A Machine Learning-Based Analysis of Tourism Recommendation Systems: Holistic Parameter Discovery and Insights

Raniah Alsahafi[1], Rashid Mehmood[2]*, Saad Alqahtany[3]
Department of Computer Science-Faculty of Computing and Information Technology,
King Abdulaziz University, Jeddah 21589, Saudi Arabia[1]
Faculty of Computer and Information Systems, Islamic University of Madinah, Madinah 42351, Saudi Arabia[2, 3]

***Abstract*—Tourism is a cornerstone of the global economy, fostering cultural exchange and economic growth. As travelers increasingly seek personalized experiences, recommendation systems have become vital in guiding decision-making and enhancing satisfaction. These systems leverage advanced technologies such as IoT and machine learning to provide tailored suggestions for destinations, accommodations, and activities. This paper explores the transformative role of tourism recommendation systems (TRS) by analyzing data from 3,013 research articles published between 2000 and 2024 using a BERT-based methodology for semantic text representation and clustering. A robust software framework, integrating tools such as UMAP for dimensionality reduction and HDBSCAN for clustering, facilitated data modeling, cluster analysis, visualization, and the identification of key parameters in TRS. We discover a comprehensive taxonomy of 16 TRS parameters grouped into 4 macro-parameters. These include Personalized Tourism; Sustainability, Health and Resource Awareness; Adaptability & Crisis Management; and Social Impact & Cultural Heritage. These macro-parameters align with all three dimensions of the triple bottom line (TBL) -- social, economic, and environmental sustainability. The findings reveal key trends, highlight underexplored areas, and provide research-informed recommendations for developing more effective TRS. This paper synthesizes existing knowledge, identifies research gaps, and outlines directions for advancing TRS to support sustainable, personalized, and innovative travel solutions.**

Keywords*—Recommendation Systems (RS); Tourism Recommendation Systems (TRS); big data analytics; machine learning; unsupervised learning; social; economic and environmental sustainability; Bidirectional Encoder Representations from Transformers (BERT); SDGs; literature review

I. Introduction

The tourism industry has undergone a transformative evolution in recent decades, driven by advancements in digital technologies and the proliferation of data-driven systems [1]–[3]. With the global tourism market reaching unprecedented scales, travelers now demand personalized experiences that cater to their unique preferences and requirements [4], [5]. Traditional methods of tourism planning, relying on guidebooks and generic travel advice, have become insufficient in addressing the complexity and diversity of modern travel needs [6], [7]. In this context, tourism recommendation systems (TRS) have emerged as pivotal tools, enabling travelers to navigate the abundance of information and make informed decisions about destinations [8], accommodations [9], activities [10], and other travel-related services [11], [12].

Recommendation systems in tourism leverage machine learning techniques [13] to deliver tailored suggestions to users [14]. By analyzing diverse datasets -- ranging from user preferences [15] and historical behaviors [16] to real-time contextual information [17] -- these systems aim to enhance user satisfaction and optimize travel experiences. Such systems play a dual role: improving the decision-making process for tourists [18] and offering a competitive edge to tourism providers by increasing customer engagement and loyalty [19].

The academic and industrial interest in tourism recommendation systems is growing, leading to a wealth of research addressing various aspects such as collaborative filtering [20], [21] content-based filtering [19], hybrid models [22], and the integration of emerging technologies such as deep learning [23], natural language processing (NLP) [23], [24], and generative AI [26], [27]. Despite the progress, challenges persist, including issues related to data sparsity [27], cold-start problems [28], interpretability of recommendations [29], and ethical concerns such as privacy and bias [30]. Addressing these challenges requires a more advanced and systematic approach to analyzing the TRS landscape.

In response, this paper presents a data-driven methodology that systematically extracts and classifies key research themes in TRS. While prior works have focused on specific aspects, our study addresses a significant gap (as outlined in Section II) by presenting a holistic taxonomy, meaning a structured and comprehensive classification of parameters and macro-parameters that captures the full breadth of TRS research. By analyzing an extensive dataset spanning 24 years, this study provides detailed insights into Personalized Tourism; Sustainability, Health & Resource Awareness; Adaptability and Crisis Management; and Social Impact & Cultural Heritage, helping to address gaps related to fragmented knowledge, evolving research trends, and emerging challenges. This structured approach allows for a deeper understanding of TRS developments while ensuring scalability and adaptability to future advancements.

Unlike existing literature, this paper incorporates a BERT-based (Bidirectional Encoder Representations from Transformers) methodology integrated with a machine learning pipeline to systematically analyze an extensive dataset spanning 24 years, from 2000 to 2024. BERT enables deep semantic analysis, allowing for more accurate extraction of key research themes and relationships across studies, thus overcoming limitations of traditional keyword-based methods. This dataset, constructed using the Scopus database, includes data from 3,013 research articles, refined through pre-processing steps such as tokenization, lemmatization, and duplicate removal. By systematically analyzing this large-scale dataset, our study ensures a broad yet structured understanding of TRS developments, reducing bias from smaller-scale literature reviews and enabling a more data-driven taxonomy.

To enable a robust analysis, we developed a comprehensive software framework consisting of four core modules: data acquisition and storage, preprocessing, modeling and parameter extraction, and validation with visualization. The system utilizes pre-trained BERT embeddings for contextual text representation, UMAP (Uniform Manifold Approximation and Projection) for dimensionality reduction, and HDBSCAN (Hierarchical Density-Based Spatial Clustering of Applications with Noise) for identifying meaningful clusters. These clusters are analyzed using a class-based TF-IDF (Term Frequency–Inverse Document Frequency) scoring method to rank word importance and derive parameters, which are then categorized into macro-parameters through expert validation. Visualization techniques, including taxonomy and similarity matrices, are employed to facilitate interpretation and ensure clarity. Python libraries such as Plotly and Matplotlib were used extensively for these purposes, supporting both analysis and presentation.

By addressing these limitations and presenting a unified framework, this study not only synthesizes current knowledge but also identifies underexplored areas and interconnected themes. It seeks to offer valuable insights for researchers and practitioners aiming to develop more effective and ethical tourism recommendation solutions. Furthermore, it explores potential directions for future work, emphasizing the need for systems that enhance personalization while aligning with sustainable tourism practices and inclusivity.

The rest of this paper is organized as follows: Section II provides a detailed literature review, highlighting prior works and identifying key gaps. Section III outlines the methodology, including data collection, pre-processing, and the design of our analytical framework. Section IV presents the findings, detailing the quantitative and qualitative analyses of the results and the taxonomy of macro-parameters. Section V summarizes the state-of-the-art in tourism recommendation systems, the challenges facing the field, and directions for future work. Finally, Section VI concludes the paper with key insights and recommendations.

II. Literature Review

TRS have been examined through various focused studies addressing specific aspects of their development and application. Hamid et al. [31] emphasize the importance of robust data management in TRS, highlighting the integration of IoT and hybrid models to handle large datasets and enable real-time, scalable recommendations. Santamaria-Granados et al. [32] focus on emotion recognition in TRS, using a scientometric review to explore how wearable devices and physiological sensors can enhance personalization by capturing emotional states. Menk et al. [33] examine the integration of social networks in TRS, showing how platforms such as Facebook and Twitter provide user-generated data to improve personalization and accuracy.

In addition to these focused studies, broader reviews of TRS offer general insights into approaches, developments, and issues within the field. Sarkar et al. [34] survey the evolution of TRS from traditional methods, such as collaborative filtering and content-based filtering, to advanced AI-driven techniques. The paper highlights how AI techniques can contribute to improving both traditional filtering methods and overall recommendation accuracy. It also emphasizes the need for innovation to address challenges such as system scalability and diverse data integration. Solano-Barliza et al. [35] offer a review of TRS trends and techniques, categorizing existing approaches and addressing challenges such as sparse data availability in emerging destinations. Their work highlights the importance of hybrid systems and data integration in enhancing system performance and user engagement. Khan et al. [36] review contextual suggestion systems within e-tourism, emphasizing the role of contextual factors such as location, time, and environmental conditions in tailoring recommendations. Their work highlights the importance of sustainability-focused recommendations while examining the methodologies and applications of context-aware TRS. Huda et al. [37] review smart tourism recommendation models, focusing on the integration of smart ICT technologies to enable real-time adaptability and personalization. Their work underscores the importance of enhancing tourist experiences through dynamic and context-aware recommendations.

The existing literature reviews provide valuable specific and general insights into TRS, offering important contributions to understanding the field. However, they fail to provide a holistic view due to limitations in scope, dataset size, methodology, findings, and the timeframes they cover. Except for Solano-Barliza et al. [35], all reviews are approximately three to five years old, making them less reflective of recent developments.

In contrast, our study addresses these limitations by employing a BERT-based methodology integrated into a novel software tool to systematically analyze a large and up-to-date dataset spanning 24 years (2000–2024). This approach allows for an in-depth exploration of the field, uncovering both a holistic taxonomy of parameters and macro-parameters and identifying interconnected themes and underexplored areas. Key areas covered include Personalized Tourism, Sustainability, Health and Resource Awareness, Social Impact & Cultural Heritage, and Adaptability & Crisis Management, addressing all three dimensions of the triple bottom line (TBL). The use of BERT enables advanced semantic analysis of academic literature, providing a significant improvement over traditional keyword-based methods. By offering a comprehensive framework for understanding TRS, this study not only addresses the shortcomings of prior works but also facilitates a deeper and more integrated understanding of the field, paving the way for future research and practical advancements.

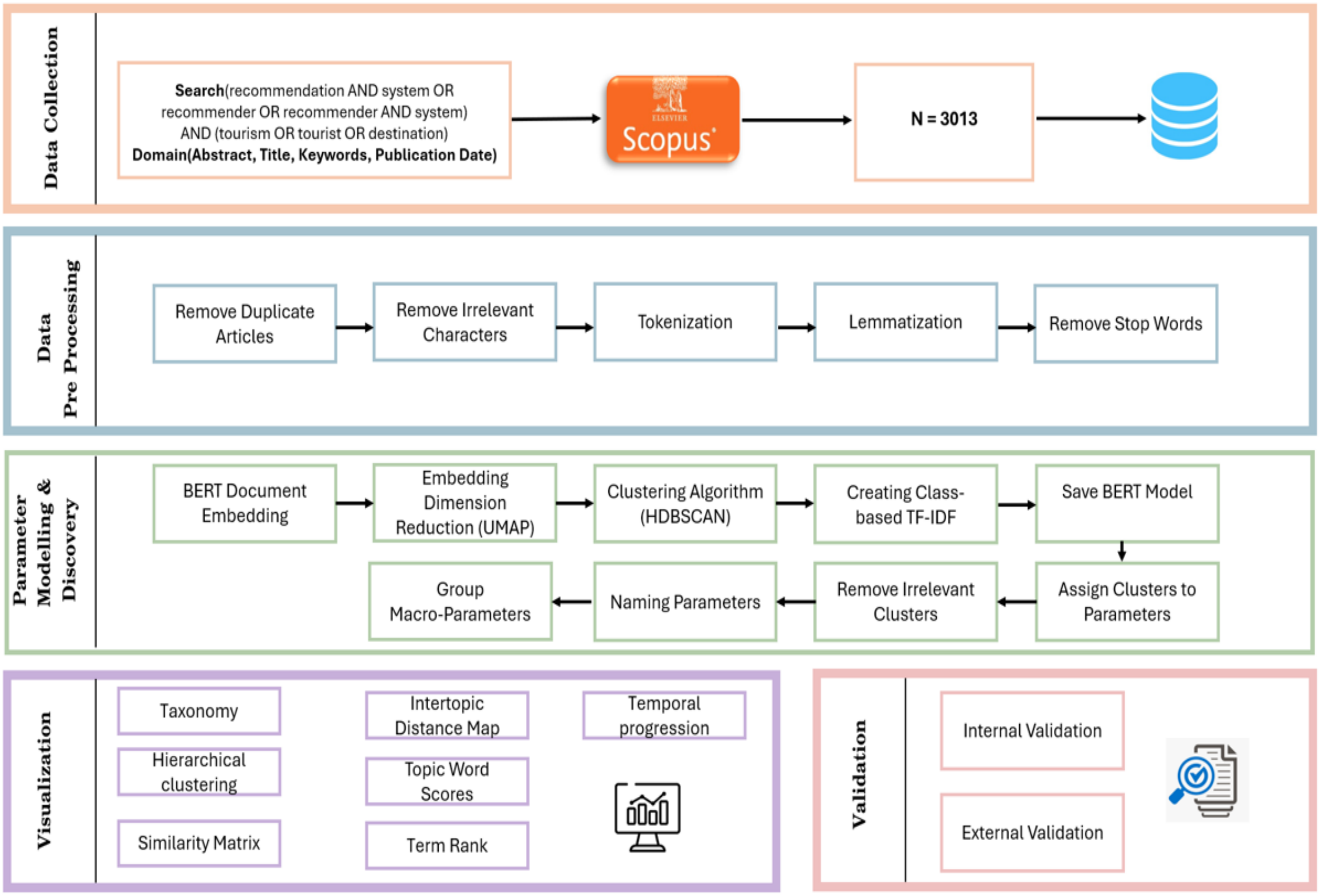

Fig. 1. System methodology and architecture.

III. Methodology

We present here the methodology and design of our system for machine-learning-based analysis and parameter discovery from academic literature on tourism recommendation systems. Further details of the broader methodology can be found in our earlier work [5]. The system architecture is illustrated in Fig. 1, detailing data collection, preprocessing, embedding creation, dimensionality reduction, clustering, and visualization.

To gather relevant data for this study, we formulated a specific search query: TITLE-ABS-KEY ((recommendation AND system OR recommender OR recommender AND system) AND (tourism OR tourist OR destination)). This query was used to extract data from Scopus, a comprehensive database containing an extensive range of academic literature across multiple disciplines. The initial dataset included publications from the years 2000 to 2024, with document types restricted to conference papers and journal articles, all written in English. After applying these filtering criteria, data from a total of 3,013 research articles were selected for further analysis.

The preprocessing phase involved several crucial steps to ensure the dataset was clean and suitable for further analysis. Initially, the collected articles were saved in CSV format and loaded into a Pandas DataFrame. Redundant and irrelevant entries were removed, including duplicate records and articles without abstracts. Subsequently, text-cleaning techniques were applied, which involved eliminating unnecessary characters and performing tokenization. The tokenization process was executed using the ‘gensim’ Python package, which facilitates breaking text into meaningful words.

To enhance the quality of extracted information, we employed stop-word removal techniques using the Natural Language Toolkit (NLTK) predefined stop words list. Additionally, the text data was lemmatized using the WordNetLemmatizer, which converts words into their base forms while preserving their meanings. These preprocessing steps ensured that only meaningful and well-structured data were retained for the next phase.

For topic modeling, we implemented the BERTopic approach, which leverages transformer-based word embeddings to identify and cluster significant topics within the dataset. The first step in this process involved generating word embeddings using BERT, a deep learning-based model designed for natural language processing. Specifically, we used the ‘distilbert-base-nli-mean-tokens’ sentence transformer model to convert each document into a dense numerical representation.

Given that high-dimensional embeddings require dimensionality reduction for efficient processing, we applied the UMAP technique. The UMAP model was fine-tuned by setting key parameters such as n_neighbors = 20 and n_components = 7, which were determined to provide optimal clustering results.

Following this step, the HDBSCAN algorithm was used to group documents into clusters based on their semantic similarities. The most critical parameters for HDBSCAN, including min_cluster_size and min_samples, were optimized to ensure high-quality clustering.

To determine the significance of words within each topic, we calculated the class-based c-TF-IDF scores. These metric measures word importance by comparing the frequency of a term within a cluster to its overall occurrence across the entire corpus. The resulting scores enabled us to derive meaningful keyword-based descriptions for each identified topic.

The final number of clusters was determined through an iterative fine-tuning process using the nr_topics parameter in BERTopic, leading to a final selection of 20 distinct clusters, including one outlier cluster. After this refinement, each cluster was carefully evaluated by the authors to ensure relevance and coherence. This process, guided by the domain expertise of the authors, involved removing any irrelevant clusters if present, merging thematically similar ones when necessary, and assigning appropriate labels. The labeled clusters were then referred to as parameters, representing distinct research themes in tourism recommendation systems (TRS). To improve interpretability and provide a structured understanding of TRS research, these parameters were further aggregated into broader macro-parameters. The concept of parameters is designed to facilitate their integration into autonomous systems, enabling dynamic updates either periodically or in response to specific events, ensuring that the latest understanding of TRS or any related topic is continuously maintained. For further details, see our earlier work [38]–[40].

To ensure the reliability and validity of our results, we conducted both internal and external validation. Internal validation involved assessing the relevance of each document assigned to a given cluster, ensuring a meaningful relationship between texts and their respective clusters. External validation was carried out by comparing the parameters with established research findings. Multiple visualization tools, including, term ranking plots, hierarchical clustering dendrograms, and similarity matrices, were used to interpret the results effectively. These visuals were generated using Python libraries such as Matplotlib [41], Seaborn [42], and Plotly [43], enabling a detailed analysis of the dataset and topic structures.

Through this methodological approach, we successfully extracted, processed, and analyzed data from research articles to identify key parameters and macro-parameters within the domain of tourism recommendation systems. The rigorous validation and visualization techniques ensured the robustness of the findings, providing a reliable foundation for further analysis and interpretation.

IV. RESULTS

We now discuss the results obtained through our machine-learning-based tool, which used academic data to dissect the field of tourism recommendation systems and highlight its cutting-edge advancements through quantitative and qualitative analysis.

A total of 2,991 documents were processed by the tool for clustering, following the removal of duplicates (n = 22). The model identified 19 clusters, one of which was irrelevant (n = 11) and removed along with an outlier cluster (n = 1,156), leaving 1,824 documents. The remaining 18 clusters were used to identify 16 parameters, with two parameters created by merging two clusters in each case due to thematic similarity. These parameters were further grouped into four macro-parameters: Personalized Tourism; Sustainability, Health & Resource Awareness; Adaptability and Crisis Management; and Social Impact and Cultural Heritage.

Fig. 2 illustrates the taxonomy of these parameters and macro-parameters identified by our BERT model. The first level of the taxonomy represents the macro-parameters, while the second level specifies the parameters, including their associated cluster numbers and document counts. For instance, “Travel Recommendation Algorithms (0, 1076)” refers to a parameter associated with cluster 0, containing 1,076 documents. These clustering results provided a structured framework for understanding and advancing the field.

These findings are detailed in the following sections. Section 4.A presents the quantitative analysis of the results, followed by a qualitative analysis of the four macro-parameters in Sections 4.B to 4.E.

A. *Quantitative Analysis*

Our analysis involves several quantitative methods, including term score, Intertopic Distance Map, hierarchical clustering, and a similarity matrix. While the clusters are linked to specific keywords, not all keywords effectively represent the parameters. As shown in Fig. 3, it reveals the required number of keywords to describe each cluster adequately. The analysis indicates that only the top seven to ten terms per parameter are truly representative.

Fig. 4 shows the hierarchical clustering of 19 recommender system clusters in tourism, organized by similarities in functionality or focus. Clusters 11, 12, 2, 5, and 7 formed a distinct group, along with Cluster 10, labeled as Personalized Tourism, reflecting high similarity.

Fig. 5 visualizes the similarity matrix between different parameters of recommendation systems in tourism, where dark blue represents the highest similarity score, and light green indicates the lowest. For example, cluster 0 (Travel Recommendation Algorithms) has a high similarity score with cluster 2 (Context-Aware Mobile Apps), as indicated by a darker cell at their intersection. This suggests that these two clusters share common features, making them closely related. Both focus on providing personalized recommendations to travelers based on their context, such as location, preferences, and behaviors. These visualizations highlight conceptual relationships between various themes of the field.

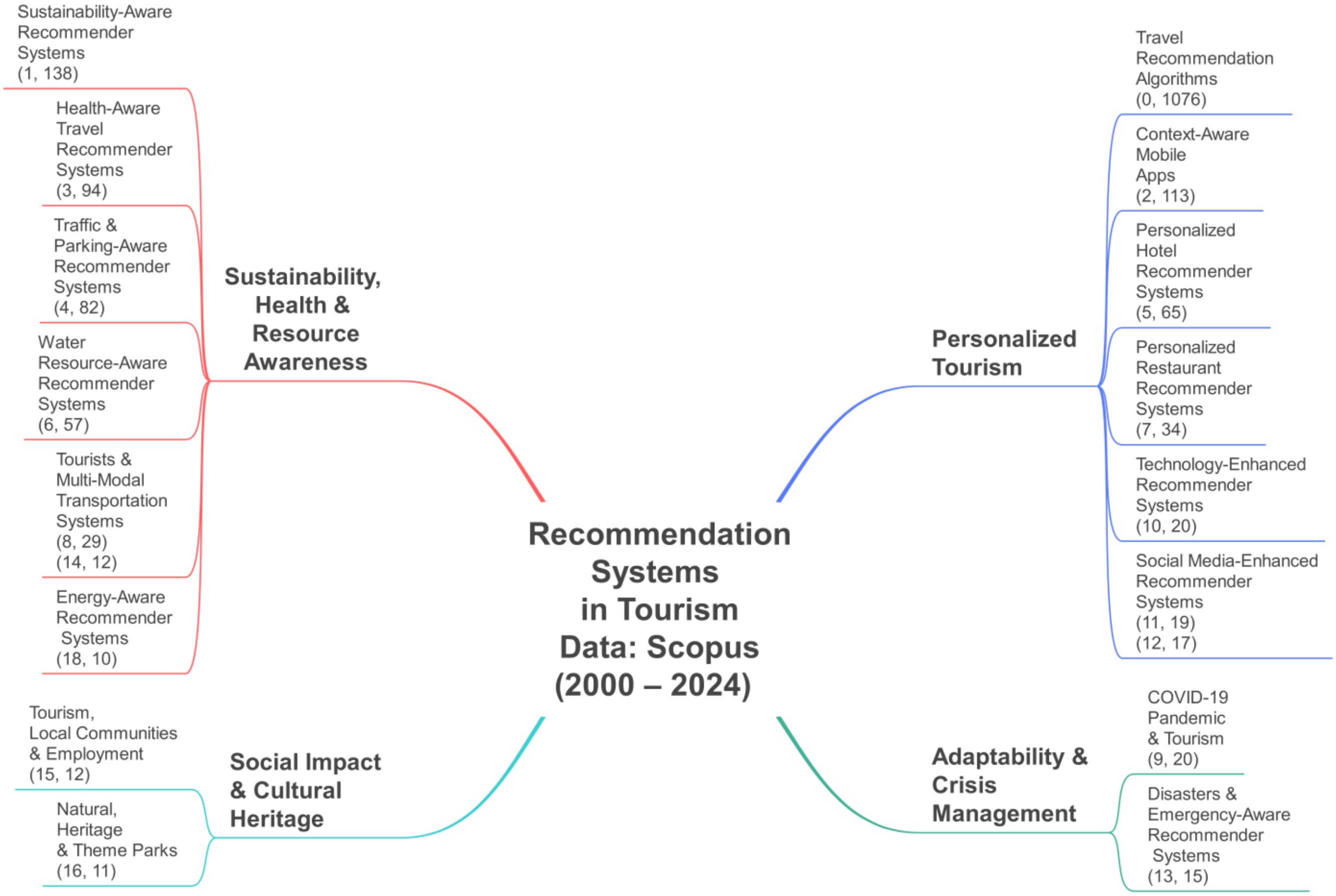

Fig. 2. Taxonomy for parameters of Tourism Recommendation System.

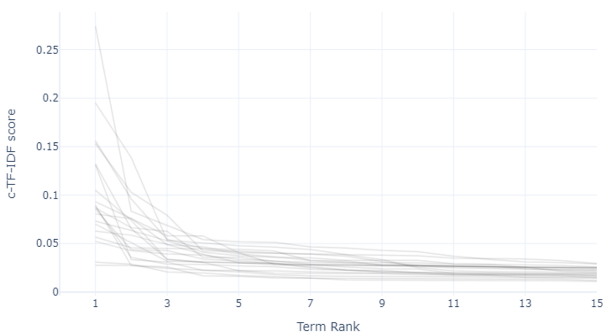

Fig. 3. Cluster term ranks.

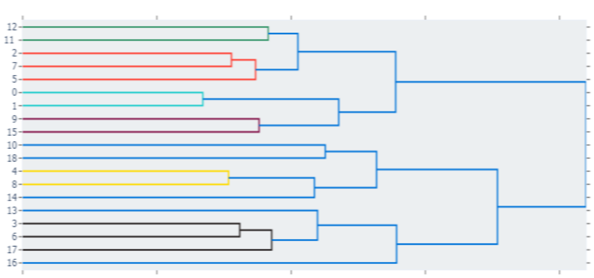

Fig. 4. Hierarchical clustering diagram.

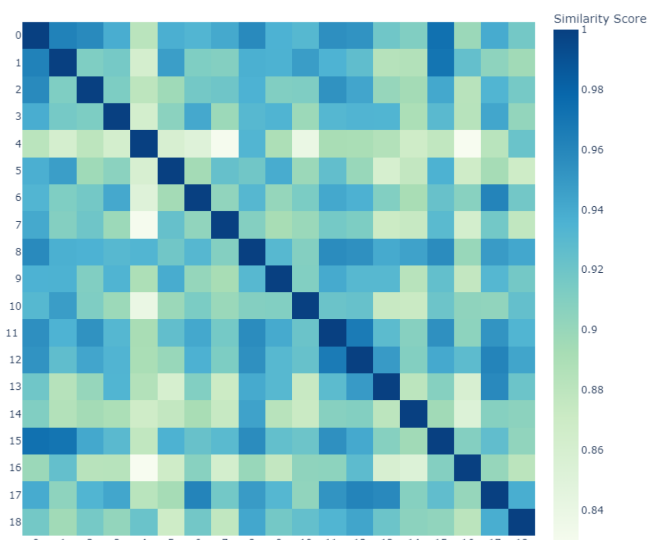

Fig. 5. Cluster similarity matrix.

Fig. 6 displays the top 10 keywords for each parameter, ranked using their c-TF-IDF importance scores. The 16 subfigures feature horizontal lines representing importance scores and vertical lines listing the parameter keywords.

Fig. 6. Keyword c-TF-IDF scores for parameters.

Note that, to ensure a comprehensive and structured analysis, we included all 19 clusters in the quantitative analysis presented in Fig. 3 to Fig. 5. This analysis allows for the validation and refinement of the clusters by assessing their coherence, identifying irrelevant or redundant clusters, and examining their semantic relationships. Through this process, we systematically refined the clusters, ultimately leading to the discovery of parameters and macro-parameters. This approach not only ensures a coherent classification of research themes in TRS but also facilitates the extraction of the underlying knowledge structure and taxonomy of the field. However, Fig. 6, which displays the top 10 keywords for each parameter, ranked using their c-TF-IDF importance scores, contains subfigures for only 16 parameters because it reflects the post-cluster analysis phase, after the discovery and labeling of the final parameters.

B. *Personalized Tourism*

Personalized Tourism focuses on customizing the travel experience to individual preferences and contexts. It employs algorithms and technologies to offer customized travel suggestions, accommodations, dining options, and social experiences. By leveraging data from various sources, including mobile apps and social media, personalized tourism recommendation systems aim to enhance the satisfaction and convenience of travelers, making their experiences uniquely suited to their interests and needs. This macro encompasses six key parameters designed to refine and customize the travel experience for individuals. The parameters are discussed below.

Travel Recommendation Algorithms are pivotal in analyzing traveler preferences to suggest destinations and activities. These recommendation algorithms and systems have notably evolved to utilize hybrid models that combine content-based and collaborative filtering with real-time, contextual, and social data inputs, greatly improving the personalization of travel suggestions [22], [44]. These systems effectively adapt to the dynamic nature of tourist needs, incorporating real-time data processing and location-based services [10], which are essential for travelers making spontaneous decisions or needing to adjust plans due to unforeseen circumstances [13], [45]–[47]. The incorporation of visual data and social media inputs further enhances the ability of these systems to deliver highly relevant and visually engaging recommendations that align with modern travel behaviors [48], [49].

Context-aware mobile Apps take situational factors into account, providing recommendations that are relevant to the user's current location and circumstances. These mobile apps are increasingly pivotal, utilizing real-time data such as location, time, and user preferences to offer hyper-localized suggestions that enhance the immediacy and relevance of the information provided to the users [17], [50], [51]. These apps are not just enhancing user satisfaction but are also raising significant privacy and security considerations, necessitating the development of privacy-by-design principles [52]. The use of advanced machine learning algorithms helps these apps learn from each interaction, progressively refining the recommendations to suit individual preferences better.

Personalized Hotel Recommender Systems focus on aligning accommodation options with the traveler's specific preferences, such as budget, amenities, and location [53]. Similarly, Personalized Restaurant Recommender Systems tailor dining suggestions to match the traveler's dietary needs and taste preferences [21]. These recommender systems leverage complex data analyses of user preferences, past behaviors, and online interactions to predict and meet individual needs, significantly enhancing customer satisfaction and operational efficiencies. These systems are increasingly using semantic analysis and contextual data to offer deep suggestions that consider dietary preferences, specific amenities, or desired experiences, which are critical in the highly competitive hospitality industry [25], [54].

Technology-Enhanced Recommender Systems leverage cutting-edge technology to offer highly personalized travel insights and options. The role of technology, particularly the integration of the Internet of Things (IoT) [55], and augmented reality (AR) [56], is transforming the tourist experience by enabling smarter, more connected environments that cater to the detailed needs and preferences of tourists. These technology-enhanced systems not only improve personalization but also ensure that services provided are efficient and timely, adapting to the individual's current context [57].

Social Media-Enhanced Recommender Systems utilize social networks to offer travel suggestions influenced by friends' recommendations, trends, or influencers, enhancing the travel planning process with a social dimension. These systems use data from platforms such as Instagram and Twitter to analyze user behaviors, preferences, and social interactions, enabling the delivery of personalized travel experiences that resonate well with users' tastes and preferences [58]. The use of big data analytics in these systems allows for a deeper understanding of individual preferences, significantly transforming the way destinations and activities are marketed and presented to potential tourists [59].

Collectively, these parameters aim to deliver a travel experience that is as unique as the travelers themselves, enhancing satisfaction through personalization. The integration of advanced algorithms, real-time data analytics, and user-centric technologies across these parameters is crafting a highly sophisticated landscape of personalized tourism recommendation systems. These systems are not only enhancing the travel experience by providing timely, relevant, and personalized recommendations but are also facing challenges such as data privacy, the need for continuous learning, and the integration of diverse technological solutions. The continuous evolution of these systems is crucial for sustaining innovation and growth in the tourism sector, promising a future where technology profoundly shapes the way tourist services are conceptualized and delivered.

C. Sustainability, Health and Resource Awareness

Sustainability, Health & Resource Awareness emphasizes promoting travel options that are environmentally sustainable, health-conscious, and resource-efficient. It includes systems designed to minimize the ecological footprint of tourism, recommend health-oriented travel options, and optimize the use of resources such as water and energy. These recommendation systems aim to support responsible tourism that respects the planet and the well-being of both tourists and local communities.

It encompasses six vital parameters designed to promote environmentally friendly and health-conscious travel practices. Sustainability-Aware Recommender Systems prioritize eco-friendly travel options, helping to reduce the ecological footprint of tourism. Health-Aware Travel Recommender Systems focus on health considerations, suggesting destinations and activities that align with travelers' health needs and preferences. Traffic & Parking-Aware Recommender Systems aim to alleviate congestion and improve efficiency by providing real-time traffic updates and parking information. Water Resource-Aware Recommender Systems emphasize conservation by promoting destinations and practices that minimize water usage. Energy-Aware Recommender Systems focus on reducing energy consumption through recommendations that favor energy-efficient options. Lastly, Tourists & Multi-Modal Transportation Systems facilitate seamless travel by integrating various modes of transportation, promoting ease of movement and reducing environmental impacts. Together, these systems strive to enhance travel experiences while being mindful of health, resource conservation, and sustainability.

Sustainability, Health and Resource Awareness in tourism recommendation systems represent a sophisticated integration of environmental stewardship, health optimization, and resource efficiency, underpinned by advanced technology and data analytics. The systems within this macro collectively address the triple bottom line of sustainability: environmental, economic, and social aspects. For example, Sustainability-Aware systems encourage visits to lesser-known sites [8], distributing economic benefits more evenly, and reducing environmental pressures on over-visited locations. Similarly, Health-Aware systems promote safety and health by integrating real-time health data, enhancing traveler well-being [60]. These approaches are mutually reinforcing. For instance, promoting less frequented sites helps manage the capacity and preserves the integrity of natural resources, aligning with the goals of Water Resource-Aware systems to manage environmental impacts effectively [61], [62].

Across all parameters, there is a heavy reliance on AI and machine learning to process real-time data and provide dynamic, context-sensitive recommendations [63]. This technological backbone enables Traffic and Parking-Aware systems to offer real-time routing adjustments just as Energy-Aware systems optimize resource use, demonstrating a cross-application of similar technological frameworks to solve varied problems within the tourism sector [64]. The integration of various types of data (e.g., traffic flow, water resource levels, energy consumption, health statistics) into a cohesive recommendation engine exemplifies a holistic approach to managing both expected and emergent challenges in tourism [65], [66].

The recommendation systems are increasingly adept at offering personalized travel suggestions that consider environmental conditions, health requirements, and individual preferences. For instance, Multi-Modal Transportation systems that recommend optimal travel modes based on user preferences and local traffic conditions overlap with Health-Aware systems that consider individual health needs [67]–[69]. This personalization extends to ensuring that recommendations are sensitive to local cultural norms and practices, enhancing the social sustainability of tourism by fostering respect and appreciation for local traditions, which is a focal point of both Sustainability-Aware and Health-Aware systems [11], [63].

The macro showcases a robust adaptability to global and local challenges, such as health emergencies or environmental crises. Systems rapidly adjust to new data, whether it's shifting health advisories during a pandemic or updating environmental regulations and conditions [70]–[73]. This resilience is critical in maintaining the trust and safety of tourists, ensuring that the tourism sector can quickly respond to and recover from disruptions, thereby supporting long-term sustainability goals [74].

The interconnected nature of these systems suggests significant policy implications, particularly in the need for coordinated action across health, environmental, and urban planning departments. The findings advocate for a policy framework that supports integrated data sharing and collaborative decision-making processes, enabling a more unified response to the multifaceted demands of sustainable tourism. Moreover, these systems serve as a model for other sectors, demonstrating how technology can bridge diverse data sources and operational goals to create more sustainable and resilient infrastructures.

In summary, Sustainability, Health & Resource Awareness illustrate a complex yet harmonious integration of multiple tourism-related aspects, driven by advanced technology and comprehensive data analytics. This integration not only enhances the efficiency and responsiveness of tourism recommendation systems but also significantly contributes to the broader objectives of sustainable development, public health, and economic equality.

D. Adaptability and Crisis Management

Adaptability and Crisis Management focuses on the flexibility of tourism recommendation systems to adapt to changing circumstances, such as global pandemics or natural disasters. It involves offering travel advice that considers safety guidelines, emergency preparedness, and the overall impact of crises on tourism. The goal is to ensure that travelers remain informed and safe, while also supporting the recovery and resilience of the tourism industry during and after crises.

Our analysis of the literature on Adaptability and Crisis Management reveals how both areas require robust, adaptable frameworks that integrate technology, policy, and localized approaches to manage crises effectively. It underscores the critical role of integrated, technology-driven solutions in managing and recovering from tourism-related crises. The effective combination of advanced recommender systems, supportive policy environments, and localized, customizable strategies facilitate not only immediate crisis management but also contribute to the long-term sustainability and resilience of the tourism industry.

The COVID-19 pandemic forced a drastic rethinking of tourism practices, highlighting the need for adaptive crisis management strategies [75]. Key findings indicate a shift towards localized, safety-focused tourism, supported by digital and smart tourism solutions [70]. This shift was not merely reactive but also strategic, leveraging information systems to promote safer travel options and to adjust to a new tourism economy severely impacted by global restrictions [76]. The necessity for adaptation was evident in the rapid integration of sustainable practices and smart technologies, which were crucial in managing the downturn in traveler numbers [71].

Parallel to the pandemic's challenges, the use of recommender systems in managing disasters and emergencies showcases a proactive use of technology to enhance safety and efficiency [12]. These systems are crucial in real-time crisis management, offering optimized evacuation routes and strategies, and facilitating the rapid adaptation of transportation and local services to emergent needs [76]. The systems' capability to utilize local data for tailored community advisories further underscores the importance of localized responses in crisis management [77], [78].

Across both domains, the integration of advanced technology with supportive policy frameworks forms a backbone for effective crisis management [74]. During the pandemic, technology helped navigate economic shocks through targeted recovery strategies, while in disaster scenarios, technology optimized real-time responses [79]. This synergy suggests that robust, flexible digital infrastructures, capable of adapting to varied and sudden changes, are essential in sustaining tourism during crises [80], [81].

A recurring theme is the focus on localized and customized solutions, whether adapting tourism practices during a pandemic or responding to a localized disaster [79]. This approach maximizes the relevance and effectiveness of the response, illustrating how tailored information and strategies can significantly impact community resilience and crisis recovery [82]. Both areas highlight the need for systems that are not just reactive but highly adaptive and resilient [74]. The ongoing evolution of tourism practices in response to the pandemic, and the dynamic adjustments in disaster management, reflect a complex interplay between immediate crisis response and longer-term, strategic planning [71]. This dual approach is vital for the development of a resilient tourism sector capable of withstanding future crises.

E. Social Impact and Cultural Heritage

In tourism recommendation systems, Social Impact & Cultural Heritage encapsulate critical aspects including Tourism, Local Communities & Employment, and Natural Heritage and Theme Parks. These parameters highlight the intersection of tourism with local societal and environmental facets. For Tourism, Local Communities and Employment, recommendation systems play a vital role in promoting tourism experiences that benefit local economies and create job opportunities. Natural Heritage and Theme Parks focuses on leveraging recommendation technologies to balance visitor numbers and preserve natural sites. These systems can suggest off-peak visit times and less-explored parks, thus managing foot traffic and reducing environmental impact.

The macro-parameter showcases a complex interaction in tourism between economic stability, cultural integrity, and environmental conservation [20]. It reveals the dynamic ways in which technology facilitates sustainable tourism, enhancing both local economies and cultural experiences [83], [84]. Recommendation systems play a crucial role in driving economic benefits by connecting tourists with local cultures and natural settings, diversifying income sources for local communities and stabilizing employment through culturally and ecologically respectful tourism [85], [86].

These systems manage both human resources, such as local guides [87], and natural resources, such as conservation sites, with a strategy that optimizes tourist flows to prevent overexploitation and ensures sustainable interactions between tourists and local resources [49]. They enhance the visitor experience by integrating local culture into tourism offerings, and educating tourists about local traditions and history while promoting respect and preservation for these cultures. In natural settings, the incorporation of cultural narratives enriches the visitor's engagement, fostering a deeper appreciation for both natural and cultural heritage [83], [88], [89]. Furthermore, directing tourists to less frequented sites mitigate environmental impacts on heavily visited locations, aiding conservation efforts and ensuring that economic benefits are broadly distributed [80], [90]. Recommendation systems also exemplify a commitment to social equity by proactively including diverse demographic groups in tourism employment, which benefits local economies and enhances the social fabric by making tourism more inclusive [89].

The focus on wellness tourism, such as forest bathing and other nature-based activities, not only promotes health benefits for tourists but also opens new economic avenues for local development, particularly in rural areas [91]. The systematic approach to enhancing both cultural and ecological tourism settings reflects a holistic view of tourism development, where various aspects of the tourist experience are assessed and integrated. This sophisticated approach supports long-term destination sustainability by meeting diverse visitor expectations and aligning with broader trends in health, conservation, and cultural engagement.

V. Discussion

We now summarize the state of the art in tourism recommendation systems, the challenges facing the field, and directions for future work.

The integration of advanced technologies and data-driven strategies within the tourism sector is profoundly reshaping the landscape of travel recommendation systems, as demonstrated by the diverse range of macro-parameters analyzed. These macro-parameters reveal a complex and interconnected framework that aims to enhance tourist experiences [23], [92], promote sustainability [89], adapt to crises [12], [76]–[78], and preserve cultural heritage while fostering social impacts [47].

Central to tourism is the profound influence of technology in reshaping tourism experiences. Advanced algorithms and machine learning techniques play a critical role, enabling the delivery of highly personalized recommendations that adapt to the changing needs and contexts of travelers [65], [93]. Real-time data processing [94], [95], location-based services [96], and the integration of social media inputs are pivotal [97], [98], transforming the way travelers interact with destinations and services. These technological advancements are not just about enhancing user satisfaction; they also introduce significant considerations for privacy and security, prompting the development of sophisticated solutions such as privacy-by-design principles [30].

Simultaneously, there’s a marked shift towards integrating sustainability and health into the core of tourism recommendation systems. These platforms strive to balance personalization with environmental consciousness and health awareness. For instance, sustainability-aware systems advocate for visiting lesser-known locales, thus alleviating the burden on popular destinations and promoting environmental preservation [8]. Health-aware systems enhance traveler safety by incorporating real-time health data [63], which is especially crucial in a post-pandemic world. This commitment extends to resource management, where systems intelligently recommend travel options that optimize energy use and minimize ecological impacts [99].

Adaptability and crisis management also feature prominently in this integrated approach. The recent global upheavals, such as the COVID-19 pandemic, have tested the flexibility and responsiveness of tourism infrastructures [71], [75], [100]. Recommendation systems have quickly adapted, offering solutions that prioritize local and safe travel options [101], thereby supporting the tourism industry’s recovery. These systems demonstrate resilience [74], [82], adjusting to new health advisories and environmental conditions swiftly, and ensuring the safety and trust of tourists.

Furthermore, the role of recommendation systems in promoting cultural heritage and social impact cannot be overstated. By steering tourists towards culturally significant sites and engaging them with local traditions, these systems play a crucial role in cultural preservation [83]. They also support local economies by diversifying income sources and promoting equitable tourism practices [86]. Such initiatives not only enrich the visitor's experience but also ensure that tourism contributes positively to local communities [88].

A. Challenges and Future Work

The journey towards enabling smart tourism through recommendation systems is fraught with multifaceted challenges that must be addressed through innovative research and collaborative efforts. Personalized tourism recommendation systems aim to create a seamless travel experience by deeply understanding individual preferences and adapting to real-time contexts [94], [95]. The future of these systems lies in the development of advanced hybrid algorithms that blend machine learning with semantic technologies, enabling more precise and context-aware recommendations [44]. By leveraging extensive datasets and real-time environmental factors [102], these systems can offer dynamic, personalized travel itineraries that adapt to changes in user mood and preferences [103]. However, achieving this level of personalization presents significant challenges. Ensuring the privacy and security of personal data is paramount, as these systems rely heavily on sensitive information [30]. Adherence to global privacy standards and regulatory compliance across jurisdictions is necessary to maintain user trust. Additionally, the complexity of managing heterogeneous data from diverse sources such as social media, user interactions, and IoT devices requires sophisticated data management strategies to ensure data integrity and timely recommendations [24], [51].

Sustainability and health awareness are critical dimensions that future tourism recommendation systems must incorporate [9]. Advanced machine learning models can predict environmental and social impacts with greater accuracy, providing actionable insights for sustainable tourism practices [81], [104], [105]. The optimization of multi-modal transportation systems using AI can enhance urban mobility and tourist satisfaction, while localized and personalized recommendations can align with local sustainability goals [68], [69], [106]. Despite these advancements, significant hurdles remain. Data availability and quality, particularly in underdeveloped regions, pose a major bottleneck. Ensuring the privacy of health data within travel recommenders necessitates advanced security frameworks such as federated learning, which allow for the private sharing of data insights while maintaining individual privacy. Additionally, the scalability of these systems to accommodate diverse tourist demographics and the integration of data from heterogeneous sources present technical challenges [104], [107].

The capability of tourism recommendation systems to adapt during crises is a critical area of future research. The development of advanced predictive analytics leveraging AI techniques such as machine learning and deep learning can enhance the accuracy and timeliness of crisis response strategies [71]. Robust models that handle dynamic, real-time data streams from diverse sources are essential for providing real-time, personalized travel recommendations during emergencies [100]. However, crisis-adaptive systems face several key challenges. The availability and reliability of data during crises are often compromised, affecting the operational efficiency of AI-driven tools. Ensuring these systems are robust enough to withstand data scarcity, potential cyber threats, and high user demand during critical periods is essential. Additionally, building and maintaining user trust through transparent systems that adhere to ethical standards and regulations is fundamental [75].

Tourism recommendation systems must also address the social impact and cultural heritage of travel destinations [3]. Advanced personalization techniques that cater to cultural interests can offer unique, culturally enriching experiences. AI can analyze extensive datasets on visitor interactions and cultural engagement patterns, enabling recommendations that resonate deeply with tourists [76]. Moreover, comprehensive tools for assessing the long-term impacts of tourism on local communities and cultural sites are necessary to ensure sustainable development [88], [89]. The challenges in this domain are significant. Data privacy and ethical concerns must be managed carefully to avoid violations and ensure that these systems benefit the communities they intend to support [30]. Ensuring cultural sensitivity and appropriateness in recommendations is crucial, as is avoiding the perpetuation of stereotypes or the misrepresentation of cultural heritages. Co-designing systems with input from local communities can help maintain cultural integrity. Balancing tourism growth with community welfare and avoiding over-reliance on technology that detracts from authentic cultural interactions presents additional challenges.

To address these challenges and realize the full potential of tourism recommendation systems, a holistic and integrated approach is required. This involves developing sophisticated and dynamic systems that leverage advanced AI techniques for deeper personalization, sustainability, and adaptability. It also necessitates fostering interdisciplinary collaborations among technology providers, tourism operators, local governments, and communities to enhance system responsiveness and efficacy. Ensuring transparency and adherence to ethical standards and regulations is crucial for building and maintaining user trust. Furthermore, aligning recommendations with sustainability goals and community welfare is essential to ensure that tourism growth does not negatively impact local residents or cultural heritage. By addressing these future research areas and challenges, the field can progress toward more resilient, responsive, and personalized tourism recommendation systems. This integrated approach will ensure that these systems contribute positively to both tourists and local communities, while respecting and enhancing the cultural heritage they aim to promote. The transformative potential of AI in tourism lies in its ability to create enriching, sustainable, and adaptive travel experiences that cater to the evolving needs and preferences of travelers worldwide.

VI. Conclusion

This paper aimed to develop and apply a machine-learning-based tool to analyze academic literature in the field of tourism recommendation systems, providing a structured taxonomy of parameters and macro-parameters to guide future research. The taxonomy offers a systematic framework for organizing the field, breaking it into clearly defined categories that facilitate understanding, highlight gaps, and direct future exploration. By identifying key parameters and their relationships, it enables researchers to prioritize areas for development, foster thematic alignment, and address emerging challenges. Despite the journal's page limit, we provided a detailed discussion of the parameters and macro-parameters, demonstrating their practical applications and aligning research priorities with real-world needs such as sustainability, health, and adaptability. These contributions provide a foundation for advancing the field and ensuring that future research and innovations are both cohesive and impactful.

This study provides a comprehensive analysis of TRS, but some limitations remain. Our analysis relies on academic literature from the Scopus database, which may exclude relevant industry reports, white papers, and non-English sources. Expanding the dataset to include other academic and non-academic sources could provide a broader perspective on TRS research. For future directions, integrating real-time data sources such as social media trends and user-generated content could enhance the adaptability of TRS. Additionally, incorporating personalization techniques based on user intent, sentiment analysis, and contextual factors could improve recommendation accuracy. Finally, addressing ethical concerns such as data privacy, fairness, and algorithmic transparency is crucial for responsible TRS development.

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