

A Pressure-Aware Pedestrian Routing Service for Tourism Data Spaces

Chenghuan Qian

Universitat de les Illes Balears

Dolores Ordóñez-Martínez

Anysolution S.L.

Maurici Ruiz-Pérez

`maurici.ruiz@uib.es`

Universitat de les Illes Balears

Research Article

Keywords: tourist itinerary planning, route optimisation, walkability, overtourism, tourism data spaces, geographic information systems

Posted Date: October 19th, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-10961957/v1>

License:   This work is licensed under a Creative Commons Attribution 4.0 International License.

[Read Full License](#)

Additional Declarations: No competing interests reported.

A Pressure-Aware Pedestrian Routing Service for Tourism Data Spaces

Abstract. Tourism data spaces can make heterogeneous territorial, mobility and attraction data reusable, but their value depends on services that turn these data into operational decisions. This study develops and tests a GIS-based optimisation service for pressure-aware pedestrian itinerary planning in the historic centre of Palma (Mallorca, Spain), with walkability retained as a route-level diagnostic. A real pedestrian network is enriched with a morphology-based walkability index derived from cadastral, terrain and LiDAR data, and tourism pressure is represented separately at three spatial levels: individual attractions (nodal), their immediate surroundings (zonal) and the corridors a route actually uses (trajectory). Routes are generated as an Orienteering Problem solved by mixed-integer linear programming under different time budgets, thematic filters, origins and closed or open route structures. Collected tourism value rises with the available time but with diminishing returns, while the walkability and corridor pressure of the selected routes change little. Nodal and zonal pressure are only weakly and non-significantly associated, so they should not be treated as interchangeable. Filtering out higher-pressure attractions substantially lowers the pressure of the places visited but barely changes exposure along the corridors used to reach them, indicating that attraction-level and corridor-level management act at different spatial scales. Because the attraction values, visit times and nodal pressure scores are prototype inputs, the results characterise the behaviour of the model rather than observed visitor responses; the contribution is a reusable, reproducible service specification and the cross-domain data assets it requires.

Keywords: tourist itinerary planning; route optimisation; walkability; overtourism; tourism data spaces; geographic information systems

1. Introduction

Visitors in historic cities often have a limited amount of time and need an itinerary that selects attractions, orders them, and connects them through the pedestrian network. For destination managers, the same itinerary influences where visitor flows concentrate and where their effects are felt (García-Hernández et al. 2017). Tourism routes have been widely studied as territorial and thematic products (Anuar and Marzuki 2022; Lin et al. 2024; Pedrosa et al. 2022), but this paper addresses a narrower operational problem: generating a feasible walking itinerary on a real pedestrian network while managing tourism pressure and explicitly assessing the quality of the pedestrian environment.

Three components need to be considered together. The first is the pedestrian environment, because street morphology affects walking comfort and attractiveness (Ewing and Handy 2009; Frank et al. 2010). The second is tourism pressure. Research on overtourism shows that visitor pressure concentrates in historic cores and is experienced across urban networks rather than only at individual attractions (Koens et al. 2018; Milano et al. 2019), although many management measures, such as timed entry, quotas and redistribution campaigns, operate at attraction level. The third is the combinatorial problem of selecting and sequencing attractions within a time budget, formalised as the Orienteering Problem (Gunawan et al. 2016; Vansteenwegen et al. 2011) and studied in tourism as the Tourist Trip Design Problem (Ruiz-Meza and Montoya-Torres 2022). These research areas address related parts of the same problem, but computational studies often reduce the pedestrian environment to travel time and, when pressure is included, treat it as another weighted term in the objective function.

A major practical difficulty is data integration. Route planning for a single historic centre requires a detailed pedestrian graph, cadastral information on street width and building form, terrain and LiDAR data for slope and greenery, a curated attraction inventory, accommodation capacity, resident population, public transport feeds, and arrival data from ports, rail and parking. These datasets are maintained by different organisations, in different formats and under different update cycles. The cost of assembling them has limited integrated pressure-aware routing to bespoke applications. Data spaces address this problem by allowing heterogeneous sources to remain under the control of their owners while making them discoverable and reusable under shared technical and governance conditions (Franklin et al. 2005; European Commission 2020; Ordóñez-Martínez et al. 2024).

The literature leaves three specific gaps. First, operational itinerary models rarely combine a detailed pedestrian graph, attraction-level pressure controls and an explicit route-level assessment of the pedestrian environment

within the same reproducible workflow. Second, route-planning studies have not clearly quantified whether directing visitors towards lower-pressure attractions also reduces exposure on the corridors used to reach them. Third, research on tourism data spaces remains largely architectural, with relatively few worked services that identify the data assets required and demonstrate how they can be combined in practice.

The central research question is whether pressure-aware pedestrian tourist routing, accompanied by explicit route-level walkability diagnostics, can be formulated as a reusable service over a tourism data space, and what such a service reveals about the relationship between attraction-level pressure management and corridor-level crowding. The study examines this question through four hypotheses, each addressing one aspect of the problem.

H1: collected value grows with the time budget but with diminishing returns, while route-level walkability and corridor pressure remain largely invariant under fixed minimum-time routing. H2: nodal and zonal POI pressure are not associated strongly enough to be treated as interchangeable measures. H3: filtering POIs by pressure lowers the pressure of the attractions visited but does not proportionally reduce trajectory pressure, because corridor exposure is a network-level property that attraction-level instruments do not directly control. H4: a peripheral origin penalises the value collected under a closed route, and allowing the route to end freely recovers much of that penalty, most markedly for routes that depend on the monumental core. Testing these hypotheses requires enriching a real pedestrian network with a morphology-based walkability index, representing tourism pressure separately at nodal, zonal and trajectory levels, solving route generation as an Orienteering Problem under different time budgets, thematic filters, origins and route structures, and mapping the required inputs and outputs to tourism data space categories.

The framework is tested in the historic centre of Palma (Mallorca, Balearic Islands, Spain), a mature Mediterranean destination with a dense, largely pedestrianised old town. The study uses an inventory of 105 POIs (96 visitable across six thematic categories and 9 auxiliary non-visitable network anchors) and a pedestrian network of 10,182 segments. It distinguishes nodal pressure, representing the assessed popularity of an individual POI; zonal pressure, representing modelled saturation around the POI; and trajectory pressure, representing exposure along the corridors actually used by a route. Nodal and zonal pressure are used to filter candidate POIs, whereas trajectory pressure is calculated after route generation. The walkability layer is derived from cadastral, terrain and LiDAR data. POI values, expected visit times and nodal pressure scores are prototype parameters, so the reported magnitudes describe model behaviour under a controlled configuration rather than observed visitor behaviour in Palma.

2. Related Work

The study draws on five related research areas: tourism routes as territorial products, tourist mobility, computational itinerary planning, walkability and tourism-pressure analysis, and tourism data spaces. The first four provide the analytical basis for the routing model; tourism data spaces provide the infrastructural context in which the service is intended to operate.

2.1. Tourism Routes as Territorial Structures

One line of research conceptualises tourism routes as territorial products linking attractions, places and identities. Reviews describe routes as stakeholder partnerships organised around a common thematic goal and note an imbalance between supply-side factors, such as participation, marketing and public strategy, and demand-side factors, such as motivation, satisfaction and loyalty (Anuar and Marzuki 2022). Food and drink routes dominate much of the empirical literature, while route planning and management remain recurring priorities for further research (Pedrosa et al. 2022). Studies of route development identify product design, goals, resources, governance, activities and performance assessment as recurrent success factors, with governance and evaluation among the less developed areas (Pedrosa et al. 2025a, b). Case studies range from rural clustering and wine routes to regional and long-distance itineraries (Briedenhann and Wickens 2004; Hashimoto and Telfer 2003; Lourens 2007; Rogerson 2007). A review of 38 cultural-route cases also catalogues planning and evaluation tools without addressing the detailed pedestrian-network and time-budget requirements of an operational route generator (Lin et al. 2024). This literature explains the territorial value of routes well, but it usually treats them as managed tourism products rather than as individual pedestrian mobility problems.

2.2. Tourist Mobility and the Route as Experiential Structure

A second line of research examines routes through tourist mobility, time-geography and visitor behaviour. Time-geographical studies describe individual travel rhythms in which movement and stationary activity concentrate at particular points of a trip (Zillinger 2007). Network analyses similarly show that connections between places can be more informative than the attractiveness of isolated destinations (Asero et al. 2016). Visitors experience the

city along trajectories, so route quality depends on the network traversed, the order of attractions, and the morphological conditions encountered along the way. Studies of pedestrian behaviour in historic centres show that visitors combine attractions, retail and public space into continuous walking episodes (Kemperman et al. 2009), while spatio-temporal analyses describe how urban tourism flows concentrate over time and space (Mou et al. 2020). Sensor-based observation can now measure such patterns directly (Gao and Schmöcker 2021), providing a potential empirical basis for calibrating modelled pedestrian pressure.

2.3. Computational Itinerary Planning and Route Optimisation

Computational research treats itinerary design as a planning problem in which POIs must be selected and sequenced under time, preference and feasibility constraints. Several studies use variants of the Orienteering Problem, including time-dependent team formulations with time windows and public transport (Gavalas et al. 2015; García et al. 2013). Other work focuses on personalisation, stochastic travel times, attention-based recommendation, or attraction data derived from user-generated sources (Rodríguez et al. 2012; Liao and Zheng 2018; Cao and Deng 2025; Cenamor et al. 2017; Zhang et al. 2016). Recent work in Information Technology & Tourism has extended this line towards sustainability-oriented attraction-sequence recommendation and city-trip recommendation that accounts for popularity, seasonality and environmental impacts (Dalla Vecchia et al. 2024; Banerjee et al. 2025). Most approaches either use a single objective and explore trade-offs through parameter changes or apply multi-objective methods that return a Pareto set (Martín-Moreno and Vega-Rodríguez 2018; Schilde et al. 2009; Ntakolia and Iakovidis 2021). Reviews note that this work has developed largely apart from the territorial and sustainability literature (Anuar and Marzuki 2022; Ruiz-Meza and Montoya-Torres 2022). A further limitation is the frequent use of abstract distance or time matrices that contain little information about the pedestrian environment. One closer example uses a Team Orienteering Problem with Time Windows and neighbourhood coverage around each POI (Heris et al. 2022), which is conceptually related to the zonal pressure measure used here.

2.4. Walkability, Tourism Pressure and Route Design

Walkability is well established in urban and transport research, but it is less developed in tourist itinerary planning. Studies of tourism routes show that route quality depends on the physical provision and environmental character of the route, not only on its attractions (Denstadli and Jacobsen 2011; Zouridaki et al. 2024). Overtourism research also shows that pressure is shaped by spatial concentration, route dependence and uneven use of urban space (García-Hernández et al. 2017; Peeters et al. 2018). In historic cities and mature island destinations, visitor flows often accumulate around a limited set of attractions and circulation corridors. Route design therefore affects pressure, and a single aggregate indicator can conceal different sources and scales of concentration. Relevant approaches include GIS-based multi-criteria prioritisation of pedestrian tourist routes (Hassanshahi et al. 2023) and segment-level walkability assessment in heritage cities (Velázquez et al. 2023). Recent contributions in Information Technology & Tourism also use GIS network analysis to generate alternative tourism routes and least-cost path methods to design sustainable geotrails (Yalçınkaya et al. 2025; Williams et al. 2025). Recommendation research further identifies popularity bias, whereby repeated individual recommendations can intensify concentration on already popular attractions (Kong et al. 2024).

2.5. Tourism Data Spaces as Enabling Infrastructure

Tourism data spaces provide the infrastructural context for the proposed service. The European strategy for data describes common European data spaces as trusted environments intended to expand access to and reuse of data while allowing data holders to retain control over their assets (European Commission 2020). A subsequent staff working document developed the sectoral data-space model (European Commission 2022), and the Commission's tourism-specific Communication set out governance, semantic interoperability, technical standards and use-case testing as key enablers of a common European tourism data space (European Commission 2023). In this model, sharing is governed through agreed conditions, technical connectors, semantic descriptions, and trust and access-control mechanisms rather than through a single central repository. This is relevant to tourism because accommodation, mobility, territorial and attraction data are distributed across many public and private organisations. The legal context is reinforced by the Data Governance Act (European Parliament and Council of the European Union 2022) and the Data Act (European Parliament and Council of the European Union 2023). Operational linked-dataspace applications in other domains also show that the model can support live analytical services rather than only data catalogues (UI Hassan et al. 2017).

Previous work on tourism data spaces argues that destination management is often constrained less by the lack of analytical methods than by the practical difficulty of combining cross-domain data under acceptable legal and technical conditions (Ordóñez-Martínez et al. 2024). Once accommodation, mobility, territorial and attraction data

are published with agreed vocabularies and access rules, an analytical service can reuse the same governed assets across studies and destinations. The route-planning framework is treated here as this type of value-added service: a reusable analytical layer that consumes interoperable assets rather than a one-off integration of local datasets.

This interpretation is consistent with smart-tourism research, which emphasises the value of interoperable data ecosystems for building and scaling digital services (Gretzel et al. 2015). Data spaces shift attention from individual applications to the governed data layer that allows many applications to be assembled. The framework is designed with this deployment logic in mind: every input it consumes corresponds to a data category that a tourism data space is expected to provide, and Sect. 3.1 makes that mapping explicit.

Two limitations apply to this positioning. The study demonstrates an analytical service that could operate over a tourism data space, but it does not implement or evaluate interoperability, governance or access control in a live data space. In addition, data availability is necessary but not sufficient for improved destination management; organisations also need the capacity and authority to act on the resulting analyses (Ordóñez-Martínez et al. 2024; Gretzel et al. 2015). The contribution is therefore limited to specifying and testing the analytical service and the data assets it requires.

2.6. Research Gap

The reviewed literature addresses the same empirical object, a walking itinerary through a historic centre, at different units of analysis. Territorial and heritage research treats the route as a destination-level product. Mobility research treats it as an observed trajectory. Computational research treats it as a sequence of nodes connected by costs. Walkability research focuses on street segments. Overtourism research usually measures pressure at destination or attraction level. Data space research operates at the level of assets, interoperability and governance. The routing problem considered here requires the segment, the POI and the complete itinerary to be represented together.

This literature leaves three methodological gaps. First, pedestrian route quality and tourism pressure are often represented separately or collapsed into composite route costs, which makes it difficult to inspect how attraction-level controls relate to the quality and pressure of the corridors actually traversed. Second, multi-criteria studies often combine dimensions into a weighted score (Nalmpantis et al. 2019) or use multi-objective formulations that return a Pareto set (Martín-Moreno and Vega-Rodríguez 2018; Schilde et al. 2009). Those approaches are useful for preference trade-offs but do not, by themselves, test whether pressure measured at different spatial levels responds in the same way. Third, the tourism data space literature describes architectures, governance and semantics (Ordóñez-Martínez et al. 2024; Deshmukh et al. 2024; Theissen-Lipp et al. 2023), but provides relatively few worked analytical services that specify the assets they consume and the outputs they produce (Gretzel et al. 2015).

Addressing these gaps requires a framework that combines a morphologically attributed pedestrian network, a curated POI inventory, realistic time constraints and a free origin, separate segment- and POI-level indicators, and a route-generation model able to compare alternative configurations without absorbing all criteria into one composite score. It should also be expressible as a service that can consume and return assets through a tourism data space.

3. Methodology

The framework is applied to the historic centre of Palma (Mallorca, Balearic Islands, Spain), a mature urban destination with a dense, largely pedestrianised old town. Fig. 1 locates the study area and shows the spatial distribution of the 105 tourism POIs across the historic core. Online Resource 1, Fig. S1 in the Supplementary Material presents the same inventory at full page size, with every POI individually labelled.

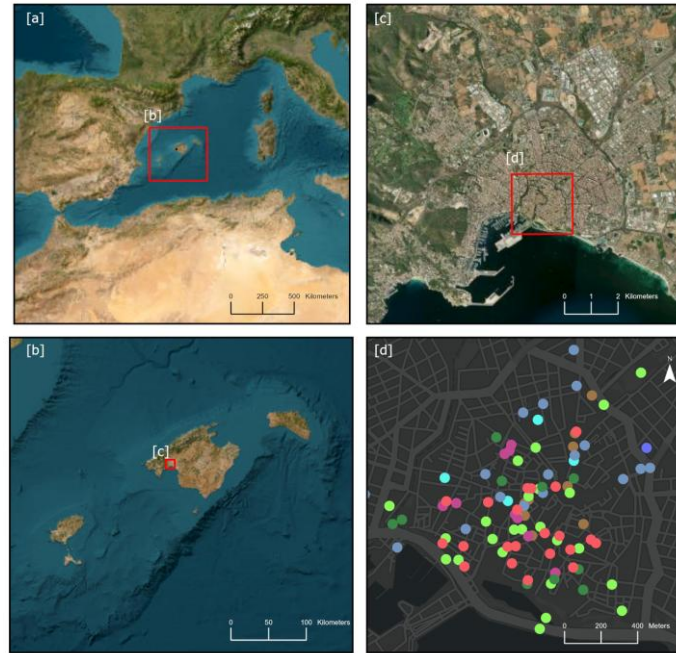


Fig. 1 Location of the study area: the historic centre of Palma (Balearic Islands, Spain) and the spatial distribution of the 105 tourism points of interest. Coordinates in UTM zone 31N (EPSG:25831)

The processing pipeline has five stages (Fig. 2). The first stage assembles the input data. GIS processing then enriches the pedestrian network with a morphology-based walkability index and a gravity-based tourism pressure surface and builds origin-destination matrices between the 105 POIs. The optimisation stage filters the candidate set where required and selects and sequences POIs within the available time budget. The analysis stage calculates route-level indicators that do not enter the objective function. The final stage exports routes and derived data as reproducible outputs.

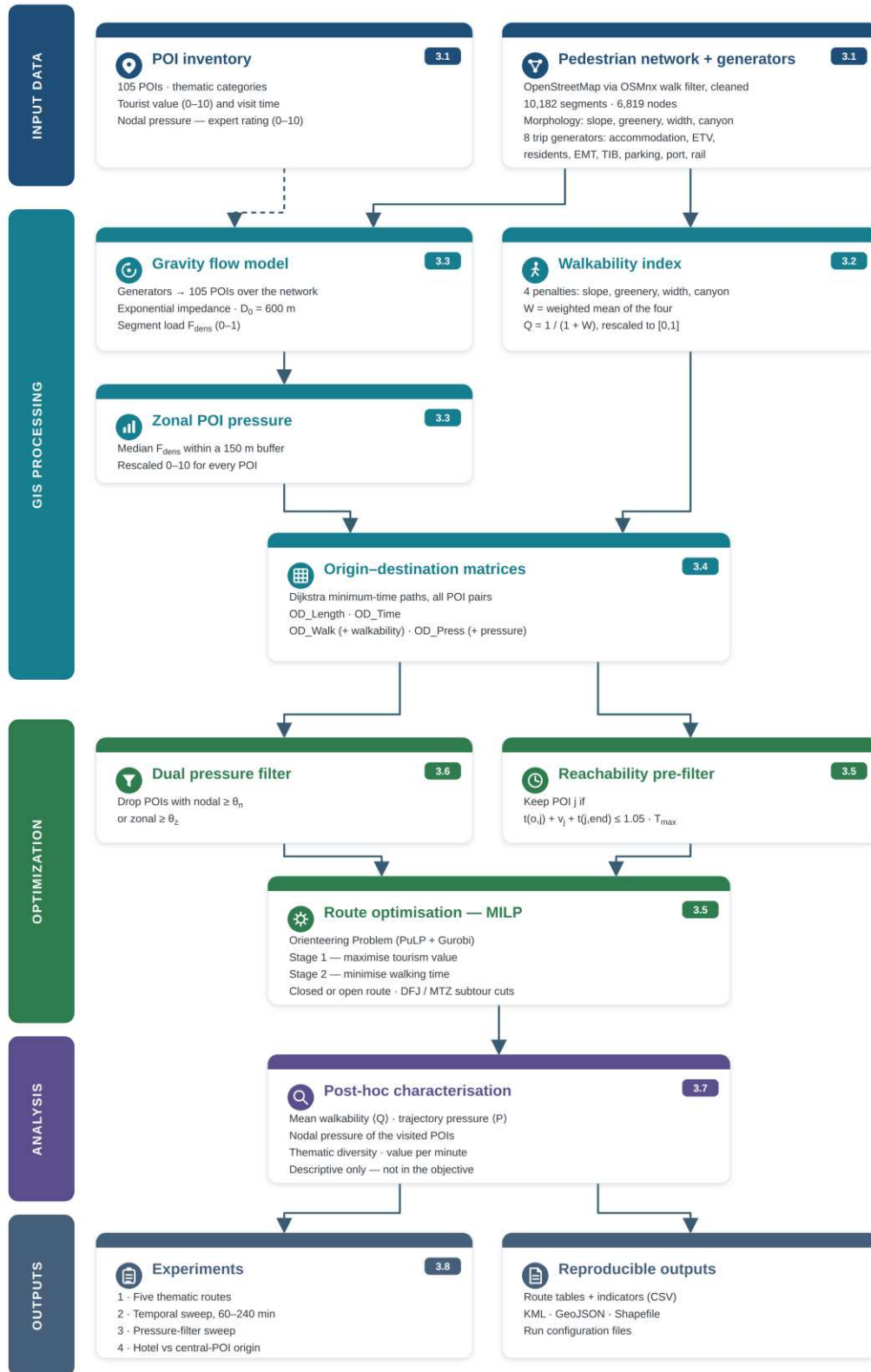


Fig. 2 Overview of the OPTIMIZA methodological pipeline for pedestrian tourism-route design in the historic centre of Palma. The workflow is organised into five stages: input data, GIS processing, optimisation, analysis and outputs. Two georeferenced inputs (a curated point-of-interest inventory and a morphologically attributed pedestrian network with eight trip generators) feed a GIS layer that derives a street-level walkability index, a gravity-based tourist pressure field, a per-POI

zonal pressure and the origin-destination (OD) matrices. A reachability pre-filter and a dual (nodal/zonal) pressure filter reduce the candidate set before a two-stage lexicographic Mixed-Integer Linear Program (Orienteering Problem) builds each route. Routes are then characterised post hoc and exported as reproducible data assets. Section numbers (3.1-3.8) refer to the corresponding subsections of the manuscript

3.1. Input Layers and Their Data-Space Sources

The required inputs fall into four broad data-space categories: territorial and morphological data, mobility data, accommodation and demand data, and attraction data. Table 1 identifies the individual layers, their original producers and the corresponding data-space category. In the present implementation these sources are assembled manually; in a mature data space they could be requested through governed connectors.

Table 1 Input layers, their originating producers, and the tourism data space category each represents. On a mature data space, each manual assembly step below becomes a standardised query against a governed connector

Layer / input	Originating producer (source)	Data-space category
Pedestrian street graph	OSM-derived base network: https://www.openstreetmap.org/export	Territorial · mobility network
Slope (derived from 2x2 m terrain model)	Centro Nacional de Información Geográfica (CNIG): https://centrodedescargas.cnig.es/CentroDescargas/home	Territorial · morphology
Urban greenery (LiDAR 2,5x2,5 m nDSM)	CNIG	Territorial · morphology
Street width & canyon (derived from cadastral parcels)	Dirección General del Catastro: https://www.se-decatastro.gob.es/Accesos/SECAccDescarga-Datos.aspx	Territorial · morphology
Registered accommodation	Open Data CAIB: https://intranet.caib.es/opendatacatalog/es/dataset/allotjaments-turistics-mallorca	Accommodation · demand
Holiday rentals (ETV)	Open Data CAIB	Accommodation · demand
Resident population (Census track)	Instituto Nacional de Estadística: https://www.ine.es/dynt3/inebase/index.htm?padre=11555&capsel=11100	Population · demand
Bus stops (EMT)	GTFS Open Data EMT Palma: https://smartoffice.palma.es/-/dades-obertes-emt-empresa-municipal-de-transportes-/ca/	Mobility · demand
Bus stops (TIB)	GTFS TIB Mallorca https://www.tib.org/es/sobre-ctm/portal-de-transparencia/datos-abiertos	Mobility · demand
Public parking	OSM and Palma Parking.info: https://palmaparking.info/es/map	Mobility · demand
Cruise arrivals (port)	Autoridad Portuaria de Balears https://www.portsdebalears.com	Mobility · demand
Rail arrivals	Serveis Ferroviaris de Mallorca (SFM): https://www.trensfm.com/es	Mobility · demand
POI inventory (105)	Field work /Curated expert inventory (6 categories)	Attraction · POI

The input set is highly heterogeneous. It includes a national geographic agency, the national cadastre and statistical office, two transit operators publishing GTFS feeds, regional open-data portals, a port authority and a rail operator. No single organisation holds all the required assets. At the same time, the layers map directly onto the territorial, mobility, accommodation, population and attraction categories expected in a tourism data space. The framework therefore provides a concrete inventory of the data needed for a pedestrian itinerary service.

The pedestrian graph is derived from OpenStreetMap with OSMnx. The extraction uses the walk network filter, which discards motorways, trunk roads and any way where pedestrian access is forbidden and ignores one-way restrictions, over a bounding box buffered 1,500 m beyond the POI envelope so that path finding is not affected by edge effects; the tag set retained at download time is extended beyond the OSMnx default to include the surface, lighting, width, sidewalk, access, incline, step count, crossing, tunnel and bridge attributes that later feed the quality indices. Because a pedestrian network is undirected, the reciprocal arc pairs returned by OSMnx are collapsed on a canonical key, multipart geometries are exploded, zero-length arcs are removed and the result is clipped to a 1,000 m buffer around the study area. Connectivity is then enforced: components holding POIs but detached from the main graph are bridged by the shortest possible synthetic link, capped at 250 m and flagged as such in the attribute table, fragments containing no POI are pruned, and a blocking check confirms that all 105 POIs belong to a single connected component. Traversal time is computed as $t = \ell / (v \cdot \rho) + \delta$, with a walking speed v of 4.5 km h⁻¹ on the flat, a factor $\rho = 0.45$ on stepped segments, and an added delay δ of 8 s at unsignalised crossings and 20 s at signalised ones. Endpoint coordinates are rounded to the millimetre so that the end-point connectivity rule of the network dataset does not generate duplicate nodes. The cleaned graph is then enriched with the morphological and pressure attributes described in Sections 3.2 and 3.3 to yield the layer on which the origin-destination matrices are computed. The implementation is organised as three reproducible notebooks, one for network extraction and cleaning, one for the origin-destination matrices and one for the optimiser, all released with the reproducibility package.

The pedestrian network itself exists in two versions. The full network, `palma_walk_edges`, covers the whole metropolitan area out to the ring road (Vía de Cintura); each segment is a polyline with start and end node identifiers, length, an estimated pedestrian traversal time and an effective width, in ETRS89 / UTM zone 31N (EPSG:25831). The gravity model of pressure runs on this full network, so that demand generators located outside the historic core still contribute load to interior segments. The optimiser instead works on a clip to the historic centre, Pedestrian Network Palma Center with 10,182 segments and 6,819 nodes, inheriting all computed attributes. Because all origins and POIs lie inside the core, minimum-time paths between them do not cross the ring road, so the two versions yield the same effective segments for routing. Online Resource 1, Fig. S3 in the Supplementary Material maps the morphological attributes computed for the network, slope, greenness and effective width, together with the resulting walkability index.

The POI inventory consists of 105 georeferenced points, of which 96 are classified into one of six thematic categories, monumental and historical heritage; museums and exhibition spaces; art galleries; urban spaces of touristic interest; emblematic commerce; and gastronomy and markets, and each carrying an expert quality-of-attraction score and an expected visit duration. Two auxiliary non-visitable categories (generic commerce and proposed connector nodes) exist only to anchor the network and are never selected as stops. As stated in Section 1, the valuations, visit times and pressure scores are prototype-level test data; the walkability layer, by contrast, is computed from real cadastral and LiDAR sources. The complete inventory is catalogued in the Supplementary Material (Online Resource 1, Table S1), which lists all 105 POIs grouped by category with their tourist value, nodal and zonal pressure, expected visit time and coordinates; Online Resource 1, Fig. S2 maps the inventory attributes across the study area: thematic category, tourist value, expected visit time and nodal pressure.

The prototype POI attributes were assigned by the research team on the basis of domain knowledge of the geography and tourism of the study area rather than through a formal multi-rater elicitation. Each POI received a quality-of-attraction score from 0 to 10, a representative visit duration, and a nodal pressure score from 0 to 10 based on observable cues such as guidebook prominence, category and known visitor concentration. These values are internally consistent test parameters, but they were not calibrated against visitor counts, ticketing data or surveys. They are used to test the framework, not to provide validated estimates of the attractiveness or crowding of individual sites. Formal multi-rater elicitation and calibration against observed demand are required before operational use.

3.2. Walkability Characterisation of the Pedestrian Network

Walkability is computed as a per-segment index from four morphological descriptors, each drawn from the territorial layers of Table 1. Slope and greenery come from the CNIG terrain and LiDAR models; effective width and

the urban-canyon ratio come from the cadastre. The rationale is that the pedestrian comfort of a street is a stable property of its physical form, how steep it is, how wide, how enclosed, how green, and can therefore be measured once, from morphology, independently of any particular route.

3.2.1. Partial penalties

Each descriptor is transformed into a bounded partial penalty. Slope penalty rises with the fraction of a segment's length exceeding 6%, used here as a reference threshold because current Spanish accessibility regulation treats inclines above 6% as ramps within accessible pedestrian itineraries (Ministerio de Transportes, Movilidad y Agenda Urbana 2021). Greenery penalty falls with tree-canopy coverage in a buffer around the segment axis (LiDAR returns above 2 m); width penalty rises as effective width falls below a 6 m reference; and the canyon penalty is a Gaussian centred on an optimal height-to-width ratio of 1.5:

$$W_{\text{slope}} = \text{clip}\left(\frac{SLP_{\text{pct}}}{15}, 0, 2\right) \quad (1)$$

$$W_{\text{green}} = \text{clip}\left(1 - \frac{GRN_{\text{pct}}}{100}, 0, 1\right) \quad (2)$$

$$W_{\text{width}} = \text{clip}\left(1 - \frac{A_{\text{eff}}}{6}, 0, 1\right) \quad (3)$$

$$W_{\text{canyon}} = 1 - \exp\left[-\frac{(\ln(HW / 1.5))^2}{2 \cdot 0.7^2}\right] \quad (4)$$

The reference thresholds (15% for slope, 6 m for width, 1.5 for the canyon ratio, 0.7 for the Gaussian width) are pipeline constants chosen by expert judgement. Slope may exceed 1 (up to 2) because a segment sustaining more than 6% grade over its whole length is heavily penalised for pedestrians; the other penalties are capped at 1. Effective width is measured by casting transects perpendicular to the segment axis and taking the median distance between cadastral parcel edges on either side; segments where this cannot be computed reliably fall back to a 4 m default.

3.2.2. Combined penalty and walkability index

The four partials are combined as a weighted mean, with slope weighted highest because it most directly conditions accessibility, width and greenery weighted equally for comfort and shade, and the canyon ratio weighted lowest because its effect is more ambient than functional:

$$W = 0.30 \cdot W_{\text{slope}} + 0.25 \cdot W_{\text{green}} + 0.25 \cdot W_{\text{width}} + 0.20 \cdot W_{\text{canyon}} \quad (5)$$

When the canyon ratio is undefined (open squares, one-sided streets), its 0.20 weight is redistributed proportionally among the other three so the weights still sum to one. The combined penalty is then mapped to a continuous walkability index:

$$Q_{\text{walk}} = \frac{1}{1 + W} \quad (6)$$

Q_{walk} lies in (0, 1], where 1 is the optimal pedestrian condition. Across the 10,182 segments it ranges from 0.462 to 0.836 with a median of 0.702, a compressed range produced partly by the $1/(1+W)$ transform. For cartography and analysis the index is rescaled to 1-10 and 0-100 percentile-rank scales so that spatial differences remain legible. The weights and thresholds are expert-defined design choices rather than a behaviourally calibrated instrument. Across the network, the combined penalty W is most strongly associated with slope (Pearson $r = 0.80$), followed by effective width (0.35), canyon ratio (-0.22) and greenery (0.11), and mean walkability declines from 0.727 in the most accessible slope class to 0.534 in the steepest class. In the experiments reported here, walkability is deliberately retained as a route-quality diagnostic rather than as an optimisation criterion. This allows the study to examine whether the pedestrian environment of selected routes changes across time budgets, pressure rules and

origins without introducing an additional set of behavioural weights. A formal sensitivity analysis of the walkability weights and an active walkability-routing variant remain necessary before the index is used prescriptively.

3.3. Tourism Pressure Characterisation

Tourism pressure is characterised in two complementary ways: at the level of street segments, through a gravity model of pedestrian flow, and at the level of POIs, through both an expert nodal score and a zonal aggregation of segment pressure around each POI. This is the block that most directly consumes the mobility and demand layers of the data space, accommodation, population, transit, port, rail and parking, and turns them into a spatial pressure surface.

3.3.1. Gravity model of pedestrian flow

The model assumes that each demand-generator layer emits a daily volume of pedestrian trips proportional to its magnitude, that these trips distribute toward the 105 POIs with a probability decreasing with distance, and that each trip follows the minimum-time pedestrian path over the network. The raw load on a segment is the sum, over all generator-POI pairs whose minimum path traverses it, of the emitted and distance-discounted trips:

$$F_{\text{raw}}(s) = 2 \cdot \sum_{g,i,j} \left[r_g \cdot w_i \cdot V_j \cdot \exp\left(-\frac{d_{ij}}{D_0}\right) \cdot 1[s \in \pi^*(i,j)] \right] \quad (7)$$

Here g indexes the eight generator layers; i indexes the individual units within each layer (each census polygon, each stop, each parking); j indexes the 105 POIs; r_g is the generation rate of layer g ; w_i the unit weight (beds, inhabitants, spaces); V_j the POI valuation; d_{ij} the minimum-path pedestrian distance; $D_0 = 600$ m the characteristic impedance distance; $\pi^*(i,j)$ the minimum-time path; and the leading factor 2 accounts for the return trip. The generation rates r_g encode markedly different intensities across generator types and carry much of the model's interpretive content (Table 2).

Table 2 Assumed daily generation rates by demand-generator layer, with the data space source of each. Rates are prototype-level modelling parameters, not measured flows

Generator layer	Rate r_g (trips·day ⁻¹ ·unit ⁻¹)	Interpretation / source
Registered accommodation	1.60	Prototype rate per registered accommodation bed
Holiday rentals (ETV)	1.40	Prototype rate per short-term rental bed
Resident population	0.15 (+ decay)	Prototype rate with additional centre-distance decay
Bus stops (EMT)	1.00	Prototype rate applied to EMT demand units
Bus stops (TIB)	1.00	Prototype rate applied to TIB demand units
Public parking	2.00	Prototype rate per parking-space demand unit
Cruise (port)	10.00 (+ cutoff)	Prototype rate with a 1,500 m walking cutoff
Rail station	0.45	Prototype rate applied to rail demand units

Two generator layers require additional corrections. Cruise passengers are assigned a 1,500 m walking cutoff, so port-POI pairs beyond this distance are excluded regardless of exponential impedance. Resident demand receives an additional decay term, $\exp(-d_{i,\text{centre}}/1,500)$, because the likelihood of walking to the tourist core decreases with residential distance from the centre. Other configuration parameters are $D_0 = 600$ m, a maximum trip distance of 3,000 m, the round-trip factor of 2, and normalisation at the 99th percentile.

3.3.2. From raw load to normalised segment pressure

Raw load is not directly comparable across segments: wide streets accumulate more absolute load than narrow alleys even when the sense of saturation is the reverse, and the distribution is heavily skewed by a few very high-load segments near the port and stations. Both problems are resolved in two steps. First, load is divided by effective width to obtain a flow density; then a normalised logarithmic transform, referenced to the 99th percentile of positively loaded segments, maps it to the unit interval:

$$F_{\text{dens}}(s) = \frac{F_{\text{raw}}(s)}{A_m(s)} \quad (\text{trips} \cdot \text{day}^{-1} \cdot \text{m}^{-1}) \quad (8)$$

$$P_{\text{dens}}(s) = \text{clip} \left[\frac{\ln(1 + F_{\text{dens}}(s))}{\ln(1 + F_{\text{dens},p99})}, 0, 1 \right] \quad (9)$$

$P_{\text{dens}} \in [0, 1]$ is the segment-level pressure used throughout the rest of the pipeline: 0 denotes no modelled flow and 1 denotes a segment at or above the reference 99th-percentile level. All pressure indicators are proxies. Fraw is modelled rather than observed, and A_m is a cadastral estimate, so the pressure surface should be interpreted ordinally, as a relative comparison between segments rather than as an absolute pedestrian density.

3.3.3. Nodal and zonal POI pressure

The optimiser's pressure filter operates on two POI-level attributes. Nodal pressure is the expert-assessed individual popularity of a POI on a 0-10 scale. Zonal pressure is a spatial aggregation of segment pressure around the POI: for each of the 105 POIs, segments within 150 m by true point-to-line distance are collected, the median of their flow density is taken, and the resulting values are rescaled to a 0-10 integer scale by quantiles across the 105 POIs. The association between the two measures was evaluated with Spearman's rank correlation. Across the 105 POIs, $\rho = -0.148$ (two-sided $p = 0.133$), with a 95% percentile-bootstrap confidence interval of $[-0.339, 0.054]$ based on 10,000 resamples. The result provides no evidence of a monotonic association strong enough to justify treating nodal and zonal pressure as interchangeable measures; it does not establish statistical independence. The two variables are therefore retained separately in the filtering experiment.

3.4. Origin-Destination Matrices

Over the enriched, clipped network, four origin-destination matrices are built between the 105 POIs. Each POI is snapped to the nearest network node (all within 65 m, median 18 m). An undirected graph is built with segment traversal time as edge weight and stored as a sparse structure for efficient Dijkstra search. For each ordered POI pair, the minimum-time path is computed once, and four quantities are accumulated along that same physical path:

$$\text{ODLength}(i,j) = \sum \text{length}_m(s), s \in \pi^*(i,j); \quad \text{ODTime}(i,j) = \sum \text{tmin}(s), s \in \pi^*(i,j) \quad 10$$

$$\text{ODWalk}(i,j) = \sum \text{tmin}(s)[1 + \beta_W W_{\text{pen}}(s)], s \in \pi^*(i,j); \quad \text{ODPress}(i,j) = \sum \text{tmin}(s)[1 + \beta_P P_{\text{dens}}(s)], s \in \pi^*(i,j) \quad 11$$

with $\beta_W = \beta_P = 1.0$. Consequently, all four values for a POI pair describe the same physical itinerary. The minimum-time path is calculated once and the four measures are accumulated over that path, rather than calculating a different path for each criterion. Walkability and pressure therefore characterise the same trajectory whose travel time is ODTime. Because the penalised matrices are bounded transformations of the same minimum-time path, much of their variation is inherited from travel time. For this reason the present experiments use pressure to restrict the admissible POI set, while walkability is evaluated diagnostically after route generation. Criterion-specific routing and multi-objective formulations are treated as comparison cases for further robustness testing.

3.5. Route Optimisation Model

Route generation is a mixed-integer linear program of Orienteering type: given a set of thematically admissible, time-reachable candidate POIs with values r_i and visit times v_i , and a travel-time matrix t_{ij} , select and sequence a subset into a route from a fixed origin O that maximises collected tourism value within a budget T_{max} . Each thematic route is solved as an independent single-route Orienteering Problem, not as a simultaneous multi-vehicle (team) problem.

Let O be the origin and $V = \{1, \dots, n\}$ the candidate POIs, with $V_0 = V \cup \{O\}$. Decision variables are $y_i \in \{0,1\}$ (POI i visited), $x_{ij} \in \{0,1\}$ (walker goes directly from i to j), and u_i (position of i in the order, for the Miller-Tucker-Zemlin (MTZ) subtour-elimination variant introduced below). The model is:

$$\begin{aligned}
& \max \quad \sum r(i)y(i), \quad i \in V & 12 \\
(C1) \quad & \sum t(i,j)x(i,j) + \sum v(i)y(i) \leq T_{\max} & 13 \\
(C2) \quad & \sum x(0,j) = 1; \quad \sum x(i,0) = 1 & 14 \\
(C3) \quad & \sum x(j,i) = y(i); \quad \sum x(i,j) = y(i), \quad \forall i \in V & 15 \\
(C4) \quad & \sum x(i,j) \leq \sum y(i) - y(k), \quad i,j \in S; \forall S \subseteq V, |S| \geq 2, k \in S & 16 \\
(C4') \quad & u(i) - u(j) + n x(i,j) \leq n - 1, \quad \forall i,j \in V & 17 \\
(C5) \quad & y(i), x(i,j) \in \{0,1\}; \quad u(i) \geq 0 & 18
\end{aligned}$$

C1 is the time budget; C2 forces the route to leave and return to the origin exactly once (closed structure); C3 couples degree to selection, so a POI is entered and left exactly once if and only if it is visited. C4 is a selection-linked Dantzig-Fulkerson-Johnson (DFJ) subtour-elimination cut, generated iteratively rather than supplied up-front or through a solver callback: the relaxation is solved, any subtour disconnected from O is detected, one cut per node k of the subtour is added, and the model is re-solved until none remains. C4' is the equivalent bounded-size MTZ alternative, used, for robustness, in one of the experiments. C5 gives the domains.

For an open route with a free endpoint the obligation to return to the origin is dropped and a binary terminal indicator z_i marks the POI at which the route ends. The closed constraints C2-C3 are then replaced by C2'-C3' below: the route still leaves the origin once but never re-enters it, every visited POI is entered once and left once except the single terminal POI, which is entered but not left, and exactly one terminal is chosen among the visited POIs:

$$\begin{aligned}
(C2') \quad & \sum x(0,j) = 1; \quad \sum x(i,0) = 0 & 19 \\
(C3') \quad & \sum x(j,i) = y(i); \quad \sum x(i,j) = y(i) - z(i), \quad \forall i \in V & 20 \\
(C6) \quad & \sum z(i) = 1; \quad z(i) \leq y(i), \quad \forall i \in V & 21
\end{aligned}$$

Experiments 1-3 use the closed structure (C2-C3); the open structure (C2'-C3', C6) is exercised in Experiment 4, from a hotel origin, as the operationally realistic case of a visitor who need not return to their starting point. Consistent with these structures, a reachability pre-filter admits POI i only if $t_{O,i} + v_i + t_{i,\text{end}} \leq 1.05 \cdot T_{\max}$, where $t_{i,\text{end}}$ is the return time to O (closed) or zero (free endpoint); the 1.05 factor is a deliberately loose necessary condition that never removes a feasible POI, serving only to shrink the model.

Because many POI subsets attain the same maximum value, a second lexicographic stage removes the residual ambiguity: with the optimal value V^* from the first stage fixed as a constraint, it minimises total travel time, selecting the least-detouring route without changing the reported value:

$$\begin{aligned}
\min \quad & \sum t(i,j)x(i,j) \quad \text{s.t.} \quad \sum r(i)y(i) = V^* \quad \text{and } C1, C2-C3 \text{ (or } C2'-C3', C6), \\
& C4/C4', C5 & 22
\end{aligned}$$

The model is built with the PuLP modelling library (Mitchell et al. 2011) and solved with Gurobi (Gurobi Optimization, LLC 2024) under an academic Web License Service credential, falling back to the open-source HiGHS and CBC solvers if no Gurobi licence is present (Gurobi Optimization, LLC 2024), so the workflow is reproducible without commercial software. Each solve call is subject to a 150 s time limit and a 0.05 relative optimality tolerance; runs that reach the limit return the best incumbent without a certificate of optimality and are reported individually with their status, an unproven rather than an absent solution.

3.6. Dual Pressure Filter

Rather than embedding pressure and walkability together in a weighted objective, the main experiments apply pressure as a pre-solver eligibility rule. Candidate POIs whose nodal pressure or zonal pressure is equal to or greater than a user-specified threshold are removed before the MILP is solved. This preserves a direct operational interpretation of the threshold and keeps nodal, zonal and trajectory pressure separate for analysis. Walkability is not used as an exclusion rule or objective term in the present experiments; it is reported as a route-quality diagnostic. The choice does not imply that threshold filtering is superior to multi-objective optimisation. A direct benchmark against weighted or Pareto formulations is required to establish how much the design choice changes the solution set.

The optimiser also offers an optional candidate cap that pre-selects the k highest-density candidates; under a uniform visit time this reduces to selecting the k highest-valued POIs, introducing a value bias. All experiments here therefore run with the cap disabled, so each route is optimised over its full set of thematically admissible, time-

reachable POIs. In practice the cap would have affected only the Panoramic route, the only theme whose reachable pool exceeds 40 POIs.

3.7. Post-hoc Route Characterisation

Once a route is generated, it is characterised by indicators computed independently of the optimisation, so they describe the itinerary rather than shape it. For each arc actually used, the underlying penalisation factors are recovered from the matrices as $\text{factor_W} = \text{ODWalk}/\text{ODTime} - 1$ and $\text{factor_P} = \text{ODPress}/\text{ODTime} - 1$, and aggregated into two distance-weighted route-level indicators: a walkability indicator $\langle Q \rangle = \text{mean of } 1/(1+\text{factor_W})$, on the same $(0,1]$ scale as the segment index, and a trajectory-pressure indicator $\langle P \rangle = \text{mean of factor_P}$. These trajectory-level indicators are conceptually distinct from the nodal pressure of visited POIs, which is reported separately. In particular, walkability is a diagnostic in the current experimental design, not an active route-shaping criterion. Additional descriptors, thematic diversity (Shannon entropy over categories) and value per minute, are also recorded.

3.8. Experimental Design

Four experiments are used, with one main factor varied at a time. Experiment 1 generates five thematic baseline routes from a central origin with a 120-minute budget. Experiment 2 varies the budget from 60 to 240 minutes. Experiment 3 applies the dual pressure filter at four severity levels to examine the trade-off between value and pressure and to compare POI-level pressure with corridor exposure. Experiment 4 replaces the central origin with a geocoded peripheral accommodation address and compares closed and open route structures. Unless stated otherwise, the shared configuration is a uniform 5-minute visit time, no candidate cap, a 0.05 solver gap, a 150 s time limit and DFJ subtour elimination. Walkability and trajectory pressure are post-hoc descriptors and do not affect route selection. Because POI values, visit times and nodal pressure are prototype inputs, the experiments evaluate the behaviour of the framework under a controlled configuration rather than visitor behaviour in Palma.

Experiment 4 illustrates one data requirement of a transferable itinerary service: an arbitrary accommodation origin must be geocoded and connected to a queryable pedestrian graph. In the present implementation this operation is performed locally. A tourism data space could provide the governed and interoperable access layer needed to obtain the underlying network and related destination assets, but this study does not test connectors, semantic interoperability or access-control mechanisms.

4. Results

The four experiments use the same core configuration unless otherwise stated: a uniform 5-minute visit time, no candidate cap, a 0.05 solver gap, a 150 s time limit and DFJ subtour elimination. Route walkability and trajectory pressure are reported as post-hoc descriptors and do not affect route selection. Values from runs that reach the time limit are best incumbents rather than certified optima and are identified in Sect. 4.5.

4.1. Experiment 1: Five Thematic Baseline Routes

From a common central origin (Plaça Major, POI 18) the optimiser produces five thematic routes, each defined by the POI categories it may visit: Panoramic (all six categories), Classic Cultural (museums and monumental heritage), Historic Walk (urban spaces and heritage), Local Experience (commerce and gastronomy) and Art Route (galleries and museums). Fig. 3 shows the five routes on the pedestrian network: all depart from the same origin but reach different parts of the historic centre, confirming that the thematic definitions yield genuinely distinct itineraries, the first, most basic thing a planner would want to verify. Online Resource 1, Fig. S6 in the Supplementary Material reproduces the five routes at full page size.

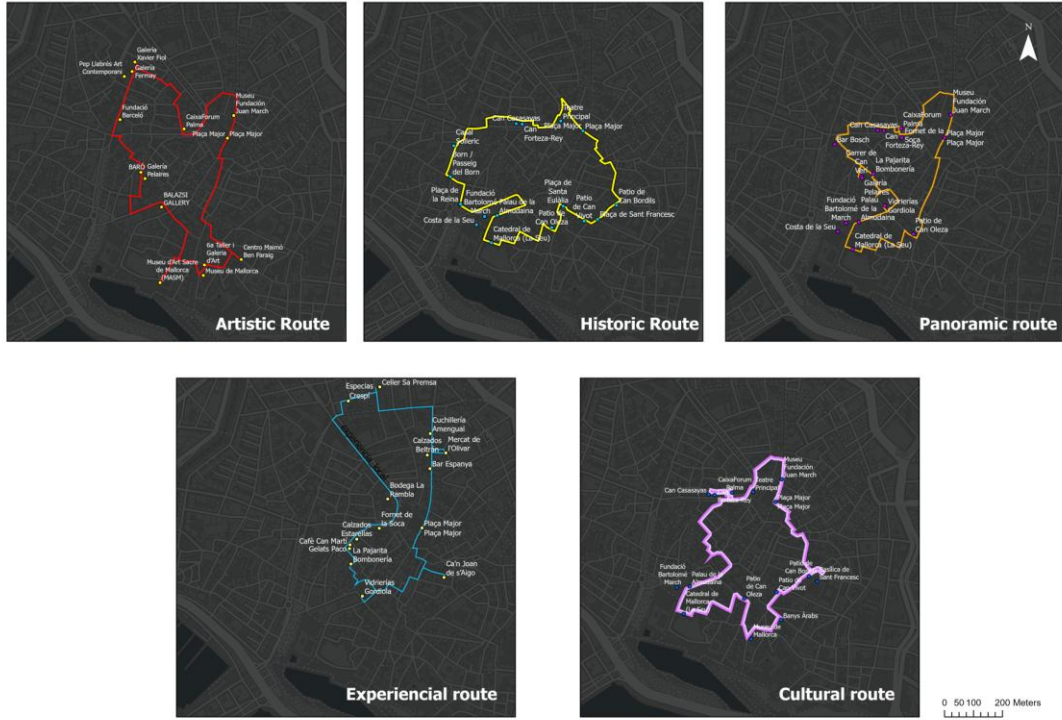


Fig. 3 The five thematic baseline routes on the pedestrian street network of the historic centre of Palma (origin at the Plaça Major, POI 18; $T_{\max} = 120$ min). Coordinates in UTM zone 31N (EPSG:25831)

Table 3 characterises the five routes. All exhaust the time budget almost exactly (117.7 to 119.9 of 120 min), so the constraint is binding. The Panoramic route attains the highest incumbent value (144.8); this run reached the 150 s time limit and its exact optimality was not certified. The narrower routes obtain less, with the Art Route lowest (96.7). Walkability is essentially uniform across routes ($\langle Q \rangle$ 0.704 to 0.722), whereas trajectory pressure varies more, lowest for Local Experience (0.793) and highest for the Art Route (0.870). This indicates that the mean walkability diagnostic varies little across the compact core, while pressure exposure depends more on the corridors selected by each thematic configuration.

Table 3 Characterisation of the five thematic baseline routes (origin POI 18, $T_{\max} = 120$ min, closed, uniform 5-min visit, no candidate cap). † Best incumbent at the 150 s time limit; optimality not certified.

Route	POIs	Time	Dist. (m)	Value	$\langle Q \rangle$	$\langle P \rangle$
Panoramic	18	119.9	2231	144.8†	0.709	0.857
Classic Cultural	17	119.5	2579	128.5	0.721	0.822
Historic Walk	17	117.7	2430	130.2	0.719	0.847
Local Experience	16	119.4	2935	106.9	0.722	0.793
Art Route	15	119.6	3337	96.7	0.704	0.870

4.2. Experiment 2: Temporal Sensitivity

The second experiment sweeps the budget of the same five routes from 60 to 240 minutes. Because the uniform visit time removes variation in dwell cost, this isolates the effect of the budget itself. Value increases monotonically for every route in the returned solutions, with the Panoramic route highest throughout (66.7 at 60 min to 276.2 at 240 min; Table 4, Fig. 4). The Panoramic solutions at 60, 90 and 120 minutes and the Historic Walk at 90 minutes reached the 150 s time limit, so those four values are best incumbents rather than certified optima.

Table 4 Total tourism value by route and time budget (min). * Best incumbent at the 150 s time limit; optimality not certified.

Route \ Tmax	60	90	120	150	180	210	240
Panoramic	66.7*	104.0*	144.8*	181.4	217.0	246.3	276.2
Classic Cultural	62.0	96.0	128.5	152.4	174.1	193.8	207.2
Historic Walk	63.5	97.4†	130.2	158.2	188.8	214.6	238.8
Local Experience	56.0	85.4	106.9	127.3	145.3	160.7	171.2
Art Route	49.4	74.4	96.7	112.1	117.6	122.8	122.8

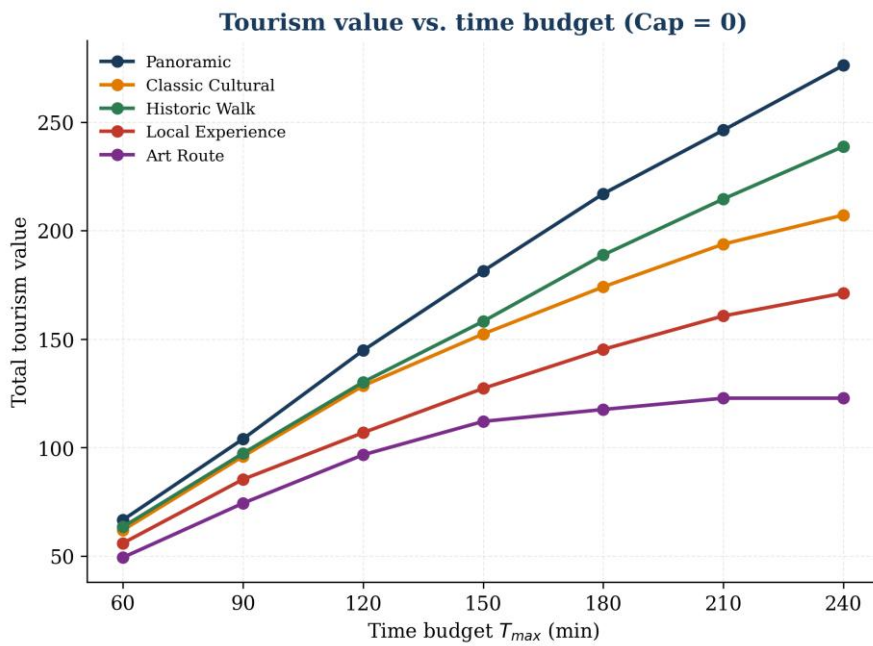


Fig. 4 Tourism value versus time budget. Value grows monotonically; the Panoramic route dominates throughout

Marginal value per minute declines as the time budget increases (Fig. 5b). The narrow Art Route reaches its maximum of 19 POIs at 210 minutes (Table 5, Fig. 5a), so an additional 30 minutes produces no extra value. The broader routes continue to add POIs, but each increment requires longer connections to remaining attractions and therefore produces smaller gains per minute.

Table 5 Number of POIs visited by route and time budget. † Corresponding optimisation reached the 150 s time limit; solution is the best incumbent.

Route \ Tmax	60	90	120	150	180	210	240
Panoramic	8†	13†	18†	23	28	33	37
Classic Cultural	8	12	17	21	24	27	30
Historic Walk	8	12†	17	21	26	30	34
Local Experience	8	12	16	19	22	25	26
Art Route	7	11	15	17	18	19	19

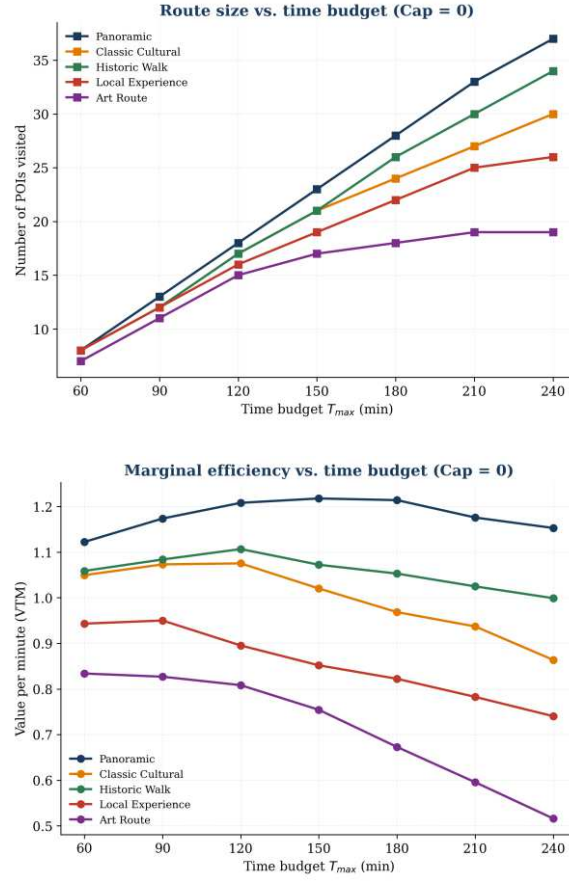


Fig. 5 (a) POIs visited versus time budget; the Art Route saturates at 19 POIs. (b) Value per minute versus time budget; marginal efficiency declines for all routes

Route walkability and trajectory pressure behave differently from value and route size. Across the 35 returned solutions, mean walkability and trajectory pressure remain stable over the full range of time budgets (Fig. 6). The pooled values are $\langle Q \rangle = 0.712$ (SD 0.012) and $\langle P \rangle = 0.838$ (SD 0.025). Under the fixed minimum-time routing used here, increasing the available time changes how many attractions can be included but does not substantially change the mean pedestrian environment traversed. Four temporal-sweep solutions reached the time limit and are reported as best incumbents; this solver status qualifies the exact objective values but does not change the descriptive pattern across the sweep.

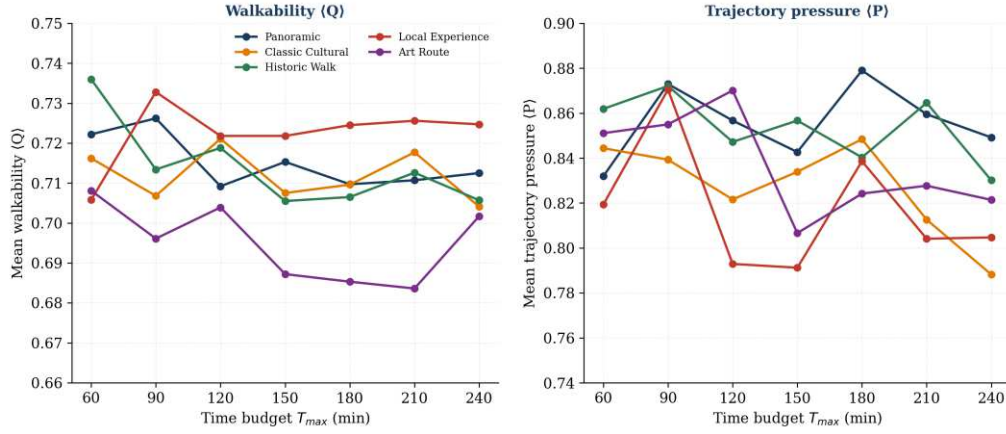


Fig. 6 (a) Mean walkability $\langle Q \rangle$ and (b) mean trajectory pressure $\langle P \rangle$ remain stable across time budgets

4.3. Experiment 3: Dual Pressure Filtering

The third experiment applies the dual filter to the candidate pool before optimisation: any POI whose nodal or zonal pressure is equal to or greater than a common threshold is removed, and the value-maximising route is solved over the survivors. Four thresholds (7, 6, 5, 4) are tested at a fixed 120-minute budget; the pool shrinks from 105 POIs to 74, 48, 33 and 21. Online Resource 1, Fig. S8 overlays the filtered routes on the unfiltered one. The unfiltered 120-minute Panoramic reference is a time-limited incumbent, and the relevant table captions identify this status. The experiment is used primarily to compare how POI-level filtering and corridor exposure respond to the same change in admissible attractions.

Value and routes contract as filtering tightens. Aggregated mean value falls from 121.4 to 32.3 at threshold 4, a 73% reduction (Table 6, Figure 7a). The effect is uneven across themes: broad routes degrade gracefully, the Panoramic route retains 10 POIs and 65.9 value at the strictest threshold by substituting filtered-out POIs with alternatives, whereas narrow routes contract sharply, the Historic Walk falling to 2 POIs and 11.4 value (Table 7, Figure 7b). Under this configuration a narrow theme combined with a strict pressure constraint leaves too few admissible low-pressure POIs to form a substantial itinerary, and the framework makes that limitation explicit rather than absorbing it into a weighted score.

Table 6 Total tourism value by route under progressive pressure filtering ($T_{\max} = 120$ min). † The unfiltered Panoramic baseline is a time-limited incumbent.

Route \ threshold	No filter	7	6	5	4
Panoramic	144.8†	123.1	104.6	84.0	65.9
Classic Cultural	128.5	88.9	64.4	33.5	18.9
Historic Walk	130.2	87.6	41.1	18.2	11.4
Local Experience	106.9	87.0	85.8	70.0	53.5
Art Route	96.7	74.7	44.0	24.7	11.7

Table 7 Number of POIs visited by route under progressive pressure filtering. † The unfiltered Panoramic baseline is a time-limited incumbent.

Route \ threshold	No filter	7	6	5	4
Panoramic	18†	17	15	13	10
Classic Cultural	17	13	10	5	3
Historic Walk	17	13	7	3	2

Route \ threshold	No filter	7	6	5	4
Local Experience	16	14	13	11	8
Art Route	15	12	7	4	2

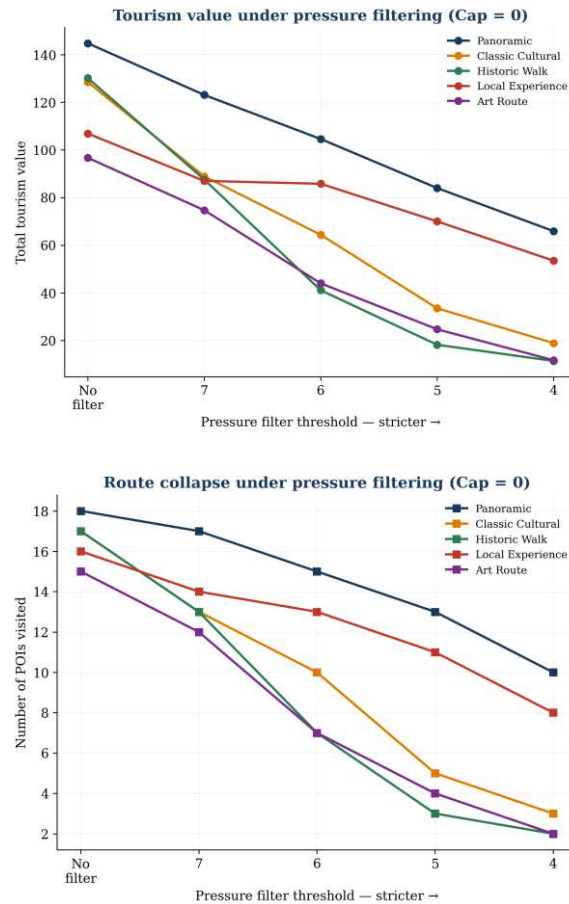


Fig. 7 (a) Tourism value and (b) route size under progressive pressure filtering

The relevant comparison is between the pressure variables targeted by the filter and corridor exposure (Table 8, Fig. 8). Mean nodal pressure among visited POIs falls monotonically from 4.18 with no filter to 2.54 at threshold 4, a reduction of 39.2%. Mean zonal pressure also falls. Trajectory pressure changes much less and non-monotonically, from 0.838 with no filter to 0.807 at threshold 4, while its lowest mean value occurs at threshold 7. Thus, under the baseline pressure-model parameterisation, the strictest filter produces a 3.7% relative reduction in mean trajectory pressure compared with a 39.2% reduction in mean nodal pressure. This is a descriptive model result, not an estimated intervention effect; its robustness depends on the parameters used to construct the pressure surface and should be tested by sensitivity analysis.

Table 8 Aggregated value, nodal pressure of visited POIs, trajectory pressure and route size by filter threshold (mean over the five routes). The unfiltered aggregate includes the time-limited Panoramic incumbent.

Scenario	Mean value	Mean nodal P	Mean zonal P	Mean traj. P	Mean POIs
No filter (105 POIs)	121.4	4.18	5.63	0.838	16.6
thr = 7 (74 POIs)	92.3	3.62	3.76	0.786	13.8

Scenario	Mean value	Mean nodal P	Mean zonal P	Mean traj. P	Mean POIs
thr = 6 (48 POIs)	68.0	3.17	3.22	0.797	10.4
thr = 5 (33 POIs)	46.1	2.89	2.29	0.790	7.2
thr = 4 (21 POIs)	32.3	2.54	1.40	0.807	5.0

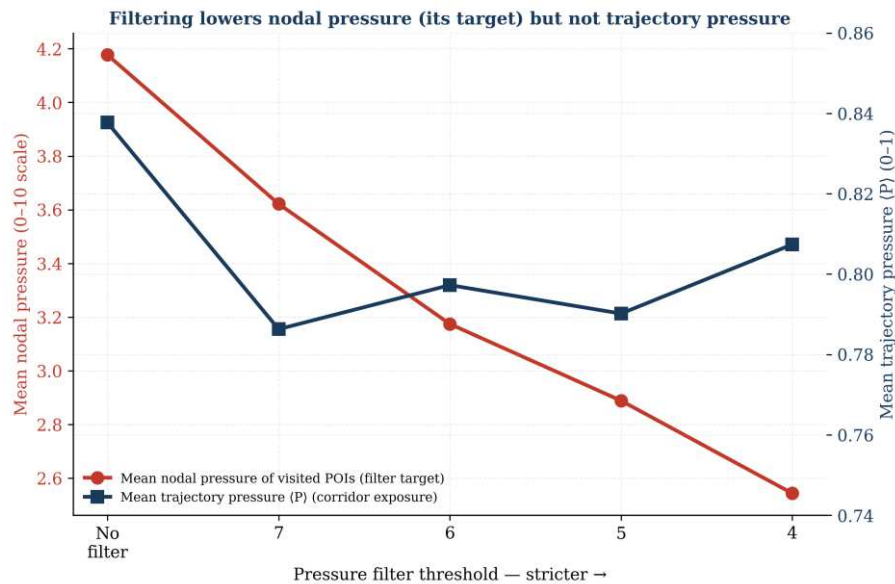


Fig. 8 As the filter tightens, the mean nodal pressure of visited POIs (left axis, the filter's target) falls monotonically, whereas mean trajectory pressure (right axis, corridor exposure) does not. The two pressure dimensions respond in clearly different ways

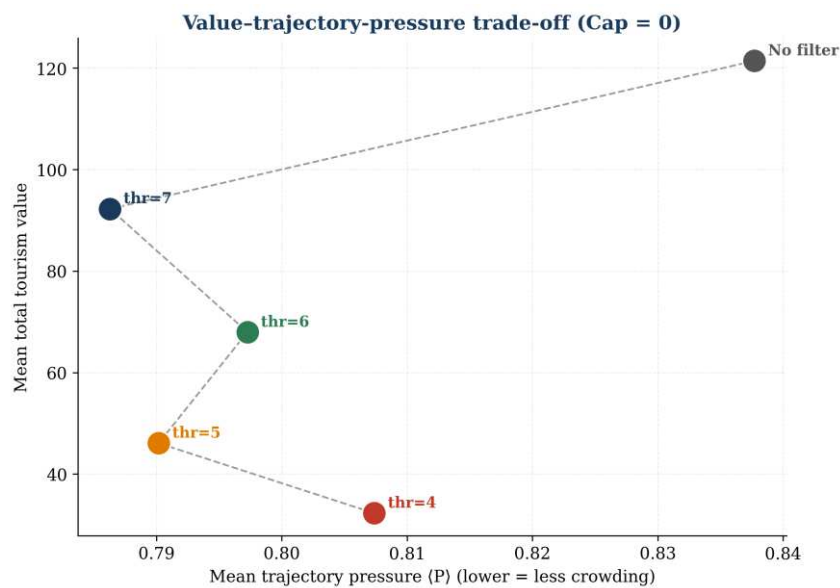


Fig. 9 Value against trajectory pressure across filter thresholds. Strict filtering sacrifices a large amount of value for only a small, non-monotone change in corridor exposure

Taken together, the results argue for keeping the pressure dimensions separate in the present routing framework. The rank-correlation analysis in Sect. 3.3.3 does not show an association strong enough to justify treating nodal and zonal pressure as interchangeable. The filtering experiment further shows that, under the baseline parameterisation, reducing POI-level pressure does not produce a comparable reduction in corridor exposure. Fig. 9 makes this trade-off visible: stricter filtering removes a substantial amount of tourism value while trajectory pressure remains within a relatively narrow range. For destination management, attraction filtering and corridor management should therefore be treated as distinct control mechanisms unless subsequent calibration shows otherwise.

4.4. Experiment 4: Hotel Origin versus Central POI, Closed versus Open

Experiment 4 uses a visitor's accommodation as the origin rather than a central landmark. A peripheral hotel address at Carrer de l'Arxiduc Lluís Salvador 46 is geocoded and snapped to the pedestrian graph. Five 180-minute routes are then solved from this origin, first as closed routes that must return to the hotel and then as open routes with a free endpoint. The comparison isolates the effect of origin and shows how route structure can compensate for the time cost of reaching the historic core.

The results show both expected effects, although two peripheral closed-route values are based on time-limited incumbents. Closed routes from the peripheral origin collect less value than the central closed baseline because part of the budget is used to reach and leave the historic core. The reduction is largest for routes that depend most on the monumental centre. Allowing a free endpoint recovers much of this loss in the returned solutions: the Panoramic route gains 22.6 value units and the Historic Walk gains 16.1 relative to their peripheral closed versions, whereas the Art Route changes little because its candidate pool is already close to exhaustion (Table 9, Fig. 10). Because the experiment does not include an open route from the central origin, the magnitude attributable specifically to a peripheral start cannot be isolated from the general benefit of an open structure.

Table 9 Hotel origin versus central POI at $T_{\max} = 180$ min. † Arxiduc closed Panoramic and Historic Walk are best incumbents at the 150 s time limit; optimality not certified.

Route	Plaça (closed)	Arxiduc (closed)	Δ_{loc}	Arxiduc (open)	Δ_{open}
Panoramic	217.0	186.9†	-30.1	209.5	+22.6
Classic Cultural	174.1	159.6	-14.5	170.3	+10.7
Historic Walk	188.8	166.8†	-22.0	182.9	+16.1
Local Experience	145.3	140.8	-4.5	150.3	+9.5
Art Route	117.6	116.6	-1.0	117.3	+0.7
Mean	168.6	154.1	-14.4	166.1	+11.9

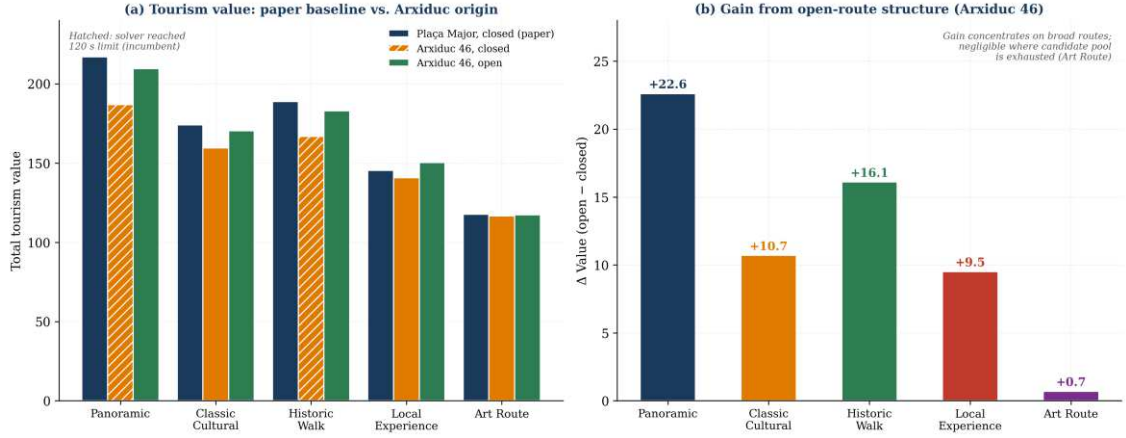


Fig. 10 Effect of origin and route structure. (a) Tourism value across the central baseline (Plaça Major, closed) and the two peripheral hotel scenarios (Arxiduc, closed and open). (b) Value gain from opening the route at the peripheral origin: the effect concentrates on broad routes and is negligible when the candidate pool is exhausted

The Panoramic route from Arxiduc retains a category entropy of 1.65 and includes all six categories, almost identical to the central-origin route. The peripheral start therefore reduces the amount of value collected more than the thematic variety of the itinerary. For practical route design, an open itinerary can partly compensate for a peripheral accommodation origin without narrowing the range of attraction types visited.

4.5. Solver Behaviour and Optimality Status

The optimisation uses a finite 150 s time limit and a 0.05 relative optimality tolerance. Some runs therefore return a best incumbent rather than a certified optimum. Of the 35 runs in the temporal sweep, 31 reached a certified optimum. Four reached the time limit: the Panoramic route at 60, 90 and 120 minutes and the Historic Walk at 90 minutes (Table 10). These incumbent values are retained for transparency and are not described as exact optima. The 120-minute Panoramic incumbent is also used as a reference in several comparisons, so the reported solver status should be considered when interpreting small numerical differences.

Table 10 Runs that reached the 150 s time limit without a certified optimum (temporal sweep, no candidate cap). Values are the best incumbent objectives obtained at the limit; optimality was not certified within the tolerance

Route	T_max (min)	POIs	Value	Status	Elapsed (s)
Panoramic	60	8	66.7	Time limit	150.5
Panoramic	90	13	104.0	Time limit	150.4
Historic Walk	90	12	97.4	Time limit	150.2
Panoramic	120	18	144.8	Time limit	150.5

In the origin-and-structure experiment, two of the ten runs, the Panoramic and Historic Walk closed routes from Arxiduc, likewise reached the limit without a certified optimum; the remaining eight reached certified optimality. Where a value in Tables 3, 4, 6, 7, 8 or 9 depends on one of these time-limited solutions, it is reported as a best incumbent rather than a proven optimum. The solver statuses limit claims about exact objective differences but do not affect the descriptive comparison between route structures.

5. Discussion

The results address two linked questions: whether pressure-aware tourist routing with explicit walkability diagnostics can be implemented as a reusable analytical service over tourism data, and whether attraction-level pressure management also changes corridor exposure. The experiments show that the framework can generate distinct time-bounded itineraries from different origins and under different pressure rules while retaining route walkability and the three pressure measures as separately inspectable quantities. They also show that the response of the routing system depends on the spatial level at which pressure is represented.

5.1. Value scales with time, while route-level walkability and pressure vary little

The temporal sweep shows that collected tourism value increases monotonically with the available budget but with diminishing returns. This is consistent with the Orienteering Problem, because later attractions usually require longer connecting trips (Gunawan et al. 2016; Vansteenwegen et al. 2011), and with the tourist-trip-design literature (Ruiz-Meza and Montoya-Torres 2022). Route-level walkability and trajectory pressure, however, remain nearly constant across budgets ($\langle Q \rangle = 0.712$, SD 0.012; $\langle P \rangle = 0.838$, SD 0.025). Under the fixed minimum-time routing used here, additional time increases the quantity of attractions that can be visited without substantially changing the pedestrian environments traversed. This supports H1. The result is specific to the routing configuration tested and does not imply that walkability- or pressure-optimised paths between the same POIs would produce the same outcome.

5.2. Attraction pressure and corridor exposure are not interchangeable

A central methodological issue is how pressure should enter the model. Multi-criteria methods can combine several dimensions into a single score (Hassanshahi et al. 2023), but the resulting weights are difficult to justify and can hide differences between indicators (Nalmpantis et al. 2019). Across the 105 POIs, nodal and zonal pressure show a weak, non-significant rank association (Spearman's $\rho = -0.148$, $p = 0.133$; 95% bootstrap confidence interval $[-0.339, 0.054]$). This does not demonstrate independence, but it provides no basis for treating the two measures as interchangeable. In the baseline filtering experiment, mean nodal pressure falls from 4.18 to 2.54 as filtering tightens, whereas trajectory pressure remains between about 0.79 and 0.84. The two scales of pressure therefore need to remain separately visible in the analysis.

This result is relevant to overtourism management, where visitor concentration in historic centres creates tensions between destination competitiveness and urban liveability (García-Hernández et al. 2017; Koens et al. 2018; Milano et al. 2019; Peeters et al. 2018; Séraphin et al. 2018). Measures such as timed entry, quotas or attraction redistribution operate mainly on individual sites. The baseline experiment indicates that redirecting visitors towards lower-pressure POIs can still leave routes on many of the same busy corridors. This is consistent with the view that overtourism is experienced at the scale of the wider urban system rather than only at individual attractions (Koens et al. 2018), but the 39.2% versus 3.7% contrast remains conditional on the current pressure-model parameterisation. The observed data are consistent with H2, and H3 is supported within the tested model configuration. A sensitivity analysis of gravity-model parameters and a direct comparison with multi-objective routing are needed before stronger generalisation.

5.3. Origin and route structure

The hotel-origin experiment shows that origin and route structure have a substantial operational effect. A peripheral accommodation reduces collected value, especially for themes concentrated in the monumental core (Asero et al. 2016). Allowing the route to end freely recovers much of that loss. Because no open route was solved from the central origin, the experiment cannot separate the general benefit of a free endpoint from the part specifically associated with a peripheral start. Even with that limitation, the result identifies a simple design option for visitor-facing services: open itineraries can make better use of the available time for users staying outside the core. The preservation of thematic diversity from the peripheral origin also suggests that location affects the amount of value collected more strongly than the variety of the itinerary. H4 is therefore supported for the location effect and only conditionally supported for the proposed compensation effect.

5.4. Tourism data spaces as the enabling infrastructure

The framework's transferability depends mainly on access to interoperable input data. Producing the Palma application required a cadastral- and LiDAR-derived description of 10,182 pedestrian segments, an inventory of 105 POIs and eight demand-generator layers from several organisations and update cycles (Table 1). Common European data spaces are intended to reduce this integration cost by providing governed access and shared semantics (European Commission 2020, 2022), while the tourism-specific European framework explicitly identifies governance, semantics, technical interoperability and tested use cases as enabling conditions (European Commission 2023). Under those conditions, the same routing logic could consume equivalent datasets from another destination without changing the core optimisation model.

In an operational implementation, a visitor would provide an accommodation address and a time budget. The application would resolve the address, request the pedestrian network, POI inventory and required pressure and morphology layers, build or retrieve the origin-destination matrices, apply the selected pressure rule and solve the itinerary problem. The visitor would receive a route and its walkability and pressure profile, while the destination

manager could analyse how repeated recommendations distribute demand across the street network. Table 1 provides a first specification of the assets needed for this service, although the present study does not prescribe the semantic identifiers or connector standards through which they should be exchanged.

This interpretation has two limits. First, the study evaluates the analytical layer rather than a live data-space implementation, so interoperability, access control and governance are not tested. Second, interoperable data do not by themselves improve destination management; organisations need the institutional capacity to interpret and act on the resulting information (Ordóñez-Martínez et al. 2024; Gretzel et al. 2015). The contribution is not a new data-space architecture or a new Orienteering Problem algorithm. It is a tested, reproducible service specification that integrates a detailed pedestrian graph, morphology-derived walkability diagnostics, multi-level tourism pressure and time-bounded itinerary optimisation, while identifying the cross-domain assets such a service requires.

5.5. Route robustness under pressure filtering

The filtering experiment also shows that route robustness depends on thematic breadth. Broad route definitions can replace excluded POIs with alternatives, whereas narrow themes contract to two or three POIs once the pressure threshold becomes restrictive. This is a structural property of the candidate set rather than a failure of the optimiser. In practical terms, a destination manager can use the model to identify which thematic products remain viable under stricter decongestion rules and which depend on a small number of high-pressure attractions. This qualification complements the route literature, which generally treats thematic coherence as an advantage (Lin et al. 2024; Nagy 2012; Szromek and Butler 2024), by showing that very narrow themes can be less robust when pressure constraints are introduced.

5.6. Limitations and future work

The study is a proof of concept. The walkability layer is based on cadastral, terrain and LiDAR data, but its transformation into a composite index depends on expert-defined thresholds and weights. The weights (0.30, 0.25, 0.25 and 0.20) have not been subjected to a formal sensitivity analysis, and walkability is diagnostic rather than prescriptive in the current experiments. The POI value scores, visit times, nodal pressure scores and gravity-model parameters are prototype inputs rather than observations of visitor behaviour. The 39.2% versus 3.7% contrast must therefore be read as a model response under the baseline parameterisation, not as an estimated effect of a tourism policy in Palma. Future robustness work should examine plausible variations in the gravity distance-decay parameter, demand-generator rates, cruise-distance cutoff and nodal-pressure scores. Calibration against ticketing or mobile-positioning data, visitor surveys and pedestrian sensing would be required for operational deployment (Gao and Schmöcker 2021).

Other limitations concern experimental coverage and transferability. Only one peripheral accommodation origin was tested, and the open-route experiment did not include an open central-origin baseline. The uniform 5-minute visit time was used to isolate the effect of the time budget, but heterogeneous dwell times would alter route selection. The current model generates one route per run; simultaneous multi-route or multi-visitor problems would require a team variant of the Orienteering Problem (Gunawan et al. 2016) and would provide a better setting for analysing recommendation-induced concentration (Kong et al. 2024). External routing services may be useful for display, but the evaluated travel times and route indicators must remain tied to the internal pedestrian graph. Threshold filtering has not yet been benchmarked against a multi-objective formulation, and transferability to another mature destination has not yet been demonstrated empirically.

6. Conclusions

This study develops a reproducible GIS and optimisation service for pressure-aware pedestrian tourist itineraries with explicit route-level walkability diagnostics and tests it in the historic centre of Palma. The framework combines a 10,182-segment pedestrian network, a morphology-based walkability index, three distinct representations of tourism pressure, and an Orienteering Problem solved under different time budgets, thematic filters, origins and route structures. The experiments keep the pressure scales and walkability diagnostic separately inspectable instead of absorbing them into a single weighted score.

The results are consistent with H1-H3 under the tested configuration and provide partial support for H4. Tourism value increases with the time budget but with diminishing returns, while route walkability and corridor pressure vary little under fixed minimum-time routing. Nodal and zonal POI pressure show a weak, non-significant rank association (Spearman's $\rho = -0.148$, $p = 0.133$; 95% bootstrap confidence interval $[-0.339, 0.054]$), so they should not be treated as interchangeable on the present evidence. Under the baseline pressure parameterisation, progressive filtering reduces mean nodal pressure among visited attractions by 39.2%, whereas trajectory pressure at the

strictest threshold is 3.7% below the unfiltered value and changes non-monotonically across thresholds. This indicates a scale mismatch between attraction filtering and corridor exposure within the model rather than an estimated causal effect in Palma. A peripheral accommodation origin also reduces collected value, and an open route recovers much of that loss in the returned solutions; two peripheral closed solutions are time-limited incumbents and are identified as such.

Two additional results are relevant for implementation. Broad thematic routes remain more robust under pressure filtering because excluded attractions can be replaced, whereas narrow themes can collapse quickly when the candidate set is restricted. In addition, starting from an accommodation address preserves thematic diversity even when it reduces the amount of value that can be collected. These results can help destination managers evaluate the practical consequences of route design rules rather than relying only on the optimal objective value.

As a proof of concept, the framework provides a methodological basis for a calibrated route-planning service rather than a ready-to-deploy recommendation system. Wider use depends on access to interoperable territorial, mobility, demand and attraction data, which is the type of integration problem addressed by tourism data space initiatives (European Commission 2023). Future work should examine the stability of the time-limited MILP solutions under longer solver runs, test the pressure result across alternative gravity-model parameterisations and plausible perturbations of nodal pressure, and compare threshold filtering with multi-objective alternatives. Subsequent validation should calibrate POI values and pressure against observed data, test open routes from both central and peripheral origins, and evaluate the method in a second destination.

Supplementary Information

Online Resource 1 contains Fig. S1, labelled inventory of the 105 points of interest; Fig. S2, POI inventory attributes; Fig. S3, pedestrian-network morphology and walkability; Fig. S4, spatial distribution of the eight demand generators; Fig. S5, normalised tourist pressure on the pedestrian network; Fig. S6, five thematic routes from the central origin; Fig. S7, effect of the 60-240 minute time budget; Fig. S8, effect of progressive dual pressure filtering; Fig. S9, five thematic routes from the peripheral accommodation origin; Table S1, the complete catalogue of 105 georeferenced POIs; and Table S2, the Spearman rank-association analysis for nodal and zonal pressure across the 105 POIs.

References

1. Anuar MAK, Marzuki A (2022) Critical elements in determining tourism routes: A systematic literature review. *Geografic* 127:319-340. <https://doi.org/10.37040/geografic.2022.010>
2. Asero V, Gozzo S, Tomaselli V (2016) Building tourism networks through tourist mobility. *Journal of Travel Research* 55:751-763. <https://doi.org/10.1177/0047287515569777>
3. Banerjee A, Mahmudov T, Adler E, Aisyah FN, Wörndl W (2025) Modeling sustainable city trips: integrating CO₂e emissions, popularity, and seasonality into tourism recommender systems. *Information Technology & Tourism* 27:189-226. <https://doi.org/10.1007/s40558-024-00303-1>
4. Briedenhann J, Wickens E (2004) Tourism routes as a tool for the economic development of rural areas: vibrant hope or impossible dream? *Tourism Management* 25:71-79. [https://doi.org/10.1016/S0261-5177\(03\)00063-3](https://doi.org/10.1016/S0261-5177(03)00063-3)
5. Cao J, Deng F (2025) Tourism route planning recommendation algorithm based on attention mechanism and multi-dimensional portrait scenarios. *Discover Computing* 28:220. <https://doi.org/10.1007/s10791-025-09752-6>
6. Cenamor I, de la Rosa T, Núñez S, Borrajo D (2017) Planning for tourism routes using social networks. *Expert Systems with Applications* 69:1-9. <https://doi.org/10.1016/j.eswa.2016.10.030>
7. Dalla Vecchia A, Migliorini S, Quintarelli E, Gambini M, Belussi A (2024) Promoting sustainable tourism by recommending sequences of attractions with deep reinforcement learning. *Information Technology & Tourism* 26:449-484. <https://doi.org/10.1007/s40558-024-00288-x>
8. Denstadli JM, Jacobsen JKS (2011) The long and winding roads: Perceived quality of scenic tourism routes. *Tourism Management* 32:780-789. <https://doi.org/10.1016/j.tourman.2010.06.014>
9. Deshmukh RA, Collarana D, Gelhaar J, Theissen-Lipp J, Lange C, Arnold BT, Curry E, Decker S (2024) Challenges and opportunities for enabling the next generation of cross-domain dataspace. *Proceedings of the Second International Workshop on Semantics in Dataspace (SDS 2024)* 3705. <https://doi.org/10.18154/RWTH-2024-06249>
10. European Commission (2020) A European strategy for data (COM(2020) 66 final). European Commission. <https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:52020DC0066>
11. European Commission (2022) Commission staff working document on common European data spaces (SWD(2022) 45 final). European Commission. <https://digital-strategy.ec.europa.eu/en/library/staff-working-document-data-spaces>

12. European Commission (2023) Towards a Common European Tourism Data Space: boosting data sharing and innovation across the tourism ecosystem. *Official Journal of the European Union* C 263:1-13. [https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:52023XC0726\(01\)](https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:52023XC0726(01))
13. European Parliament, Council of the European Union (2022) Regulation (EU) 2022/868 of the European Parliament and of the Council of 30 May 2022 on European data governance and amending Regulation (EU) 2018/1724 (Data Governance Act). *Official Journal of the European Union* L 152:1-44. <https://data.europa.eu/eli/reg/2022/868/oj>
14. European Parliament, Council of the European Union (2023) Regulation (EU) 2023/2854 of the European Parliament and of the Council of 13 December 2023 on harmonised rules on fair access to and use of data and amending Regulation (EU) 2017/2394 and Directive (EU) 2020/1828 (Data Act). *Official Journal of the European Union* L 2023/2854. <https://data.europa.eu/eli/reg/2023/2854/oj>
15. Ewing R, Handy S (2009) Measuring the unmeasurable: Urban design qualities related to walkability. *Journal of Urban Design* 14:65-84. <https://doi.org/10.1080/13574800802451155>
16. Frank LD, Sallis JF, Saelens BE, Leary L, Cain K, Conway TL, Hess PM (2010) The development of a walkability index: Application to the Neighborhood Quality of Life Study. *British Journal of Sports Medicine* 44:924-933. <https://doi.org/10.1136/bjsm.2009.058701>
17. Franklin M, Halevy A, Maier D (2005) From databases to dataspace: A new abstraction for information management. *SIGMOD Record* 34:27-33. <https://doi.org/10.1145/1107499.1107502>
18. Gao Y, Schmöcker JD (2021) Estimation of walking patterns in a touristic area with Wi-Fi packet sensors. *Transportation Research Part C: Emerging Technologies* 128:103219. <https://doi.org/10.1016/j.trc.2021.103219>
19. García A, Vansteenwegen P, Arbelaitz O, Souffriau W, Linaza MT (2013) Integrating public transportation in personalised electronic tourist guides. *Computers & Operations Research* 40:758-774. <https://doi.org/10.1016/j.cor.2011.03.020>
20. García-Hernández M, de la Calle-Vaquero M, Yubero C (2017) Cultural heritage and urban tourism: Historic city centres under pressure. *Sustainability* 9:1346. <https://doi.org/10.3390/su9081346>
21. Gavalas D, Kasapakis V, Konstantopoulos C, Pantziou G, Vathis N, Zaroliagis C (2015) The eCOMPASS multimodal tourist tour planner. *Expert Systems with Applications* 42:7303-7316. <https://doi.org/10.1016/j.eswa.2015.05.046>
22. Gretzel U, Sigala M, Xiang Z, Koo C (2015) Smart tourism: Foundations and developments. *Electronic Markets* 25:179-188. <https://doi.org/10.1007/s12525-015-0196-8>
23. Gunawan A, Lau HC, Vansteenwegen P (2016) Orienteering problem: A survey of recent variants, solution approaches and applications. *European Journal of Operational Research* 255:315-332. <https://doi.org/10.1016/j.ejor.2016.04.059>
24. Gurobi Optimization, LLC (2024) Gurobi Optimizer reference manual. Gurobi Optimization, LLC. <https://www.gurobi.com/documentation/>
25. Hashimoto A, Telfer DJ (2003) Positioning an emerging wine route in the Niagara region: Understanding the wine tourism market and its implications for marketing. *Journal of Travel & Tourism Marketing* 14:61-76. https://doi.org/10.1300/J073v14n03_04
26. Hassanshahi G, Soltani A, Roosta M, Askari S (2023) Walking as soft mobility: A multi-criteria GIS-based approach for prioritizing tourist routes. *Frontiers of Architectural Research* 12:1080-1096. <https://doi.org/10.1016/j.foar.2023.09.001>
27. Heris FSM, Ghannadpour SF, Bagheri M, Zandieh F (2022) A new accessibility based team orienteering approach for urban tourism routes optimization (a real life case). *Computers & Operations Research* 138:105620. <https://doi.org/10.1016/j.cor.2021.105620>
28. Kemperman ADAM, Borgers AWJ, Timmermans HJP (2009) Tourist shopping behavior in a historic downtown area. *Tourism Management* 30:208-218. <https://doi.org/10.1016/j.tourman.2008.06.002>
29. Koens K, Postma A, Papp B (2018) Is overtourism overused? Understanding the impact of tourism in a city context. *Sustainability* 10:4384. <https://doi.org/10.3390/su10124384>
30. Kong Y, Yi K, Wang L, Peng C, Nguyen LM, Ma Q (2024) RPMTD: A route planning model with consideration of tourists' distribution. *IEEE Access* 12:69488-69504. <https://doi.org/10.1109/ACCESS.2024.3400373>
31. Liao Z, Zheng W (2018) Using a heuristic algorithm to design a personalized day tour route in a time-dependent stochastic environment. *Tourism Management* 68:284-300. <https://doi.org/10.1016/j.tourman.2018.03.012>
32. Lin X, Shen Z, Teng X, Mao Q (2024) Cultural routes as cultural tourism products for heritage conservation and regional development: A systematic review. *Heritage* 7:2399-2425. <https://doi.org/10.3390/heritage7050114>
33. Lourens M (2007) Route tourism: A roadmap for successful destinations and local economic development. *Development Southern Africa* 24:475-490. <https://doi.org/10.1080/03768350701445574>
34. Martín-Moreno R, Vega-Rodríguez MA (2018) Multi-objective artificial bee colony algorithm applied to the bi-objective orienteering problem. *Knowledge-Based Systems* 154:93-101. <https://doi.org/10.1016/j.knsys.2018.05.005>
35. Milano C, Novelli M, Cheer JM (2019) Overtourism and tourismphobia: A journey through four decades of tourism development, planning and local concerns. *Tourism Planning & Development* 16:353-357. <https://doi.org/10.1080/21568316.2019.1599604>

36. Ministerio de Transportes, Movilidad y Agenda Urbana (2021) Orden TMA/851/2021, de 23 de julio, por la que se desarrolla el documento técnico de condiciones básicas de accesibilidad y no discriminación para el acceso y la utilización de los espacios públicos urbanizados. Boletín Oficial del Estado 187. <https://www.boe.es/eli/es/o/2021/07/23/tma851/con>
37. Mitchell S, O'Sullivan M, Dunning I (2011) PuLP: A linear programming toolkit for Python. University of Auckland
38. Mou N, Yuan R, Yang T, Zhang H, Tang J, Makkonen T (2020) Exploring spatio-temporal changes of city inbound tourism flow: The case of Shanghai, China. *Tourism Management* 76:103955. <https://doi.org/10.1016/j.tourman.2019.103955>
39. Nagy K (2012) Heritage tourism, thematic routes and possibilities for innovation. *Club of Economics in Miskolc* 8:46-53. <https://ssrn.com/abstract=3639435>
40. Nalmpantis D, Roukouni A, Genitsaris E, Stamelou A, Naniopoulos A (2019) Evaluation of innovative ideas for public transport proposed by citizens using multi-criteria decision analysis (MCDA). *European Transport Research Review* 11:22. <https://doi.org/10.1186/s12544-019-0356-6>
41. Ntakolia C, Iakovidis DK (2021) A swarm intelligence graph-based pathfinding algorithm (SIGPA) for multi-objective route planning. *Computers & Operations Research* 133:105358. <https://doi.org/10.1016/j.cor.2021.105358>
42. Ordóñez-Martínez D, Seguí-Pons JM, Ruiz-Pérez M (2024) Conceptual framework and prospective analysis of EU tourism data spaces. *Sustainability* 16:371. <https://doi.org/10.3390/su16010371>
43. Pedrosa A, Martins F, Breda Z (2022) Tourism routes: A scoping review. *European Journal of Tourism Research* 32:3216. <https://doi.org/10.54055/ejtr.v32i.2575>
44. Pedrosa A, Martins F, Breda Z (2025b) The critical success factors for tourism routes development: A systematic review. *European Journal of Tourism Research* 39:3903. <https://doi.org/10.54055/ejtr.v39i.3439>
45. Pedrosa A, Martins F, Breda Z, Lois González R, Costa AP (2025a) Tourism routes development: Critical success factors. *Tourism Review* 80:553-567. <https://doi.org/10.1108/TR-01-2024-0029>
46. Peeters P, Gössling S, Klijs J, Milano C, Novelli M, Dijkmans C, Eijgelaar E, Hartman S, Heslinga J, Isaac R, Mitas O, Moretti S, Nawijn J, Papp B, Postma A (2018) Research for TRAN Committee: Overtourism - impact and possible policy responses. European Parliament, Directorate-General for Internal Policies, Policy Department for Structural and Cohesion Policies. <https://doi.org/10.2861/919195>
47. Rodríguez B, Molina J, Pérez F, Caballero R (2012) Interactive design of personalised tourism routes. *Tourism Management* 33:926-940. <https://doi.org/10.1016/j.tourman.2011.09.014>
48. Rogerson CM (2007) Tourism routes as vehicles for local economic development in South Africa: The example of the Magaliesberg Meander. *Urban Forum* 18:49-68. <https://doi.org/10.1007/s12132-007-9006-5>
49. Ruiz-Meza J, Montoya-Torres JR (2022) A systematic literature review for the tourist trip design problem: Extensions, solution techniques and future research lines. *Operations Research Perspectives* 9:100228. <https://doi.org/10.1016/j.orp.2022.100228>
50. Schilde M, Doerner KF, Hartl RF, Kiechle G (2009) Metaheuristics for the bi-objective orienteering problem. *Swarm Intelligence* 3:179-201. <https://doi.org/10.1007/s11721-009-0029-5>
51. Szromek AR, Butler RW (2024) A re-positioning of post-industrial heritage in upper Silesia, Poland, into an integrated thematic tourist route. *Journal of Heritage Tourism* 19:310-330. <https://doi.org/10.1080/1743873X.2023.2281440>
52. Séraphin H, Sheeran P, Pilato M (2018) Over-tourism and the fall of Venice as a destination. *Journal of Destination Marketing & Management* 9:374-376. <https://doi.org/10.1016/j.jdmm.2018.01.011>
53. Theissen-Lipp J, Kocher M, Lange C, Decker S, Paulus A, Pomp A, Curry E (2023) Semantics in dataspaces: Origin and future directions. *Companion Proceedings of the ACM Web Conference 2023*:1504-1507. <https://doi.org/10.1145/3543873.3587689>
54. Ul Hassan U, Hasan S, Derguech W, Hannon L, Clifford E, Kouroupetroglou C, Smit S, Curry E (2017) Water analytics and management with real-time linked dataspaces. *Public Administration and Information Technology* 32:173-196. https://doi.org/10.1007/978-3-319-63743-3_7
55. Vansteenwegen P, Souffriau W, Van Oudheusden D (2011) The orienteering problem: A survey. *European Journal of Operational Research* 209:1-10. <https://doi.org/10.1016/j.ejor.2010.03.045>
56. Velázquez J, Infante J, Gómez I, Hernando A, Gülçin D, Herráez F, Rincón V, Castanho RA (2023) Walkability under climate pressure: Application to three UNESCO World Heritage cities in central Spain. *Land* 12:944. <https://doi.org/10.3390/land12050944>
57. Williams MA, Rolls S, McHenry MT (2025) Optimising geotrail planning by leveraging least-cost path for sustainable geotourism development: a case study on a Tasmanian west coast post-mining landscape. *Information Technology & Tourism* 27:477-512. <https://doi.org/10.1007/s40558-024-00308-w>
58. Yalçinkaya NM, Arca D, Keskin Citioglu H (2025) Producing alternative tourism routes using network analysis to promote Seferihisar cittaslow concept. *Information Technology & Tourism* 27:705-737. <https://doi.org/10.1007/s40558-025-00319-1>
59. Zhang C, Liang H, Wang K (2016) Trip recommendation meets real-world constraints: POI availability, diversity, and traveling time uncertainty. *ACM Transactions on Information Systems* 35:5:1-5:28. <https://doi.org/10.1145/2948065>

60. Zillinger M (2007) Tourist routes: A time-geographical approach on German car-tourists in Sweden. *Tourism Geographies* 9:64-83. <https://doi.org/10.1080/14616680601092915>
61. Zouridaki M, Apostolakis A, Kourgiantakis M (2024) Cultural routes through the perspective of sustainable mobility: A critical literature review. *International Journal of Tourism Research* 26:e2756. <https://doi.org/10.1002/jtr.2756>

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- [ITTESM1Sourceupdated.docx](#)