

“AI-driven eco-routing and tourist behavior modeling for sustainable destination marketing”

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AI-DRIVEN ECO-ROUTING AND TOURIST BEHAVIOR MODELING FOR SUSTAINABLE DESTINATION MARKETING

Abstract

The growing pressure on tourism systems caused by overtourism, environmental degradation, and uneven spatial distribution of tourist flows highlights the need for adaptive and sustainability-oriented management approaches. This study develops and tests an AI-driven eco-routing and tourist behavior modelling framework (ER-TBM) as a choice-architecture tool for sustainable destination marketing. The framework combines a fixed graph representation of a synthetic destination, Markov decision states, tabular Q-learning, and congestion-sensitive recommendations. To address reproducibility, the benchmark specifies ten points of interest, 22 undirected edges, all edge attributes, tourist preference and fatigue distributions, Poisson arrivals, recommendation compliance, congestion and emission functions, training settings, stopping rules, and random seeds. Five baselines and ER-TBM were evaluated under normal, peak, and event-demand conditions using 30 paired independent runs per scenario with 120, 180, and 240 agents, respectively. Relative to Dijkstra routing, ER-TBM reduced mean congestion exposure by 5.1-5.3% and increased tourist utility by 0.6-0.7%, while mean CO₂ remained statistically indistinguishable and monetary route cost was 9.4-9.8% higher. The simulation-based Tourism Sustainability Index ranged from 0.712 to 0.732 for ER-TBM and did not show practically meaningful superiority over optimized baselines. The findings indicate that behavior-aware eco-routing can redistribute simulated visitor flows without a statistically significant increase in emissions, although this benefit is accompanied by higher monetary route costs. From a sustainable destination marketing perspective, the proposed framework represents a computational choice-architecture proposition. Its potential to influence actual tourist behavior, recommendation acceptance, destination image, satisfaction, and revisit intention requires further field-based validation.

Keywords

tourist behavior modelling, eco-routing, tourist
decision-making, sustainability-oriented management,
destination marketing, AI-driven framework

JEL Classification

D11, Q01, M31, M15, Z39

INTRODUCTION

The tourism industry is experiencing rapid transformation driven by digitalization, increasing environmental awareness, and the growing complexity of tourist mobility. According to the United Nations World Tourism Organization (UN Tourism), international tourist arrivals reached 1.52 billion in 2025, exceeding pre-pandemic levels and confirming the continued expansion of global tourism. While this growth generates substantial economic benefits, it also intensifies environmental and social challenges, including overtourism, congestion, excessive pressure on destination infrastructure, and increasing greenhouse gas emissions. Tourism currently accounts for approximately 8% of global carbon emissions (Sustainable Travel Int., n.d.), emphasizing the need to reconcile tourism development with sustainability objectives. These challenges have exposed the limitations of conventional destination management approaches, which predomi-

nantly rely on static planning and historical demand patterns. Contemporary tourism systems are inherently dynamic, where tourist decisions continuously interact with environmental conditions, infrastructure capacity, and destination attractiveness. Consequently, sustainable destination management increasingly requires intelligent decision-support systems capable of adapting to changing conditions in real time.

Recent advances in artificial intelligence have created new opportunities for sustainable tourism management. Techniques such as reinforcement learning, graph-based modelling, and eco-routing enable adaptive optimization of tourist flows while accounting for environmental and operational constraints. However, these approaches are typically investigated in isolation. Existing studies rarely integrate tourist behavior modelling, spatial representations, adaptive learning, and environmental optimization into a unified framework, leaving the potential of AI for comprehensive sustainable destination management insufficiently explored.

This challenge is particularly relevant for Ukraine. Despite possessing considerable cultural, historical, and natural tourism resources, the country's tourism sector has experienced significant structural changes caused by the full-scale Russian invasion, resulting in damaged infrastructure, altered tourist mobility patterns, and increasing disparities in regional tourism development. These conditions reinforce the need for innovative digital solutions capable of supporting post-war recovery while promoting sustainable and balanced tourism development. Artificial intelligence-based decision-support systems offer significant potential for optimizing tourist flows, improving visitor experiences, and reducing environmental pressure on destinations. However, their application within the Ukrainian tourism context remains largely unexplored.

Against this background, the present study develops and evaluates an integrated AI-driven framework that combines eco-routing, tourist behavior modelling, graph-based spatial representation, and reinforcement learning to support sustainable destination management. By integrating these components into a unified decision-support framework, the study addresses an important gap in the current literature and contributes to the development of intelligent and environmentally responsible tourism systems.

In this study, sustainable destination marketing is conceptualized as a potential application of algorithmic choice architecture, whereby personalized route recommendations may influence the spatial distribution of visitor attention and mobility. The empirical scope of the research is limited to computational evaluation under synthetic destination conditions. Accordingly, the study does not assess actual marketing effectiveness, consumer acceptance, destination image, visitor satisfaction, or revisit intentions. These outcomes are considered potential directions for subsequent field-based validation rather than demonstrated effects of the proposed framework.

1. LITERATURE REVIEW

In general, the rapid evolution of tourism systems toward digitally enhanced and sustainability-oriented ecosystems has stimulated extensive interdisciplinary research at the intersection of artificial intelligence, mobility modeling, and destination management. However, despite the growing body of literature, existing studies remain fragmented across several domains, including smart tourism, eco-routing, tourist behavior modeling, and reinforcement learning-based optimization.

A critical synthesis of these streams reveals both substantial progress and persistent research gaps.

The concept of smart tourism ecosystems (Gretzel et al., 2015; Li et al., 2017; Zheng et al., 2021; Bhuiyan et al., 2022; Chuang, 2023; Buhalis & Yang, 2024), emphasizes the role of advanced information technologies in enabling real-time interaction between tourists, service providers, and destinations. This perspective was further expanded by emphasizing the transformative impact of big data analytics on tourism decision-making (Xiang et

al., 2017; Li et al., 2018; Vrasida & Vlaseros, 2025). While these studies establish the importance of data-driven systems, they largely focus on information flows and digital infrastructure rather than on adaptive behavioral optimization or environmental sustainability.

A broader perspective on digital tourism is provided by Luo et al. (2022), who conducted a bibliometric analysis of 1,013 publications indexed in the Web of Science database between 1991 and 2022 using CiteSpace. Their findings identify technological innovation, tourism consumption, tourist reviews, and digital transformation as prominent research directions. Although this approach offers a systematic overview of the intellectual structure of digital tourism research, its bibliometric nature does not establish whether digital technologies can improve tourist mobility decisions or environmental outcomes. Complementing this perspective, Sungthong et al. (2025) examined 303 Thai hotels and demonstrated positive relationships between digital transformation capabilities, strategic learning, organizational agility, and competitive and innovative performance. However, their organizational-level analysis does not explain how digital capabilities can be translated into adaptive tourist-level decisions under changing destination conditions. Together, these studies suggest that digitalization and organizational adaptability provide important foundations for intelligent tourism management, while the operational integration of behavioral preferences, spatial congestion, and environmental constraints remains a distinct research challenge.

Besides, research in eco-routing and sustainable mobility has demonstrated that routing decisions can significantly influence environmental outcomes. Work by Kellner (2016) and studies by Barth and Boriboonsomsin (2008, 2009) show that optimizing routes for fuel efficiency and emissions reduction can lead to measurable environmental benefits. However, these approaches are predominantly grounded in transportation engineering and assume rational, deterministic decision-making. As such, they fail to capture the inherently behavioral and experiential nature of tourism mobility, where decisions are influenced not only by cost and time but also by preferences, emotions, and contextual factors.

A complementary stream of research focuses on tourist behavior modeling, particularly through spatial-temporal analysis of movement patterns. Studies reveal that tourist movements are highly irregular, influenced by attraction density, personal interests, and situational constraints (Lew & McKercher, 2006; Shoval & Isaacson, 2007; Shoval, 2010; Ferrante & Cantis, 2015). These findings challenge the assumptions of traditional optimization models and suggest that tourism systems should be conceptualized as complex adaptive systems. However, most existing models remain descriptive rather than predictive, lacking mechanisms for real-time adaptation or decision optimization.

Recent empirical research further highlights the importance of distinguishing between the measurement of tourist behavior, behavioral intentions, and actual mobility decisions. Cruz-Tarrillo (2025) evaluated the psychometric properties and measurement invariance of a tourist behavior scale using 778 responses from visitors to destinations in the Peruvian jungle. The study contributes to the methodological understanding of tourist behavior by examining the measurement of heterogeneous tourist characteristics. Nevertheless, psychometric validation does not itself provide a dynamic representation of how tourists select and modify routes in response to changing spatial conditions. A complementary perspective is offered by Hammami (2026), who examined the relationship between ChatGPT adoption disposition and sustainable travel planning intention using partial least squares structural equation modeling. Based on 186 valid responses, the study found that the direct relationship was not statistically significant, whereas indirect relationships through engagement and AI-assisted planning experience were significant. These findings challenge the assumption that adopting an intelligent recommendation technology necessarily leads to sustainable behavioral intentions. Moreover, intention-based and cross-sectional evidence cannot establish whether tourists will follow algorithmically recommended routes in real destination environments. This distinction is particularly important for behavior-aware routing systems, where recommendation compliance should be treated as an empirically testable behavioral parameter rather than an automatically guaranteed outcome.

Recent advances in artificial intelligence, particularly reinforcement learning (RL), offer promising solutions to these limitations. Mnih et al. (2015) demonstrated the capability of deep reinforcement learning to learn optimal policies in complex environments without explicit supervision. Subsequent studies have applied RL to mobility and traffic optimization (e.g., Wei et al., 2017; Wang et al., 2021), showing significant improvements in adaptive control and decision-making under uncertainty. Nevertheless, applications of RL in tourism remain limited and often overlook key domain-specific factors such as environmental sustainability and experiential quality.

In parallel, graph-based modeling approaches, particularly Graph Neural Networks (GNNs), have gained traction for representing spatial dependencies and network dynamics. A number of researches (Kipf & Welling, 2017; Zhou et al., 2020; Chami et al., 2022; Mahmud et al., 2022; Khemani et al., 2024; Ponzi & Napoli, 2025) demonstrate the effectiveness of GNNs in capturing complex relational structures. In tourism contexts, such approaches can model interactions between POIs, transportation networks, and tourist flows. However, these models are typically used for prediction rather than for decision-making and optimization.

Finally, the growing concern over overtourism and sustainability has prompted research into managing tourist flows and reducing environmental pressure. Studies highlight the negative impacts of excessive tourism concentration, including environmental degradation, infrastructure strain, and reduced quality of life for local communities (Gössling et al., 2018; Milano et al., 2019). While these studies provide important conceptual frameworks, they lack computational mechanisms for dynamically controlling tourist distribution.

The behavioral dimension of sustainable tourism is further emphasized by Riofrio-Carbajal et al. (2023), who investigated emerging tourist needs and perceptions of sustainability in Peru's Paracas National Reserve during the COVID-19 pandemic. Their survey of 83 respondents highlighted the importance of visitor experience,

perceived safety, and environmental awareness in destination evaluation. However, the geographically and temporally specific sample limits the extent to which these findings can be generalized to tourist behavior under ordinary destination conditions. Similarly, Bilan et al. (2025), using survey evidence from 385 domestic tourists in Armenia, identified associations between sustainability awareness, environmental responsibility, and willingness to adopt more sustainable travel practices. Their findings also highlighted information constraints and higher costs as barriers to sustainable choices. Although these studies offer valuable empirical evidence on tourists' sustainability perceptions, they primarily examine self-reported attitudes and preferences rather than observed responses to congestion-sensitive route recommendations. Consequently, a methodological gap remains between understanding tourists' environmental attitudes and operationalizing these attitudes within adaptive destination-level mobility systems. This distinction is essential because environmentally preferable recommendations may involve additional travel costs or changes in the expected visitor experience.

Recent studies have also begun to examine the transformation of tourism systems in the face of external shocks and crises, particularly in the context of Ukraine. For example, Iu. Kostynets and V. Kostynets (2023) analyze consumer resilience in the tourism market during wartime, highlighting significant changes in tourist behavior, demand patterns, and decision-making processes. Their findings suggest that tourism behavior is becoming more adaptive, context-dependent, and sensitive to external uncertainties. This reinforces the need for dynamic and adaptive modeling approaches that can capture behavioral changes under unstable conditions. In this regard, the use of AI-driven frameworks, such as routing based on reinforcement learning and behavior modeling, is particularly relevant, as they provide real-time adaptation to rapidly changing environmental and socio-economic conditions.

At the strategic management level, recent studies have increasingly emphasized the interdependence of sustainability, innovation, and or-

ganizational resilience in tourism. Harazneh et al. (2026), examining tourism and hotel recovery in Jordan using data for 2010–2024, reported positive associations between innovation, sustainability, and sector recovery, including a significant positive interaction between innovation and sustainability. These findings support the relevance of coordinated innovation and sustainability strategies, although aggregate recovery indicators cannot reveal how individual tourist decisions influence spatial congestion or environmental pressure. From a complementary perspective, Khosravi et al. (2026) synthesized environmental, social, and governance strategies in tourism enterprises and proposed a systems-based understanding of sustainable management. Their approach emphasizes in-

terdependencies, feedback mechanisms, and governance coordination rather than isolated sustainability interventions. Nevertheless, a strategic ESG framework should not be equated with a computational model capable of selecting tourist routes under dynamically changing demand. Considered together, these studies reinforce the need to connect sustainability objectives with measurable operational decisions. In this context, behavior-aware eco-routing can be investigated as a potential decision-support mechanism, while its effectiveness in improving broader destination sustainability and resilience requires validation beyond simulated mobility outcomes.

Table 1 summarizes the literature review.

Table 1. Critical review of related studies*

Author	Area of research	Method	Strengths	Limitations
Gretzel et al. (2015), Li et al. (2017), Xiang et al. (2017), Buhalis and Yang (2024), Bhuiyan et al. (2022)	Smart tourism and digital ecosystems	Conceptual frameworks; data-driven analysis	Establish foundations of smart tourism and role of digital platforms in decision-making	Limited focus on adaptive optimization and environmental sustainability integration
Zheng et al. (2021), Chuang (2023)	Smart tourism platforms and value co-creation	Conceptual and integrative models	Emphasize user interaction and co-creation in smart environments	Lack formal computational or behavioral modeling
Barth and Boriboonsomsin (2008, 2009), Kellner (2016)	Eco-routing and transport emissions	Optimization and simulation models	Demonstrate environmental benefits of routing optimization	Focus on transport systems; ignore tourist behavior and experience
Gössling et al. (2018), Milano et al. (2019), Vrasida and Vlaseros (2025)	Sustainability and overtourism	Conceptual and policy-oriented analysis	Highlight environmental and social impacts of tourism concentration	Lack computational tools for dynamic flow management
Shoval and Isaacson (2007), Shoval (2010), Ferrante and De Cantis (2015)	Tourist movement and spatial behavior	Empirical tracking (GPS), spatial analysis	Provide realistic insights into tourist mobility patterns	Descriptive; lack predictive and adaptive decision models
Iu. Kostynets and V. Kostynets (2023)	Tourism under crisis (Ukraine)	Empirical market analysis	Captures behavioral adaptation and resilience under uncertainty; strong contextual relevance	Context-specific; lacks formal modeling and predictive capabilities
C. White III and D. White (1989)	Sequential decision-making (MDP theory)	Mathematical modeling	Provides theoretical foundation for modeling dynamic decision processes	Not applied to tourism context
Mnih et al. (2015); Wei et al. (2017), Wang et al. (2021)	Reinforcement learning in dynamic systems	Deep RL; optimization models	Enable adaptive decision-making under uncertainty	Limited application to tourism and sustainability contexts
Kipf and Welling (2017), Zhou et al. (2020), Chami et al. (2022), Khemani et al. (2024), Ponzi and Napoli (2025), Mahmud et al. (2022)	Graph-based and GNN modeling	Graph neural networks; ML methods	Capture spatial dependencies and complex network structures	Primarily predictive; lack integration with behavioral decision-making
Lew and McKercher (2006)	Destination-level movement modeling	Spatial modeling	Highlights local movement dynamics	Limited scalability and lack of adaptive mechanisms

Table 1 (cont.). Critical review of related studies*

Author	Area of research	Method	Strengths	Limitations
Luo et al. (2022), Sunthong et al. (2025)	Digital tourism and organizational adaptability	Bibliometric analysis; SEM	Map digital tourism research and establish links between digital capabilities and strategic agility	Don't evaluate adaptive tourist routing or destination-level congestion outcomes
Cruz-Tarrillo (2025), Hammami (2026)	Tourist behavior and AI adoption	Psychometric analysis; PLS-SEM	Examine behavioral measurement and mechanisms linking AI engagement to sustainable travel intentions	Cross-sectional evidence; no observed dynamic route compliance
Riofrio-Carbajal et al. (2023), Bilan et al. (2025)	Sustainability perceptions and tourist choices	Cross-sectional surveys; statistical analysis	Identify environmental attitudes, visitor needs, and barriers to sustainable choices	Context-specific self- reported evidence; no dynamic flow optimization
Harazneh et al. (2026), Khosravi et al. (2026)	Sustainable tourism management and resilience	Regression analysis; systematic literature review	Link innovation, sustainability, resilience, and integrated ESG governance	Don't test congestion- aware routing or tourist- level adaptive decisions

Note: * formed by authors.

A critical synthesis of the literature reveals a clear fragmentation:

- smart tourism research emphasizes digital infrastructure, but lacks optimization mechanisms;
- eco-routing focuses on environmental efficiency, but ignores behavioral complexity;
- tourist behavior studies capture movement patterns, but lack predictive and adaptive capabilities;
- reinforcement learning enables adaptive optimization, but is rarely applied in tourism contexts;
- graph-based models capture spatial dependencies but are not integrated with decision-making frameworks.

In view of the above, this study proposes an integrated AI-driven eco-routing and tourist behavior modeling framework (ER-TBM) that combines graph-based spatial representation of tourism destinations, Markov Decision Process (MDP) modeling of tourist behavior, reinforcement learning for adaptive decision-making and environmental feedback mechanisms for sustainability optimization. Unlike prior studies, the proposed approach does not treat routing, behavior, and sustainability

as separate problems but as interdependent components of a single adaptive system.

This study aims to develop and reproducibly evaluate an AI-driven eco-routing and tourist behavior modeling framework and to examine its potential applicability to sustainable destination marketing. Specifically, the framework tests whether personalized, congestion-aware route recommendations can improve simulated tourist utility and redistribute visitor flows while accounting for environmental impacts and monetary route costs. Sustainable destination marketing is treated as a prospective application domain rather than a directly measured outcome. The proposed framework is therefore conceptualized as a computational choice-architecture mechanism that may support sustainability-oriented destination positioning, subject to empirical validation of tourist acceptance, satisfaction, destination image, and behavioral responses.

2. METHOD

2.1. Integrated conceptual model

The proposed study introduces an integrated AI-driven Eco-Routing and Tourist Behavior Modeling framework (ER-TBM) designed to jointly optimize tourist routing decisions, environmental sustainability, and experiential satis-

faction within tourism destinations. The system is formalized as a coupled structure consisting of three interdependent components: spatial graph representation of the destination, behavioral decision model based on Markov Decision Processes (MDP), reinforcement learning-based optimization mechanism. Formally, the destination is represented as a fixed undirected weighted graph:

$$G = (V, E), \quad (1)$$

where V denotes Points of Interest (POIs), and E denotes transitions between them.

Each edge $e_{ij} \in E$ is associated with a multi-dimensional attribute vector:

$$w_{ij} = (t_{ij}, c_{ij}, e_{ij}, s_{ij}), \quad (2)$$

where t_{ij} – travel time between POIs i and j , c_{ij} – economic cost of movement, e_{ij} – environmental cost (CO₂ emissions), s_{ij} – experiential or scenic value.

This representation enables simultaneous modeling of mobility efficiency, environmental impact, and tourist satisfaction.

The overall system architecture is illustrated in Figure 1. Figure 1 illustrates the unified architecture of the proposed ER-TBM framework, which consists of four tightly coupled layers: the Spatial Layer, Behavioral Layer, Learning Layer, and Environmental Feedback Layer.

The Spatial Layer represents the tourism destination as an undirected weighted graph $G=(V,E)$, where nodes correspond to Points of Interest (POIs) and edges encode travel time, cost, emissions, and scenic value. This layer provides the structural foundation for all routing decisions.

The Behavioral Layer models tourists as autonomous agents operating under a Markov Decision Process (MDP). Each agent observes its current POI, assigned destination, preference profile, fatigue, and congestion, and selects an adjacent POI as the next action. This layer captures heterogeneous and stochastic mobility behavior.

The Learning Layer integrates a reinforcement learning module that optimizes routing policies by maximizing cumulative expected reward. This module learns adaptive strategies that balance tourist satisfaction and environmental sustain-

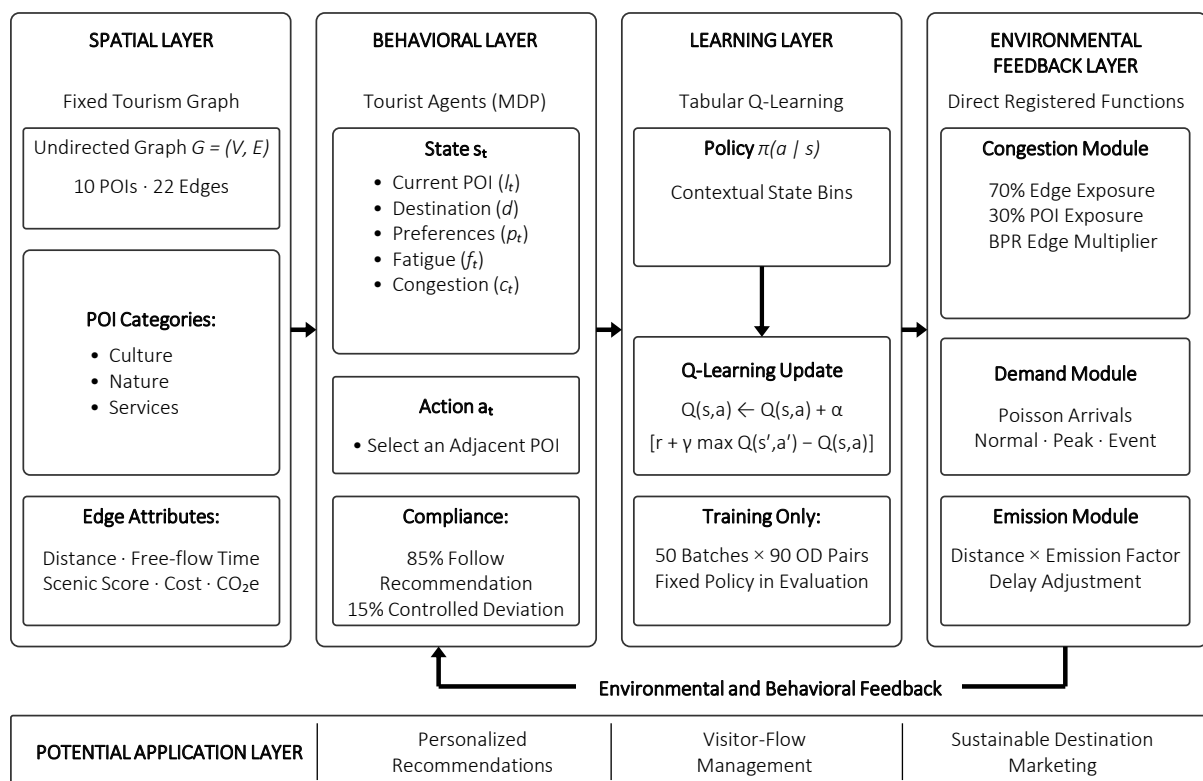


Figure 1. The proposed AI-driven Eco-Routing and Tourist Behavior Modeling (ER-TBM) architecture

ability through continuous interaction with the environment.

The Environmental Feedback Layer directly computes dynamic congestion, environmental load, and demand variation from the registered simulation functions. These updated signals are returned to the routing policy at each decision step. Graph neural networks remain a possible future extension but are not part of the implemented or evaluated model.

The interaction between these four layers forms a closed-loop adaptive system, where tourist decisions influence environmental conditions, and updated environmental states in turn reshape future routing recommendations.

2.2. Tourist behavior modelling (MDP formulation)

Tourist decision-making is modeled as a Markov Decision Process defined by:

$$M = (S, A, P, R, \gamma), \quad (3)$$

where

State space S :

$$s_t = (l_t, d, p_t, f_t, c_t), \quad (4)$$

where l_t – current location (POI), d – assigned destination; p_t – preference vector of the tourist; f_t – fatigue level; c_t – local congestion level.

Action space A :

$$A(s_t) = \{v : (l_t, v) \in E\}, \quad (5)$$

where E is the set of edges representing feasible direct movements between connected POIs, l_t is the tourist's current POI, and v is an adjacent POI available as the next action. It means that each action represents a behavioral decision affecting trajectory evolution.

Transition function P :

$$P(s_{t+1} | s_t, a_t) \quad (6)$$

defines the probability of transitioning to a new state based on current state and action, capturing stochastic mobility and environmental uncertainty.

Reward function R :

$$r_t = -0.10 \frac{T_t}{30} - 0.05 K_t - 0.45 \frac{E_t}{120} - 0.25 C_t + 0.18 S_t + 1.8 U_t 1(l_{t+1} = d), \quad (7)$$

where T_t – travel time; K_t – monetary route cost; E_t – CO₂ emissions; C_t – congestion exposure; S_t – scenic value; U_t – terminal tourist utility; $1(l_{t+1} = d)$ – indicator that the tourist has reached the destination.

The objective is to maximize cumulative discounted reward:

$$\max_{\pi} E \left[\sum_{t=0}^T \gamma^t R(s_t, a_t) \right], \quad (8)$$

where π is the policy and γ is the discount factor.

The tourist decision process is formalized as a Markov Decision Process, as shown in Figure 2. At decision step t , the state is represented by $s_t = (l_t, d, p_t, f_t, c_t)$, comprising the tourist's current POI, assigned destination, preference profile, fatigue level, and local congestion level. The feasible action set $A(s_t)$ consists of the adjacent POIs v for which $(l_t, v) \in E$, thus, an action determines the next directly connected POI. Recommendation compliance is modeled separately from the action space: a tourist follows the recommended route with probability 0.85 and, with probability 0.15, selects one of the three shortest feasible routes at random.

Following the selected action, the tourist's location and fatigue are updated, while travel time is affected by the registered stochastic shock and current edge load. Edge and POI loads evolve as agents arrive according to the specified Poisson process and determine the congestion exposure used in route evaluation. The reward function combines travel time, monetary cost, CO₂ emissions, congestion exposure, scenic value, and terminal tourist utility. Q-learning updates are performed dur-

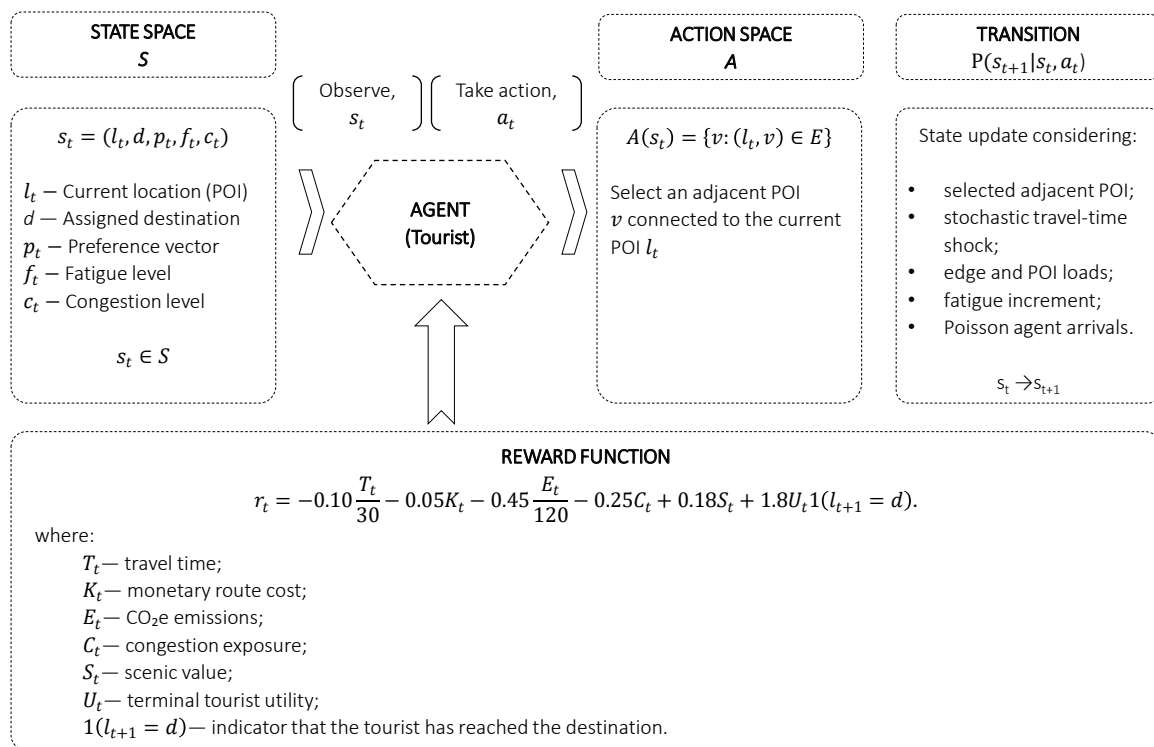


Figure 2. State, action, transition, and reward structure of the MDP implemented in the ER-TBM benchmark

ing training only; the learned policy remains fixed throughout the evaluation runs.

The reward function $R(s_t, a_t)$ integrates multiple competing objectives, including tourist utility, environmental impact, congestion cost, and scenic value. This multi-objective formulation ensures that the learned policy optimizes both individual satisfaction and system-level sustainability.

2.3. Eco-routing optimization model

Eco-routing is formulated as a multi-objective optimization problem:

$$\min_P \sum_{(i,j) \in P} (\alpha t_{ij} + \beta c_{ij} + \theta e_{ij}), \quad (9)$$

$$\max_P \sum_{(i,j) \in P} s_{ij}, \quad (10)$$

where P is a candidate tourist route.

To unify the objectives, a scalarized function is introduced:

$$L(P) = w_1 T(P) + w_2 C(P) + w_3 E(P) - w_4 S(P), \quad (11)$$

where $T(P)$ – total travel time; $C(P)$ – total cost; $E(P)$ – environmental impact; $S(P)$ – scenic value; w_i – normalization weights.

The experimental component is a fully specified synthetic benchmark rather than an empirical digital twin of a named destination. Ten POIs and 22 undirected links form a fixed connected graph. Node attributes, capacities, edge distances, free-flow times, scenic scores, monetary costs, blended emission factors, and base CO₂e values are reported in Appendix A. The same graph and feasible route sets are used by every method.

At each decision step, an agent observes its current POI, destination, preference profile, fatigue bin, and local congestion bin. ER-TBM selects a feasible route using the learned contextual Q-values combined with the registered environmental and congestion terms; the environment then updates edge occupancy, travel time, emissions, cost, fatigue, and utility.

1. Training uses tabular Q-learning with learning rate 0.15, discount factor 0.92, and epsilon-greedy exploration decreasing linearly from 0.25 to 0.03.
2. One training episode is defined as a batch containing all 90 ordered origin-destination pairs. Both Q-learning policies are trained for 50 episodes; seeds 202501 and 202502 are used for the non-contextual and ER-TBM policies, respectively.
3. Evaluation is performed after training. No test-run rewards are used to update either policy.
4. The registered ER-TBM step reward penalizes normalized time, cost, CO₂e, and congestion and rewards scenic value and terminal preference utility. The baseline Q-learning reward excludes congestion and behavioral state variables.
5. All methods face identical agents, preferences, arrival realizations, and edge shocks within each scenario-seed pair. This common-random-numbers design isolates differences attributable to the routing policy.

A route stops when the assigned target is reached or after seven learned transitions; if the learned policy has not reached the target, an exact shortest-time suffix completes the route. Training trajectories stop at the target or after nine transitions.

The comparison includes a random feasible policy, Dijkstra, A* with an admissible Euclidean-time heuristic, a static multi-objective policy, non-contextual tabular Q-learning, and ER-TBM. Dijkstra and A* optimize the same dynamic travel-time objective and should therefore return equivalent routes; A* is retained as an implementation check rather than as evidence of a different sustainability strategy.

$$\pi = \arg \max_{\pi} E \left[\sum \lambda^t R_t \right]. \quad (12)$$

For a state-action pair, the Q update is $Q(s,a) \leftarrow Q(s,a) + \alpha[r + \gamma \max_{a'} Q(s',a') - Q(s,a)]$. Exact implementation details and executable code are provided in Supplementary Material S1.

$$Q(s,a) \leftarrow Q(s,a) + \alpha \left[[R + \gamma \max_{a'} Q(s',a') - Q(s,a)] \right], \quad (13)$$

where α – learning rate; γ – discount factor.

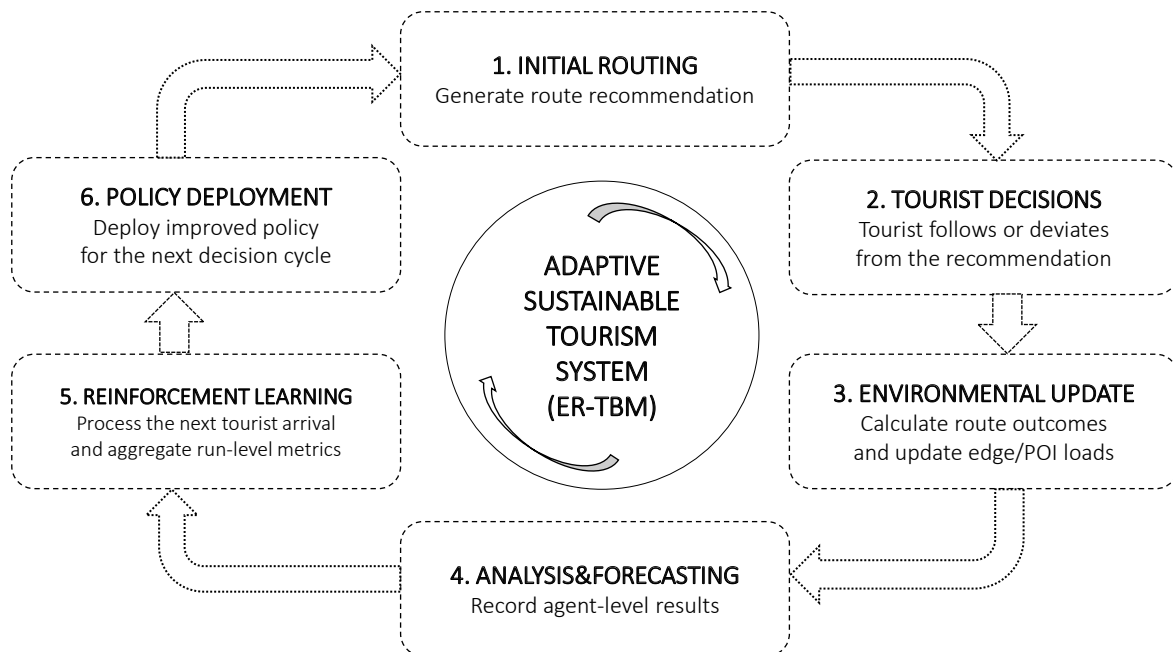


Figure 3. Closed-loop ER-TBM evaluation cycle with direct environmental feedback and tabular Q-learning

The dynamic feedback mechanism and iterative learning process are illustrated in Figure 3, highlighting the closed-loop interaction between tourists, environment, and the reinforcement learning module.

Figure 3 illustrates the dynamic feedback loop used in the tested implementation. The environmental feedback is computed directly from the registered congestion and emission functions.

2.4. Experimental application and evaluation results (simulation-based)

The evaluation uses exactly 10 POIs and 22 undirected edges. Normal, peak, and event scenarios contain 120, 180, and 240 agents, respectively.

- Agent arrivals follow homogeneous Poisson processes with rates of 2, 3, and 4 agents per minute. Edge occupancy decays exponentially with a 30-minute persistence parameter.
- For each scenario and seed, multiplicative travel-time shocks follow a clipped lognormal distribution, $\text{LogNormal}(0, 0.08)$, restricted to $[0.82, 1.22]$. Scenario multipliers are 1.00, 1.10, and 1.20.
- Tourist category preferences follow Dirichlet (2.0, 2.0, 1.5); initial fatigue follows $0.35 \times$

$\text{Beta}(2, 8)$. Origins are POIs 0, 4, and 9 with probabilities 0.45, 0.30, and 0.25. Destinations are sampled from attractiveness weighted by category preference.

- Recommendation compliance equals 0.85. With probability 0.15, the agent deviates and selects one of the three shortest feasible routes at random. This rule is identical across methods.

Thirty independent paired evaluation runs are conducted for each scenario using seeds 202601-202630. A run is the unit of statistical inference. Means and 95% confidence intervals are reported; paired t-tests use the seed-matched outcomes. Table 2 summarizes all registered parameters.

The Tourism Sustainability Index used here is an author-defined simulation summary, not an official destination statistic. It is calculated from run-level outputs as follows:

$$\text{TSI} = 0.35U + 0.25[1 - \min(\text{CO}_2\text{e}/1000, 1)] + 0.25[1 - \min(\text{CG}/2, 1)] + 0.15[1 - \min(C/3, 1)],$$
 where U is mean tourist utility on $[0,1]$, CO_2e is grams per completed tourist route, CG is mean congestion exposure, and C is route cost in benchmark monetary units. The weights and anchors are fixed before evaluation. Because alternative defensible weights can change close rankings, TSI is treated as a secondary descriptive outcome; the disaggregated metrics are primary.

Table 2. Specified simulation and evaluation parameters

Source: Developed by the authors. All parameter values are prespecified assumptions of the synthetic benchmark rather than estimates from an observed destination.

Component	Specification
Initial network state	all edge flows and POI loads are set to zero at the beginning of each independent run.
Destination graph	10 POIs; 22 undirected edges; 24 lowest-free-flow-time simple paths per ordered OD pair; maximum seven edges
Demand scenarios	Normal: 120 agents, $\lambda=2/\text{min}$; Peak: 180, $\lambda=3/\text{min}$; Event: 240, $\lambda=4/\text{min}$
Origins	POI 0/4/9 with probabilities 0.45/0.30/0.25
Preferences	Dirichlet(2.0, 2.0, 1.5) over culture, nature, and services
Initial fatigue	$0.35 \times \text{Beta}(2, 8)$; increment equals realized edge time/360; clipped to 1
Compliance	0.85; otherwise random choice among the three shortest feasible routes
Travel-time shocks	Clipped $\text{LogNormal}(0, 0.08)$, range $[0.82, 1.22]$; scenario multipliers 1.00/1.10/1.20
Congestion	70% mean edge exposure + 30% destination-POI exposure; edge BPR multiplier $1 + 0.15(\text{flow}/35)^4$; POI exposure = occupancy/capacity; loads decay with 30-minute persistence
Emissions	base edge CO_2e = distance $\times (75 - 65 \times \text{scenic score})$; delay multiplier $1 + 0.30 \max(0, \text{realized-time multiplier} - 1)$
POI capacity	[80, 45, 55, 50, 70, 40, 60, 45, 65, 75] for POIs 0-9
Training	50 batches $\times$ 90 ordered OD pairs; $\alpha=0.15$; $\gamma=0.92$; epsilon 0.25 to 0.03
Stopping	Evaluation: target or 7 learned transitions plus exact suffix; training: target or 9 transitions
Seeds and runs	training 202501/202502; evaluation 202601-202630; 30 independent paired runs per scenario

Table 3. Pooled performance across demand scenarios (mean [95% CI])

Source: Created by authors.

Method	Utility	CO ₂ e g	Cost	Congestion	TSI
Random	0.564 [0.562, 0.566]	296.649 [294.459, 298.840]	2.406 [2.395, 2.417]	0.317 [0.298, 0.335]	0.613 [0.610, 0.617]
Dijkstra	0.582 [0.580, 0.584]	162.384 [161.104, 163.663]	1.245 [1.238, 1.252]	0.206 [0.195, 0.218]	0.725 [0.723, 0.727]
A*	0.582 [0.580, 0.584]	162.234 [160.939, 163.529]	1.244 [1.238, 1.251]	0.207 [0.195, 0.219]	0.725 [0.723, 0.727]
Static multi-objective	0.585 [0.583, 0.586]	165.467 [164.300, 166.635]	1.346 [1.339, 1.353]	0.188 [0.177, 0.199]	0.722 [0.721, 0.724]
Q-learning	0.581 [0.580, 0.583]	163.648 [162.337, 164.959]	1.246 [1.239, 1.253]	0.202 [0.190, 0.213]	0.725 [0.723, 0.727]
ER-TBM	0.586 [0.584, 0.587]	161.809 [160.532, 163.086]	1.364 [1.357, 1.371]	0.196 [0.185, 0.207]	0.722 [0.720, 0.724]

The registered experiment does not support a claim of universal superiority. Pooled results in Table 3 show that optimized methods occupy a narrow TSI range, whereas the random policy performs substantially worse. ER-TBM is therefore evaluated through its disaggregated trade-offs rather than by selecting a single favorable composite score.

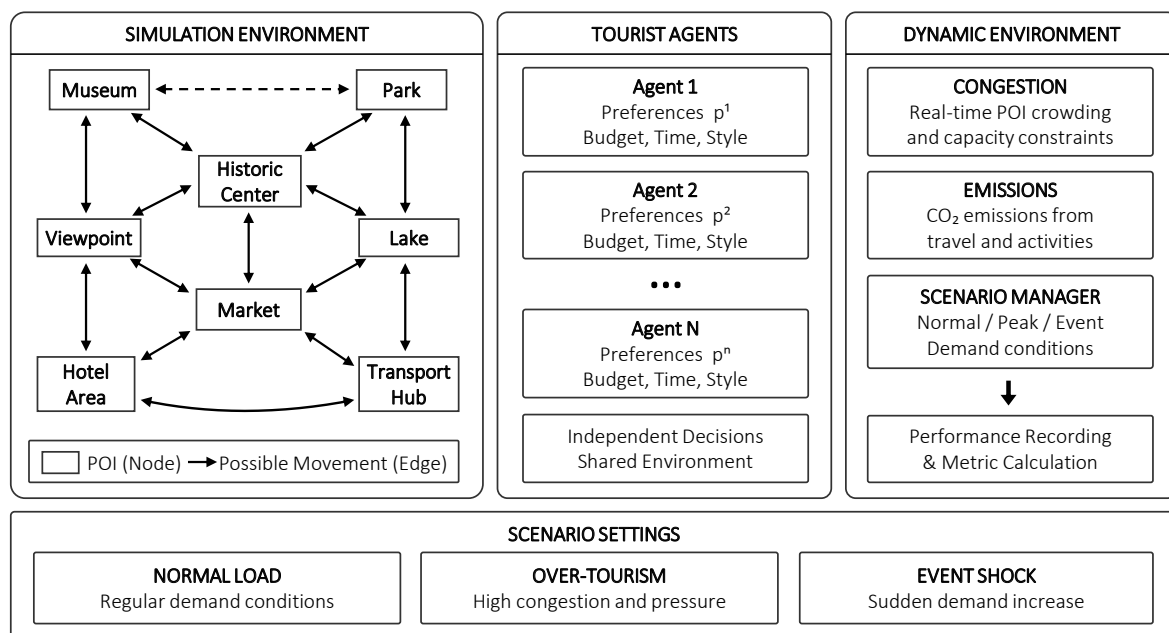
The contextual policy changes the composition of selected routes: it reduces exposure to heavily loaded edges and produces slightly higher preference utility, while accepting a modest increase in route cost.

Critical observation is that ER-TBM changes spatial allocation rather than simply reproducing

shortest paths. Whether this change is preferable depends on the destination manager's registered objective weights and acceptable visitor cost.

The agent-based simulation environment used for experimental evaluation is depicted in Figure 4, showing multi-agent interactions under dynamic tourism demand scenarios.

Figure 4 illustrates the concept of experimental simulation environment used for evaluating the proposed framework. The environment consists of multiple autonomous tourist agents interacting within a shared spatial graph representing a tourism destination. Each agent independently follows an MDP-based decision policy while simultane-

**Figure 4.** Conceptual illustration of Agent-based simulation environment for evaluating the ER-TBM framework

ously competing for shared spatial resources such as POIs and transportation routes.

This multi-agent interaction leads to emergent system-level dynamics, including congestion formation and spatial redistribution of tourist flows. The environment dynamically updates key variables such as congestion intensity, environmental load, and POI capacity constraints. These updates influence both the reward structure and transition probabilities of agents, enabling realistic modeling of over-tourism and demand fluctuation scenarios. Three simulation scenarios are embedded within the environment: normal tourism load, peak-season congestion, and event-driven demand shocks, allowing robust evaluation of system performance under varying operational conditions.

3. RESULTS AND DISCUSSION

3.1. Overall system performance and comparative evaluation

The experimental evaluation uses tourist utility, CO₂e per completed route, route cost, congestion exposure, and the secondary simulation-based TSI. Table 3 reports means and 95% confidence intervals over 90 scenario-seed runs per method; Table 4 reports scenario-specific results.

Across the three scenarios, ER-TBM obtains mean TSI values of 0.732, 0.722, and 0.712. These values are practically close to Dijkstra, A*, static multi-objective routing, and non-contextual Q-learning.

The obtained results are consistent with previous studies demonstrating the potential of artificial intelligence to enhance tourism management through adaptive decision-making. For example, U. Gretzel, M. Sigala and Z. Xiang (2015) argue that smart tourism ecosystems require intelligent technologies capable of continuously adapting to changing environmental and user conditions, while L. Li, L. Xu and L. Tang (2017) emphasize the importance of integrating intelligent information services into destination management. However, these studies remain largely conceptual and do not provide computational mechanisms for balancing environmental sustainability with tourist behavior. In contrast, the proposed ER-

TBM framework operationalizes these concepts by combining behavioral modelling, reinforcement learning, and eco-routing within a unified optimization framework. Consequently, the present study extends existing smart tourism research from conceptual system design toward practical decision-support implementation.

The disaggregated outcomes reveal a trade-off. Relative to Dijkstra, ER-TBM raises mean utility by 0.57-0.69% and reduces congestion exposure by 5.01-5.13%. Mean CO₂e differs by -0.65% to -0.07% and is not statistically different in any scenario, whereas route cost is 9.36-9.79% higher. The proposed policy therefore achieves spatial dispersion at a measurable cost rather than dominating every criterion.

The scenario-based analysis uses normal, peak, and event demand while preserving the same graph, behavioral distributions, and evaluation rules. Results are shown in Table 4.

The results in Table 4 show that absolute congestion exposure rises with demand for every method. Nevertheless, ER-TBM preserves a 5.1-5.3% congestion reduction relative to Dijkstra across all three scenarios. Its CO₂e performance remains statistically indistinguishable from Dijkstra, while utility is consistently but modestly higher. This pattern supports robustness of the spatial-dispersion effect.

Overall, the findings indicate that the proposed framework offers one defensible congestion-utility trade-off under the registered synthetic assumptions. External validity must be established with observed destination data.

The robustness of the proposed framework under peak-season and event-driven scenarios also supports findings reported in the sustainable tourism literature. Gössling et al. (2018) emphasize that increasing tourist concentrations create significant environmental pressure and require adaptive destination management strategies rather than static planning approaches. Similarly, Milano et al. (2019) identify overtourism as a dynamic phenomenon driven by continuously changing visitor flows. Unlike these studies, which primarily discuss policy implications, the proposed framework

Table 4. Scenario-based performance comparison (mean [95% CI])*

Scenario	Method	Utility	CO ₂ e g	Congestion	TSI
Normal	Dijkstra	0.584 [0.580, 0.587]	158.447 [156.401, 160.494]	0.138 [0.134, 0.142]	0.735 [0.733, 0.737]
Normal	Q-learning	0.583 [0.580, 0.587]	159.495 [157.404, 161.586]	0.134 [0.131, 0.138]	0.735 [0.733, 0.737]
Normal	ER-TBM	0.588 [0.584, 0.591]	157.896 [155.851, 159.940]	0.131 [0.128, 0.133]	0.732 [0.729, 0.734]
Peak	Dijkstra	0.582 [0.580, 0.584]	161.543 [159.873, 163.214]	0.208 [0.203, 0.212]	0.725 [0.724, 0.727]
Peak	Q-learning	0.581 [0.579, 0.584]	162.909 [161.329, 164.488]	0.203 [0.198, 0.207]	0.725 [0.724, 0.727]
Peak	ER-TBM	0.586 [0.584, 0.588]	160.494 [158.937, 162.052]	0.197 [0.193, 0.201]	0.722 [0.721, 0.724]
Event	Dijkstra	0.580 [0.578, 0.583]	167.161 [165.452, 168.869]	0.274 [0.270, 0.279]	0.715 [0.713, 0.716]
Event	Q-learning	0.579 [0.577, 0.582]	168.540 [166.686, 170.394]	0.268 [0.264, 0.273]	0.715 [0.713, 0.716]
Event	ER-TBM	0.584 [0.581, 0.586]	167.036 [165.447, 168.626]	0.260 [0.256, 0.264]	0.712 [0.710, 0.713]

Note: *created by authors.

provides a computational mechanism capable of dynamically redistributing tourist movements in response to congestion and environmental conditions. This demonstrates how artificial intelligence can transform sustainability principles into operational destination management and marketing tools.

The methods shared identical agent characteristics, arrival streams, and edge-level travel-time shocks within each scenario-seed pair. Method-specific random streams were used only for recommendation deviations and tie-breaking. Table 5 reports percentage differences between ER-TBM and Dijkstra with paired t-tests.

The paired analysis confirms that congestion reduction and the small utility increase are statistically detectable, whereas the CO₂e difference is not. Route cost is consistently higher. ER-TBM

TSI values were 0.40–0.50% lower than those of Dijkstra; although statistically detectable, these differences were practically small. The result is consistent with sequential decision theory: adding context can change the policy selected under congestion. It does not, by itself, prove that reinforcement learning is superior to every static multi-objective formulation.

Together, these findings narrow the contribution to reproducible behavior-aware flow redistribution and explicit trade-off measurement.

The framework connects eco-routing, tourist behavior, and sustainable destination marketing by treating route recommendations as personalized choice architecture. Its computational contribution is the reproducible integration of preference, fatigue, congestion, emissions, and compliance under common evaluation conditions.

Table 5. Paired ER-TBM differences relative to Dijkstra*

Scenario	Outcome	Difference %	p value	Result
Normal	Utility	+0.69%	<0.0001	higher
Normal	CO ₂ e	−0.35%	0.3428	n.s.
Normal	Cost	+9.79%	<0.0001	higher
Normal	Congestion	−5.01%	0.0007	lower
Normal	TSI	−0.50%	<0.0001	lower
Peak	Utility	+0.68%	<0.0001	higher
Peak	CO ₂ e	−0.65%	0.1089	n.s.
Peak	Cost	+9.43%	<0.0001	higher
Peak	Congestion	−5.13%	<0.0001	lower
Peak	TSI	−0.40%	<0.0001	lower
Event	Utility	+0.57%	<0.0001	higher
Event	CO ₂ e	−0.07%	0.8039	n.s.
Event	Cost	+9.36%	<0.0001	higher
Event	Congestion	−5.13%	<0.0001	lower
Event	TSI	−0.41%	<0.0001	lower

Note: *created by authors.

Importantly, the marketing implications of the ER-TBM framework should be interpreted as a computational choice-architecture proposition rather than evidence of empirically validated marketing effectiveness. The simulation demonstrates that congestion-aware recommendations can influence the spatial distribution of modeled tourist movements while producing modest improvements in simulated utility and maintaining statistically comparable CO₂e outcomes, albeit at higher monetary route costs. However, recommendation compliance is imposed as a model parameter rather than estimated from observed tourist behavior.

The observed behavioral patterns of the proposed ER-TBM framework, particularly the adaptive redistribution of tourist flows and the avoidance of congested areas, provide important insights into how AI-driven systems can influence real-world tourism dynamics. These findings are consistent with the concept of smart tourism ecosystems proposed by Gretzel et al. (2015) and further elaborated by Buhalis and Yang (2024), who argue that intelligent tourism systems should continuously adapt to changing visitor behavior and environmental conditions. However, previous studies have primarily focused on conceptual architectures and digital service ecosystems, without providing computational mechanisms capable of dynamically optimizing tourist movements. The proposed ER-TBM framework extends these concepts by integrating adaptive learning and behavioral decision-making into an operational destination management model.

The clearest finding is a stable reduction in congestion exposure relative to shortest-path and non-contextual Q-learning baselines. This redistribution is induced through recommendation scores and partial user compliance; it should not be interpreted as evidence of autonomous self-regulation outside the simulated conditions.

In practical terms, personalized routing could serve as a destination-marketing decision-support instrument by directing tourist attention toward less congested points of interest and potentially diversifying the experienced destination portfolio.

This statement supports previous studies emphasizing that overtourism should be addressed through proactive demand management rather than reac-

tive regulatory measures. Milano et al. (2019) and Gössling et al. (2018) argue that sustainable destination management requires flexible mechanisms capable of redistributing visitor flows before environmental and social thresholds are exceeded. Unlike these policy-oriented approaches, the proposed framework demonstrates how reinforcement learning can operationalize adaptive visitor redistribution through personalized routing recommendations, thereby translating sustainability principles into practical decision-support mechanisms.

Another important implication relates to the diversification of tourist demand. By encouraging exploration of less-visited areas, the ER-TBM framework contributes to a more balanced utilization of destination resources. This has significant economic and social benefits, particularly for regions that are underrepresented in tourism flows. In the context of regional development, such redistribution can support local economies, reduce spatial inequalities, and enhance the resilience of tourism systems.

These findings also complement empirical studies on tourist mobility. As Lew and McKercher (2006), as Shoval and Isaacson (2007) demonstrated that tourist movements are highly heterogeneous and rarely follow optimal spatial patterns. While these studies provide valuable empirical evidence regarding visitor behavior, they do not propose adaptive mechanisms capable of influencing movement dynamics. The ER-TBM framework advances this line of research by transforming descriptive mobility knowledge into predictive and optimization-oriented routing strategies.

The results highlight the importance of system-aware personalization. Unlike popularity-only recommendations, ER-TBM includes congestion and environmental signals, but the current experiment does not measure real consumer acceptance, destination image, revisit intention, or willingness to follow recommendations.

From a technological perspective, the tested implementation combines a fixed graph with tabular Q-learning and registered environmental feedback. GNN and DQN architectures were not implemented and are not included among the empirical claims.

Table 6. Positioning of the proposed framework within existing research*

Research direction	Representative studies	Main contribution of previous studies	Advancement achieved in this study
Smart tourism	Gretzel et al. (2015), Buhalis and Yang (2024)	Conceptual smart tourism ecosystems	AI-enabled operational decision support
Tourist behavior	Lew and McKercher (2006), Shoval and Isaacson (2007)	Empirical mobility analysis	Adaptive behavioral modeling
Eco-routing	Barth and Boriboonsomsin (2009), Kellner (2016)	Emission-aware routing	Eco-routing adapted to tourism destinations
Reinforcement learning	Mnih et al. (2015)	Sequential adaptive learning	Sustainable tourist flow optimization
Graph modeling	Kipf and Welling (2017), Zhou et al. (2020)	Spatial representation learning	Destination graph for routing optimization
Sustainable destination management	Gössling et al. (2018), Milano et al. (2019)	Sustainability challenges and overtourism	Computational support for adaptive sustainability management

Note: * created by authors.

From a methodological perspective, the study demonstrates how an AI-routing proposition can be evaluated without conflating conceptual modules with implemented algorithms. Table 6 positions the narrower contribution within prior research.

Table 6 positions the proposed ER-TBM framework within the broader landscape of smart tourism, sustainable destination marketing, and artificial intelligence research.

The proposed framework advances prior work by making the behavioral and sustainability trade-offs operational and reproducible. It does not establish real-world effectiveness; rather, it supplies a benchmark that can be populated with observed mobility, emissions, and consumer-choice data.

Within the synthetic benchmark, the contextual policy remains responsive to congestion under higher loads. This is a necessary but insufficient condition for application in non-stationary real destinations.

The practical implementation of such a framework could take the form of integration into digital tourism platforms, including mobile applications, navigation systems, and smart destination infrastructures. By embedding sustainability-aware routing algorithms into widely used services, destination managers can influence tourist behavior at scale without requiring direct intervention. This aligns with the broader concept of smart tourism ecosystems, where technology acts as an intermediary between users and the environment.

In the Ukrainian context, these findings are particularly relevant. Many tourist destinations face challenges related to uneven spatial distribution of visitors, with a small number of well-known attractions receiving the majority of tourist flows. The adoption of AI-driven routing systems could help redistribute demand toward less-visited cultural and natural sites, supporting more balanced regional development. Furthermore, such systems could play a role in post-crisis recovery by optimizing resource use and enhancing the overall efficiency of tourism infrastructure.

The relevance of such adaptive approaches is particularly evident in the Ukrainian context. V. Kostynets and Iu. Kostynets (2023) demonstrate that tourism demand under crisis conditions becomes increasingly adaptive and sensitive to external shocks, requiring more flexible management approaches. While their study focuses on consumer resilience and market transformation, the present research complements these findings by proposing a computational framework capable of supporting adaptive destination management under dynamic conditions.

From a policy perspective, the results suggest that data-driven and adaptive management strategies should complement traditional regulatory approaches. Rather than relying solely on restrictions or infrastructure expansion, policymakers can leverage intelligent systems to guide behavior in a more flexible and responsive manner. This represents a shift toward algorithmic governance in tourism, where decisions are supported by real-time data and predictive analytics.

This conclusion is also consistent with recent studies emphasizing the growing importance of data-driven governance in tourism. Vrasida and Vlaseros (2025) argue that big data analytics should become an essential component of strategic overtourism management. The present study extends this perspective by demonstrating how artificial intelligence can move beyond descriptive analytics toward autonomous and adaptive decision-support systems capable of continuously optimizing tourism flows.

At the same time, the deployment of such systems raises important considerations related to data availability, transparency, and user acceptance.

Effective implementation requires access to high-quality mobility and environmental data, as well as mechanisms for ensuring that recommendations are perceived as trustworthy and beneficial by users. Future research should therefore explore not only the technical performance of such systems but also their social and behavioral acceptance.

Overall, the results support behavior-aware eco-routing as a potentially useful component of sustainable destination marketing. The principal demonstrated effect is lower congestion exposure with similar emissions and slightly higher utility, accompanied by higher route cost. Claims beyond these outcomes require field validation.

CONCLUSIONS

The study aims to develop and reproducibly evaluate an AI-driven eco-routing and tourist behavior modeling framework and to examine its potential applicability to sustainable destination marketing. The simulation-based experiment specifies the graph, stochastic processes, behavioral distributions, learning parameters, evaluation seeds, stopping rules, and benchmark implementations, enabling exact regeneration of the reported outputs. Across 30 paired runs in each of three demand scenarios, ER-TBM reduced congestion exposure by approximately 5% relative to Dijkstra and produced a small increase in simulated tourist utility. CO₂e remained statistically indistinguishable, route cost increased by approximately 9-10%, and TSI differences were practically small. The evidence therefore supports a congestion-management trade-off.

These findings support the computational feasibility of behavior-aware route recommendations as a potential choice-architecture mechanism for sustainable destination marketing. Under the registered synthetic assumptions, the framework reduces congestion exposure and produces a modest increase in simulated tourist utility, while CO₂e outcomes remain statistically indistinguishable from the shortest-path benchmark and monetary route costs increase. Accordingly, the proposed marketing application should be regarded as a hypothesis for subsequent empirical testing.

From a practical perspective, the framework can be tested in destination applications through transparent personalized recommendations, A/B tests of compliance, and monitoring of visitor dispersion, route cost, satisfaction, and destination image. Deployment should retain user autonomy and disclose why a less congested route is recommended.

The main limitation is that all results come from a synthetic benchmark. The parameters are now fully disclosed but are not calibrated to an observed destination; consequently, the experiment establishes computational behavior, not real-world effect size.

The current model uses three preference categories, stylized fatigue, a blended emission proxy, fixed compliance, and tabular Q-learning. It does not test DQN, GNN, or a genetic multi-objective algorithm, and no claim is made about outperforming those methods.

Future research should estimate parameters from GPS and ticketing data, validate CO₂e factors by transport mode, test alternative TSI weights, and measure marketing outcomes such as recommendation acceptance, destination image, satisfaction, and revisit intention.

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DECLARATION OF GENERATIVE AI IN THE WRITING PROCESS

In preparing this paper, the authors used AI-tools (OpenAI GPT-5) for assistance in the search, synthesis and summarization of literature sources relevant to the development of the theoretical framework. Following the use of this tool, the authors have reviewed and edited the content as necessary and take full responsibility for the content of the published article.

ETHICS STATEMENT

This study was conducted in accordance with international research ethics guidelines, including the principles of the Committee on Publication Ethics (COPE). The research does not involve direct interaction with human participants or the collection of personally identifiable information. All data used are either publicly available, anonymized, or synthetically generated. All data were processed in a manner that ensures confidentiality and anonymity. Non-sensitive data and simulation materials can be made available upon reasonable request. The authors declare no conflicts of interest and no external funding influencing the study.

DATA AND CODE AVAILABILITY

The benchmark is fully synthetic. Supplementary Material S1 contains the executable Python script, and Supplementary Material S2 contains all run-level outputs. Running S1 regenerates S2 from the fixed training and evaluation seeds reported above.

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APPENDIX A

FIXED BENCHMARK INPUTS

Table A1. POI attributes

POI	x	y	Category	Capacity	Attractiveness
0	0	0	Culture	80	0.35
1	1	1.2	Culture	45	0.82
2	2.2	0.2	Nature	55	0.72
3	3.4	1.3	Culture	50	0.88
4	4.5	0.1	Services	70	0.42
5	0.5	3	Nature	40	0.68
6	2	3.2	Services	60	0.78
7	3.5	3.1	Culture	45	0.91
8	5	3	Services	65	0.62
9	2.6	5	Nature	75	0.74

Table A2. Exact undirected edge attributes

u	v	km	min	Scenic	Cost	EF g/km	Base CO ₂ e g
0	1	1.60	18	0.50	0.532	42.50	68.00
0	2	2.25	22	0.35	0.675	52.25	117.56
0	5	3.05	30	0.70	0.851	29.50	89.97
1	2	1.75	17	0.45	0.565	45.75	80.06
1	5	1.85	19	0.75	0.587	26.25	48.56
1	6	2.25	23	0.65	0.675	32.75	73.69
2	3	1.65	16	0.40	0.543	49.00	80.85
2	6	3.00	29	0.55	0.840	39.25	117.75
2	7	3.20	31	0.60	0.884	36.00	115.20
3	4	1.70	17	0.35	0.554	52.25	88.83
3	6	2.40	24	0.62	0.708	34.70	83.28
3	7	1.85	19	0.58	0.587	37.30	69.01
3	8	2.30	23	0.48	0.686	43.80	100.74
4	8	2.95	29	0.40	0.829	49.00	144.55
5	6	1.55	16	0.85	0.521	19.75	30.61
5	9	3.05	30	0.90	0.851	16.50	50.32
6	7	1.55	16	0.72	0.521	28.20	43.71
6	9	2.45	24	0.82	0.719	21.70	53.17
7	8	1.55	16	0.55	0.521	39.25	60.84
7	9	2.25	22	0.78	0.675	24.30	54.67
8	9	3.10	30	0.68	0.862	30.80	95.48
4	7	3.05	30	0.45	0.851	45.75	139.54

Notes: Each listed edge is traversable in both directions with identical base attributes. Edge congestion and stochastic travel-time adjustments are applied during simulation as specified in Table A2.