ISSN 2616-5775 Vol. 9, Issue 7: 52-57, DOI: 10.25236/AJCIS.2026.090707

A Review of AI-Enabled Low-Carbon Tourism: From Carbon Assessment to Intelligent Decision Support

Yan Jinghui[1,a], Zhang Yanhua[1,b,*], An Xiang[1,c], Zhang Wendu[1,d]

[1]*Xizang Minzu University, Xianyang, Shaanxi, 712082, China*
[a]*2457570791@qq.com,* [b]*553737258@qq.com,* [c]*1371997324@qq.com,* [d]*835167597@qq.com*
[*]*Corresponding author*

Abstract: *This paper conducts a scoping review of AI-related applications in low-carbon tourism based on representative studies from 2016 to 2025. A Python-assisted, rule-based literature screening pipeline was used to classify studies into carbon assessment, tourist behavior analysis, and intelligent decision support. The review shows that traditional methods such as carbon footprint accounting, STIRPAT, LMDI, system dynamics, and DEA remain dominant in tourism carbon studies, while AI-related methods such as machine learning, clustering, GIS-based analysis, recommendation algorithms, and optimization models are emerging in behavioral analytics and decision support. Based on these findings, an AI-enabled framework is proposed to integrate data acquisition, carbon accounting, intelligent modelling, application decision-making, and feedback optimization.*

Keywords: *Low-carbon Tourism, Artificial Intelligence, Text Mining, Feature Extraction, System Architecture*

1. Introduction

Tourism drives economic growth and employment but also causes substantial carbon emissions. Transport, accommodation, scenic operations, catering, and shopping are key sources. Low-carbon transition is therefore important for destination management[24,30].

Previous studies examined low-carbon experiences[27], green trust[26], short-video interventions[25], and nudging strategies[29]. These studies link low-carbon tourism with carbon management, tourist behavior, and digital governance.

Current research mainly uses carbon accounting, footprint analysis, decoupling analysis, efficiency evaluation, and scenario simulation. Representative studies addressed emission forecasting[1], scenario evolution[2], and carbon-footprint-based planning[3]. However, traditional models often rely on annual data and static assumptions.

AI, ML, big data, GIS, and optimization methods have expanded low-carbon tourism research[11-23]. However, existing applications remain fragmented. This review classifies AI-related studies from 2016 to 2025 and proposes a closed-loop management framework for carbon assessment, behavior analysis, and intelligent decision support.

2. Python-Assisted Rule-Based Text Mining and Literature Processing Pipeline

This study adopts Python-assisted rapid screening and classification program. The corpus was collected from Chinese and English academic databases, with the time span limited to 2016-2025. The overall workflow is shown in Figure 1.

ISSN 2616-5775 Vol. 9, Issue 7: 52-57, DOI: 10.25236/AJCIS.2026.090707

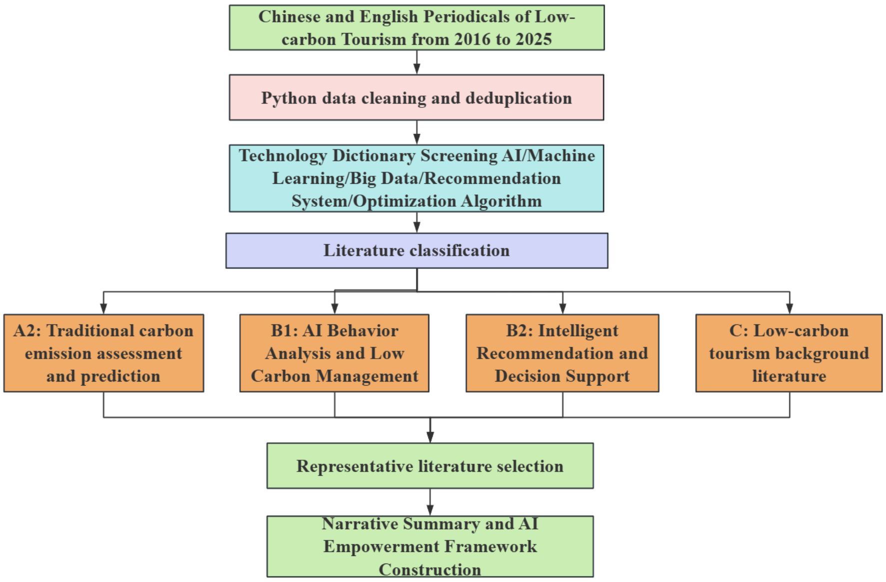

Figure 1: Literature screening and classification workflow

This review did not use TF-IDF, Word2Vec, BERT, or LDA as the main method. Its purpose was not topic discovery, but the classification of a small interdisciplinary corpus into predefined application-oriented categories. Therefore, rule-based text mining and dictionary screening were adopted to improve interpretability, reproducibility, and manual verification.

As shown in Table 1, the Python-assisted pipeline included four steps. First, pandas and regular expressions were used to extract bibliographic fields and clean missing values, redundant spaces, and HTML noise. Second, titles, keywords, and abstracts were merged into a unified text field for rule-based matching.

Third, bilingual dictionaries were developed for nine dimensions, including tourism, carbon and energy, prediction, AI, GIS, behavior management, optimization, and exclusion terms. Each paper was transformed into a Boolean feature vector. Fourth, hierarchical rules classified papers into traditional carbon assessment and prediction, AI-related behavior and management, intelligent recommendation and decision support, or background and exclusion categories.

Table 1: Python-based screening pipeline and technical implementation

Step	Processing task	Main technique	Python library or tool	Output
1	Data parsing	Structured metadata extraction	pandas	Title, keywords, abstract
2	Data cleaning	Missing value removal, year extraction	pandas, re	Cleaned bibliographic records
3	Corpus construction	Concatenation of title, keywords	pandas	Retrieval corpus
4	Dictionary matching	Rule-based keyword matching	re, custom dictionaries	Boolean feature vector
5	Hierarchical classification	Rule-based category assignment	Python functions	Literature categories
6	Manual validation	Full-text and academic relevance checking	Manual review	Final representative literature set
7	Visualization	Basic workflow	matplotlib	Figures and tables

The script was designed for literature screening and classification rather than predictive modelling or unsupervised semantic topic modelling. Therefore, libraries such as NLTK, spaCy, gensim, scikit-learn, and deep learning frameworks were not used as core tools. Its main computational logic consisted of metadata cleaning, regular expression matching, dictionary-based text mining, Boolean feature construction, hierarchical rule classification, and manual academic validation.

After automated screening, the candidate literature was manually reviewed for methodological relevance, low-carbon tourism relevance, and suitability for inclusion. Finally, 30 representative papers were selected and grouped into four categories: traditional carbon emission assessment and prediction studies, AI-related tourist behavior analysis studies, intelligent recommendation and decision-support studies, and background studies on low-carbon tourism mechanisms. Their classification and function are summarized in Table 2.

ISSN 2616-5775 Vol. 9, Issue 7: 52-57, DOI: 10.25236/AJCIS.2026.090707

Table 2: Literature Classification and Function

Category	Document type	Representative references	Typical methods or topics	function
A2	Traditional carbon emission assessment and prediction	1-10	Carbon footprint, STIRPAT, LMDI, system dynamics, DEA	Supports carbon accounting, footprint analysis
B1	AI and Tourists' Behavior Analysis	11-15	Machine learning, clustering, GIS visualization	Supports low-carbon behavior modelling through machine learning and clustering.
B2	Intelligent recommendation and decision support	16-23	Route recommendation, supply chain coordination	Supports route recommendation, location optimization
C	Background and mechanism of low-carbon tourism	24-30	Low-carbon tourism experiences, destination management	It is used to support the construction of introduction logic

3. Carbon Emission Assessment and Prediction in Low-Carbon Tourism

Carbon emission assessment is fundamental to quantifying highly dispersed emission sources. Existing literature widely employs Life Cycle Assessment, Input-Output analysis, and Undesirable SBM-DEA models for quantitative accounting and efficiency measurement[3,4,6,7,10]. In the realm of prediction, macroscopic models such as STIRPAT still maintain dominance[1, 2, 5, 8, 9].

However, traditional models have limited generalizability in large-scale real-world applications. They are prone to overfitting or underfitting when modeling high-frequency time-series data, struggle to integrate heterogeneous features such as meteorological, economic, and tourist-density variables, and are constrained in conducting high-resolution carbon-flow tracking at fine spatial scales.

The carbon management of low-carbon tourism urgently requires the introduction of data-driven paradigms. Machine Learning (ML) models (e.g., Random Forests, Gradient Boosting Trees) can efficiently capture non-linear mapping relationships within the feature space through tree-structured ensemble learning. Furthermore, Deep Learning (DL) architectures possess inherent advantages in processing high-frequency time series and multi-source dynamic spatial data.

4. Data Mining and Precise Identification of Tourist Behavior Patterns

Tourist decisions are important for emission reduction. Traditional studies mainly use static models, such as structural equation modeling (SEM)[14,28]. AI reframes this field as a data-mining and user-profiling task.

Machine learning can extract behavioral features from unstructured data[11]. Clustering supports data-driven tourist segmentation[13,15]. XAI and spatial visualization improve factor attribution and management efficiency[12]. Algorithmic nudges further support closed-loop low-carbon behavior management[25,29].

5. Spatial Optimization and Intelligent Decision Support

At the micro level, spatial analysis supports the identification of environmental factors. Zhang et al. combined Random Forest and GIS to assess the effects of hotel built environments on low-carbon travel[16]. Improved clustering methods, such as DIANA, also support dynamic low-carbon route planning[17].

At the meso and macro levels, low-carbon tourism supply chains involve multi-party decision-making. Zhang et al. and Ma et al. integrated big-data tags into O2O tourism supply-chain models[18,21]. Xu et al., Ma et al., and Chen et al. applied network optimization and differential game models for multi-agent coordination[19,20,23]. Li et al. used evolutionary algorithms to balance economic, social, and carbon-emission objectives[22].

6. AI Framework and Pseudocode for Low-Carbon Tourism

Synthesizing the preceding analysis, this paper innovatively proposes an End-to-End (E2E) AI computational architecture tailored for low-carbon tourism (illustrated in Figure 2), formalizing its core

ISSN 2616-5775 Vol. 9, Issue 7: 52-57, DOI: 10.25236/AJCIS.2026.090707

logic into an executable system workflow. This framework aims to dismantle data silos, enabling stream computing and closed-loop feedback.

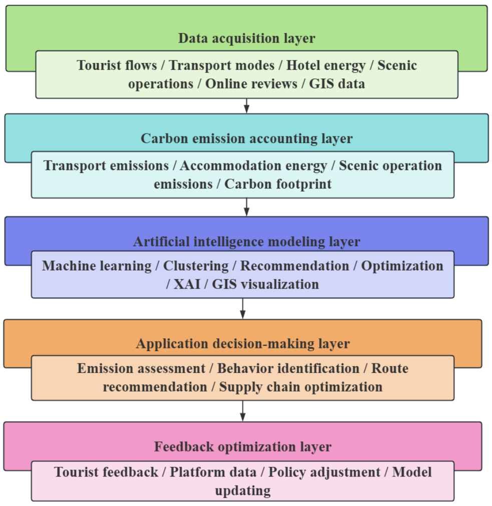

Figure 2: Artificial Intelligence Empowerment Framework for Low-carbon Tourism

To further elucidate the technical implementation logic of this computational architecture, we abstract it into a comprehensive data pipeline comprising data perception, carbon emission accounting, intelligent modeling, application decision-making, and online updating. The corresponding pseudocode is presented in Algorithm 1.

Algorithm 1 AI-enabled Low-carbon Tourism Framework

Input:

```
    Tourist flow data Tf, Transport mode data Tm, Hotel energy data He,
    Scenic area operation data So, Online review data Ro, Short video data Vs,
    GIS spatial data Gs, Carbon emission factors Ef, Tourist feedback data Fb.
```

Output:

```
    Carbon emission assessment Ce, Low-carbon behavior identification Bl,
    Low-carbon route recommendation Rl, Decision support results Ds,
    Updated model parameters θ'.
Step 1: Data Sensing and Cleaning
    D_raw ← {Tf, Tm, He, So, Ro, Vs, Gs}
    D_clean ← DataCleaning(D_raw)    // Clean missing values, abnormal data
    D_std ← DataStandardization(D_clean) // Align structured/unstructured data
Step 2: Carbon Emission Accounting
    For each tourism activity i in D_std:
        C_i ← ActivityData_i × EmissionFactor_i
    Ce ← Sum(C_transport, C_hotel, C_scenic, C_other)
    CF ← CarbonFootprint(Ce)
    CEI ← CarbonEfficiency(Ce, tourism_output)
Step 3: AI-based Modelling
    X ← ExtractFeatures(D_std, CF, CEI) // Construct Multimodal Feature Set
    If task == "carbon_prediction":
        Model(θ) ← TrainPredictionModel(X, Ce)
    Else If task == "behavior_identification":
        Model(θ) ← TrainBehaviorModel(X, low_carbon_labels)
    Else If task == "route_recommendation":
        Model(θ) ← TrainRecommendationModel(X, tourist_preference, carbon_cost)
    Else If task == "decision_optimization":
        Model(θ) ← TrainOptimizationModel(X, management_constraints)
    Y_pred ← Model(X)
Step 4: Application and Decision Support
    Match Output Type(Y_pred):
        Case "warning": Ds ← GenerateEmissionWarning(Y_pred)
        Case "behavior": Bl ← IdentifyBehaviorPatterns(Y_pred)
        Case "routing": Rl ← RecommendRoutes(Y_pred, constraints)
        Case "supply_chain": Ds ← OptimizeManagementDecision(Y_pred)
Step 5: Feedback and Model Updating
    Fb_new ← CollectFeedback(App_Interface)
    Performance ← Evaluate(Ds, Fb_new, emission_reduction_effect)
    θ' ← UpdateModel(Model(θ), Fb_new, Performance) // Online Learning
    Return Ce, Bl, Rl, Ds, θ'
```

7. Computational Challenges and Future Trajectories

Despite the potential of AI for low-carbon tourism, five challenges remain. First, IoT and digital twins are needed to collect fine-grained spatiotemporal data. Second, carbon accounting mechanisms should be integrated into neural networks to avoid physically unreasonable predictions. Third, graph computing should be used to model spatial spillovers and temporal dependencies in tourism transport networks. Fourth, SHAP and LIME should be applied to improve model interpretability. Fifth, federated learning and differential privacy are needed to protect sensitive trajectory and consumption data during cross-platform model training.

8. Conclusion

From the interdisciplinary perspective of Computer Science and Information Systems, this paper systematically maps the computational trajectory of AI-empowered low-carbon tourism. The study indicates that low-carbon tourism governance is undergoing a fundamental paradigm shift: transitioning from static mathematical statistics to high-dimensional data modeling and dynamic collaborative computing. The AI technology stack—spearheaded by machine learning, recommendation systems, and multi-objective optimization—is rapidly emerging as the core computational backbone for resolving the intractable constraints of emission reduction. The data mining assessment pipeline, the End-to-End computational architecture, and the associated pseudocode innovatively proposed in this paper do not merely bridge underlying data links. More importantly, they provide a lucid, system-level engineering blueprint for the future development of a highly robust, self-evolving, smart low-carbon tourism ecosystem.

References

[1] He Y ,Wang L ,Zhu H , et al. Tourism Carbon Emission Forecasting, the Decoupling Effect and Its Driving Factors in the Yangtze River Economic Belt under the "Double Carbon" Target[J]. Journal of Resources and Ecology,2023,14(6):1329-1343.

[2] Wang L ,Zhu H .Multi-scenario Evolution of Tourism Carbon Emissions in Jiangxi Province under the "Carbon Peak and Neutrality" Target[J]. Journal of Resources and Ecology,2023,14(2):265-275.

[3]Luo Y ,Mou Y ,Wang Z , et al. Scenario-based planning for a dynamic tourism system with carbon footprint analysis: A case study of Xingwen Global Geopark, China[J]. Journal of Cleaner Production,2020,254,119999-120004.

[4] Li J ,Li Y ,Xia B , et al. Low-Carbon Pathways for Ski Tourism: Integrated Carbon Accounting and Driving Factors in a City Hosting the Winter Olympics[J].Sustainability,2025,17(24):11379-11383.

[5] Long Y ,Li F .Policy simulation and analysis of the optimal growth path of carbon emissions in Hubei Province's tourism industry under low-carbon scenario[J]. Frontiers in Environmental Science,2025,13,1595465-1595468.

[6] Jing W ,Shen W ,Yuling L , et al. Measurement of Tourism-Related CO2 Emission and the Factors Influencing Low-Carbon Behavior of Tourists: Evidence from Protected Areas in China[J]. International Journal of Environmental Research and Public Health,2023,20(2):1277-1280.

[7] Yufeng C ,Zhitao Z ,Lin Z .Exploring the Ecological Performance of China's Tourism Industry: A Three-Stage Undesirable SBM-DEA Approach with Carbon Footprint[J].International Journal of Environmental Research and Public Health,2022,19(22):15367-15370.

[8] Wang Liguo, Zhu Hai, Ye Yanting, et al. Spatio-temporal Differentiation and Simulation of Carbon Neutralization of Tourism in China Province [J]. Journal of Ecology, 2024, 44(2):625-636.

[9] Tang Chengcai, Cha Jianping, Zhang Jiekuan, et al. The goal of "double carbon" in China's tourism industry under high-quality development: evaluation and forecast, main challenges and realization path [J]. China Eco-tourism, 2021,11(4):471-497.

[10] Cha Jianping. Development efficiency, emission reduction potential and emission reduction path of low-carbon tourism in China [J]. Journal of Tourism, 2016,31(9):101-112.

[11] Lin S ,Zhang H ,Wang X , et al. The impact of spatial perception at agricultural heritage sites on tourists' carbon reduction behavior[J].npj Heritage Science,2025,13(1):190-194

[12] Gongyi J ,Weijun G ,Meng X , et al. Geographic Information Visualization and Sustainable Development of Low-Carbon Rural Slow Tourism under Artificial Intelligence[J]. Sustainability, 2023,15(4):3846-3850.

[13] Cheng J ,Li S ,Wang Z , et al. The Characteristic Differences between Ecological Culture and Low-carbon Tourism Cognition under the Vision of Carbon Neutrality[J].Journal of Resources and

ISSN 2616-5775 Vol. 9, Issue 7: 52-57, DOI: 10.25236/AJCIS.2026.090707

Ecology,2022,13(5):936-945.

[14] Xiao Jianhong, Chen Yufei, Wang Min, et al. Study on the willingness of self-driving tourists to low-carbon tourism transportation and its influencing factors-taking Putuo Golden Triangle tourist area in Zhoushan, Zhejiang Province as an example [J]. Journal of Environmental Science, 2017,37(12):4798-4806.

[15] Wang Huajie, Yang Pingheng. Research on the Subdivision of Public Low-carbon Tourism Motivation in Coal-exhausted Cities —— Taking Huaibei City as an Example [J]. Journal of Southwest University (Natural Science Edition), 2016,38(7):158-166.

[16] Z Ryan, Zhang Yutong, Dong Hongjie, et al. Driving factors of built-up environment around economical hotels on tourists' low-carbon travel and location optimization —— Taking Tianjin as an example [J]. Journal of the City, 2024,(5):60-69.

[17] Xiao Z ,De Z ,Jiangpeng T , et al.Low-Carbon Tour Route Algorithm of Urban Scenic Water Spots Based on an Improved DIANA Clustering Model[J].Water,2022,14(9):1361-1371.

[18] Lu Z ,Deqing M ,Jinsong H .Research on the Sustainable Operation of Low-Carbon Tourism Supply Chain under Sudden Crisis Prediction[J].Sustainability,2021,13(15):8228-8234.

[19] Yuqiu X ,Qianqian C ,Kaiying C , et al.Optimal channel choices and online refund policies in a low-carbon tourism supply chain considering carbon reduction level[J].INFOR: Information Systems and Operational Research,2023,61(1):34-66.

[20] Shigui M ,Yong H ,Ran G .Low-carbon tourism supply chain network optimisation with vertical and horizontal cooperations[J].International Journal of Production Research,2023,61(18):6251-6270.

[21] Deqing M ,Jinsong H ,Fanjun Y .Big Data Empowering Low-carbon Smart Tourism Study on Low-carbon Tourism O2O Supply Chain Considering Consumer Behaviors and Corporate Altruistic Preferences[J].Computers & Industrial Engineering,2020,(prepublish):107061-107067.

[22] Qian L ,Meiwei T ,Chengbo L .A study on the multiobjective optimization model for tourism development – Take Shanghai as example[J].Tourism Economics, 2020, 27(4):135481662090193-135481662090199.

[23] Chen Zhezhi, Zhao Liming, Xu Jing. Research on low-carbon cooperation of tourism supply chain based on differential game [J]. Journal of Tourism, 2016,31(6):38-49.

[24] Gössling S ,Higham J .The Low-Carbon Imperative: Destination Management under Urgent Climate Change[J].Journal of Travel Research,2020,60(6):004728752093367.

[25] Xin C ,Feng Z C .The impact of environment-friendly short videos on consumers' low-carbon tourism behavioral intention: A communicative ecology theory perspective [J].Frontiers in Psychology, 2023,14,1137716-1137732.

[26] Sung P. L., Hsiao T. Y., Huang L., Morrison A. M. The influence of green trust on travel agency intentions to promote low-carbon tours for the purpose of sustainable development[J]. Corporate Social Responsibility and Environmental Management, 2021,14(6):568-579.

[27] Lee H T ,Jan F .The Low-Carbon Tourism Experience: A Multidimensional Scale Development[J]. Journal of Hospitality & Tourism Research,2019,43(6):890-918.

[28] Wang L ,Wang J ,Shen P , et al.Low-Carbon Travel Behavior in Daily Residence and Tourism Destination: Based on TPB-ABC Integrated Model[J].Sustainability,2023,15(19):14349-14356.

[29] Haiyan S ,Hongrun W ,Hanyuan Z .Can nudging affect tourists' low-carbon footprint travel choices?[J].International Journal of Contemporary Hospitality Management,2024,36(5):1534-1556.

[30] Shuxin W ,Genxu W ,Yiping F .Factors Influencing the Energy Efficiency of Tourism Transport in China[J].Journal of Resources and Ecology,2016,7(4):246-253.