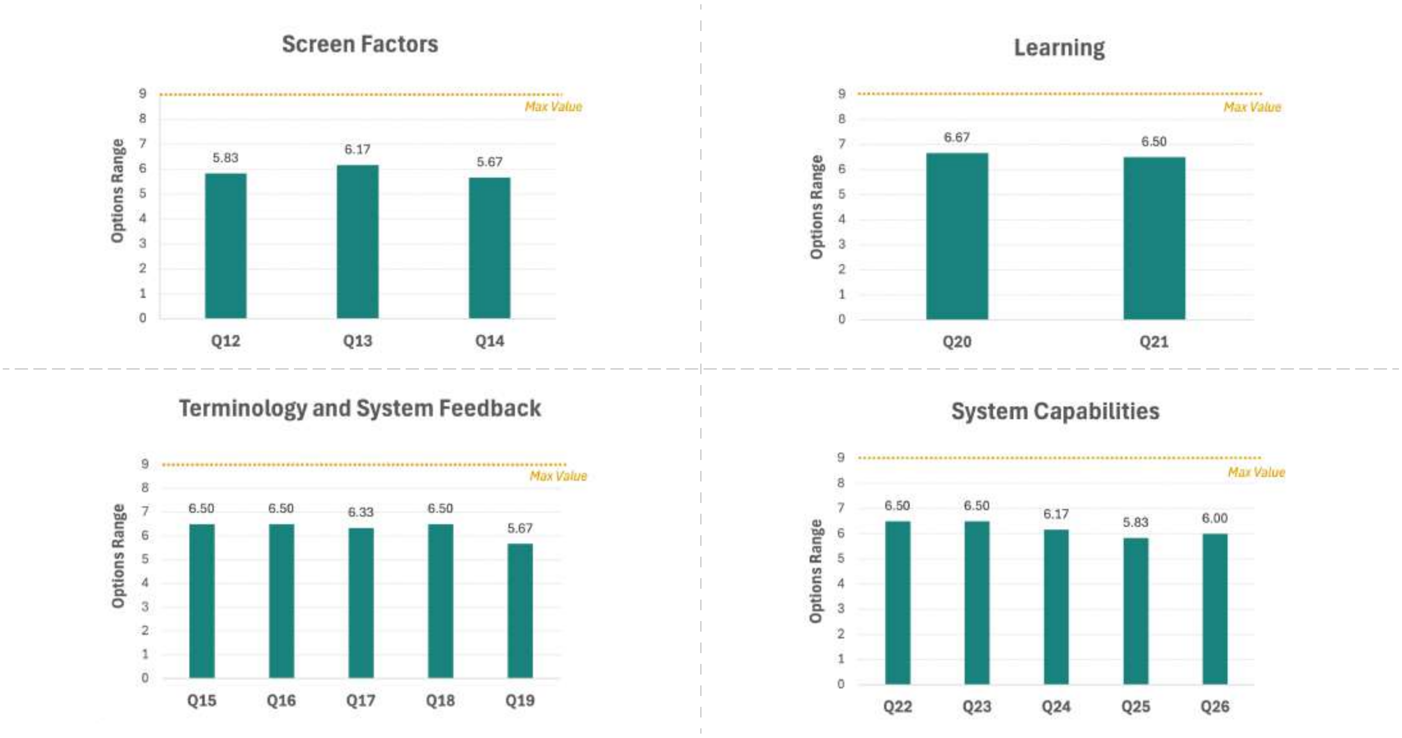


Figure 7. Results from the satisfaction survey.

It is important to highlight that participants generally reported no significant issues when using the application, with all scores at least one point above the mean. However, it is clear that a future version must improve the flexibility regarding the types of events that can be created.

A limitation of this validation was that participants interacted with the application exclusively as Providers, thereby restricting their evaluation to the activity administration interface. The User-facing functionalities were not assessed given the absence of a real event database; all events for this initial version were AI-generated. This factor may have influenced participants' perception of the application's overall utility and the usability efforts invested in recommending activities based on user profiles.

4.2. Recommender System Evaluation

The effectiveness of the recommendation algorithms has been verified using four rank-based evaluation metrics: AP@K (Average Precision) [42], NDCG@K (Normalized Discounted Cumulative Gain) [43], ERR@K (Expected Reciprocal Rank) [44], and HITS@K (Hit Ratio). Each metric was computed at several values of K, evaluating how well each algorithm ranks relevant activities for the user. All experiments have been performed on the recommendations generated from the synthetic data of users, activities and reviews described in Section 3.2.1.

The recommendation performance for the three methods—collaborative filtering, TF-IDF, and semantic embedding—is illustrated in Figure 8. Below is a summary of findings for each metric:

- **AP@K**: the TF-IDF recommender consistently achieves the highest AP@K across all values of K, followed by the semantic and collaborative filtering approaches, respectively. Both content-based methods outperform collaborative filtering at most cutoffs, and the semantic method shows only slightly lower AP@K than TF-IDF.
- **NDCG@K**: the TF-IDF recommender again leads, especially at higher ranks. However, both TF-IDF and semantic methods show increasing NDCG@K as K increases, suggesting both provide relevant recommendations deeply into the list. Collaborative filtering achieves similar performance to semantic at higher values of K.
- **ERR@K** and **HITS@K**: for ERR@K, TF-IDF matches or slightly outperforms others, with semantic search remaining solidly competitive. HITS@K approaches 1 for all recommenders at higher K, indicating very high recall.

The results highlight that, while TF-IDF is slightly superior across most metrics, the semantic embedding recommender delivers nearly equivalent quality, especially in NDCG and HITS metrics—showing its strength for capturing deeper contextual similarity.

Maintaining both content-based pipelines in the backend enables flexible experimentation and easy integration of hybrid recommendation strategies, allowing the system to adapt as more user interaction data becomes available or as new tourism content is introduced. Storing the source type for each recommendation further supports A/B testing [45] and fine-grained control over which recommendations are shown for each user or activity.

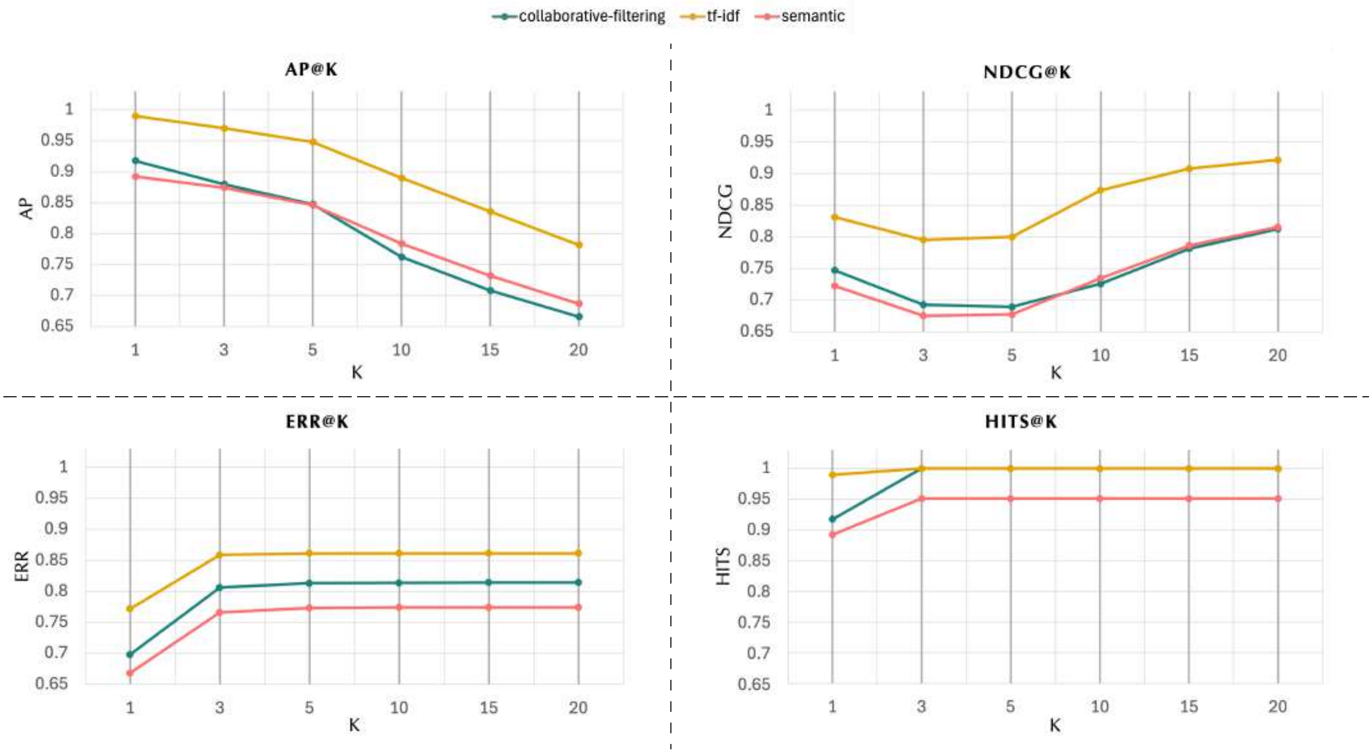


Figure 8. Evaluation of the recommendation algorithms implemented by the Recommendation System.

5. Discussion and Future Works

The study and experimentation conducted provide evidence of how digital technologies can play a decisive role in shaping the future of tourism in ways that transcend the traditional focus on business growth. By directly linking providers with users, TOEP reduces the centralization of tourism offerings and promotes a more distributed and diversified model of territorial development. In doing so, it encourages the discovery of cultural events, local traditions, and authentic experiences that are deeply embedded in communities, contributing not only to economic growth but also to the cultural enrichment and resilience of destinations.

This research underscores the evolving role of digital innovation in tourism, moving beyond a simple technological upgrade to a strategic tool for balancing competitiveness with sustainability. The TOEP platform, for instance, embodies a vision of digital humanism where innovation supports social responsibility, cultural awareness, and equitable opportunities. It also redefines tourist space, expanding it from physical geography into relational and digital dimensions where experiences are shaped through interaction and accessibility. Within this context, the use of geospatial data, interactive maps, and recommendation systems becomes crucial for sustainable territorial analysis and planning.

The contribution of TOEP resonates with international policy frameworks that prioritize sustainability and digitalization, such as the UNWTO's Vision for a Responsible Recovery of Tourism and the European Commission's Transition Pathway for Tourism. The platform illustrates how micro-level research and experimentation can support macro-level strategies, aligning technological progress with global sustainability goals.

Furthermore, this work demonstrates how digital platforms can address pressing challenges like overtourism by diffusing visitor flows, fostering local entrepreneurship, and promoting responsible tourism through integrated sustainability logics. Specifically, TOEP addresses these issues through different integrated mechanisms. Firstly, the platform ensures greater visibility for lesser-known destinations by incorporating real-time sustainability and contextual scores into its recommendation engine logic. This enables the redistribution of tourist flows both spatially and temporally [46]. Spatially, it reduces pressure on so-called ‘honeypots’ while directing economic benefits toward under-visited areas; temporally, it encourages activity during the low season or off-peak hours by highlighting seasonal events and alternative experiences, thereby smoothing the unsustainable peaks of the high season. Secondly, the platform’s ability to include a diverse range of local points of interest—including small-scale cultural activities—promotes a more equitable distribution of tourism expenditure, supporting local entrepreneurship that might otherwise be overshadowed by global brands [47]. Finally, as an experimentation platform, TOEP enables the empirical validation of which recommendation strategies actually foster sustainable behaviour through its A/B testing infrastructure. As [48] points out, the integration of advanced technologies–such as the system presented here–into tourist destinations enhances the travel experience through personalization and situational awareness, while providing destination managers with the tools for real-time monitoring and flow management.

As regards the performance of the recommendation engine, the results show that content-based approaches (TF-IDF and Semantic Embedding) are particularly effective when dealing with niche points of interest that lack extensive user interaction data [49,50]. This is, in fact, typical of the ‘hidden gems’ that TOEP aims to promote. Furthermore, the high usability scores obtained via the USE and QUIS questionnaires are in line with the findings of [51], confirming that user-centred design is a fundamental prerequisite for the adoption of smart tourism tools. By providing a scientifically grounded assessment of both algorithmic accuracy and user satisfaction, this work goes beyond mere technical implementation to offer a validated framework for sustainable destination management.

An important element reinforcing the usability and accessibility of TOEP is its connection to a dedicated mobile application. The app represents the practical gateway for providers and users alike: for providers, it facilitates the direct management of activities and the promotion of local events in real time; for users, it offers an intuitive tool to explore, select, and engage with unique experiences. This dual interface makes the platform not merely a conceptual model or a research prototype, but a tangible digital solution capable of improving the tourism experience, enhancing inclusivity, and ensuring that innovation translates into everyday practices. The initial validation of the platform confirmed the robustness of its provider interface and the general satisfaction of participants, while also pointing to the need for more extensive testing with end-users in real-world conditions.

Thus, the significance of TOEP lies in its ability to demonstrate how digital technologies can simultaneously serve the goals of enterprise innovation and territorial sustainability. By explicitly aligning with global and European policy frameworks—ranging from the UN SDGs to the EU Tourism Transition Pathway—and by providing a mobile application that operationalizes its vision in daily tourism practices, the platform represents a step forward in consolidating more equitable tourism ecosystems, where local communities and visitors are equally engaged in shaping meaningful, sustainable, and innovative experiences.

While this study provides a detailed heuristic evaluation of TOEP provider interface, several limitations must be acknowledged. First, the empirical validation relied on a panel of $N = 7$ experts. Although literature in usability engineering suggests that a small group of experts can identify the vast majority of core systemic issues [52–54], this sample size may not capture the full spectrum of edge-case user behaviors. Furthermore, the scope of this evaluation was intentionally restricted to the provider-facing functionalities. Consequently, the usability and effectiveness of the platform from the perspective of the primary end-users, specifically tourists and local residents, have not yet been empirically tested.

Future work will focus on two phases: platform refinement and field validation. Refinement involves enhancing the core recommendation system by integrating measurable sustainability indicators to dynamically balance tourism's economic, environmental, and socio-cultural dimensions. We will then deploy TOEP in a live environment, conducting a comprehensive user-side field study with real users (including necessary UX/UI improvements). This phase will allow us to quantitatively measure the application's local impact, generating the empirical evidence required to demonstrate its effectiveness in promoting a responsive and sustainable tourism model.

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Abbreviations

The following abbreviations are used in this manuscript:

TOEP	Tourism Open-Ended Experimentation Platform
SDGs	Sustainable Development Goals
SaaS	Software-as-a-Service
TF-IDF	Term Frequency-Inverse Document Frequency
USE	Usefulness, Satisfaction, and Ease of use
QUIS	Questionnaire for User Interface Satisfaction
AP@K	Average Precision
NDCG@K	Normalized Discounted Cumulative Gain
ERR@K	Expected Reciprocal Rank
HITS@K	Hit Ratio
UI/UX	User Interfaces/User Experience

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