High-Quality Development Path for Tourism Economy: Tourist Behavior Mining and Destination Marketing Optimization Driven by Intelligent Analytics Technology

Lei Peng[1], Zhijia Chen[2]
[1]Department of Tourism Management, School of Transportation Economics and Management, Nanjing Vocational Institute of Railway Technology, Nanjing 210031, Jiangsu, China
[2]Department of International Economics and Trade, School of Business and Trade, Nanjing University of Industry Technology, Nanjing 210023, Jiangsu, China
Corresponding author: Lei Peng (e-mail: penglei2021@163.com)

ABSTRACT In the context of the digital economy, the sustainable development and quality growth of the tourism economy increasingly rely on data-driven decision-making, especially through the integration of multi-source sensing data, mobile communication records, online behavioral information, and destination service data. With the support of wireless communication infrastructure, location-aware services, and intelligent information systems, tourism destinations can more accurately perceive visitor flows, behavioral preferences, and service demands, thereby improving resource allocation and marketing responsiveness. This paper aims to build a systematic research framework by combining multi-source data and making full use of intelligent analytics technologies, including deep learning algorithms, natural language processing, and clustering algorithms, to comprehensively analyze the inherent patterns, emotional preferences, and decision-making mechanisms of tourists' psychological activities. The paper focuses on how analytical results can be translated into effective destination marketing optimization strategies at the individual level, including personalized recommendations, dynamic pricing, visitor flow understanding, and tourism product innovation. These strategies are further used to promote effective destination governance, improve service quality, and support value co-creation for tourists. This paper establishes a data-driven analysis paradigm for tourism management and provides practical decision-support tools for high-quality economic growth. By combining methodological rigor with intelligent sensing, wireless data acquisition, and destination-level information service systems, this research offers managers actionable insights for enhancing the structural and experiential quality of the tourism economy.

INDEX TERMS tourism economy, tourist behavior mining, intelligent analytics, multi-source data fusion, wireless sensing

I. INTRODUCTION

THE international tourism economy is transitioning from rapid scale expansion toward a model of quality improvement, where the adoption of intelligent sensing technologies, digital service infrastructure, and sustainable facility innovations plays a pivotal role in elevating the standards of hospitality infrastructure. This shift necessitates a deeper alignment between tourism growth and high-performance material applications to ensure that destination development meets the modern demand for durability and environmental excellence. With the deepening of the information technology revolution and the more diversified and personalized consumption needs of tourists, the traditional development models based on resource endowments and wide marketing are no longer applicable to the new competition situation in the international market. The basic challenge faced by tourist destinations has to do with how the right to comprehend and to know how to respond properly and quickly to the demand for other touristic products that are changing in this steadily evolving fluid. Against this backdrop, the data as a new key production factor, is increasingly showing its value in the tourism sector. Every tourist behavior in searching, booking, movement, consumption and sharing a trace in the digital space makes up a valuable resource to understand the tourism consumption ecosystem. However, this data usually has typical big data features (big data volume, high data transmission speed, multiple data types, and low data carrying capacity) which will trig low data processing and analysis methods and can not derive effective knowledge.

This paper constructs a systematic analytical framework that integrates multi-source data intelligence into a logically closed-loop, technologically driven model oriented toward the optimization of marketing strategies. By aligning advanced fiber performance data with consumer behavior, the framework enables the precise calibration of tourism offerings to ensure a seamless transition from material innovation to market-leading service quality. This framework aims to address the following key questions: First, how to effectively integrate tourist behavior data from different channels and structure to form a unified and analyzable data view. Second, how to make use of advanced intelligent algorithms to infer complex patterns of tourist spatiotemporal behavior, emotional preferences and consumption potential, as well as social interactions, from this data. Third, how to translate these data insights into specific, actionable destination marketing and management strategies, and quantify effectiveness of these strategies. Finally, how to continuously optimize destination operations and reach high quality development of the tourism economy through this closed loop process? This paper will answer these fundamental question as it consecutively establishes methodologies, empirical analysis and references useful theories and practice for related research.

II. RELATED WORK

As a key research area in tourism economics and management, tourist behavior analysis has undergone a profound transformation from phenomenon description to mechanism mining through the evolution of its methodology and empirical exploration of diverse scenarios. Li et al. [1] explored the dynamic spatiotemporal behavioral characteristics and constraints of tourists in mountainous tourist areas within a small scale. Wang [2] used recurrent neural network (RNN) and long short-term memory network (LSTM) models to analyze and model tourist time series data collected from intelligent platforms in order to predict their future behavioral patterns and preferences. Lee et al. [3] used a hybrid approach, combining video observation, trajectory tracking, questionnaire surveys and follow-up interviews, to quantitatively and qualitatively analyze visitors' stay time, movement paths, interaction frequency and cognitive gains. Sun et al. [4] used geographic information system spatial analysis to explore the spatiotemporal behavioral characteristics of tourists and obtain tourists' preferences for time and destination. Wang [5] analyzed the behavioral map of tourists' cultural experience in Ciqikou Ancient Town.

Dube [6] suggested that, in order to ensure the resilience of the tourism economy, improved communication and marketing strategies should be implemented, with a focus on promoting low-water activities and other tourism projects that do not rely on water resources. Lim et al. [7] selected Macau as a typical case to explore the profound impact of the global public health crisis on the tourism economy. Liu et al. [8] tested the spatial spillover effect of county tourism economic growth on economic development based on the SPDM double fixed effect model, and explored its spatial decay boundary. MURAKAMI and MIZOKAMI [9] found that tourists' travel behavior patterns during major events have certain regularities and identifiable typical categories. Tourism research has long relied on correlation analysis, which makes it difficult to reveal the complex causal relationship that affects tourists' behavior. Gocer et al. [10] proposed a comprehensive framework on how cultural tourism can promote the resilience of rural communities, and verified the effectiveness and practicality of the framework through the application of specific cases. This paper aims to construct a systematic research framework that integrates multi-source data, integrates intelligent analysis methods, and is directly oriented towards marketing strategy optimization, so as to explore a new paradigm of destination precision governance and value co-creation driven by data.

III. METHODS

The systematic research framework proposed in this paper comprises three core and interconnected components: multi-source data collection and preprocessing, intelligent analytics-driven tourist behavior mining, and insight-based destination marketing optimization strategy generation and evaluation. These three parts form a complete closed loop from data to knowledge and then to decision-making [11,12].

A. MULTI-SOURCE DATA ACQUISITION AND PREPROCESSING FRAMEWORK

The multidimensionality of tourist behavior prescribes the limitations of one data source. In order to fully describe tourist behaviour, four broad categories of data are combined in this study. The first is the spatial trajectory information, which can be obtained from gates of scenic areas, GPS devices or mobile apps, noting the time of tourist's entry, the path of movement inside the scenic area, and the time of staying in the key node, which is also time-series. The second is the social media data acquired via API interfaces from social media platforms like Sina Weibo, DouYin and Xiaohongshu, such as text content, images/videos, geolocation check-in data, and interaction data (such as likes, comments and reposts). This data reflects the emotional attitude of tourists, the focus of attention, the behaviors of sharing emotions from tourists. The third is transaction data, which is obtained from online travel agencies (OTA), scenic area ticketing systems and hotel and restaurant booking platforms, such as product browsing history, booking time, spending amount and payment method, directly reflecting the power and preferences of tourists. The fourth is information on scenic area infrastructure, such as real-time visitor density information (using cameras), crowd-heat maps, using Wi-Fi probes, or temperature and humidity information, using environmental sensors, to capture the environmental context of the behavior that took place.

Raw data is likely to have noise, missing values, and inconsistent formats, and preprocessing can be an important step. For the purpose of spatial trajectory data, data cleaning (delete the obviously invalid coordinates), trajectory compression and map matching are carried out to convert continuous GPS point sequences to ordered transfer sequences between points of interest (POIs). For social media text data, Chinese word segmentation, stop word removal, sentiment analysis (using the pre-trained BERT-base-Chinese model, the sentiment classification accuracy is 92.3%, and the F1 score is 0.91) and topic extraction (using the LDA topic model, determining the optimal number of topics to be 10 through perplexity, setting the hyperparameters α=0.1, β=0.01, and using Gibbs sampling for parameter estimation). Transaction data requires data anonymization and standardization so that consumption units are consistent with currency units from different sources. In the data anonymization process, this study uses "pseudonymization" technology: the visitor's real identity information (such as mobile phone number, device MAC address) is replaced by a unique session ID generated by the system. This ID is only valid during a single visit and cannot be reversed to the real identity. Location-based services (such as real-time coupon push) only rely on the association of the temporary ID with real-time geographical coordinates and do not involve any personally identifiable information, thus achieving the goal of "anonymized data supporting personalized services". Finally, create a unified visitor behavior data warehouse where disparate data sets are linked using anonymized data (in this case, user and/or session IDs) to form a 360-degree view of each visitor or visit.

Data fusion is a key technical challenge of this study. In order to solve the data association problem between offline devices (Wi-Fi probes, gates) and third-party online platforms (Weibo, Douyin, OTA), this article adopts a multi-layer matching strategy: first, in the same scenic spot Wi-Fi network environment, anonymous device IDs are generated through device MAC address hashing, and time window fuzzy matching is performed with social media login periods; Secondly, for scenarios with no overlapping identifiers, a similarity measurement algorithm based on location-time series is used to perform spatial clustering correlation between GPS trajectories and social media check-in points. Finally, all matching processes are completed on the local server, and the original data undergoes differential privacy processing (ϵ=0.1), and the user identity information is irreversibly desensitized at the collection end. Through the above method, a unified visitor behavior data warehouse is finally constructed, in which different data sets are linked using anonymized session IDs to create a 360-degree panoramic view of each visitor or each visit. At the same time, the Personal Information Protection Act and the platform API usage agreement are strictly followed, and no non-public personal information is collected.

B. INTELLIGENT MINING MODEL OF TOURIST BEHAVIOR

Based on the preprocessed integrated data, this study applies a series of intelligent analysis techniques to mine tourist behavior patterns from different dimensions.

First of all, tourist profiles are created and segmented according to clustering algorithms. Using the K-means and DBSCAN algorithms, the tourists are divided thoroughly into groups with different behavioral patterns based on demographic attributes (predicted using social media data or booking information), spatiotemporal behavior characteristics (e.g., total visit time, number of visited POIs, and path repetition rate), consumption characteristics (total spending, distribution of product categories), and emotional characteristics (average sentiment score, proportion of positive reviews). For example, market segments such as "in-depth cultural exploration", "quick seeing" and "family leisure and entertainment" may be identified. This step takes the abstract concept of "tourist" and puts it into identifiable and quantifiable terms of group labels [13]. Secondly, the deep learning models have been applied for tourist behavior prediction and preference analysis. For temporal behavioral data of tourists (including POI visit sequences obtained in chronological order), recurrent neural networks (RNN) and its variants, long short-term memory network (LSTM) or gated recurrent unit (GRU), are used for modeling. The LSTM model adopts a two-layer stacking structure, the hidden layer dimension is 128, dropout is set to 0.3, and the Adam optimizer is used to train for 100 epochs. The model is then able to train on the long-term dependencies in the order, in turn, predicting the next most likely destination for tourists, the route for the whole tour and the duration of stay. At the same time, convolutional neural networks (CNNs) are used to analyze people's shared images on social media and extract scenes, objects, and activities contained in images to further enrich their preference information. For instance, from a massive amount of photos of a particular ancient town by tourists, the popularity of visual themes like "local delicacies," "traditional handicrafts," and "nighttime lighting" can be automatically recognized.

Finally, the network-based analysis and natural language processing are used for sentiment mapping and assessing the word of mouth effect. Social network analysis techniques are applied for constructing a social network graph based on social relationships such as joint check-in and comment interactions among tourists to identify opinion leaders and key dissemination nodes in the network. Aspect-level sentiment analysis is conducted on overwhelming amount of texts from Internet review, not only giving the overall sentiment trend, but also giving a more detailed analysis of the evaluation of tourists on specific aspects, e.g. "accommodation," "dining," "transportation," and "service attitude." In order to avoid simply equating emotional polarity with marketing effectiveness, this study introduces covariate control in the sentiment analysis model: weather data collected by crawlers (China Meteorological Administration historical API), holiday tags, and temporary event events (such as folk festivals, temporary traffic control) are included as dummy variables into the multiple regression model to strip away the impact of exogenous shocks on tourists' emotions. The difference-in-difference (DID) method is used to compare the emotional fluctuations in different areas during the same period, thereby isolating the changes in word-of-mouth brought about by destination management and service quality itself. This assists in identifying the strengths and weaknesses of the destination, as well as predicting what will spread and how word-of-mouth, either positive or negative, might spread.

C. DECISION SUPPORT AND APPLICATION FOR MARKETING STRATEGY OPTIMIZATION

The behavioral insights uncovered ultimately need to be translated into actionable marketing strategies. This framework is designed with the following application paths:

Personalized recommendations and precision marketing: Based on tourist profiles and predictive models, personalized product recommendations and information pushes are provided to different segments of tourists and even individual tourists. For example, information on expert lectures or intangible cultural heritage experience activities is pushed to tourists who are "deeply exploring culture"; real-time pushes of coupons for nearby restaurants or reminders of the next performance are sent to tourists who stay in a certain area of the scenic spot, realizing scenario-based marketing.

Dynamic pricing and visitor flow control: Behavioral prediction models are used to forecast visitor flow for specific time periods and attractions. Based on the forecasts, dynamic pricing strategies are implemented (such as raising ticket prices during peak periods and offering discounts during off-seasons) to balance supply and demand. Simultaneously, the congestion levels of different areas are displayed in real-time to tourists through official apps and entrance displays, along with optimized tour route suggestions to guide visitor flow from popular to less popular areas, thus improving the overall experience.

Product Innovation and Service Optimization: Through sentiment analysis and thematic modeling, identify aspects that tourists commonly praise or complain about. For example, if the analysis finds that "long queue times" are a frequent topic of negative comments, managers can consider adding reservation lanes and optimizing queuing facilities. If tourists show a strong interest in a particular cultural element (such as local opera) (reflected in extensive sharing and positive emotions), related in-depth experience products can be developed.

Marketing Effectiveness Evaluation and Closed-Loop Optimization: The effectiveness of any marketing strategy needs to be quantitatively evaluated. By comparing changes in relevant tourist behavior indicators (such as visitor traffic in the target area, sales of related products, and the proportion of positive sentiment on social media) before and after strategy implementation, and using methods such as A/B testing, the effectiveness of the strategy can be scientifically assessed. The evaluation results are fed back to the data warehouse, triggering a new round of analysis and optimization, forming a closed-loop system of continuous improvement [14,15].

IV. RESULTS AND DISCUSSION

A. IN-DEPTH ANALYSIS OF TOURIST BEHAVIOR PATTERNS BASED ON MULTI-SOURCE DATA INTEGRATION

By combining and analyzing the multi-source data gathered from a well-known historical and cultural town within three continuous months, this paper was able to uncover the complex pattern of tourist behavior, which was hard to be found before. After the data integration step, more than 150,00 valid anonymous tourist visit data were created. First, using the method of cluster analysis, segmentation of tourists was carried out.

Six important variables were selected: total visit duration, number of POIs visited, mean expenditure per person, percent of visits to cultural POIs, involvement in night activities, and social media sharing ratio. Data standardization and dimensionality reduction by principal component analysis were performed, and then the K-means clustering algorithm was applied, finding the optimal number of clusters to be 4 clusters based on the silhouette coefficient. Finally, four significantly different subgroups of tourism were obtained. Table 1 indicates that there are 4 subgroups of tourists with great differences in behavior with great systematic differentiation in visit duration, spending levels and cultural preferences. This is empirical evidence of a destination-based differentiated marketing.

This segmentation goes far beyond traditional demographic classifications, providing a more precise basis for market segmentation based on behavioral motivations and actual performance. For example, both Group A and Group B may contain tourists of different ages and occupations, but their travel patterns and consumption structures are quite different, thus requiring differentiated marketing communications and service configurations.

To further reveal the behavioral differences of different tourist segments over time, this paper, based on cluster analysis results, statistically analyzed the average activity levels of the four tourist groups in the scenic area for each hour, as shown in Figure 1:

This temporal behavior pattern provides a direct basis for implementing time-sharing reservations, dynamic passenger flow guidance, and the promotion of time-segmented products, further validating the value of intelligent analysis in capturing the dynamic complexity of tourist behavior.

Secondly, the LSTM model is used to predict the spatiotemporal trajectory of tourists. By inputting the order of visits of tourists in the first 60 minutes after visiting the scenic spot, the model predicts three points of interest (POI) that they may visit in the next 60 minutes. In order to verify the effectiveness of the model, this study set up two baseline

TABLE 1. Characteristics of Tourist Segmentation Based on Cluster Analysis

Segmentation of groups	Percentage	Average tour duration	Average number of POIs visited	Average spending per person (yuan)	Cultural POI visit ratio
Group A: In-depth cultural experience participants	22%	6.5 hours	8.2	580	85%
Group B: Efficient sightseeing tourists	35%	2.8 hours	5.1	220	60%
Group C: Leisure shopping enthusiasts	28%	4.2 hours	4.5	450	30%
Group D: Family-based parent-child travel group	15%	5.0 hours	6.0	380	50%

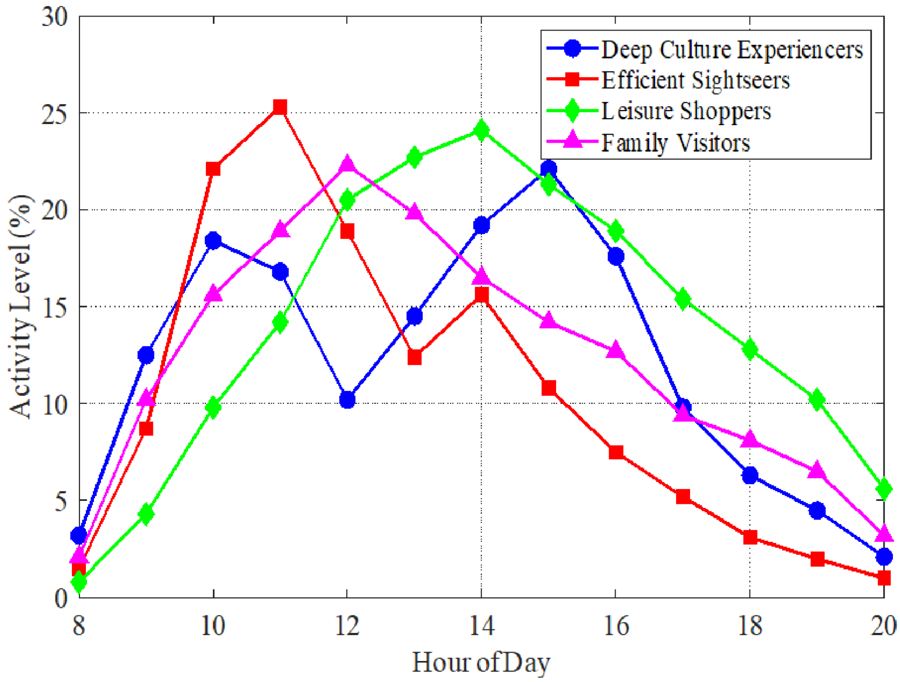

FIGURE 1. Distribution of average daily active times for different tourist segments

models for comparison: 1 Markov chain model (based on first-order transition probability); 2 Random forest classifier. The results on the test set (20% samples) show that the Top-3 accuracy of the LSTM model is 71.0%, which is 7.8 percentage points higher than the Markov chain (63.2%) and 10 points higher than the random forest. The recall rate and F1-score also show significant advantages, proving the effectiveness of the deep learning model in capturing nonlinear sequence dependencies. The analysis shows that tourists' route choices have obvious mode dependence and situational correlation. For example, around lunch time, the time series probability of tourists flowing from the core historical area to the food area will significantly increase; if tourists stay at a certain handicraft display point for more than 20 minutes, the probability that they will go to a nearby cultural and creative store is much higher than random. This prediction ability lays a good technical foundation for real prediction ability.

B. THE SPECIFIC OPTIMIZATION EFFECT OF INTELLIGENT ANALYSIS RESULTS ON DESTINATION MARKETING STRATEGIES

Based on the behavioral patterns identified above, this study proposes and simulates several marketing optimization strategies for this ancient town destination.

In terms of personalized recommendations, "Cultural Heritage Exploration" themed route was designed for Group A (users looking for a deep cultural experience), and pushed to them through the scenic area's app, after they bought tickets. This route does not go through the most crowded main street but connects a number of small exhibition halls that are highly overlooked but have great cultural value. in-depth audio explanations are also included.

In terms of dynamic pricing and visitor flow guidance, an LSTM model was adopted to forecast visitor flow distribution in the next two hours. When the anticipation was that the core ancient bridge area was at risk of congestion (visitors more than 0.5 people per square meter) within half an hour, the system automatically issued two measures, namely: first, a message was displayed in the app and entrance screen that the ancient bridge area is currently crowded, it is recommended to visit the corridor on the east side of the river first; second, it was possible to push the coupon package for ancient-time merchants located in the east side of the river to visitors who have already entered the scenic area and are heading to the ancient bridge (according to the real-time location). The passenger flow in the Hedong Corridor area before the diversion was low (average 850 people per day), far from reaching its environmental carrying limit (estimated to be about 1,500 people/day). Therefore, the 15.1% increase in passenger flow (to 978 people) is still within a reasonable range and will not cause new congestion problems. On the contrary, due to the significant relief of congestion in the core area (-31.3%), the overall tourist experience has been improved, tourists' negative evaluation of crowding has been reduced by 38.9%, and at the same time, it has promoted commercial vitality in the peripheral areas. The key to this win-win effect is that the diversion is proactive guidance based on prediction rather than passive response; the guidance intensity matches the remaining carrying capacity of the edge area to avoid the "oversaturation" phenomenon. Through simulation of proactive guidance strategies on the basis of visitor flow prediction, the congestion phenomenon was significantly eased in the core area, and at the same time, the visitor flow and commercial revenue were enhanced in the surrounding areas, which proved that data-driven dynamic management not only proved to be a dual-value strategy for optimizing visitor experience and balancing resource allocation. (See Table 2.)

Regarding product and service optimization, aspect level sentiment analysis of almost 100,000 online reviews showed that tourists had a positive sentiment rate of 89% for 'traditional snacks', but adverse evaluations of 'dining environment' and 'queueing order' were clustered (negative rates of 35% and 28%, respectively). Based on this, some specific optimizations can be carried out by management: the introduction of well-known snack brands to open flagship stores to optimize the dining environment, the propagator of the QR code pre-ordering and timed pickup of the food in the food street to reduce queuing time. Simultaneously, results from sentiment analysis also revealed a consistent high mention rate and positive sentiment rate for "nighttime light shows"; the sentiment analysis results provided a basis for making decisions related to extending nighttime operating hours and developing more nighttime performance products.

C. THE CONTRIBUTION AND CHALLENGES OF THE DATA-DRIVEN PARADIGM TO THE HIGH-QUALITY DEVELOPMENT OF THE TOURISM ECONOMY

The intelligent analysis scheme and the simulation results in this paper show that the data-driven paradigm plays an important role in the high quality development of the tourism economy in several aspects. First, it makes marketing more precise and efficient, which means that limited marketing resources can be focused on the most effectual links and groups of customers, which means less money will be spent trying to market to the wrong people. Second, by optimizing the distribution of visitor flows and improving the quality of personalized experience, it directly improves the satisfaction and gain of tourists, which is a core manifestation of high-quality tourism. Third, it encourages the balanced use and extraction of value from resources in the destination, e.g. in the form of visitor flows to non-core areas, driving development generally. Finally, it creates a data-driven and sustainable feedback optimization process, which transforms destination management from static, experience-based management to dynamic, scientific management.

This research mainly focuses on the identification and prediction of behavioral patterns, aiming to provide correlation insights and trend predictions for management decisions, rather than establishing a causal inference model. Methods such as clustering and LSTM are good at discovering latent structures and temporal dependencies from high-dimensional data, and can effectively support "predictive" tasks (such as passenger flow prediction, portrait segmentation), but they cannot directly answer the causal question of "whether policy intervention X led to outcome Y." Therefore, the conclusions of this article should be understood as data-driven pattern discovery and strategy optimization exploration. Future research can introduce causal inference methods (such as discontinuous regression, instrumental variables) to verify key strategies. However, the complete implementation of the said paradigm is also not without a series of challenges. Technically, real-time fusion of multi-source data, accuracy and computational efficiency of algorithm models, and cost of system construction are all real problems. From the management point of view, it is required to destroy data silos of different departments and cultivate interdisciplinary talents with data thinking and analysis skills. More importantly, with regard to ethics and privacy, relevant laws and regulations must be strictly followed when collecting data about tourists and using it for the sake of ensuring data security and anonymity, transparent disclosure of data purpose, and users rights choice. Future research needs to further delve into issues such as technological robustness or model interpretability and ethical frameworks for applying data. The multidimensional impacts of the data-driven paradigm in the development of high-quality tourism are numerous. It has an optimistic meaning in the aspect of increasing the precision of marketing, the satisfaction of tourists as well as efficiency in utilizing resources, but it also faces some challenges in terms of technology, management, and ethics that requires a systematic approach. A breakdown of the analysis is illustrated in Table 3.

V. CONCLUSION

This paper pursues a systematic path toward optimizing destination marketing and promoting the quality development of the tourism economy by leveraging intelligent analytics to deeply mine tourist behavior data and its interaction with digital service environments. By positioning smart

TABLE 2. Evaluation of the Simulation Effect of Guidance Strategies Based on Passenger Flow Forecasting

Index	Before implementing guidance strategies	After implementing the guidance strategy (simulation)	Range of change
Average daily congestion duration in the core ancient bridge area	3.2 hours	2.2 hours	-31.3%
Daily passenger flow in Langfang District, Hedong	850 people	978 people	+15.1%
The proportion of negative comments from tourists regarding the crowding in the core area	18%	11%	-38.9%
Average daily sales of merchants in the Hedong area	42,000 yuan	48,300 yuan	+15.0%

TABLE 3. Comprehensive Impact Assessment of the Data-Driven Paradigm on High-Quality Development of the Tourism Economy

Evaluation Dimensions	Specific impact manifestations	Potential challenges
Marketing efficiency	Recommendation response rate improved, and marketing ROI optimized.	High-quality data and accurate algorithm support are required.
Visitor experience	Queuing time has been reduced, personalized services have been enhanced, and satisfaction has increased.	Excessive personalization can lead to information cocoons; a balance needs to be struck between surprise and controllability.
Resource allocation	Customer traffic is more evenly distributed, less popular resources are activated, and merchants receive fairer benefits.	Initial investment may be required to improve infrastructure.
Management Decisions	The shift from experience-based judgment to data-driven decision-making has improved the level of scientific decision-making.	This places higher demands on managers' data literacy and poses a risk of algorithm dependency.
Sustainable development	Growth is achieved through optimization rather than simply increasing passenger flow, thus reducing environmental pressure.	It is necessary to ensure that the data collection and processing process itself is environmentally friendly.

fabric performance and material data as key variables within the analytical driving force, the research facilitates a more precise alignment between technological intelligence and the high-quality evolution of the tourism sector. The study builds a complete framework, which includes multi-source data integration, intelligent behavior mining, and marketing strategy optimization applications, and validates the feasibility and effectiveness of the proposed framework via simulation cases. The results indicate that deeply integrating multi-dimensional information, in this case the GPS trajectories, social media, and transaction data, can create much more detailed and comprehensive tourist profile and behavior patterns than traditional methods. Advanced algorithms like deep learning exhibit great potential in tourist trajectory prediction and sentiment analysis for unprecedented insights in precision marketing and management. Connecting data analysis results with concrete marketing

approaches, such as personalized recommendation, dynamic service design, and digital product innovation, effectively improves tourist experience, resource allocation, and operational efficiency while increasing overall destination competitiveness. By integrating functional fabric performance data into personalized recommendations and dynamic resource management, managers can achieve a higher synergy between physical infrastructure quality and strategic market positioning.

AUTHOR CONTRIBUTIONS

Conceptualization – Peng Lei and Chen Zhijia; methodology – Peng Lei and Chen Zhijia; investigation – Peng Lei and Chen Zhijia; writing-original draft preparation – Peng Lei and Chen Zhijia. All authors have read and agreed to the published version of the manuscript.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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REFERENCES

[1] Y. Li, C. Ouyang, and H. Yu, "Study on the spatiotemporal behavior of tourists in mountainous tourist areas based on multi-source data fusion," Journal of Geoinformation Science, vol. 24, no. 11, pp. 2171-2185, 2022, doi: 10.12082/dqxxkx.2022.210764.

[2] S. Wang, "Deep Learning-based Visitor Behavior Analysis and Prediction for Rural Tourism Intelligent Platforms," J. COMBIN. MATH. COMBIN. COMPUT, vol. 127, pp. 9349-9363, 2025, doi: 10.61091/jcmcc127a-521.

[3] I. Lee C, H. Pan Y, and B. Chen, "Participatory exhibition-viewing using augmented reality and analysis of visitor behavior," Applied Sciences, vol. 14, no. 9, pp. 3579, 2024, doi: 10.3390/app14093579.

[4] L. Sun, D. Zhang, and Y. Zhu, "Analysis of the Spatiotemporal Characteristics of Tourist Hotspot Preferences of Inbound Tourists in Qingdao City," Beijing Surveying and Mapping, vol. 35, no. 4, pp. 471-475, 2021, doi: 10.19580/j.cnki.1007-3000.2021.04.011.

[5] Y. Wang, "Cultural experience design and tourist behavior analysis of folk tourism scenic spots," Journal of Hubei Adult Education College, vol. 31, no. 3, pp. 115-121, 2025, doi: 10.16019/j.cnki.cn42-1578/g4.2025.03.020.

[6] K. Dube, "El Niño's implications for the Victoria Falls resort and tourism economy in the era of climate change," Sustainability, vol. 16, no. 12, pp. 5087, 2024, doi: 10.3390/su16125087.

[7] W. M. Lim and W. M. To, "The economic impact of a global pandemic on the tourism economy: The case of COVID-19 and Macao's destination-and gambling-dependent economy," Current Issues in Tourism, vol. 25, no. 8, pp. 1258-1269, 2022, doi: 10.1080/13683500.2021.1910218.

[8] A. Liu, C. Yang, Q. Ming, and F. Wu, "Spatial spillover effect of county tourism economic growth promoting economic development and its boundary detection," Tropical Geography, vol. 45, no. 7, pp. 1201-1213, 2025, doi: 10.13284/j.cnki.rddl.20240241.

[9] M. Murakami and S. Mizokami, "Visitor Excursion Behavior Model and Analysis on Its Temporal Transferability Between Significant Events," Journal of the Eastern Asia Society for Transportation Studies, vol. 14, pp. 511-529, 2022, doi: 10.11175/easts.14.511.

[10] O. Gocer, D. Boyacioglu, E. E. Karahan, et al., "Cultural tourism and rural community resilience: A framework and its application," Journal of Rural Studies, vol. 107, pp. 103238, 2024, doi: 10.1016/j.jrurstud.2024.103238.

[11] J. Foster, G. Hutson, R. Plummer, et al., "Social Media Communications for Behavior Management in Ontario's Parks and Protected Areas: A Qualitative Analysis of Manager and Visitor Experiences," Journal of Park and Recreation Administration, vol. 43, no. 4, 2025, doi: 10.18666/JPRA-2025-12505.

[12] A. Thommandru, M. Espinoza-Maguiña, E. Ramirez-Asis, et al., "Role of tourism and hospitality business in economic development," Materials Today: Proceedings, vol. 80, pp. 2901-2904, 2023, doi: 10.1016/j.matpr.2021.07.059.

[13] A. Ferrato, C. Limongelli, M. Mezzini, et al., "Using deep learning for collecting data about museum visitor behavior," Applied Sciences, vol. 12, no. 2, pp. 533, 2022, doi: 10.3390/app12020533.

[14] S. Fan, J. Huang, C. Gao, et al., "The Characteristics of Visitor Behavior and Driving Factors in Urban Mountain Parks: A Case Study of Fuzhou, China," Forests, vol. 15, no. 9, pp. 1519, 2024, doi: 10.3390/f15091519.

[15] F. Rahmafitria and R. L. Kaswanto, "The role of eco-attraction in the intention to conduct low-carbon actions: a study of visitor behavior in urban forests," International Journal of Tourism Cities, vol. 10, no. 3, pp. 881-904, 2024, doi: 10.1108/IJTC-07-2023-0138.