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MOBITUR: ADVANCING SMART TOURISM PLANNING WITH AI FOR SUSTAINABLE MOBILITY MANAGEMENT. A TESTING IN A REGIONAL CONTEXT

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ABSTRACT

The goal of this work is to present MOBITUR, an AI-based methodology that supports Destination Management Organisations (DMOs) in policymaking by analysing visitors' mobility patterns in relation to tourist infrastructure and attractions. Tested in the Region of Murcia (Spain), it provides empirical evidence on planned tourist behaviour through a hetero-intelligent system that combines human and artificial intelligence. Results highlight

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38 sub-strategies from existing attributes and 14 additional ones addressing seasonal disturbances.

Keywords: smart tourism planning; management of tourist flows; Artificial Intelligence; theory of planned tourist behaviour.

MOBITUR: Avanzando en la planificación turística inteligente con IA para la gestión sostenible de la movilidad. Una validación en un contexto regional

RESUMEN

El objetivo de este trabajo es presentar MOBITUR, una metodología basada en inteligencia artificial que apoya a las Organizaciones de Gestión de Destinos (DMOs) en la formulación de políticas mediante el análisis de los patrones de movilidad de los visitantes en relación con la infraestructura y las atracciones turísticas. Probada en la Región de Murcia (España), ofrece evidencia empírica sobre el comportamiento turístico planificado a través de un sistema hetero-inteligente que combina inteligencia humana y artificial. Los resultados señalan 38 subestrategias basadas en atributos existentes y 14 adicionales que abordan perturbaciones estacionales.

Palabras clave: planificación turística inteligente; gestión de flujos turísticos; Inteligencia Artificial; teoría del comportamiento turístico planificado.

1. INTRODUCTION

The tourism industry, generating over one billion USD in revenue in 2022 (UNWTO, 2023), has become a focal point for developing ICT-driven solutions aimed at enhancing business processes, improving customer experiences (Baptista *et al.*, 2020; Gössling, 2021), and optimising tourism planning (Soares *et al.*, 2022). In particular, artificial intelligence (AI) is fostering transformative changes in tourism, with an increasing role anticipated in both tourism business operations (Buitrago *et al.*, 2024; Dhoundiyal & Mohanty, 2022; Doborjeh *et al.*, 2022; Dogru *et al.*, 2025; Dwivedi *et al.*, 2024; Henriques *et al.*, 2024; Polo-Peña *et al.*, 2025) and destination planning (Mason, 2020).

Mobility emerges as a key challenge in sustainable tourism planning (Flores-Crespo *et al.*, 2022; Insch, 2020; Viana-Lora *et al.*, 2023), revealing the need for AI applications to analyse and support mobility management for sustainable outcomes (Veiga *et al.*, 2018). AI-powered solutions have facilitated various approaches for diagnosing tourist mobility patterns across multiple scales, ranging from cities to entire regions. These approaches generally fall into two categories based on their primary focus.

First, certain studies analyse features of the tourism infrastructure, such as accommodations and attractions, to create regional profiles. These profiles are often based on spatial diversity (Roman *et al.*, 2020) or the impact of tourism infrastructure on a region's appeal

(Sánchez-Martín *et al*., 2020). Second, another research stream focuses on uncovering tourist behaviour patterns, particularly in their movement – where, when, and how tourists travel within or to specific regions (Chen *et al*., 2021; Islam *et al*., 2021; Vu *et al*., 2020). This includes understanding tourist flows to inform planning and resource allocation (Chantre-Astaiza *et al*., 2019).

Despite these advances, there remains a gap in methodologies that integrate tourist mobility behaviour with existing infrastructure and attractions in a destination. For instance, assessing how tourist arrivals vary based on the spatial distribution of rural and urban accommodations could offer insights into the attractiveness of these areas. Such assessments would allow for strategic predictions and decisions in smart tourism planning to manage tourist flows effectively. Additionally, the rise of open data has become integral to sustainable tourism planning, enabling solutions that are better aligned with destination needs (Celdrán *et al*., 2018; Günther *et al*., 2022; Hamid *et al*., 2021; Masiero *et al*., 2022; Mendoza-Moreno *et al*., 2021).

This study introduces MOBITUR, an AI-based methodology designed to assist destination management organisations (DMOs) in policy formulation by analysing visitor mobility patterns relative to tourism infrastructure and attractions within a specified region. The methodology's effectiveness is demonstrated through a case study in the Region of Murcia, Spain – a southeastern region where tourism significantly contributes to the local economy.

Two key research questions guide this study:

> RQ1. How can AI techniques facilitate the study of tourism-related mobility patterns in relation to existing attractions and infrastructure?
> RQ2. Can AI complement human intelligence to optimise tourism mobility challenges within a smart tourism policy framework?

The rest of the paper is structured as follows: Section 2 reviews current trends in tourism data analysis for regional profiling, followed by a detailed description of the MOBITUR methodology in Section 3. Section 4 presents a case study to evaluate MOBITUR, and Section 5 concludes with the key findings.

2. LITERATURE REVIEW

2.1. Tourism Infrastructure and Mobility Analysis

Tourism infrastructure – including accommodations, attractions, and transport networks – constitutes a fundamental element of enhancing a region's appeal to visitors. However, fully understanding the impact of these resources requires a deep analysis of their spatial distribution and accessibility, which can provide critical insights for effective regional planning. Studies such as Sánchez-Martín *et al*. (2020) emphasise that the spatial arrangement of tourism infrastructure can substantially affect an area's attractiveness by facilitating or constraining visitor access, thus underscoring the need for infrastructure that aligns with strategic tourism goals. A well-planned infrastructure not only bolsters the appeal of a destination but also plays a key role in managing visitor flows, reducing overcrowding, and minimising environmental impacts.

Furthering this notion, Roman *et al.* (2020) discuss how spatial diversity in tourism infrastructure contributes to creating specific regional profiles, which can be instrumental in developing tailored strategic plans. This perspective becomes particularly relevant in diverse regions, where the infrastructure's characteristics and layout can be leveraged to balance visitor distribution, attract targeted demographics, and ensure sustainable growth. MOBITUR builds on these foundations by combining tourism infrastructure data with real-time mobility insights to generate detailed regional profiles. This integration allows destination management organisations (DMOs) to align infrastructure more closely with visitor demand, creating a balanced system that optimises both resource distribution and visitor satisfaction.

Recent research on tourist behaviour patterns supports this integrated approach, highlighting the necessity of understanding the temporal and spatial movement patterns of visitors within destinations. For example, Chen *et al.* (2021) and Vu *et al.* (2020) use data mining techniques to map visitor movements, providing essential insights for resource allocation and infrastructure optimisation. These studies demonstrate how data-driven approaches can refine the allocation of resources by identifying spatial and temporal trends in tourist flows, which is crucial for congestion management and enhancing the visitor experience. Building on this, Chen *et al.* (2024) suggest that the big data era enables a far broader set of data sources – ranging from mobile phone signals to social media and sensor networks – yet theoretical models explaining tourist mobility have not evolved at the same pace. Their review highlights privacy and representativeness concerns, as well as the need to integrate qualitative and quantitative perspectives when using large-scale mobility datasets. MOBITUR expands upon these methodologies by analysing mobility patterns in relation to the existing infrastructure, enabling DMOs to predict visitor flows and make real-time adjustments to resources. This dual consideration of infrastructure and behaviour addresses a critical gap in the literature by creating a model that combines both elements to inform strategic planning.

Further studies, such as Camatti *et al.* (2024) and Kovács *et al.* (2023), emphasise the importance of these integrative approaches, although their research predominantly centres on mobility patterns without fully accounting for the influence of infrastructure on tourists' decision-making processes. Complementing this body of work, Kim *et al.* (2024) reveal that the adoption of AI and smart travel applications plays a decisive role in shaping tourists' use of public transport according to the usefulness of smart apps in relation to age and gender cohorts, with seniors and male travellers particularly influenced by AI-driven functionalities. These findings highlight the importance of tailoring digital mobility tools to diverse demographic segments, a principle that MOBITUR incorporates by modelling heterogeneous visitor profiles and their technology-mediated mobility choices. MOBITUR provides DMOs with actionable insights derived from the interplay of infrastructure and mobility data, thereby facilitating a deeper understanding of visitor behaviours and preferences within different regional contexts.

Moreover, the role of AI has become indispensable in contemporary research as a means of acquiring and analysing new data sources, designing innovative strategies, and even generating synthetic data for training machine learning models (Li *et al.*, 2021). Recent surveys, such as those conducted by Bustamante *et al.* (2020) and Zhao *et al.* (2022), indicate that AI applications in tourism have primarily focused on forecasting tourist flows, with search engine data as the dominant data source, while multimodal data from online social networks (OSNs) have recently garnered increasing attention. These studies reveal that the majority of current forecasting techniques rely on time series and econometric models, although the use of AI – particularly neural networks and support vector regression – remains relatively underexplored. Expanding this perspective, Manoharan *et al.* (2024) demonstrate that AI now permeates every layer of the tourism value chain, from real-time data analysis and intelligent predictive applications to social media opinion mining, personalised itinerary design, and dynamic destination management. Their work highlights how machine learning and deep learning allow firms to create adaptable, responsive environments that optimise operations, allocate staff efficiently, and deliver customised visitor experiences, thereby reinforcing the strategic potential of AI for both competitiveness and sustainable management.

In this context, several works have demonstrated the efficacy of AI in forecasting tourism demand based on the type of infrastructure and attractions available in specific regions. For instance, Park *et al.*

. (2020) introduce BITOUR, an AI-driven business intelligence platform that fuses data from OSNs, such as Twitter and TripAdvisor, with geolocation data from OpenStreetMap. BITOUR's unique data integration approach uses online analytical processing (OLAP) cubes and data mining to align social media content (e.g., tweets and reviews) with specific accommodations, using sentiment analysis to rank the impact of these accommodations on the regional tourism sector. Similarly, Lau *et al.* (2019) incorporate real-time arrival counts at tourist attractions and propose a variational autoencoder framework to forecast visitor numbers, factoring in interaction dependencies among attractions. This dynamic approach enhances the predictive accuracy of visitor behaviour by identifying the sequence and preference patterns in tourists' attraction visits.

Swain *et al.* (2020) explore the distribution of intra-destination travel patterns and spatial interactions among attractions in major South Korean cities. Their research uncovers significant inequalities in tourism demand across destinations, indicating a propensity among tourists to visit primary attractions more frequently than secondary ones, an observation aligned with gravity theory in tourism. MOBITUR advances these findings by using AI to concurrently analyse visitor mobility and infrastructure, thereby providing DMOs with critical insights that support sustainable and balanced tourism development.

2.2. Theory of Planned Tourist Behaviour

The theory of planned behaviour (TPB), developed by Ajzen (1991), provides a structured framework for understanding how attitudes, subjective norms, and perceived behavioural control influence tourists' intentions and actions within a destination.

The TPB has been widely adopted in tourism research, serving as a basis for examining factors that shape tourist behaviours, including their choices regarding travel, destination engagement, and sustainable practices. Within the context of tourism, attitudes refer to tourists' positive or negative evaluations of specific activities or locations; subjective norms involve social influences on behaviour; and perceived behavioural control reflects individuals' beliefs about their ability to execute specific actions within a given environment.

Studies by Mariani *et al.* (2018) and Mich (2022) emphasise the TPB's efficacy in uncovering insights into tourist mobility patterns. Their research illustrates that the TPB can be enriched by incorporating advanced data analytics, offering a nuanced understanding of how various factors guide tourists' decision-making processes. These studies underscore the need for DMOs to consider behavioural theories when analysing data, as doing so can yield more accurate predictive models of tourist behaviour.

In recent years, the TPB has increasingly been integrated with data-driven approaches, such as AI and machine learning, to further examine tourist behaviour on both individual and collective levels. This integration allows researchers to track and interpret complex data, including tourists' spatial and temporal movements, with greater accuracy and depth. For example, Maltese and Zamparini (2023) investigate the role of the TPB in promoting sustainable mobility among young tourists in Italy, finding that attitudes, social norms, and perceived control significantly shape preferences for environmentally friendly travel options. These insights reinforce the value of using the TPB to model how tourists interact with mobility options, which in turn informs the design of strategic plans promoting sustainable transportation. Building on this perspective, Christensen *et al.* (2024) extend the TPB framework to the emerging context of generative AI, showing how travellers' awareness of AI hallucination interacts with perceived usefulness and trust to influence their tourism decision making. Further extending this line of inquiry, Koo *et al.* (2025) examine the adoption of AI-driven smart tourism technologies in the United Arab Emirates and demonstrate that ethical AI practices and high levels of personalisation significantly foster tourists' willingness to engage with these tools.

MOBITUR's methodology advances these theoretical applications by applying the TPB at a regional scale, focusing on how the availability of infrastructure and seasonal variations influence collective tourist behaviours. Unlike previous studies that often apply the TPB on a micro or individual level, MOBITUR scales the theory to encompass regional dynamics, enabling DMOs to anticipate and manage destination-wide visitor behaviours. By applying the TPB in this broader context, MOBITUR aligns with calls from researchers, such as Camatti *et al.* (2024), who advocate for approaches that integrate behavioural theory with big data analysis to address tourism's complex mobility patterns. This integration allows DMOs to better align mobility management strategies with tourist preferences, enabling them to promote sustainable tourism that respects environmental constraints and enhances visitor experience.

Furthermore, as Park *et al.* (2020) discuss, utilising the TPB within a data-centric framework allows DMOs to refine strategic plans with insights into tourists' planned behaviours in relation to infrastructure availability. MOBITUR builds on this by employing the TPB to guide DMOs in designing adaptive, data-informed strategies that can dynamically respond to tourist demand, infrastructure conditions, and seasonal shifts. By understanding the driving factors behind tourists' intentions, DMOs are better equipped to influence behaviours toward sustainable travel options, ultimately contributing to a more balanced and resilient tourism sector.

MOBITUR takes this concept further by applying the TPB on a regional scale, examining how infrastructure availability and seasonal variations impact planned tourist behaviours. By integrating the TPB within a data-driven, AI-supported framework, MOBITUR enables DMOs to anticipate not only tourist destinations but also the infrastructure factors and perceived convenience that shape these choices. This approach aligns with the research of Chen *et al*. (2021) and Park *et al*. (2020), who advocate for a comprehensive understanding of tourism mobility through AI. By incorporating the TPB, MOBITUR delivers a nuanced view of tourist decision making, providing DMOs with the information needed to promote sustainable mobility choices tailored to regional dynamics.

The large-scale application of the TPB is further supported by Maltese and Zamparini (2023), who examine sustainable mobility choices among young tourists in Italy. Their study finds that individual attitudes, social norms, and perceived behavioural control significantly influence preferences for green and multimodal transportation options. These insights highlight how behavioural factors can be incorporated into large-scale models like MOBITUR to support the design of sustainable and effective mobility solutions that resonate with tourists' environmental preferences.

3. THE MOBITUR METHODOLOGY

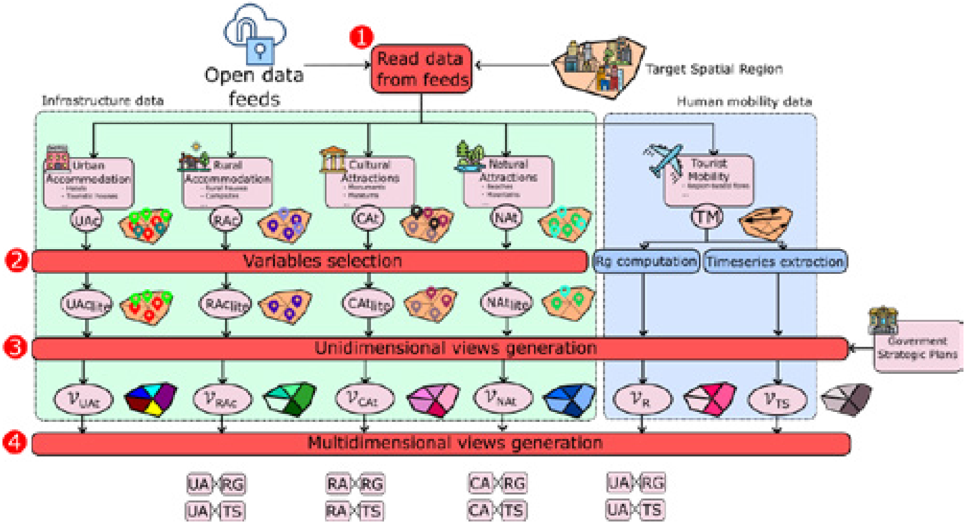
The MOBITUR methodology establishes connections between the distance travelled by tourists to visit a place, based on the existing tourist infrastructure and attractions within a region. First, the concept of Target Spatial Region (TSR) is defined as follows:

> **Definition 1**. A TSR, $R = \langle r_1, r_2, ..., r_n \rangle$, is a geographically bounded area that encloses n (n > 1) non-overlapped sub-areas r_i defined at a specific administrative level (e.g., villages, cities, or neighbourhoods).

As Figure 1 shows, MOBITUR's goal is achieved by means of a four-step pipeline. The following subsections explain these stages in detail.

Figure 1

GENERAL OVERVIEW OF THE MOBITUR METHODOLOGY. GIVEN A TSR R, WE FIRSTLY COLLECT DIFFERENT TYPES OF OPEN DATA RELATED TO ITS TOURISTIC INFRASTRUCTURE AND MOBILITY. NEXT, FROM SUCH RAW DATA WE EXTRACT THE TOURISTIC FEATURES OF R THAT ARE SUITABLE FOR FURTHER ANALYSIS. BASED ON THE CURATED FEATURES, WE COMPOSE A PALETTE OF UNIDIMENSIONAL VIEWS TO AGGREGATE THE SUB-REGIONS $R_I \in R$ IN TERMS OF SIMILARITY WITH RESPECT TO A PARTICULAR TOURISTIC FEATURE. IN THE FOURTH AND FINAL STEP, A SET OF MULTIDIMENSIONAL VIEWS ARE COMPOSED BY OVERLAPPING THE UNIDIMENSIONAL CLUSTERS. THE RESULTING MULTIDIMENSIONAL VIEWS ALLOW THE DEFINING OF CONNECTIONS, IN TERMS OF COMMON SUB-REGIONS, BETWEEN CLUSTERS DEFINED ON DIFFERENT FEATURES



3.1. Open Data Collection in the MOBITUR Methodology

As observed in Figure 1, the methodology relies on two large dimensions of data, one related to the touristic infrastructure and attractions of the TSR, and the other focusing on the mobility characterisation of the tourists moving to such a region.

3.1.1. Touristic Accommodation and Attractions Data

Regarding the touristic infrastructure of the TSR, we have defined four different categories to represent such a dimension: the *Urban Accommodation* (UAc), *Rural Accommodation* (RAc), *Cultural Attractions* (CAt), and *Natural Attractions* (NAt) datasets. The definition of each of them are given next.

The Urban Accommodation of a TSR R, UAc^R, comprises all the quantitative features of R related to the accommodation facilities, which are usually located in the urban settlements of each sub-region of R. This is the case for hotels, touristic houses, and hostels. Thus, UAc^R takes the form of a matrix $R^{n\times|fuac|}$ where n is the total number of sub-regions in R and f_{uac} is the set of extracted urban features.

The Rural Accommodation of a TSR R, RAc^R, comprises all the quantitative features of R related to the accommodation facilities, which are usually located in the rural environments of each sub-region in R. This is the case for campsites, rural houses, or rural guesthouses. Thus, RAc^R takes the form of a matrix $R^{n\times|frac|}$ where n is the total number of sub-regions in R and f_{rac} is the set of extracted rural features.

The Cultural Attractions of a TSR R, CAt^R, comprises all the quantitative features of R related to the attractions and points of interest that the cultural ecosystem of each subregion in R brings. This is the case for museums or monuments. Thus, CAt^R takes the form of a matrix $R^{n\times|fcat|}$ where n is the total number of sub-regions in R and f_{cat} is the set of cultural features.

The Natural Attractions of a TSR R, NAt^R, comprises all the quantitative features of R related to the natural environment of each sub-region in R that are interesting from a touristic point of view. This is the case for the number of mountains or the length of the coastline. Thus, NAt^R takes the form of a matrix $R^{n\times|fnat|}$ where n is the total number of sub-regions in R and f_{nat} is the set of cultural features.

3.1.2. Touristic Mobility Data

As far as the tourist mobility data is concerned, our work relies on a dataset comprising the region-based flows of tourists during a particular time period, defined as follows:

> The Tourist Mobility dataset of a TSR R, $TM^R = \langle OD_1, OD_2, ..., OD_T\rangle$, comprises the sequence of Origin–Destination (OD) matrices for a time period of T consecutive days. A matrix $OD_i \in N^{N\times N}$, $(N \geq n)$ comprises the number of tourists moving from each pair of sub-regions at the i-th day under consideration.

At this point, it should be noted that the OD matrices included in a TM dataset not only reflects the tourist mobility among the sub-regions in R but also other regions defined at the same administrative level. This is because MOBITUR evaluates both the inner movement of tourists within the TSR and the incoming touristic flows from sub-areas that are geographically external to the TSR. As shown in Section 3.3, this enables a more suitable view of the actual mobility of tourists in the area of interest.

3.1.3. Touristic Action Plans

MOBITUR also takes as an input labelled data coming from national or regional touristic action plans. These plans usually classify the areas of interest into different categories (e.g., rural, cultural, sun and sea, etc.) to develop ad-hoc campaigns to promote the touristic activity in such places depending on their assigned label. This is represented as the following dataset:

> The Official Categorisation dataset of a TSR R, OC^R, comprises the official classification made by public authorities of each sub-area in R based on its touristic profile. Hence, OC^R takes the form of a vector of length n, n being the total number of sub-regions in R.

Note that OC^R allows MOBITUR to consider the official viewpoint of the TSR during the analysis. It helps, for example, to discover if the official figures of a region are supported by its touristic infrastructure, as shown in Section 5.

3.2. Selection of the Features

Once all the infrastructure and tourist mobility data are collected, the next step of MOBITUR is to select the features that provide useful knowledge to perform the downstream profiling analysis. As explained in the previous section, the touristic infrastructure of a TSR takes the form of a set of matrices (UAc^R, RAc^R, CAt^R and NAt^R), each one comprising a number of attributes. In certain cases, some of these attributes might suffer from redundancies or multicollinearities with respect to other ones. For example, one attribute in UAc^R might report the number of 2-star hotels in each sub-area in R and another one is reporting the total number of hotels. In certain TSRs, these features might be strongly correlated and, hence, one of them could be removed from the analysis.

To perform this filtering process, the principal feature analysis (PFA) algorithm proposed by MacQueen (1967) has been applied. In brief, this mechanism facilitates the selection of the subset of the most relevant features of a tabular dataset by combining the principal component analysis (PCA) and the K-means clustering algorithm. As it follows an unsupervised approach, PFA can be used to perform the feature selection independently of the data mining algorithms to be applied in further steps of the methodology.

As a result of applying the PFA to the four infrastructure-based matrices, a new set of smaller datasets are generated: $UAc^R_{lite} \in R^{n\times|f^l_{uac}|}$, $RAc^R_{lite} \in R^{n\times|f^l_{rac}|}$, $CAt^R_{lite} \in R^{n\times|f^l_{cat}|}$, and $NAt^R_{lite} \in R^{n\times|f^l_{nat}|}$. Hence, f^l_{uac} ($\subset f_{uac}$) is the subset of relevant urban accommodation features of R. Similar definitions are given for f^l_{rac}, f^l_{cat}, and f^l_{nat}.

3.3. Computation of Mobility Features

Given the raw mobility data contained in TM^R, MOBITUR extracts two different features to model the behaviour of tourists in terms of displacements with respect to R. To begin with, we calculate the *radius of gyration* of each sub-region r_i in R. Briefly, the radius of gyration is a well-known metric within the discipline of human-mobility analysis (Giorgino, 2009). This metric allows for measuring the distance travelled by an individual or a population during a particular time period. Based on this metric, we have defined the radius of gyration of a sub-region $r_i \in R$, g_{ri}, by means of the following formula:

$$gr_i = \sqrt{\frac{1}{n_{r_i}} \sum_{j=1}^{n_{r_i}} dist(r_i, r_j)^2}$$

where $dist(r_i,r_j)$ is the distance in kilometres between the r_i and the *j*-th area, and n_{ri} is the total number of areas that r_i is meaningfully connected to. Therefore, an area r_a is meaningfully connected to another area r_b if at least 5% of the outgoing touristic trips from r_b arrive to r_a. Thus, a large g_{ri} indicates that the origins of the tourists coming to r_i are quite far away. Meanwhile, a small value reflects that tourists coming to r_i are from nearby regions.

Furthermore, we also extract from TM^R a time series $t_{s_{ri}}$ for each sub-area $r_i \in R$. This time series takes the form of a sequence $t_{s_{ri}} = \langle v^i_1, v^i_2, ..., v^i_T \rangle$ where v^i_j reports the *normalised* number of tourists visiting the *i*-th region in the *j*-th day of the study. This sequence can be easily computed as a row-based aggregation of each OD matrix in TM^R followed by a min-max normalisation. The reason for defining normalised flows instead of the raw ones is that it allows for a better identification of patterns in terms of the seasonality of the touristic visits in each sub-region. This feature is crucial for composing more useful unidimensional and multidimensional views, which will be discussed in Section 5.

Using these two features, it is possible to characterise the spatial distribution of the tourists of each sub-area by means of the radius of gyration along with the *temporal distribution* of such visits by means of the time series feature. Finally, the sets G^R and TS^R comprising the radius of gyration and the time series of each sub-area in *R*, respectively, are generated.

3.4. Artificial Intelligence Components of MOBITUR

MOBITUR integrates a hetero-intelligent framework that combines expert knowledge with machine-learning algorithms to analyse tourist mobility patterns. After data preparation and indicator construction, the AI layer provides an automated and reproducible pipeline for feature selection, clustering, and temporal–spatial analysis. In particular, PFA – a procedure that merges PCA with K-means clustering – was applied to reduce multicollinearity and retain the most informative variables. Tourist movements were then segmented using K-means algorithms combined with dynamic time warping (DTW) to capture both spatial and temporal similarities in visitors' trajectories, enabling the generation of multidimensional mobility profiles and the calculation of indicators such as the radius of gyration. All AI procedures were executed in open-source environments to ensure full reproducibility: Python 3.11 was employed with standard libraries such as scikit-learn for PCA and K-means and dtw for time series alignment, while R 4.3 was used with complementary packages including FactoMineR and cluster. It is important to note that MOBITUR does not rely on large-language-model or prompt-based generative AI; the artificial intelligence component is entirely algorithmic and parameter-driven, and no textual prompts are involved.

The choice of algorithms was guided by their suitability for large, spatio-temporal tourism datasets. K-means was preferred over alternatives such as DBSCAN or Gaussian mixture models because it efficiently minimises intra-cluster variance and produces easily interpretable partitions (MacQueen, 1967; Jain, 2010). DTW was adopted to compare time series with different phases or seasonal peaks, providing robust alignment of visitor-flow patterns (Sakoe & Chiba, 1978; Keogh & Ratanamahatana, 2005). PFA was employed to reduce dimensionality and capture latent factors explaining common variance among the indicators (Jolliffe & Cadima, 2016).

The number of clusters (k) in K-means was determined using a combination of the elbow method and the silhouette coefficient (Rousseeuw, 1987), testing k values from 2 to 10 and selecting the solution that maximised both cohesion and separation. For DTW, a Sakoe–Chiba constraint window of 10 % of the series length was applied to avoid excessive warping (Sakoe & Chiba, 1978). In the PFA, factors were retained when eigenvalues exceeded 1 and when the scree plot indicated a clear inflection, ensuring that the retained factors explained more than 70% of the cumulative variance (Jolliffe & Cadima, 2016).

To validate the clustering results, we calculated internal quality indices – silhouette, Davies–Bouldin, and Calinski–Harabasz (Rousseeuw, 1987; Davies & Bouldin, 1979; Calinski & Harabasz, 1974), performed bootstrap resampling (n = 500) to test the stability of cluster assignments. We compared the final clusters with independent tourism indicators such as hotel occupancy and average visitor expenditure to confirm external consistency.

3.5. Generation of Unidimensional Views

As Figure 1 shows, the third stage of the proposed methodology is the generation of an initial profile of the TSR by considering each touristic-infrastructure or touristic-mobility feature in an isolated manner. In this context, given a TSR R, a unidimensional touristic profile of R with respect to a touristic feature F is defined as follows:

> **Definition 2.** The unidimensional view of a TSR R with respect to a feature F, $V_F^R = \langle R_1^f, R_2^f, \dots, R_k^f \rangle$, is a set of k ($k < n$) disjoint feature regions ($R_l^F \cap R_m^F = \emptyset\ \forall l, m \in [1, k]$). Each feature region $R_j^F \subset R$ comprises a set of sub-areas that exhibit a strong similarity among them with respect to F.

Note that V_F^R aggregates the sub-regions in the TSR on the basis of the target feature at hand. Thus, it provides a coarse-grained definition of the TSR in terms of how the feature F spatially distributes within the target region. To generate these views, MOBITUR follows the procedure described in Algorithm 1.

Algorithm 1: Pseudo-code of the mechanism to generate unidimensional views in MOBITUR.

```
Input: $UAc_{lite}^R$, $RAc_{lite}^R$, $CAt_{lite}^R$, $NAt_{lite}^R$, $OC^R$, $G^R$, $TS^R$
Output: Unidimensional touristic views: $\langle V_{UAc}^R, V_{RAc}^R, V_{CAt}^R, V_{NAt}^R, V_G^R, V_{TS}^R \rangle$
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1 for each $F_{lite}^R \in \langle UAc_{lite}^R, RAc_{lite}^R, CAt_{lite}^R, NAt_{lite}^R, G^R \rangle$ do
2     $F^R \leftarrow F_{lite}^R \cup OC^R$
3     $\boldsymbol{k} \leftarrow select\_num\_clusters(F^R)$
4     $V_F^R \leftarrow kMeans(F^R, k)$
5 end for each
6 $\boldsymbol{k} \leftarrow select\_num\_clusters(TS^R)$
7 $V_{TS}^R \leftarrow DTW(TS^R, k)$
8 return $\langle V_{UAc}^R, V_{RAc}^R, V_{CAt}^R, V_{NAt}^R, V_G^R, V_{TS}^R \rangle$
```

Algorithm 1 takes as input the *lite* matrices generated in the *Selection of Features* stage (Section 3.2), the mobility feature sets (G^R and TS^R), and the official categorisation set, OC^R. Then, it merges each touristic-infrastructure matrix with OC^R (line 2 of Algorithm 1). The resulting matrix, F^R, feeds an instance of the K-means clustering algorithm (Gobierno de Murcia, 2022) to generate the unidimensional view related to a particular feature (line 4).

By means of this algorithm, we can group together the sub-areas in *R* that have similar values with respect to the relevant features f^l_{uac}, f^l_{rac}, f^l_{cat}, or f^l_{nat} and then compose the feature regions F^R. Previously, it selects the optimal number of feature regions, k, to be generated by the algorithm (line 3). In the case of the time series dataset TS^R, the algorithm uses the DTW clustering algorithm (Ministerio de Transportes, Movilidad y Agenda Urbana, 2020), as it better aggregates data in a series format than as a tabular one (lines 5 and 6).

It should be noted that the input matrix of K-means, F^R, also comprises the features from OC^R. This makes the aforementioned aggregation to be *biased* by the labelling made by public institutions. As a result, it is possible to discover whether the current touristic infrastructure or mobility of *R* is aligned with the pre-defined categorisation made by public institutions. As stated later in Section 5, this has important implications for evaluating the feasibility of the tourism strategic plan of a particular zone.

3.6. Generation of Multidimensional Views

The last important feature of MOBITUR is the generation of multidimensional views of a TSR. It allows for the connecting and correlating of different unidimensional views in a pairwise manner. A multidimensional view of a TSR is defined as follows:

> The multidimensional view of a TSR *R* with respect to a set of p unidimensional views $P = \langle V_{F1}^R, V_{F2}^R, \dots, V_{Fp}^R \rangle$ is a p-dimensional matrix, $V_P^R \in \mathbb{R}^{|V_{F1}^R| \times |V_{F2}^R| \times \dots \times |V_{Fp}^R|}$. Each element $C_{i_1}, C_{i_2}, \dots, C_{i_t} \in F_P^R$ indicates the number of sub-areas in *R* that belong, at the same time, to the p features regions $\langle R_{i_1}^{F1}, R_{i_2}^{F2}, \dots, R_{i_p}^{Fp} \rangle$.

As an illustrative example, let us suppose a TSR comprising six different sub-areas, $R = \langle r_1, r_2, r_3, r_4, r_5, r_6 \rangle$, and the following two unidimensional views, $V_{UAc}^R = \langle R_1^{UAc} = \langle r_1, r_3, r_6 \rangle, R_2^{UAc} = \langle r_2, r_4 \rangle, R_3^{UAc} = \langle r_5 \rangle \rangle$ and $V_{CAt}^R = \langle R_1^{CAt} = \langle r_1, r_4, r_5 \rangle, R_2^{CAt} = \langle r_2, r_3, r_6 \rangle \rangle$. While the view based on the urban accommodation V_{UAc}^R comprises three different feature regions, the one related to the cultural attractions, V_{CAt}^R, comprises two. Given these two unidimensional views, it is possible to compose a multidimensional $V_{UAc,CAt}^R \in \mathbb{R}^{3 \times 2}$ as

$$V_{UAc,CAt}^{R} = \begin{pmatrix} 1 & 2 \\ 1 & 1 \\ 1 & 0 \end{pmatrix}$$

where the first row indicates that one of the sub-areas R_1^{UAc} in is included in R_1^{CAt}(r_1) and that the other two are part of R_2^{CAt} (r_3, r_6). Similarly, the second row indicates how the two sub-regions in distribute among the two CAt feature regions.

As observed, the connections among features provided by a multidimensional view are quite convenient for checking whether the aggregation of sub-regions is consistent and aligned across unidimensional views. As illustrated in the example, sub-areas in *R* that are aggregated together when considering a feature F_a may be grouped in a totally different manner when another feature F_b is considered. Thus, the detection of discrepancies or strong correlations among features are quite useful for uncovering the potential impact that one feature has on another one (for instance, as depicted in the example, the cultural attractions of a TSR with respect to its urban accommodation).

4. USE CASE DESCRIPTION

This section describes in detail the use case setting used to evaluate the MOBITUR methodology.

4.1. Target Spatial Region

The TSR R selected for the use case corresponds to the Region of Murcia, a Spanish autonomous community located in the southeast of the country (see Figure 2). This region has a population of around 1.5 million people and comprises 39 municipalities in an area of 11,313 km^2. Bearing in mind Def. 1, in this study, the 39 municipalities take the role of the different sub-regions comprising the TSR (n=39).

Figure 2
LOCATION OF THE REGION OF MURCIA (IN BLUE) WITH RESPECT TO THE REST OF THE AUTONOMOUS COMMUNITIES IN SPAIN AND THE SPATIAL BOUNDARIES OF ITS 39 MUNICIPALITIES

From a touristic point of view, this TSR was chosen for its lack of an integrated transportation system from different touristic areas in the region. This implies that all the analysed movements of tourists can be better profiled, as private transport becomes the main transport mode of tourists coming from other regions as well as of those visiting a location within the TSR. The selected area has an average tourism growth of 5.4% (Arbués *et al.*, 2016). Thus, mobility and tourism make a proper combination as an AI-applied case study within a smart tourism planning process (Puig-Cabrera & Foronda-Robles, 2025) related to sustainability.

4.2. Touristic Features

For the chosen TSR, the UAc^{R}, RAc^{R}, CAt^{R}, and NAt^{R} datasets were collected from the open data cloud of the Regional Center of Statistics of Murcia. For each of the 39 cities in the TSR, we collected 45 different variables related to 2021, 25 for UAc^{R}, 10 for RAc^{R}, four for CAt^{R}, and six for NAt^{R}. Table 1 shows the variables contained in each dataset along with the ones that were eventually marked as relevant by the PFA algorithm (Section 3.2). For the sake of clarity, given the table, the dimensions of the matrix UAc^{R}_{lite} would be 39 × 6, since there are 39 cities and six relevant features.

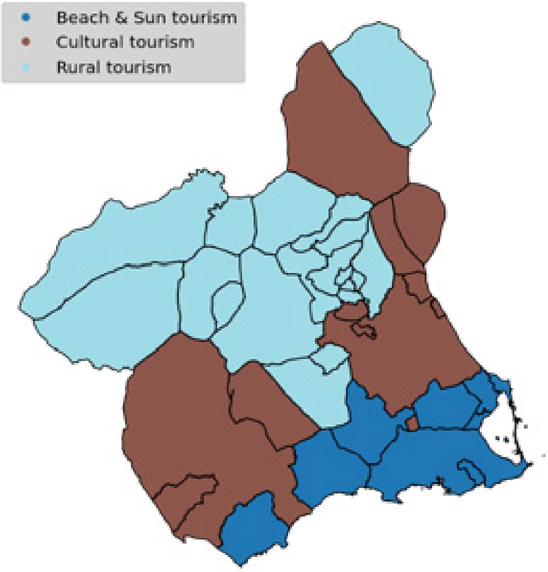
Table 1
LIST OF ALL THE TOURIST FEATURES INCLUDED IN THE UAC, RAC, RAC, CAT, AND NAT DATASETS. THE RELEVANT FEATURES SELECTED FOR THE *LITE* VERSION OF THE DATASETS ARE MARKED IN BOLD

Dataset	Feature	Dataset	Feature	Dataset	Feature
UAc	Number of hotels and hostels	***UAc***	Number of vacancies in hostels	***RAc***	Number of rural houses
	Number of hotels		Number of tourist apartments		Number of vacancies in rural houses
	Number of 5-star hotels		Number of 3-star tourist apartments		Number of rural guesthouses
	Number of 4-star hotels		Number of 2-star tourist apartments		Number of vacancies in rural guesthouses
	Number of 3-star hotels		Number of 1-star tourist apartments	***CAt***	Number of museums

Dataset	Feature	Dataset	Feature	Dataset	Feature
UAc	Number of 2-star hotels	***UAc***	Number of vacancies in tourist apartments	***CAt***	Number of interpretation centres
	Number of 1-star hotels		Number of vacancies in 3-star tourist apartments		Number of monuments
	Number of hostels		Number of vacancies in 2-star tourist apartments		Number of wineries
	Number of vacancies in hotels and hostels		Number of vacancies in 1-star tourist apartments	***NAt***	Amount of protected natural areas
	Number of vacancies in hotels		Number of tourist houses		Number of mountains
	Number of vacancies in 5-star hotels	***RAc***	Number of campsites		Maximum altitude of a mountain
	Number of vacancies in 4-star hotels		Number of first-class campsites		Number of golf courses
	Number of vacancies in 3-star hotels		Number of second-class campsites		Number of diving centres
	Number of vacancies in 2-star hotels		Number of campsites' vacancies		Kilometres of beach
	Number of vacancies in 1-star hotels		Number of first-class campsites' vacancies		

Regarding the OC^R, we made use of the official Strategic Tourism Plan of the Region of Murcia (Gobierno de Murcia, 2022). As Figure 3 shows, this plan splits the region into three different zones, each one comprising a set of cities with a common touristic profile in terms of *cultural tourism*, *sun and sea tourism*, and *rural tourism*. Unsurprisingly, all the coastal cities are included the third category; the interior cities are included in the cultural or rural profiles.

Figure 3
TOURIST CATEGORISATION OF THE CITIES IN THE REGION OF MURCIA ACCORDING TO THE OFFICIAL TOURISM STRATEGIC PLAN (OCR), REFLECTING THE TOURISM SPECIALISATION OF THE 39 MUNICIPALITIES IN THE REGION OF MURCIA. EACH COLOUR REPRESENTS THE PREVAILING TOURISM PRODUCT – SUN AND SEA, CULTURAL, OR RURAL – BASED ON THE RELATIVE WEIGHT OF ATTRACTIONS AND VISITOR FLOWS



4.3. Tourist Mobility

The TM^{R} matrix has been retrieved from the nation-wide human mobility report initially released by the Spanish Ministry of Transportation in December 2020. It covers a 15-month period from February 29, 2020, to May 10, 2021, indicating the number of trips among 3,216 ad hoc administrative areas (*Mobility Areas, MA*) per hour in Spain both in its peninsular and insular extension. A *single trip* stands for the spatial displacement of an individual with a distance greater than 500 meters. Consequently, this dataset could be regarded as a set of tuples where each one takes the form

$$\langle \mathrm{date}, \mathrm{hour}, \mathrm{morigin}, \mathrm{mdest}, \mathrm{aorigin}, \mathrm{adest}, \mathrm{ntrp}, \mathrm{dist} \rangle$$

reporting that there were n_{trp} human trips from the MA m_{origin} with a_{origin} as the primary activity to the MA m_{dest} with a_{dest} as the primary activity and whose distance was *dist* km during the indicated *date* and *hour*. Regarding the primary activities, the study only indicates *home*, *work*, and *other* as possible values. As a result, the study distinguishes flows related to frequent movements (e.g., *home*-to-*work* trips) or infrequent ones (e.g., *work*-to-*other* trips).

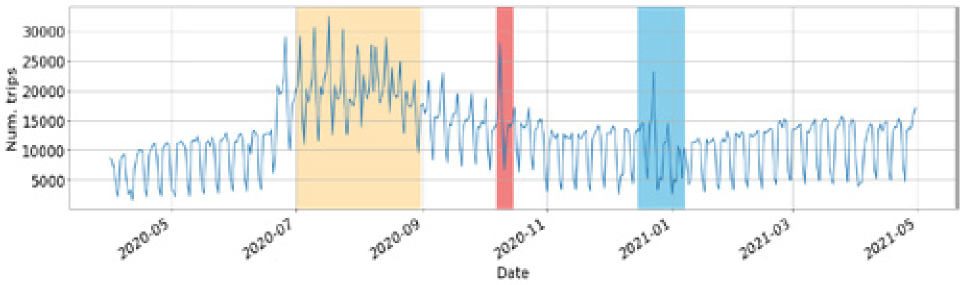
According to the official documents (Hall *et al*., 2019), these mobility data were collected through call detail records (CDRs) from 13 million users of an unspecified mobile phone carrier. Once anonymised, this dataset was used to infer representative mobility statistics at the nation level of the population of Spain and made publicly available as open data. Note that this dataset captures the movement of people regardless of the means of transport used for their displacements.

The original dataset contained the overall mobility flows in Spain. However, we were only interested in the touristic flows related to the Region of Murcia. Therefore, we needed to clean the original dataset to extract such flows. To do so, we first selected the records from 2020-04-01 to 2021-04-30 in order to remove the records within the lockdown interval imposed by the Spanish government due to the COVID-19 pandemic. This is a reasonable filter, since this lockdown policy seriously restricted mobility in the country. Then, we filtered the remaining records by keeping those accomplishing the following three conditions: (1) $a_{dest} = other$, (2) $dist \geq 100$, and (3) $mdest \in \mathbf{R}$.

Therefore, we only considered long displacements (i.e., distance greater than 100 km) whose destination was not a frequent spot for the travellers (i.e., destination activity neither *home* nor *work*) and was any of the cities in the Region of Murcia. Regarding the 100-km threshold, touristic trips are usually considered as long-distance displacements in the literature (Hardy & Aryal, 2020).

For the sake of completeness, Figure 4 shows the resulting time series with the volume of daily incoming touristic trips for the Region of Murcia. As noted, the time series follows a coherent behaviour, with notable increments of touristic flows during the summer and Christmas seasons along with a national bank holiday in October.

Figure 4
TIME SERIES OF THE TOURISTIC FLOWS USED IN THE STUDY. THE YELLOW AREA REPRESENTS THE SUMMER SEASON, THE RED AREA REPRESENTS A NATIONAL BANK HOLIDAY, AND THE BLUE AREA REPRESENTS THE CHRISTMAS SEASON



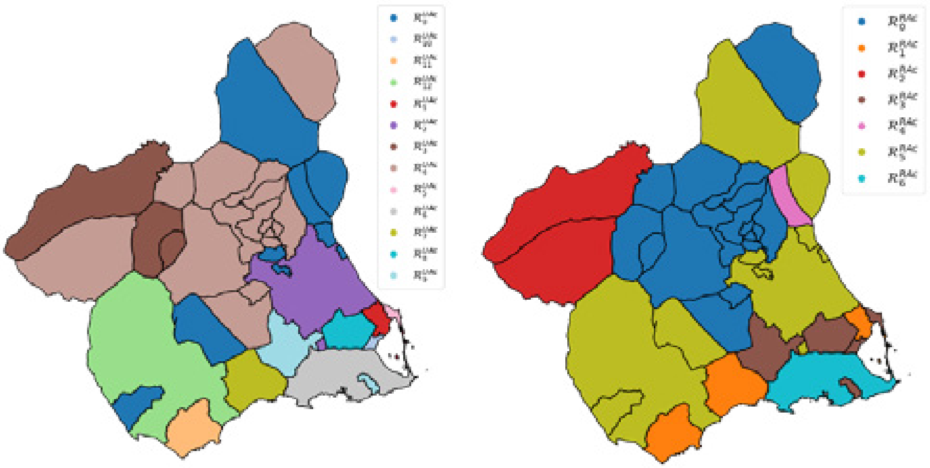
5. EVALUATION OF THE MOBITUR METHODOLOGY

This section assesses the different touristic views of the Region of Murcia that MOBITUR was able to generate for the use case described in the previous section.

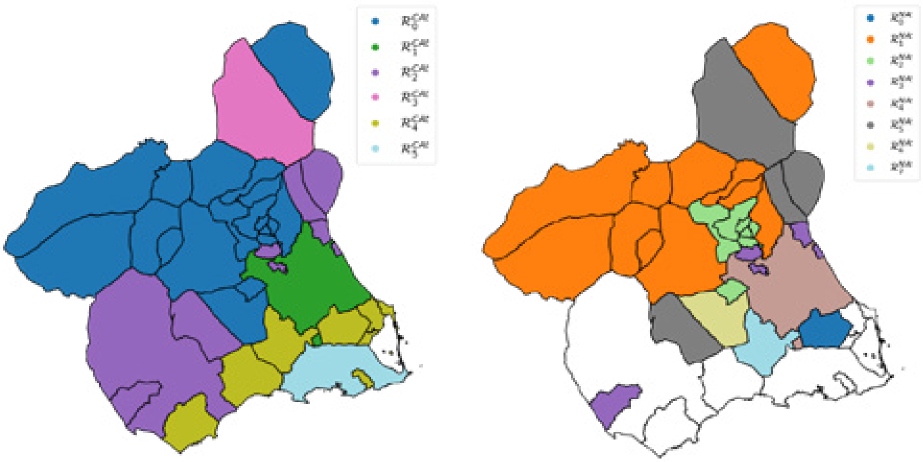
5.1. Unidimensional Views: Contrasting the Clustering of Tourism Destinations for a Strategic Plan – Human Intelligence Versus Artificial Intelligence

To begin, Figure 5 shows the unidimensional views extracted from the touristic infrastructure. At this point, it should be noted that the natural attractions (NAt^R) have been split into two different unidimensional views, one comprising the coastline sub-areas only, $V^R_{NAt,coast}$ (Fig. 5e), and another including the interior sub-areas of the TSR, $V^R_{NAt,int}$ (Fig. 5d). It was performed in this manner because the natural resources of the coastline regions were quite different from the ones of the regions located in the interior of the TSR.

Figure 5
UNIDIMENSIONAL CLUSTER VIEWS OF TOURISTIC INFRASTRUCTURE IN THE 39 MUNICIPALITIES IN THE REGION OF MURCIA BASED ON (A) URBAN ACCOMMODATION, (B) RURAL ACCOMMODATION, (C) CULTURAL ATTRACTIONS, (D) INTERIOR NATURAL ATTRACTIONS, AND (E) COASTAL NATURAL ATTRACTIONS. EACH COLOUR REPRESENTS A PARTICULAR FEATURE REGION, INDICATING MUNICIPALITIES GROUPED BY SIMILARITY USING A K-MEANS ALGORITHM

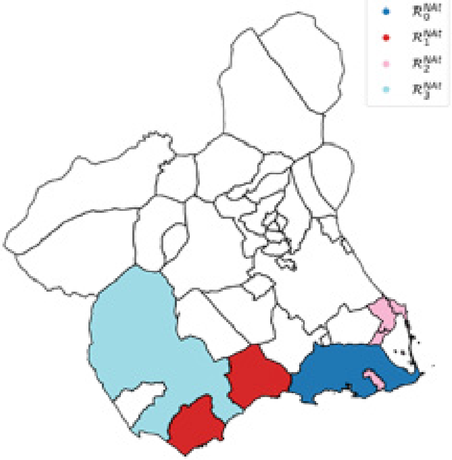


(a) V^R_{UAc} (b) V^R_{RAc}



(c) V^{R}_{CAt}

(d) V^{R}_{NAt} (interior sub-areas)



(d) V^{R}_{NAt} (coastal sub-areas)

Regarding all these views, an important fact related to the clustering of destinations was revealed when a tourism strategic plan was drafted, in comparison to the applied human intelligence criteria. The analysed strategic plan clustered destinations according to the modalities of tourism products intended to be developed in the area of study (Section 3.1.3). As shown in Figure 3, this consists of three typologies of destinations proposed in the strategic plan: 1) sun and sea destinations (seven out of 28 destinations), 2) cultural destinations (12 out of 38 destinations), and 3) rural destinations (19 out of 38 destinations).

In contrast, Figure 5 gives an overview of applying MOBITUR for the clustering of destinations, suggesting five different groups with a total of 38 sub-groups, thus requiring at least five different specific strategies and 38 corresponding sub-strategies. Specifically, MOBITUR identified several clusters of destinations regarding the datasets of UAc^{R}, RAc^{R}, CAt^{R}, and NAt^{R} in both interior sub-areas and coastal sub-areas.

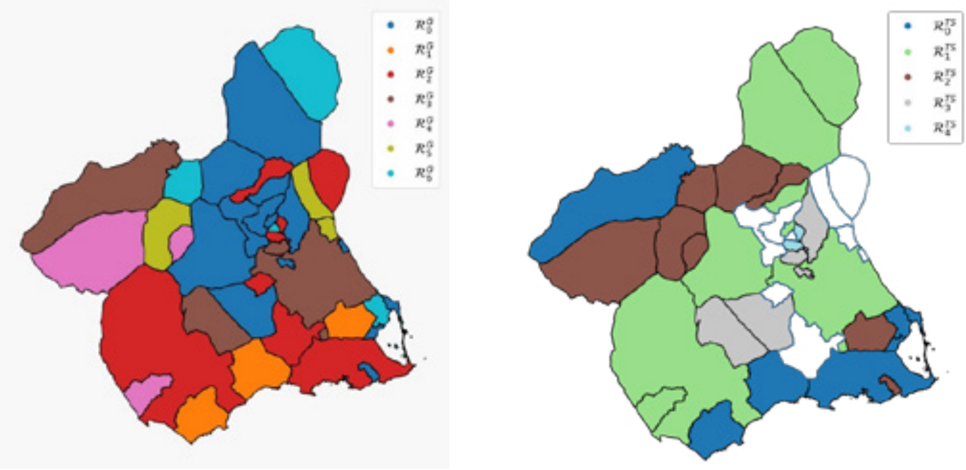
For the cases of and V^{R}_{RAc}, a total of 13 and seven sub-groups were simultaneously proposed (Figures 5a, 5b). Thus, the intensity and typologies of lodging infrastructure become important criteria to be considered for optimisation in a strategic tourism plan for the analysed sample area.

5.2. Multidimensional Views: Radius of Gyration and Stationarity

Regarding the multidimensional views, Figure 6 shows a total of 17 clustering of destinations identified by the MOBITUR methodology according to both tourist mobility or radius of gyration (Figure 7) and the seasonality of tourist mobility (Figure 8).

Figure 6

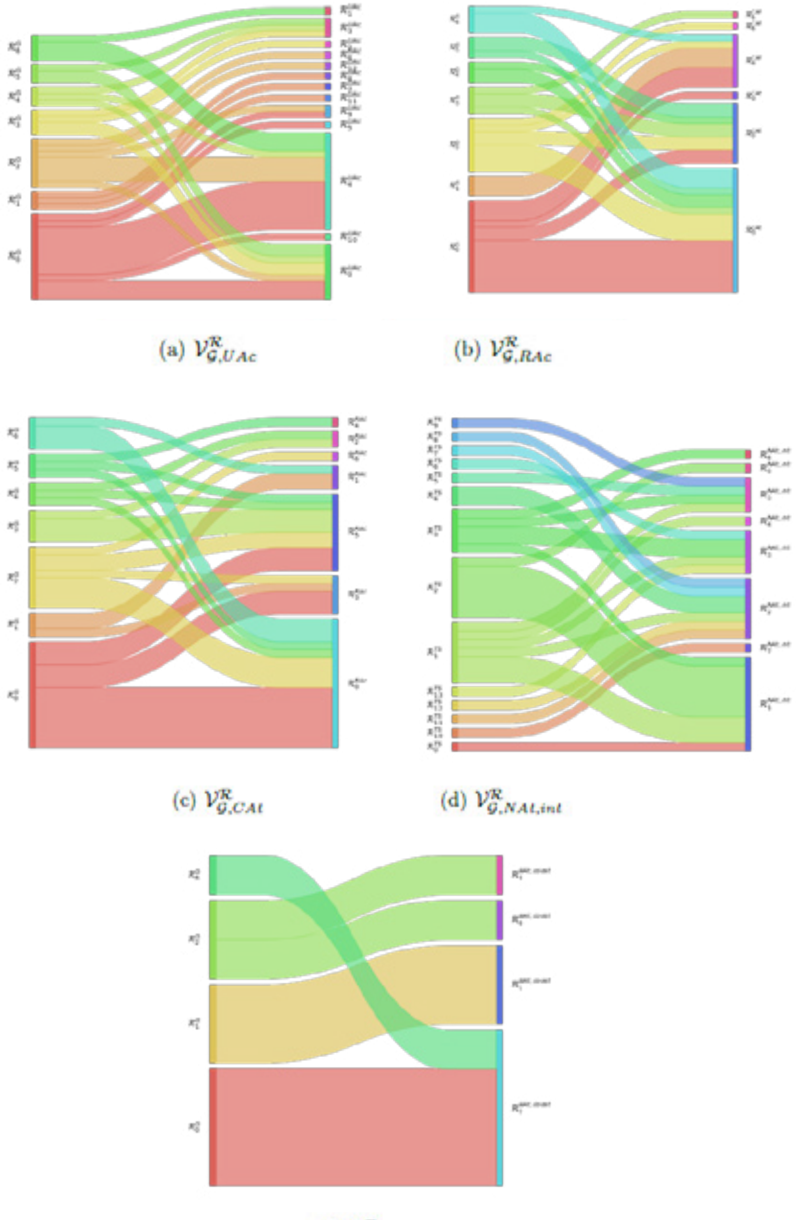
UNIDIMENSIONAL CLUSTER VIEWS OF THE REGION OF MURCIA BASED ON INCOMING TOURIST MOBILITY: (A) GLOBAL MOBILITY INTENSITY AND SPATIAL PATTERNS AND (B) TEMPORAL/SEASONAL DYNAMICS. EACH COLOUR REPRESENTS A PARTICULAR FEATURE REGION, INDICATING MUNICIPALITIES GROUPED BY SIMILARITY USING K-MEANS CLUSTERING FOR MOBILITY INDICATORS



(a) $V_G^{\mathbf{R}}$ (b) $V_{TS}^{\mathbf{R}}$

Figure 7

MULTIDIMENSIONAL VIEWS COMPRISING THE V^{R}_{TS} VIEW AND THE ACCOMMODATION AND ATTRACTION-BASED ONES



(a) $\mathcal{V}^{\mathcal{R}}_{\mathcal{G},UAc}$

(b) $\mathcal{V}^{\mathcal{R}}_{\mathcal{G},RAc}$

(c) $\mathcal{V}^{\mathcal{R}}_{\mathcal{G},CAt}$

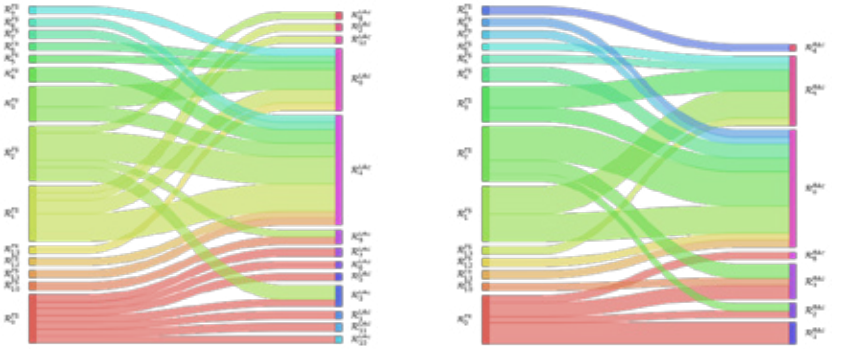
(d) $\mathcal{V}^{\mathcal{R}}_{\mathcal{G},NAt,int}$

(e) $\mathcal{V}^{\mathcal{R}}_{\mathcal{G},NAt,coast}$

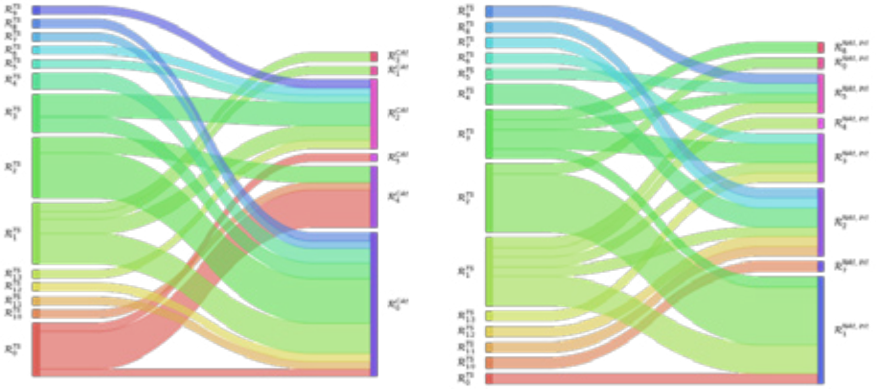
The attraction power of destinations and tourist mobility patterns is commonly analysed according to lodging infrastructure (Hall *et al*., 2019) and tourist attractions (Hardy & Aryal, 2020). As shown in Figure 6a and Table A.1, MOBITUR proposes a total of seven destination clusters, according to a series of mobility-related patterns of tourists that could be interpreted according to three different effects: 1) dormitory effect, 2) orange effect, 3) blue effect.

Figure 8

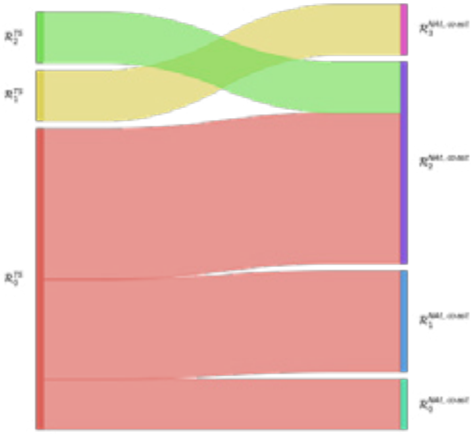
MULTIDIMENSIONAL VIEWS COMPRISING THE V^{R}_{TS} VIEW AND THE ACCOMMODATION AND ATTRACTION-BASED ONES



(a) $\mathcal{V}^{R}_{TS,UAc}$ (b) $\mathcal{V}^{R}_{TS,RAc}$

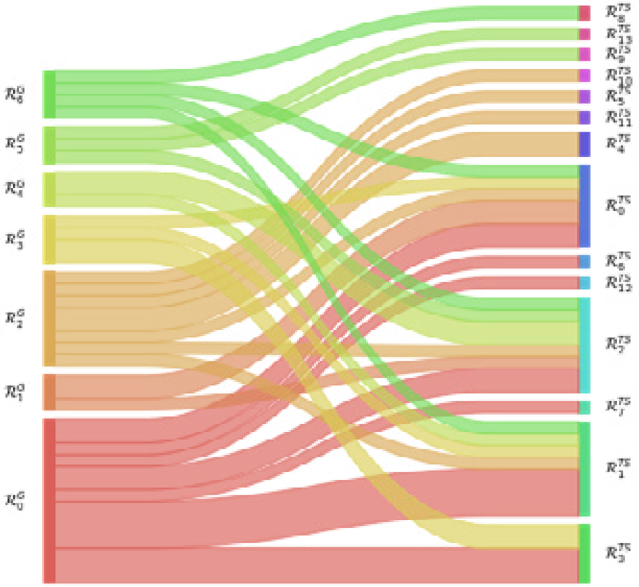


(c) $\mathcal{V}^{R}_{TS,CAt}$ (d) $\mathcal{V}^{R}_{TS,NAt,int}$



(e) $\mathcal{V}^{\mathcal{R}}_{TS,NAt,coast}$

Figure 9
MULTIDIMENSIONAL VIEW COMPRISING THE RADIUS OF GYRATION AND THE MOBILITY TIME SERIES FEATURES (V^R_{TS})



The *dormitory effect* suggests that the existence of large values in the features of V^{R}_{UAc} and V^{R}_{RAc} in a destination has 65% of correlated attraction power for tourists, thus becoming a competitive advantage for destinations with larger amounts of lodging establishments and spaces. This is the case of connections such as $R^{G}_{6} \leftrightarrow R^{UAc}_{2}$ (Figure 7a) or $R^{G}_{2} \leftrightarrow R^{RAc}_{6}$ (Figure 7b). In contrast, destinations in clusters such as $R^{G}_{0} \leftrightarrow R^{UAc}_{4}$ or $R^{G}_{0} \leftrightarrow R^{RAc}_{0}$ with weak or small accommodation facilities could face difficulties in attracting tourists in the area of study.

The *orange effect* suggests that V^{R}_{CAt} and specifically the existence of museums and monuments have a correlated attraction power for tourists of around 80%, which could become another pathway for destinations to gain visitors. According to Figure 7c, some cases of these cluster connections are remarkable in $R^{G}_{0} \leftrightarrow R^{CAt}_{3}$ or $R^{G}_{3} \leftrightarrow R^{CAt}_{1}$. Also, the V^{R}_{CAt} reveals that tourism resources such as wineries are still not representative enough in destinations to really become a real motivation for visiting them.

The *blue effect* suggests that V^{R}_{NAt} has 46.6% of correlated attraction power for tourists. This effect is explained by the number of golf areas as well as diving centres, which make destinations gain a series of differentiating factors to compete with other neighbouring destinations in the sun and sea category. In fact, variables such as the number of beach kilometres become an insignificant factor to really attract tourists from far away. This is reflected in cluster connections such as $R^{TS}_{3} \leftrightarrow R^{NAt,int}_{6}$ (Figure 7d) or RTS2 ↔ $R^{NAt,cost}_{3}$ (Figure 7e). Thus, according to RQ1, the revealed effects offer destination management organisations (DMOs) a dashboard of several cause-and-effect mobility- related patterns according to the existing lodging infrastructure and cultural and natural attractions of destinations. Thus, corresponding decisions can be made according to this preset behaviour and also facilitate more effective public policies for attracting or redistributing tourist flows.

Regarding the stationarity of the TSR, the MOBITUR methodology clustered the 39 destinations in five different groups according to the degree of volatility and distribution of tourist flows through time (Figure 6b). Table A.2 reveals the existing seasonality and standard deviation of the TSR during July and August in the summer period. For example, destinations such as R^{TS}_{0} concentrate 47.8% of total tourism volume during July and August. However, destinations that were included in R^{TS}_{4} have a more sustainable distribution of visitors throughout the year, with 19.1% of stationarity, and they do not suffer from high tourism pressure. Also, intermediate positions of stationarity were found in R^{TS}_{5}, R^{TS}_{2}, and R^{TS}_{3}, with respective concentrations of visitors in July of 21.8%, 24.1%, and 27.7%.

According to Figure 8, there is a relationship between stationarity and the existing lodging infrastructure (UAc^{R} and RAc^{R}) and tourist attractions (CAt^{R} and NAt^{R}), and 14 different strategies to address the existing seasonality were suggested by AI techniques. Regarding lodging infrastructure (Figures 8a, b), extreme connections such as $R^{TS}_{0} \leftrightarrow R^{RAc}_{(1,2)}$, $R^{TS}_{4} \leftrightarrow R^{UAc}_{4}$, and $R^{TS}_{4} \leftrightarrow R^{RAc}_{0}$ reveal that the fact of a destination reaching a threshold number of vacancies in hotels and campsites could be a symptom of seasonality, with a trend of developing a mass-based tourism model that might need to be addressed. However, no evidence was found according to the typology of lodging infrastructure.

Regarding tourist attractions, the number of cultural resources (CAt^{R}) was found to be a potential predictor of less seasonality in destinations with a larger number of monuments, such as $R^{TS}_{0} \leftrightarrow R^{CAt}_{5}$ (Figure 8c). Also, destinations based on wine tourism could represent an opportunity to address seasonality, as it is reflected in the $R^{TS}_{13} \leftrightarrow R^{CAt}_{3}$ interrelationship.

Regarding the number of natural attraction (NAt^{R}), connections such as $R^{TS}_{1} \leftrightarrow R^{(NAt,int)}_{4}$ in Figure 8d suggest that a larger extent of protected natural areas could contribute to better addressing seasonality in comparison to sun and sea destinations with golf camps and diving centres, as reflected in connections $R^{TS}_{6} \leftrightarrow R^{(NAt,int)}_{3}$ in Figure 8d or $R^{TS}_{0} \leftrightarrow R^{(NAt,coast)}_{0}$ in Figure 8e.

Finally, regarding RQ2, the findings reveal the need to use AI to address tourism challenges in destinations so that the configuration of destinations can be properly made according to the correlated power of attraction of different elements that could help control the tourist flows.

6. CONCLUSION

The fact of the increasingly smart development of societies implies that traditional challenges are also being addressed with technology-based solutions within the so-called smart city model. This is also the case in the tourism sector, which is going through a transformation process from traditional to smart destinations worldwide. In this context, this work revealed that concerning public policies and, specifically, the design of strategic tourism plans, new smart approaches could contribute to better MOBITUR and address the existing tourism challenges that destinations are facing.

In this study, we addressed the main challenges of a Spanish tourism region concerning mobility, tourist flow distribution, and stationarity in relation to existing tourism infrastructure and attractions (RQ1). To do so, we analysed the current strategic tourism plan of the region by applying the MOBITUR methodology.

The results suggested that human mobility and AI become a utilitarian combination that could optimise the design of a tourism strategy (RQ2). Specifically, the integration of AI techniques gives an overview of the dimensionality and heterogeneity of mobility patterns in relation to the existing tourism infrastructure and attractions in the destinations. Furthermore, five specific strategies and 38 corresponding sub-strategies were identified as necessary according to the AI suggestions in the unidimensional analysis. Additionally, if we consider the radius of gyration and seasonality in the multidimensional analysis, AI suggested a total of 14 strategies that should be adapted according to the particularities of each group to better address mobility issues and seasonality in the region, including tourism infrastructure and attractions.

Finally, this work offers novel empirical evidence with two specific innovative approaches. The first concerns applying AI techniques to tourist mobility, forecasting visitors in several areas of a tourism region according to the existing tourism infrastructure and attractions. Second, it shows that public policies and strategic plans in particular should combine human intelligence and AI to better address challenges, including holistic and heterogeneous approaches.

6.1. Limitations and Future Work

Although data filtering excluded the months of strict lockdown, it is important to acknowledge that the COVID-19 pandemic had residual effects on tourist mobility beyond that specific period. Travel restrictions, shifts in visitor preferences, and changes in transport availability during the subsequent months may have influenced both the intensity and the spatial patterns of mobility captured by MOBITUR. Consequently, the conclusions drawn from this study should be interpreted with caution, as the observed trends could partly reflect pandemic-related behaviours rather than structural characteristics of the destination.

A future line of research could integrate AI to test its contribution to optimising and addressing other sustainability-related challenges in tourism, such as energy efficiency and carbon footprints, climate change mitigation, human talent management, carrying capacity management, and the development of tourism innovation products and services, among others.

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Appendix A

CENTROIDS OF THE UNIDIMENSIONAL VIEWS

This appendix includes the centroids associated to the following unidimensional views

- V_G^R (Table A.1), and
- V_{TS}^R (Table A.2)

Table A.1
VALUES OF THE RELEVANT VARIABLES FOR EACH OF THE FEATURE REGIONS OF THE UNIDIMENSIONAL VIEW V_G^R. THE MEANING OF THE ACRONYMS OF THE OC LABEL IS C: CULTURAL TOURISM, R: RURAL TOURISM, B&S: BEACH AND SUN TOURISM

Variables	R^G	R^G	R^G	R^G	R^G	R^G	R^G
Radius of gyration	146.229	125.863	155.247	288.956	114.637	249.028	134.536
Number of hotels	2.57	6.67	4.38	9.00	2.67	3.33	3.50
Number of vacancies in hotels	234.50	671.67	835.62	1190.25	125.33	155.67	557.75
Number of vacancies in 2-star hotels	26.29	92.33	16.25	209.25	48.67	49.00	71.75
Number of hostels	0.71	5.00	1.50	2.50	1.00	0.67	1.00
Number of touristic apartments	43.57	145.67	76.00	15.00	22.00	11.00	151.00
Number of touristic houses	48.86	367.33	131.62	110.00	6.33	18.67	173.25
Number of campsites	0.07	1.67	0.38	0.75	0.33	1.00	0.50
Number of campsites' vacancies	13.50	963.33	1,006.62	345.50	116.67	191.00	323.50
Number of rural houses	5.36	5.00	8.50	61.50	42.33	15.67	3.50
Number of rural houses' vacancies	33.93	18.33	54.25	368.50	242.67	98.67	22.50
Number of rural guesthouses	0.43	0.33	0.38	0.75	2.00	0.33	0.50
Number of rural guesthouses' vacancies	9.29	3.67	6.38	31.25	52.00	8.00	10.25
Number of interpretation centers	0.21	1.33	0.62	1.25	0.33	0.00	0.00
Number of monuments	2.50	9.67	10.38	10.00	5.33	0.00	1.50
Number of wineries	1.14	0.00	0.00	0.25	1.67	0.67	1.25
Kilometers of beach	6,011.00	1,805.67	4,455.25	9,966.25	0.00	4,033.33	2,653.00
Max. altitude	570.86	588.67	663.75	1169.00	864.67	832.67	516.50
Kilometers of beach	0.99	6.64	4.69	0.00	0.00	0.00	5.22
Number of golf courses	0.21	1.67	0.75	1.50	0.00	0.00	0.25
Number of diving centers	0.21	1.67	2.00	0.00	0.00	0.00	0.00
OC label	C-R	B&S	C-R-B&S	C	C-R	R	R-B&S

Table A.2
STATIONARITY (RATE OF TRIPS IN JULY AND AUGUST) AND STANDARD DEVIATION OF THE TIMESERIES CENTROIDS

	R_o^{TS}	R_2^{TS}	R_3^{TS}	R_4^{TS}	R_5^{TS}
Stationarity	0.478	0.241	0.277	0.191	0.218
Std. Deviation	0.257	0.187	0.189	0.181	0.154