

Article

A Sustainability Assessment of Artificial Intelligence Applications in Tourism Management Using an Entropy–TOPSIS Framework

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Abstract

Artificial intelligence (AI) is increasingly transforming tourism management by improving operational efficiency, enhancing visitor experiences, and supporting sustainability objectives. However, existing studies primarily focus on individual AI technologies and lack a comprehensive framework for comparing their sustainability performance. Therefore, this study evaluates and ranks major AI applications used in tourism management from a sustainability perspective. An integrated Entropy–TOPSIS framework was developed to assess six AI applications: Generative AI Systems, AI Chatbots, Digital Twin Systems, Smart Destination Management, Smart Governance, and Open Data Tourism Platforms. Ten evaluation criteria covering economic, environmental, social, managerial, and ethical dimensions were identified through a comprehensive literature review. The Entropy method was employed to determine objective criterion weights, while the TOPSIS method was used to rank the alternatives. The results indicate that personalization capability, privacy and ethical risk, and energy efficiency are the most discriminating evaluation criteria, with weights of 0.2217, 0.2190, and 0.2108, respectively. Smart Destination Management achieved the highest sustainability performance (CC = 0.5968), followed closely by Digital Twin Systems (CC = 0.5950) and Open Data Tourism Platforms (CC = 0.4978). The findings suggest that AI applications integrating sustainability-oriented destination management, operational intelligence, and personalized visitor services outperform solutions focusing on isolated technological functions. The proposed framework offers a practical decision support tool for tourism managers and policymakers seeking to prioritize AI investments that maximize sustainability outcomes while supporting responsible digital transformation.

Keywords: artificial intelligence; sustainable tourism management; entropy; TOPSIS; digital twin; Smart Destination Management



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1. Introduction

The tourism industry is experiencing a profound transformation driven by rapid advances in artificial intelligence (AI), digital technologies, and data-driven management systems. Emerging technologies such as generative artificial intelligence (GenAI), conversational chatbots, digital twins, Smart Governance systems, and open data platforms are increasingly integrated into tourism and hospitality operations to improve service quality, optimize managerial processes, and enhance visitor experiences. Collectively, these technologies have become fundamental components of destination competitiveness, visitor satisfaction, and destination management practices (Aguiar Castillo et al., 2026; Arif et al., 2026; Bingöl & Yang, 2025). Similarly, Meyer-Waarden et al. (2026) argue that AI-powered systems provide real-time assistance, personalized recommendations, and

adaptive communication, thereby transforming the way tourists interact with destinations and tourism services. Simultaneously, sustainability has emerged as one of the most significant challenges facing tourism destinations worldwide. The continuous growth of tourism activities has intensified concerns related to resource depletion, environmental degradation, greenhouse gas emissions, overtourism, and increasing pressure on local communities. Consequently, tourism destinations are increasingly required to balance economic growth with environmental protection and social well-being (Bayramoğlu, 2025). S. Wang et al. (2026) emphasize that sustainable tourism development should simultaneously achieve environmental, economic, and social objectives, while Rosselló-Nadal and Sard (2026) highlight the importance of developing resilient and sustainable destinations capable of addressing growing visitor pressures and tourism externalities. In this context, artificial intelligence has increasingly been recognized as a key enabler of sustainable tourism development. AI-supported systems facilitate real-time monitoring, forecasting, adaptive management, and resource optimization, allowing tourism stakeholders to make more informed and sustainable decisions. Lakhmiri et al. (2026) demonstrate that smart technologies contribute to sustainability through environmental monitoring, resource management, forecasting, and adaptive decision-making processes. Likewise, Bingöl and Yang (2025) suggest that the integration of AI and smart technologies into destination ecosystems promotes sustainable tourism growth while enhancing destination management capabilities. Several AI applications have emerged as prominent solutions within tourism management. Generative AI Systems provide personalized travel assistance and help tourists navigate increasingly complex sustainability-related information (Shen et al., 2026). Meyer-Waarden et al. (2026) found that GenAI significantly reduces information overload, improves decision quality, strengthens trust, and encourages environmentally responsible behaviour among tourists. AI Chatbots improves customer service through automated communication and personalized support, while digital twin technologies enable real-time optimization of tourism facilities and infrastructure (Yamagishi et al., 2026). Furthermore, Smart Governance systems enhance monitoring, stakeholder engagement, and collaborative decision-making, whereas open data platforms facilitate transparency, innovation, and evidence-based destination management. According to Mandić and Kennell (2021), Smart Governance can improve citizen engagement, environmental performance, and destination management effectiveness. Similarly, Celdrán-Bernabéu et al. (2026) argue that open data initiatives contribute to sustainability, governance, competitiveness, and innovation within smart tourism destinations (Qiao et al., 2026). Despite the increasing interest in AI applications, the existing literature remains fragmented. Most previous studies have focused on individual technologies such as GenAI, chatbots, digital twins, Smart Governance systems, or open data platforms separately. In addition, sustainability-oriented studies frequently examine isolated environmental, social, or economic outcomes without providing a comprehensive comparison among alternative AI applications. Lakhmiri et al. (2026), in their systematic review of green-smart integration in tourism, emphasize the absence of harmonized indicators and comprehensive evaluation frameworks capable of assessing sustainability performance across different technological solutions. Similarly, Bingöl and Yang (2025) note that empirical evidence regarding the practical implementation of AI-supported destination ecosystems remains limited. As a result, tourism managers and policymakers currently lack objective decision support tools for identifying which AI applications offer the greatest overall contribution to sustainable tourism management. To address this research gap, the present study develops a multi-criteria sustainability assessment framework for evaluating AI applications in tourism management. Six major AI-based tourism applications, namely Generative AI Systems, AI Chatbots, Digital Twin Systems, Smart Destination Management, Smart Governance, and Open Data Tourism

Platforms, are assessed using sustainability-related criteria derived from the literature. An integrated Entropy–TOPSIS methodology is employed to determine criterion weights objectively and rank alternative AI applications according to their sustainability performance. By providing a systematic and quantitative evaluation framework, this study contributes to the emerging literature on sustainable tourism digitalization and offers practical guidance for destination managers, policymakers, and tourism businesses seeking to maximize the sustainability benefits of AI investments. The novelty of this study does not stem from the Entropy–TOPSIS methodology itself, but from the development of a comprehensive literature-based evaluation framework that enables the systematic comparison of multiple AI applications across economic, environmental, social, managerial, and ethical sustainability dimensions within a single decision-making model.

The selected AI applications do not represent an exhaustive list of AI technologies used in tourism. Instead, they were selected as representative applications that collectively address operational, managerial, destination-level, and visitor-oriented functions while providing sufficient evidence for comparative sustainability assessment.

2. Materials and Methods

2.1. Research Design

This study proposes a multi-criteria decision-making (MCDM) framework to evaluate the sustainability performance of artificial intelligence (AI) applications in tourism management. The framework integrates the Entropy weighting method and the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) method to objectively assess and rank alternative AI applications according to their contributions to sustainable tourism development.

The research process consists of four main stages. First, a comprehensive review of recent tourism and hospitality literature was conducted to identify the most prominent AI applications adopted within tourism management. Second, sustainability-related evaluation criteria were derived from the literature and grouped into environmental, economic, social, managerial, and ethical dimensions. Third, a decision matrix was constructed using a literature-based scoring approach. Finally, the Entropy method was employed to determine objective criterion weights, and the TOPSIS method was applied to rank the selected AI applications according to their overall sustainability performance. The proposed methodological framework is illustrated in Figure 1.

2.2. Selection of AI Applications

Based on a comprehensive review of 35 peer-reviewed references, six AI applications that are frequently discussed in tourism management and sustainable tourism research were selected as evaluation alternatives. The selection of AI applications was guided by three criteria: (i) the application had to be explicitly discussed in the tourism or hospitality literature; (ii) sufficient evidence had to be available to evaluate the application across the ten predefined sustainability criteria; and (iii) the application had to represent a distinct AI-based approach with practical relevance for tourism management rather than a minor variation of another technology. The selected alternatives are:

- A1: Generative AI Systems
- A2: AI Chatbots
- A3: Digital Twin Systems
- A4: Smart Destination Management
- A5: Smart Governance
- A6: Open Data Tourism Platforms

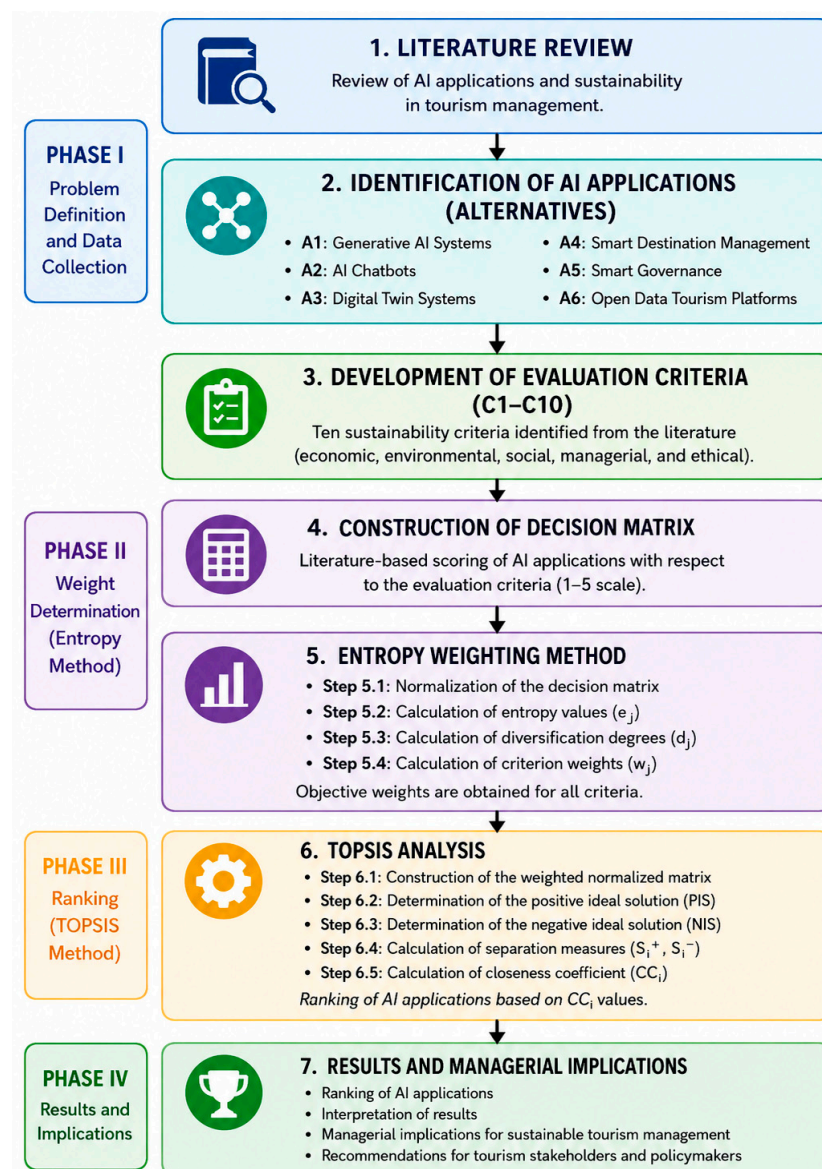


Figure 1. Research framework of the Entropy–TOPSIS approach for evaluating AI applications in sustainable tourism management.

2.3. Secondary Data Collection and Construction of the Decision Matrix

Since this study did not involve primary data collection, the decision matrix was developed using secondary data derived from the existing literature. The secondary data consisted of 35 peer-reviewed references focusing on artificial intelligence applications in tourism management, sustainable tourism, smart destinations, and related digital technologies. Rather than extracting numerical values directly from individual studies, the findings reported in the reviewed literature were comparatively synthesized to evaluate each AI application across the predefined sustainability criteria. Consequently, the assigned scores represent a structured synthesis of the available scientific evidence rather than numerical values reported in individual publications.

The six AI applications included in the evaluation were selected because they were repeatedly discussed in the reviewed literature, represented distinct AI-based approaches, and provided sufficient evidence for comparative assessment across the ten sustainability criteria. Applications that lacked sufficient evidence or represented only minor variations of existing technologies were excluded from the evaluation.

To ensure consistency during the literature-based evaluation, a five-point scoring scale was adopted. For benefit criteria (C1–C9), scores ranged from 1 (very low contribution) to 5 (very high contribution). For the cost criterion C10 (privacy and ethical risk), scores ranged from 1 (very low privacy and ethical risk) to 5 (very high privacy and ethical risk).

2.4. Development of Evaluation Criteria

The evaluation criteria were identified through a systematic review of the recent literature on artificial intelligence, smart tourism, sustainable tourism, and destination management. Previous studies emphasize that the assessment of technological solutions in tourism should not be limited to economic performance alone but should also consider environmental, social, managerial, and ethical dimensions. Accordingly, ten evaluation criteria were established.

A. Economic Dimension

C1. Operational Efficiency: Represents the capability of AI applications to improve operational performance, automate tasks, and enhance productivity.

C2. Cost Reduction: Measures the ability of AI systems to reduce operational and management costs.

B. Environmental Dimension

C3. Energy Efficiency: Evaluates the contribution of AI applications to reducing energy consumption and improving resource utilization.

C4. Sustainability Contribution: Measures the overall contribution of AI technologies to environmental sustainability and responsible tourism development.

C. Social Dimension

C5. Customer Satisfaction: Represents the impact of AI applications on tourist satisfaction and service outcomes.

C6. Personalization Capability: Measures the ability of AI systems to provide personalized services and recommendations.

C7. Visitor Experience Enhancement: Evaluates the contribution of AI applications to improving overall visitor experiences.

D. Managerial Dimension

C8. Data-Driven Decision-Making: Measures the capability of AI applications to support evidence-based management and decision-making processes.

C9. Social Welfare Contribution: Represents the contribution of AI technologies to community well-being and sustainable destination development.

E. Ethical Dimension

C10. Privacy and Ethical Risk: Measures potential concerns associated with privacy, data security, transparency, and ethical use of AI systems.

Among these criteria, C1–C9 are benefit criteria, while C10 is considered a cost criterion. Table 1 presents the evaluation criteria employed in the study.

The proposed evaluation criteria were developed by synthesizing sustainability dimensions commonly emphasized in the sustainable tourism literature. The framework integrates economic, environmental, social, managerial, and ethical perspectives, thereby reflecting the multidimensional nature of sustainable tourism management. Conceptually, these dimensions are consistent with the principles of the Triple Bottom Line (economic, environmental, and social sustainability) while extending the framework to include managerial effectiveness and ethical considerations that are particularly relevant to AI-enabled tourism systems.

Table 1. Sustainability evaluation criteria for AI applications in tourism management.

Code	Criterion	Dimension	Type
C1	Operational Efficiency	Economic	Benefit
C2	Cost Reduction	Economic	Benefit
C3	Energy Efficiency	Environmental	Benefit
C4	Sustainability Contribution	Environmental	Benefit
C5	Customer Satisfaction	Social	Benefit
C6	Personalization Capability	Social	Benefit
C7	Visitor Experience Enhancement	Social	Benefit
C8	Data-Driven Decision-Making	Managerial	Benefit
C9	Social Welfare Contribution	Social	Benefit
C10	Privacy and Ethical Risk	Ethical	Cost

2.5. Construction of the Decision Matrix

A decision matrix was constructed to evaluate the sustainability performance of the selected AI applications. Since the objective of this study is to compare AI applications based on evidence reported in the literature, a literature-based scoring approach was adopted. Similar approaches have been widely employed in sustainability assessment and multi-criteria decision-making studies when direct quantitative measurements are unavailable and when the evaluation involves emerging technologies characterized by multidimensional impacts (T.-C. Wang & Lee, 2009; Zavadskas et al., 2014).

The evaluation criteria were identified through a comprehensive review of recent studies on artificial intelligence, sustainable tourism, smart destinations, Smart Governance, and digital transformation in tourism. Previous research has highlighted that AI technologies contribute to tourism sustainability through improvements in operational efficiency, resource management, visitor experience, personalization, decision-making quality, and destination governance (Bingöl & Yang, 2025; Lakhmiri et al., 2026; Mandić & Kennell, 2021; Meyer-Waarden et al., 2026). Conversely, the literature also emphasizes challenges related to privacy, ethics, and data security associated with AI adoption (Meyer-Waarden et al., 2026).

Following the literature synthesis, each AI application was evaluated according to the selected criteria using a five-point rating scale ranging from 1 (very low contribution) to 5 (very high contribution). The assigned scores reflect the relative contribution of each AI application to sustainable tourism management based on the findings reported in previous studies. For example, Digital Twin Systems received higher scores for energy efficiency and operational efficiency due to their demonstrated capability to optimize building operations and reduce resource consumption. Similarly, Generative AI Systems and AI Chatbots received higher scores for personalization capability and customer satisfaction because of their ability to provide customized recommendations and interactive customer support. Smart Destination Management, Smart Governance, and Open Data Platforms received relatively higher scores for data-driven decision-making and sustainability contribution due to their ability to support evidence-based destination management and stakeholder collaboration (Celdrán-Bernabéu et al., 2026).

To improve the transparency and reproducibility of the scoring process, the literature-based scores were assigned through a structured synthesis of evidence rather than relying on a single publication for each AI application. For each alternative, findings from multiple peer-reviewed studies addressing operational efficiency, sustainability, environmental performance, customer satisfaction, personalization capability, governance, and decision support were reviewed and compared. The evidence was then synthesized to evaluate the relative contribution of each AI application to the ten sustainability criteria using a five-point ordinal scale (1 = very low contribution, 5 = very high contribution). When several studies consistently reported similar strengths or weaknesses, higher confidence

was assigned to the corresponding score. Therefore, the decision matrix represents a comparative synthesis of current literature rather than the results of any individual study. To ensure consistency during the literature-based evaluation, a five-point scoring scale was adopted for all criteria. For benefit criteria (C1–C9), scores ranged from 1 (very low contribution) to 5 (very high contribution). For the cost criterion C10 (privacy and ethical risk), scores ranged from 1 (very low privacy and ethical risk) to 5 (very high privacy and ethical risk). The assigned scores were determined through a structured comparative synthesis of the reviewed literature rather than being directly extracted from individual studies.

The resulting decision matrix consists of six alternatives and ten evaluation criteria. This matrix serves as the primary input for Entropy weighting and TOPSIS ranking procedures. Table 2 presents the literature-based decision matrix used in the study.

Table 2. Literature-based decision matrix.

Alternative	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	Refs.
A1	4	3	1	4	5	5	5	4	3	5	(Jin et al., 2026; Giri et al., 2026; Meyer-Waarden et al., 2026)
A2	4	3	1	3	5	4	4	3	3	4	(Yamagishi et al., 2026; Bingöl & Yang, 2025; Srivastava et al., 2024)
A3	5	4	3	5	3	2	4	5	3	2	(Dang et al., 2023; Tian, 2026; Lakhmiri et al., 2026)
A4	4	3	2	5	5	4	5	5	5	3	(Carpentiere & Ardito, 2025; Celdrán-Bernabéu et al., 2026; Nieves-Pavón et al., 2024)
A5	3	2	1	5	2	1	3	5	5	1	(Mandić & Kennell, 2021; Siddiqui et al., 2024; Marchesani & Ceci, 2026)
A6	4	3	2	5	3	3	4	5	5	3	(Jiang et al., 2026; Celdrán-Bernabéu et al., 2026)

Note: Scores were assigned using a structured literature-based evidence-coding procedure. For each AI application–criterion pair, findings from multiple peer-reviewed studies were synthesized and evaluated comparatively. A score of 5 indicates consistent evidence of a very strong and direct contribution; 4 indicates a strong contribution; 3 indicates moderate, mixed, or indirect evidence; 2 indicates limited evidence; and 1 indicates a very limited contribution or the absence of meaningful supporting evidence. Where studies reported differing findings, the assigned score reflected the dominant pattern of evidence across the reviewed literature. The cited references represent the principal sources supporting each alternative, while the criterion-level evidence and scoring rationales are reported in Appendix A.

As shown in Table 2, Digital Twin Systems (A3) received the highest scores in energy efficiency, cost reduction, and sustainability contribution, reflecting their strong capability to optimize operational performance and resource utilization. In contrast, Generative AI Systems (A1) and AI Chatbots (A2) achieved higher scores in customer satisfaction, personalization capability, and visitor experience enhancement due to their ability to provide customized and interactive tourism services. Smart Destination Management, Smart Governance, and Open Data Tourism Platforms demonstrated comparatively stronger performance in data-driven decision-making and sustainability-oriented destination management functions.

2.6. Entropy Weighting Method

The Entropy method was employed to determine the objective weights of the evaluation criteria. Originally derived from information theory, Entropy measures the degree of uncertainty or disorder associated with a dataset (Shannon, 1948). In multi-criteria decision-making applications, the Entropy method determines criterion weights according to the amount of information provided by each criterion. Criteria exhibiting greater variability among alternatives are assigned higher weights because they possess stronger discriminating power (T.-C. Wang & Lee, 2009).

Compared with subjective weighting approaches that rely on expert judgments, the Entropy method provides an objective weighting mechanism based solely on the characteristics of the decision matrix. Therefore, it is particularly suitable for studies aiming to minimize subjective bias and derive criterion weights directly from the available data (T.-C. Wang & Lee, 2009; Zavadskas et al., 2014). The Entropy weighting procedure consists of four steps.

Step 1. Normalization of the Decision Matrix: The normalized value of each criterion is calculated as Equation (1) (Kumar & Pamucar, 2025; Sahoo et al., 2025):

$$P_{ij} = \frac{x_{ij}}{\sum x_{ij}} \quad (1)$$

where P_{ij} is the normalized value of alternative i under criterion j ; x_{ij} represents the original value of alternative i under criterion j .

Step 2. Calculation of Entropy Values: The Entropy value for each criterion is computed as Equation (2) (Liu et al., 2023; Saraiva, 2023):

$$e_j = -k \sum (P_{ij} \cdot \ln(P_{ij})) \quad (2)$$

where $k = 1/\ln(m)$ and e_j denotes the Entropy value of criterion j ; m denotes the number of alternatives.

Step 3. Calculation of Diversification Degree: The degree of diversification is determined by Equation (3):

$$d_j = 1 - e_j \quad (3)$$

where d_j represents the information utility of criterion j .

Step 4. Determination of Criterion Weights. The objective weight of each criterion is calculated as Equation (4):

$$w_j = \frac{d_j}{\sum d_j} \quad (4)$$

where w_j denotes the weight assigned to criterion j . The resulting criterion weights are subsequently incorporated into the TOPSIS method to rank the selected AI applications according to their overall sustainability performance.

Accordingly, higher Entropy weights indicate greater discriminatory information contained in the decision matrix and should not be interpreted as representing the inherent importance of the corresponding evaluation criteria.

2.7. TOPSIS Method

Following the determination of criterion weights using the Entropy method, the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) method was employed to rank the selected AI applications. The TOPSIS method was originally developed by Hwang and Yoon (Hwang & Yoon, 1981) and is one of the most widely used multi-criteria decision-making methods due to its simplicity and ability to simultaneously consider the best and worst solutions.

The fundamental principle of the TOPSIS method is that the optimal alternative should have the shortest distance from the Positive Ideal Solution (PIS) and the farthest distance from the Negative Ideal Solution (NIS) (Zournatzidou et al., 2025).

Step 1. Construction of the Normalized Decision Matrix:

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^m x_{ij}^2}} \quad (5)$$

where r_{ij} is the normalized value of alternative i under criterion j , x_{ij} is the original value of alternative i under criterion j , and m is the number of alternatives (Yılmaz et al., 2024).

Step 2. Construction of the Weighted Normalized Matrix:

$$v_{ij} = w_j \cdot r_{ij} \quad (6)$$

where v_{ij} is the weighted normalized value and w_j = the weight of criterion j .

Step 3. Determination of the Positive Ideal Solution (PIS):

$$A^+ = \langle \max(v_{ij}) | J \in J_b, \min(v_{ij}) | J \in J_c \rangle \quad (7)$$

where J_b is the set of benefit criteria and J_c = the set of cost criteria.

Step 4. Determination of the Negative Ideal Solution (NIS):

$$A^- = \langle \min(v_{ij}) | J \in J_b, \max(v_{ij}) | J \in J_c \rangle \quad (8)$$

Step 5. Calculation of the Separation Measures:

Distance from the Positive Ideal Solution is given in Equation (9) (Behzadian et al., 2012):

$$S_i^+ = \sqrt{\sum_{j=1}^n (v_{ij} - v_j^+)^2} \quad (9)$$

where S_i^+ is the distance from the Positive Ideal Solution and S_i^- is the distance from the Negative Ideal Solution. The distance from the Negative Ideal Solution is given in Equation (10):

$$S_i^- = \sqrt{\sum_{j=1}^n (v_{ij} - v_j^-)^2} \quad (10)$$

where S_i^+ is the distance from the Positive Ideal Solution and S_i^- is the distance from the Negative Ideal Solution.

Step 6. Calculation of the Relative Closeness Coefficient:

$$CC_i = \frac{S_i^-}{S_i^+ + S_i^-} \quad (11)$$

where CC_i is the closeness coefficient of alternative i and $0 \leq CC_i \leq 1$. A higher CC_i value indicates better overall sustainability performance. Therefore, alternatives are ranked in descending order according to their closeness coefficients. The alternative with the highest CC_i value is considered the most preferable AI application for sustainable tourism management.

Although the scoring process inevitably involves a degree of researcher interpretation, the use of a structured evidence-coding procedure, predefined evaluation criteria, explicit scoring rules, and criterion-level justifications was intended to minimize subjectivity and enhance reproducibility.

3. Results and Discussion

3.1. Entropy Weighting Results

The Entropy method was employed to determine the objective criterion weights according to the discriminatory information contained in the decision matrix. The calculated Entropy values (e_j), diversification degrees (d_j), and criterion weights (w_j) are presented in Table 3.

Table 3. Entropy weights of the evaluation criteria.

Criterion	e_j	d_j	w_j
C1	0.9941	0.0059	0.0231
C2	0.9895	0.0105	0.0414
C3	0.9464	0.0536	0.2108
C4	0.9913	0.0087	0.0341
C5	0.9706	0.0294	0.1158
C6	0.9436	0.0564	0.2217
C7	0.9922	0.0078	0.0305
C8	0.9913	0.0087	0.0341
C9	0.9824	0.0176	0.0693
C10	0.9443	0.0557	0.2190

The Entropy results reveal substantial differences in the discriminatory power of the evaluation criteria across the assessed AI applications. Among all criteria, personalization capability (C6) received the highest weight (0.2217), followed closely by privacy and ethical risk (C10) (0.2190) and energy efficiency (C3) (0.2108). Together, these three criteria account for approximately 65.15% of the total weighting structure, indicating that they provide the greatest discriminatory information for distinguishing the performance of AI applications in sustainable tourism management.

The relatively high weight assigned to energy efficiency (C3) suggests that AI applications differ considerably in their capacity to optimize resource utilization and improve environmental performance. This finding is consistent with recent studies highlighting the increasing importance of energy management and sustainability within tourism and hospitality operations. Likewise, the greatest discriminating capability of personalization capability (C6) reflects the growing demand for customized services and visitor-centred experiences, which have become key drivers of competitiveness in smart tourism destinations. The high weight of privacy and ethical risk (C10) further demonstrates that concerns related to data privacy, transparency, and the responsible use of AI have become critical factors in evaluating tourism technologies.

In contrast, operational efficiency (C1), sustainability contribution (C4), data-driven decision-making (C8), cost reduction (C2), visitor experience enhancement (C7), and social welfare contribution (C9) received comparatively lower weights. This indicates that the evaluated AI applications exhibit more similar performance levels with respect to these criteria, resulting in lower discriminatory power within the Entropy weighting process.

Overall, the Entropy analysis indicates that personalization capability (C6), privacy and ethical risk (C10), and energy efficiency (C3) provide the greatest discriminatory power for distinguishing among the evaluated AI applications within the proposed decision matrix. It should be emphasized that the Entropy weights reflect the variability of the evaluation criteria across alternatives rather than their intrinsic theoretical or practical importance for sustainable tourism management.

3.2. TOPSIS Ranking Results

Following the determination of criterion weights, the TOPSIS method was applied to rank the selected AI applications according to their overall sustainability performance. The separation measures from the Positive Ideal Solution (S_i^+), the Negative Ideal Solution (S_i^-), and the relative closeness coefficients (CC_i) are presented in Table 4.

The TOPSIS rankings should be interpreted within the context of the literature-based decision matrix developed in this study. Since the rankings depend on both the assigned scores and the Entropy-derived criterion weights, they represent comparative outcomes

of the proposed evaluation framework rather than definitive measures of the real-world sustainability performance of AI applications.

Table 4. TOPSIS results and ranking.

Alternative	S_i^+	S_i^-	CC_i	Rank
A4 Smart Destination Management	0.0771	0.1141	0.5968	1
A3 Digital Twin Systems	0.0879	0.1292	0.5950	2
A6 Open Data Tourism Platforms	0.0927	0.0918	0.4978	3
A1 Generative AI Systems	0.1453	0.1114	0.4340	4
A5 Smart Governance	0.1462	0.1107	0.4308	5
A2 AI Chatbots	0.1290	0.0909	0.4136	6

The revised TOPSIS analysis indicates that Smart Destination Management (A4) achieved the highest closeness coefficient ($CC_i = 0.5968$), ranking first among all evaluated AI applications. This superior performance can be attributed to its consistently high scores across multiple criteria, particularly sustainability contribution (C4), customer satisfaction (C5), visitor experience enhancement (C7), data-driven decision-making (C8), and social welfare contribution (C9). Unlike technologies focusing on a single operational aspect, Smart Destination Management provides an integrated framework that combines digital technologies, stakeholder collaboration, sustainable governance, and destination intelligence. This finding supports previous studies emphasizing that smart destinations enhance both destination competitiveness and long-term sustainability through the integration of AI, IoT, and data-driven management approaches (Nieves-Pavón et al., 2024; Carpentiere & Ardito, 2025).

Digital Twin Systems (A3) ranked second with a closeness coefficient of 0.5950, only marginally lower than Smart Destination Management. Their strong performance is mainly associated with operational efficiency (C1), cost reduction (C2), sustainability contribution (C4), and data-driven decision-making (C8). Digital twins enable real-time monitoring, simulation, predictive analysis, and intelligent resource management, making them particularly effective for improving operational performance in tourism and hospitality facilities. Although Digital Twin Systems demonstrated comparatively lower scores in personalization capability (C6), their excellent performance in operational and sustainability-related criteria ensured a highly competitive overall ranking (Dang et al., 2023; Tian, 2026).

Open Data Tourism Platforms (A6) ranked third ($CC_i = 0.4978$). Their strong performance in data-driven decision-making (C8), sustainability contribution (C4), and social welfare contribution (C9) reflects the growing importance of open data ecosystems for evidence-based destination management, transparency, innovation, and stakeholder collaboration. However, their relatively limited contribution to personalization capability (C6) and energy efficiency (C3) prevented them from outperforming the two highest-ranked alternatives (Jiang et al., 2026; Celdrán-Bernabéu et al., 2026).

Generative AI Systems (A1) ranked fourth with a closeness coefficient of 0.4340. Their strong performance in personalization capability (C6), customer satisfaction (C5), and visitor experience enhancement (C7) demonstrates the growing importance of conversational AI and intelligent recommendation systems in tourism. Nevertheless, relatively weak performance in energy efficiency (C3) together with the comparatively high privacy and ethical risk (C10) reduced their overall sustainability performance (Meyer-Waarden et al., 2026; Giri et al., 2026; Jin et al., 2026).

Smart Governance (A5) achieved the fifth position ($CC_i = 0.4308$). Although this alternative received excellent scores in data-driven decision-making (C8), sustainability contribution (C4), and social welfare contribution (C9), its limited contribution to operational

criteria, particularly personalization capability (C6) and energy efficiency (C3), reduced its overall ranking. This result suggests that governance-oriented AI applications play an important strategic role but provide fewer direct operational benefits than destination- or technology-oriented solutions (Mandić & Kennell, 2021; Siddiqui et al., 2024).

Finally, AI Chatbots (A2) ranked sixth with a closeness coefficient of 0.4136. Although chatbots demonstrated strong performance in customer satisfaction (C5) and personalization capability (C6), they exhibited relatively limited contributions to sustainability-related operational criteria such as energy efficiency (C3) and sustainability contribution (C4). Consequently, their overall performance remained lower than that of more comprehensive AI applications designed to support strategic destination management and sustainable tourism development (Srivastava et al., 2024; Bingöl & Yang, 2025).

3.3. Discussion of Findings

The findings reveal that AI applications integrating strategic destination management with sustainability-oriented digital technologies achieve higher overall sustainability performance than solutions focusing on a single operational function. The first-ranked position of Smart Destination Management demonstrates the value of combining sustainability principles, stakeholder collaboration, data-driven governance, and visitor-oriented digital services within a unified management framework. This result suggests that holistic destination-wide AI strategies provide greater overall sustainability benefits than isolated technological applications.

Digital Twin Systems, which ranked second with a very similar closeness coefficient, further highlight the importance of intelligent monitoring, simulation, and resource optimization in sustainable tourism management. Their strong performance confirms that AI technologies capable of improving operational processes and supporting evidence-based management remain fundamental components of sustainable destination development.

Another important finding is the greatest discriminating capability of personalization capability (C6), privacy and ethical risk (C10), and energy efficiency (C3), which together account for approximately 65.15% of the total Entropy weighting structure. The high weight assigned to personalization capability indicates that individualized services, adaptive recommendations, and customized visitor experiences have become key differentiating factors among AI applications. At the same time, the substantial weight of privacy and ethical risk demonstrates that responsible AI implementation, data protection, and transparency have become equally important considerations in evaluating tourism technologies. Likewise, the significant contribution of energy efficiency highlights the continuing importance of environmental performance and resource optimization within sustainable tourism management.

Although Open Data Tourism Platforms and Smart Governance achieved lower overall rankings than the leading alternatives, this does not diminish their strategic importance. Rather, the Entropy weighting process emphasizes criteria that exhibit greater variability among alternatives. Consequently, governance-oriented and open data-based solutions continue to play a critical role in supporting long-term planning, stakeholder collaboration, transparency, and evidence-based policymaking, even though they provide fewer direct operational benefits than Smart Destination Management or Digital Twin Systems.

Overall, the results suggest that the proposed framework may assist organizations in identifying promising AI applications with relatively stronger sustainability performance within the scope of the selected evaluation criteria. However, investment decisions should also consider organization-specific factors such as implementation costs, technological maturity, organizational readiness, infrastructure availability, investment risks, and expected return on investment, which were beyond the scope of the present study. Accordingly, the

identified ranking should be interpreted as a decision support outcome derived from the proposed literature-based framework rather than as an absolute ranking of AI technologies. Different empirical datasets, expert judgments, or alternative scoring assumptions may lead to different weighting structures and ranking results.

4. Conclusions

This study developed an integrated Entropy–TOPSIS framework to comparatively evaluate artificial intelligence (AI) applications for sustainable tourism management. Six representative AI applications were assessed using ten sustainability-related criteria covering economic, environmental, social, managerial, and ethical dimensions. The Entropy analysis identified personalization capability (C6), privacy and ethical risk (C10), and energy efficiency (C3) as the most discriminating criteria, with weights of 0.2217, 0.2190, and 0.2108, respectively, accounting for 65.15% of the total weighting structure. The TOPSIS analysis ranked Smart Destination Management first ($CC_i = 0.5968$), followed closely by Digital Twin Systems ($CC_i = 0.5950$) and Open Data Tourism Platforms, highlighting the growing importance of integrated digital ecosystems for sustainable destination management.

The findings suggest that AI applications delivering balanced performance in sustainability, operational efficiency, visitor experience, and responsible governance provide greater potential to support sustainable tourism. Accordingly, the proposed framework may serve as a practical decision support tool for tourism stakeholders when comparing AI technologies, while recognizing that technology adoption should also consider organizational readiness, implementation costs, technological maturity, and investment risks.

Compared with previous studies, which have largely focused on individual AI technologies or specific tourism functions, this study provides an integrated comparative framework for evaluating multiple AI applications within a unified sustainability perspective. In doing so, it addresses an important gap in the tourism literature and offers a transparent, literature-based approach that can be updated using empirical evidence or expert judgments.

This study is subject to several limitations. The decision matrix was developed using a structured literature-based scoring approach rather than empirical observations and did not include expert validation, Delphi consensus, inter-rater reliability assessment, or sensitivity analysis. Therefore, the proposed framework should be interpreted as a literature-based comparative decision support model rather than a direct measure of the real-world sustainability performance of AI technologies. Future research should validate and extend the framework using expert panels, empirical datasets, sensitivity analysis, and alternative MCDM techniques to further improve its robustness and applicability.

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Appendix A

Table A1. Generative AI Systems.

Criterion	Score	Evidence Level	Evidence-Based Justification	Main References
C1	4	SI	Multiple studies report automation of information retrieval, itinerary generation, conversational assistance, and decision support, improving operational efficiency, although not directly optimizing tourism infrastructure.	Meyer-Waarden et al. (2026) ; Giri et al. (2026)
C2	3	LI	Automation may reduce customer service workload and content creation effort, but no study has quantitatively demonstrated a reduction in tourism costs.	Meyer-Waarden et al. (2026) ; Giri et al. (2026)
C3	1	NE	None of the reviewed studies directly evaluate energy efficiency resulting from Generative AI adoption.	Meyer-Waarden et al. (2026) ; Jin et al. (2026)
C4	4	SI	Studies consistently show that GenAI facilitates environmentally responsible decision-making by simplifying access to information on sustainable tourism.	Meyer-Waarden et al. (2026)
C5	5	D	User experience, trust, engagement, and behavioural intention are directly improved.	Meyer-Waarden et al. (2026) ; Giri et al. (2026)
C6	5	D	Personalized recommendations and adaptive interactions are repeatedly identified as key capabilities.	Meyer-Waarden et al. (2026) ; Giri et al. (2026)
C7	5	D	Studies directly report enhanced tourist engagement and improved travel experiences.	Meyer-Waarden et al. (2026) ; Giri et al. (2026)
C8	4	SI	GenAI supports information synthesis and decision support, although its use in strategic destination management remains limited.	Jin et al. (2026)
C9	3	LI	Social benefits are discussed indirectly through accessibility and better information availability.	Meyer-Waarden et al. (2026)
C10	5	D	Privacy, hallucination, bias, misinformation, and ethical concerns are explicitly discussed. Because C10 is a cost criterion, a higher score denotes a higher level of privacy and ethical risk.	Jin et al. (2026) ; Meyer-Waarden et al. (2026)

Table A2. AI Chatbots.

Criterion	Score	Evidence Level	Evidence-Based Justification	Main References
C1	4	D/SI	AI Chatbots automate repetitive language-based tasks and customer interactions, provide continuous support, and reduce reliance on human service personnel. Srivastava et al. specifically note that firms can serve customers without maintaining a full 24 h human support team. Nevertheless, chatbots primarily improve communication efficiency rather than physical tourism operations.	Srivastava et al. (2024) ; Bingöl and Yang (2025)
C2	3	SI	The automation of customer support can reduce staffing needs and service delivery costs. However, the reviewed studies do not provide direct tourism-specific monetary estimates or a quantitative cost-saving analysis. Therefore, the evidence supports a moderate rather than a very high score.	Srivastava et al. (2024)
C3	1	NE	None of the reviewed chatbot studies directly examine reductions in energy consumption, building energy use, transport energy demand, or physical resource utilization. Chatbots may reduce some information search effort, but this does not constitute demonstrated operational energy efficiency.	Yamagishi et al. (2026) ; Srivastava et al. (2024) ; Bingöl and Yang (2025)
C4	3	LI/SI	Chatbots can provide accessible information, guide tourist choices, and potentially communicate responsible or sustainable alternatives. However, the principal chatbot studies focus mainly on information quality, trust, service interaction, and behavioural intention rather than direct environmental outcomes. Their sustainability contribution is therefore mostly indirect and context-dependent.	Bingöl and Yang (2025) ; Yamagishi et al. (2026)
C5	5	D	The literature directly links chatbot usefulness, responsiveness, information quality, trust, and service quality with satisfaction, loyalty, recommendation acceptance, and behavioural intention. These are central customer-oriented outcomes, justifying a very high score.	Yamagishi et al. (2026) ; Srivastava et al. (2024) ; Bingöl and Yang (2025)
C6	4	D	Chatbots can provide individualized assistance and recommendations, and support personalized care. Smart tourism research also identifies personalization as an important factor affecting visitor satisfaction and experience. However, conventional chatbot personalization is generally narrower and less adaptive than advanced GenAI systems, so a score of 4 rather than 5 is appropriate.	Srivastava et al. (2024) ; Bingöl and Yang (2025)
C7	4	D/SI	Chatbots improve visitor experience by providing immediate information, responsive assistance, destination-related guidance, and more convenient service interactions. The evidence supports a strong contribution, although the effect depends on information accuracy, interface quality, and user trust.	Yamagishi et al. (2026) ; Bingöl and Yang (2025)

Table A2. Cont.

Criterion	Score	Evidence Level	Evidence-Based Justification	Main References
C8	3	LI	Chatbots collect interaction data and can assist users in comparing alternatives and completing tasks. However, the reviewed evidence is stronger for tourist-level decision assistance than for strategic, organization-level, or destination-level managerial decision-making. A moderate score is therefore more defensible.	Srivastava et al. (2024) ; Bingöl and Yang (2025)
C9	3	LI	Continuous and accessible conversational support may broaden access to tourism information and assist users who need immediate or individualized guidance. Nevertheless, the reviewed chatbot studies do not directly measure community well-being, resident quality of life, inclusion, or local social development.	Srivastava et al. (2024) ; Bingöl and Yang (2025)
C10	4	D	Privacy, incorrect information, trust, transparency, and data quality concerns are repeatedly identified in conversational AI research. Because C10 is a cost criterion, a score of 4 denotes relatively high privacy and ethical risk rather than strong ethical performance.	Yamagishi et al. (2026) ; Srivastava et al. (2024) ; Bingöl and Yang (2025)

Table A3. Digital Twin Systems.

Criterion	Score	Evidence Level	Evidence-Based Justification	Main References
C1	5	D	Digital twins enable real-time monitoring, data integration, simulation, predictive management, and intelligent operational control. These capabilities substantially improve operational efficiency in tourism and cultural heritage management.	Dang et al. (2023) ; Tian (2026)
C2	4	SI	Digital twins improve monitoring, predictive management, and resource utilization, potentially reducing maintenance and operational costs. However, the reviewed studies do not provide quantitative evidence of tourism cost savings; therefore, a score of 4 is more appropriate than 5.	Dang et al. (2023) ; Tian (2026)
C3	3	LI	The reviewed studies emphasize intelligent resource management and optimization rather than direct measurements of energy savings. Therefore, digital twins indirectly support energy efficiency, but explicit evidence remains limited.	Tian (2026) ; Dang et al. (2023)
C4	5	D	Digital twins contribute directly to sustainable management through conservation, monitoring, optimized resource utilization, and long-term management of cultural and tourism assets.	Dang et al. (2023) ; Tian (2026)
C5	3	LI	Visitor benefits arise indirectly through improved destination management and more reliable services. However, customer satisfaction is not directly evaluated in the reviewed studies.	Tian (2026)

Table A3. Cont.

Criterion	Score	Evidence Level	Evidence-Based Justification	Main References
C6	2	NE/LI	Digital twins primarily support infrastructure and destination management rather than personalized visitor interaction. Limited evidence exists regarding individualized services.	Dang et al. (2023)
C7	4	D	The literature reports immersive visualization, intelligent guides, virtual–real interaction, improved cultural interpretation, and enhanced visitor engagement, all contributing positively to visitor experience.	Tian (2026) ; Dang et al. (2023)
C8	5	D	Real-time sensing, data fusion, simulation, and predictive analytics provide strong support for evidence-based operational and strategic decision-making.	Dang et al. (2023) ; Tian (2026)
C9	3	LI	Better preservation of cultural heritage and improved destination management may generate broader societal benefits, although these outcomes are discussed only indirectly.	Dang et al. (2023) ; Tian (2026)
C10	2	LI	The reviewed studies pay relatively little attention to privacy or ethical concerns. Risks associated with sensor data and digital infrastructure exist but are not the primary focus of the literature.	Dang et al. (2023) ; Tian (2026)

Table A4. Smart Destination Management.

Criterion	Score	Evidence Level	Evidence-Based Justification	Main References
C1	4	D	Smart Tourism Destination Management integrates ICT, knowledge management, stakeholder collaboration, and digital technologies to improve destination coordination, service delivery, and managerial efficiency. Although operational optimization is a major objective, it is implemented primarily at the destination level rather than individual facilities.	Carpentiere and Ardito (2025)
C2	3	LI	Better coordination and knowledge sharing may improve resource allocation and reduce management inefficiencies. However, the reviewed studies do not quantify economic savings or operational cost reductions.	Carpentiere and Ardito (2025)
C3	2	LI	Smart tourism technologies may contribute indirectly to resource-efficient destination management, but neither study explicitly evaluates reductions in energy consumption or energy performance.	Carpentiere and Ardito (2025) ; Nieves-Pavón et al. (2024)
C4	5	D	Sustainability constitutes one of the core dimensions of the Smart Tourism Model Canvas. The framework explicitly integrates environmental, social, cultural, governance, and knowledge-management perspectives into destination planning.	Carpentiere and Ardito (2025)

Table A4. Cont.

Criterion	Score	Evidence Level	Evidence-Based Justification	Main References
C5	5	D	Smart destination initiatives improve tourist satisfaction through enhanced service quality, positive emotions, memorable experiences, destination loyalty, and stronger word-of-mouth intention.	Nieves-Pavón et al. (2024)
C6	4	SI	Smart destinations increasingly employ AI, digital platforms, real-time information, and personalized services to better address visitor needs. Although personalization is not the primary focus of the framework, it represents an important component of smart destination services.	Carpentiere and Ardito (2025)
C7	5	D	Enhancing visitor experience represents one of the principal objectives of smart tourism destinations through digital services, emotional engagement, communication, and destination intelligence.	Nieves-Pavón et al. (2024) ; Carpentiere and Ardito (2025)
C8	5	D	Smart tourism destinations rely on ICT, knowledge management, analytics, and data-driven governance to support strategic planning, destination intelligence, and evidence-based management decisions.	Carpentiere and Ardito (2025)
C9	5	D	The reviewed framework explicitly emphasizes stakeholder collaboration, social inclusivity, participatory governance, knowledge sharing, and long-term community sustainability, demonstrating a strong contribution to social welfare.	Carpentiere and Ardito (2025)
C10	3	LI	Although smart destinations depend heavily on digital technologies and extensive data collection, privacy and ethical governance are discussed only indirectly. The literature recognizes these issues but does not identify them as dominant implementation barriers.	Carpentiere and Ardito (2025)

Table A5. Smart Governance.

Criterion	Score	Evidence Level	Evidence-Based Justification	Main References
C1	3	SI	Smart Governance improves coordination among government agencies, stakeholders, and digital services, thereby enhancing administrative efficiency. However, it does not directly optimize tourism operations or service delivery processes.	Mandić and Kennell (2021) ; Marchesani and Ceci (2026)

Table A5. Cont.

Criterion	Score	Evidence Level	Evidence-Based Justification	Main References
C2	2	LI	Better governance and coordination may reduce administrative inefficiencies and duplicated processes. Nevertheless, the reviewed studies provide no quantitative evidence of operational or financial cost reductions.	Marchesani and Ceci (2026)
C3	1	NE	None of the reviewed governance studies directly investigate energy optimization or reductions in energy consumption.	Siddiqui et al. (2024) ; Marchesani and Ceci (2026)
C4	5	D	Smart Governance is explicitly designed to support sustainable urban and destination development through policy integration, institutional coordination, stakeholder participation, and long-term governance frameworks.	Mandić and Kennell (2021) ; Marchesani and Ceci (2026)
C5	2	LI	Governance frameworks improve public service quality indirectly, but tourist satisfaction is not directly evaluated in the reviewed literature.	Marchesani and Ceci (2026)
C6	1	NE	Smart Governance focuses on institutional coordination, regulations, and public administration rather than personalized tourist services.	Siddiqui et al. (2024)
C7	3	LI	Improved governance can indirectly enhance visitor experiences by improving public services, destination coordination, and infrastructure planning. However, visitor experience is not the primary focus of these studies.	Mandić and Kennell (2021) ; Marchesani and Ceci (2026)
C8	5	D	Smart Governance relies on data governance, data value chains, interoperability, digital infrastructure, and evidence-based policymaking. Decision support represents one of its strongest documented capabilities.	Marchesani and Ceci (2026) ; Siddiqui et al. (2024)
C9	5	D	The reviewed studies consistently emphasize public value creation, stakeholder participation, transparency, collaboration, citizen well-being, and sustainable governance, indicating a very strong societal contribution.	Mandić and Kennell (2021) ; Marchesani and Ceci (2026)
C10	1	D	Security governance, privacy protection, interoperability, access control, accountability, and data governance constitute the principal themes of the reviewed literature. If C10 is treated as a benefit criterion (privacy and ethical management), Smart Governance deserves the highest score. If C10 represents privacy risk, the interpretation should be reversed.	Siddiqui et al. (2024) ; Marchesani and Ceci (2026)

Table A6. Open Data Tourism Platforms.

Criterion	Score	Evidence Level	Evidence-Based Justification	Main References
C1	4	D	Open data platforms improve destination management by facilitating information sharing, interoperability, and data accessibility, enabling more efficient operational planning and coordination among tourism stakeholders.	Jiang et al. (2026) ; Celdrán-Bernabéu et al. (2026)
C2	3	SI	Open data reduces information asymmetry, improves resource allocation, and promotes service innovation. Although these mechanisms can lower transaction and management costs, direct quantitative evidence of tourism cost reduction is limited.	Jiang et al. (2026)
C3	2	LI	Open data contributes indirectly to resource optimization through better planning and decision-making. However, the reviewed studies do not directly evaluate reductions in energy consumption or improvements in energy efficiency.	Celdrán-Bernabéu et al. (2026) ; Jiang et al. (2026)
C4	5	D	Both studies explicitly identify open data as a key enabler of sustainable tourism by supporting governance, transparency, innovation, environmental management, and evidence-based destination planning.	Jiang et al. (2026) ; Celdrán-Bernabéu et al. (2026)
C5	3	LI	Open data enhances information availability and supports the development of better tourism services. Nevertheless, customer satisfaction is not directly measured in the reviewed studies, making the contribution indirect.	Celdrán-Bernabéu et al. (2026)
C6	3	LI	Open data provides the information infrastructure necessary for personalized services, but personalization itself is delivered by downstream AI applications rather than by open data platforms directly.	Celdrán-Bernabéu et al. (2026)
C7	4	SI	Open data supports innovative tourism applications, better visitor information, smart services, and destination intelligence, contributing to improved visitor experiences. However, these effects are generally indirect.	Celdrán-Bernabéu et al. (2026) ; Jiang et al. (2026)
C8	5	D	Data openness is explicitly presented as a foundation for evidence-based policy, destination intelligence, governance, service innovation, and strategic tourism planning. This is one of the strongest documented capabilities of open data platforms.	Jiang et al. (2026) ; Celdrán-Bernabéu et al. (2026)
C9	5	D	The reviewed studies consistently highlight transparency, stakeholder participation, entrepreneurship, innovation, public value creation, and regional sustainable development, demonstrating a strong societal contribution.	Jiang et al. (2026) ; Celdrán-Bernabéu et al. (2026)
C10	3	LI	Open data initiatives require careful governance regarding privacy, data ownership, anonymization, and responsible data sharing. While these concerns are acknowledged, they are not identified as the dominant barriers in the reviewed literature.	Celdrán-Bernabéu et al. (2026) ; Jiang et al. (2026)

Appendix B

Table A7. Evidence level, definition, and interpretation.

Evidence Level	Definition	Interpretation
D—Direct Evidence	The reviewed studies explicitly evaluate or demonstrate the contribution of the AI application to the corresponding criterion.	Strongest level of evidence. The criterion is directly investigated and supported by empirical or conceptual findings.
SI—Strong Indirect Evidence	The criterion is not explicitly measured, but multiple studies consistently report findings that strongly imply its contribution.	High confidence based on consistent interpretation across the reviewed literature.
LI—Limited Indirect Evidence	Only limited or context-dependent evidence supports the criterion. The contribution can be inferred but is not consistently demonstrated.	Moderate confidence. The assigned score relies partly on comparative interpretation.
NE—No Evidence	No relevant evidence supporting the criterion was identified in the reviewed studies.	The assigned score reflects the absence of the supporting literature rather than negative evidence.

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