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PAPER

Integration of Mobile Interaction Technology in the Tourism Industry and Its Impact on Tourism Consumption Patterns

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ABSTRACT

The introduction of mobile interaction technology has fundamentally transformed the delivery of tourism services, enabling travelers to access real-time information, engage in online interactions, and enjoy personalized services through smart devices. This innovative consumption model not only enhances tourist engagement and satisfaction but also drives innovation and transformation in the tourism industry. However, despite existing studies exploring the impact of technology on tourism, most research focuses primarily on the technology itself, lacking a systematic analysis of its deeper implications for reshaping consumption patterns, enhancing industry resilience, and addressing market uncertainties. Current studies are predominantly centered on applications related to big data and consumer behavior analysis, often overlooking how to measure the resilience of tourism consumption patterns through specific indicators and failing to investigate the long-term sustainability of consumption models transformed by interactive technologies. To address these research gaps, this study introduces a novel perspective by constructing a mobile interaction network model, defining resilience indicators for tourism consumption patterns, and systematically evaluating them using a comprehensive assessment approach. This study aims to provide a new theoretical framework for the digital transformation of the tourism industry and practical guidance for enhancing industry resilience and improving risk resistance capabilities.

KEYWORDS

mobile interaction technology, tourism industry, consumption patterns, resilience indicators, network model, comprehensive assessment

1 INTRODUCTION

With the rapid development of information technology, mobile internet and interaction technologies have gradually integrated into various industries. As one of the largest service industries globally, the tourism industry has experienced

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significant transformations in this process [1–5]. In particular, the introduction of mobile interaction technology has not only optimized the provision of tourism services but also significantly enhanced consumer engagement and experience, thereby promoting innovation and transformation in tourism consumption patterns [6–9]. Through mobile devices and online platforms, tourists can access real-time information, engage in online interactions, and complete the entire service process from booking to experience. This "instantaneous, interactive, and personalized" service model is progressively shaping the future development trends of the tourism industry.

However, despite the progress made in applying mobile interaction technology in the tourism industry, existing studies primarily focus on technological implementation and short-term benefits, lacking systematic theoretical discussions on its deeper impacts on tourism consumption patterns and sustainable development [10–12]. Current study tends to remain at the descriptive level of technological applications, overlooking more complex issues such as how technology transforms tourist consumption behavior, enhances tourism industry resilience, and improves risk resistance capabilities [13–17]. Therefore, it is of significant academic and practical importance to analyze in depth the impacts of mobile interaction technology on tourism consumption patterns and to explore its potential in improving industry resilience and responding to market fluctuations and environmental changes [18–24].

This study focuses on three key aspects: first, it proposes a mobile interaction network model to explore how interaction technology reshapes the tourism industry's network structure; second, it defines and establishes resilience indicators to evaluate the adaptability and risk resistance of tourism consumption patterns across scenarios; third, it applies the entropy-weighted TOPSIS method to systematically assess the resilience of tourism consumption patterns under market fluctuations and environmental changes. By addressing these aspects, the study enriches the theoretical framework for the tourism industry's digital transformation and offers practical strategies to enhance resilience and manage uncertainties, fostering sustainable development.

2 MOBILE INTERACTION NETWORK MODEL IN THE TOURISM INDUSTRY

In modern tourism, consumer demands are increasingly diverse and personalized, making traditional service models inadequate to meet expectations for instantaneous, interactive, and customized services. The introduction of mobile interaction technology has provided unprecedented opportunities for innovation in the tourism industry, enabling tourists to interact with tourism resources in real-time through smart devices, anytime and anywhere. Therefore, constructing a "Mobile Interaction Network Model for the Tourism Industry" that adapts to these new dynamics has become an inevitable research trend. This model integrates mobile internet technology, social networking platforms, and big data analysis, connecting tourists, tourism service providers, and related industry resources into an efficient information exchange and interaction platform.

Figure 1 presents the structural diagram of the mobile interaction network in the tourism industry. Within this model, the upstream, midstream, and downstream segments represent the different stages of the industry chain, which are interrelated to form the overall structure and operational mechanism of the tourism industry.

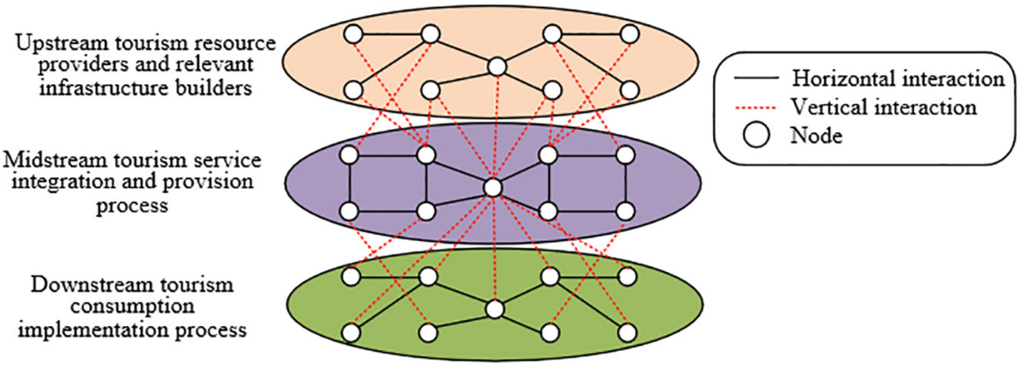

Fig. 1. Structural diagram of the mobile interaction network in the tourism industry

Upstream: This segment includes tourism resource providers and infrastructure developers, such as scenic areas, transportation companies, hotels, and suppliers of tourism equipment. With the advancement of mobile interaction technology, this segment not only serves as a traditional resource provider but also takes on the responsibility of generating and sharing information.

Midstream: Representing the integration and provision of tourism services, this segment includes travel agencies, online travel agencies (OTAs), tour guides, and customized travel services. The midstream is the core of the mobile interaction network model in tourism, responsible for consolidating various upstream resources and delivering personalized, real-time services to consumers via mobile technology.

Downstream: This segment refers to the final implementation of tourism consumption, encompassing consumer behavior and feedback as well as experiences and evaluations during the tourism process. In the mobile interaction network model, downstream activities also include real-time feedback and social sharing from tourists about tourism products and services. As social media and interactive platforms evolve, tourist reviews and suggestions spread quickly, influencing the decision-making processes of other potential tourists.

Figure 2 illustrates the topology of a local tourism mobile interaction network. In the model, nodes, edges, in-degree, and out-degree are fundamental elements that describe its structure and functionality.

Nodes: Represent entities or elements in the network, such as scenic areas, hotels, transportation companies, tourism resource providers, service platforms, tourists, and travel agencies. Each node has unique attributes and functions, such as generating, transmitting, or receiving information, contributing collectively to the tourism ecosystem.

Edges: Represent resource flow, information exchange, or service transactions. For example, an edge between a tourist node and a tourism platform node might indicate the booking of a tourism product, while an edge between a scenic area node and a tourism platform might signify the display and update of scenic information on the platform.

In-degree and out-degree: These are critical indicators of the interaction level of nodes in the network.

In-degree: Refers to the amount of information or resources a node receives from other nodes, reflecting the node's importance as an information receiver. For example, a high in-degree for a tourism platform node indicates that a large volume of tourism resources is delivered to tourists via this platform.

Out-degree: Refers to the amount of information or resources a node transmits to other nodes, reflecting the node's influence as an information provider. A tourism platform node with a high out-degree implies that it delivers information or services to multiple nodes, such as tourists and tourism service providers.

Analyzing the in-degree and out-degree of nodes provides insights into the operational efficiency of the network, the directionality of information flow, and the critical stages within the tourism industry chain.

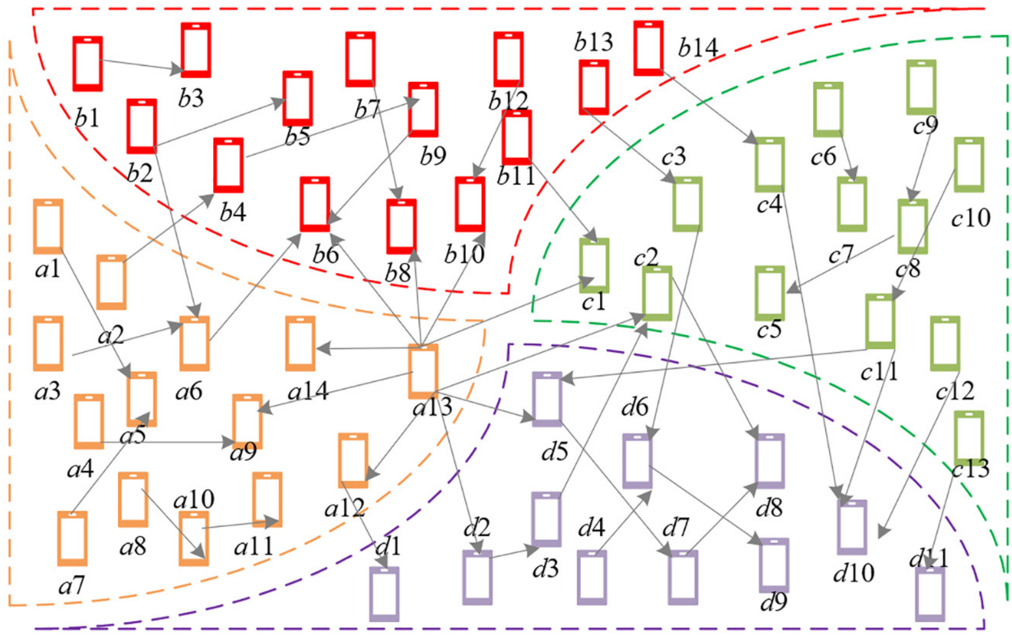

Fig. 2. Topology of a local tourism mobile interaction network

3 RESILIENCE INDICATORS OF TOURISM CONSUMPTION PATTERNS

The tourism industry faces numerous uncertainties, such as economic fluctuations, natural disasters, and epidemic outbreaks, which may lead to sudden changes in tourist demand or temporary market stagnation. Resilience in consumption patterns reflects how the tourism industry can flexibly respond, adjust strategies, and optimize resource allocation to cope with these changes, minimize recovery time, and maintain sustainable development. In the mobile interaction network model, the key to consumption pattern resilience lies in the ability to quickly respond to market changes, providing intelligent and personalized services to meet the evolving needs of tourists while ensuring efficient resource utilization. This study measures the resilience of tourism consumption patterns from the perspective of complex mobile interaction network topology analysis and constructs a resilience indicator system from the dimensions of resistance capacity and adaptive capacity, aiming to reveal the interaction patterns of various nodes, information flow paths, and their response capabilities to external shocks.

Constructing a resilience indicator system based on the two dimensions of resistance capacity and adaptive capacity can more comprehensively reflect the performance and response of the tourism industry when facing external shocks. Resistance capacity refers to the ability of the network to maintain normal operations when encountering external disturbances such as epidemics, natural disasters, and economic crises. This ability reflects the interaction strength between nodes within the tourism network and the stability of its key nodes. Through topological analysis, it is possible to identify these key nodes and assess their impact on tourist flows and consumption patterns during emergencies. A tourism network with strong resistance capacity can effectively mitigate or avoid negative impacts from emergencies, maintaining the stability of tourism consumption patterns. Therefore, this study selects four core evaluation indicators for resistance capacity: degree centrality, betweenness centrality, relative value of the largest connected component, and network connectivity integral. The specific calculation formulas are as follows:

1. Degree centrality: Degree centrality measures the extent of consumer spending in the mobile interaction process, specifically referring to the number of connections a node has in the network. In the tourism industry, consumer nodes with high degree centrality typically indicate significant influence on the choice of tourism services or products. If the degree centrality of a consumer node is extremely high, it suggests that the node may have a substantial impact on overall consumption patterns, and changes in its consumption behavior could affect the entire network. Specifically, the degree centrality $J(n_u)$ of node n_u is calculated as:

$$J(n_u) = \sum\nolimits_{k \neq u} q_{uk} \tag{1}$$

2. Betweenness centrality: Betweenness centrality measures the intermediary role of nodes in the tourism mobile interaction network, specifically referring to how many shortest paths a node is located on and its ability to connect different parts of the network. Nodes with high betweenness centrality often act as bridges in the network, serving as hubs for information and resource flow between different groups or services. In the tourism network, nodes such as tourism platforms, travel agencies, and major scenic spots may have high betweenness centrality because they connect tourists, service providers, transportation systems, and other nodes. If these high betweenness centrality nodes experience failures or external shocks, the mobility and resilience of the entire tourism consumption network will be severely affected. Assuming the number of shortest paths from n_j to n_k is represented by δ_{kj}, and the number of paths in which n_u acts as an intermediary is $\delta_{kj}(n_u)$, the calculation formula is:

$$Y(n_u) = \sum\nolimits_{k \neq u \neq j} \frac{\delta_{kj}(n_u)}{\delta_{kj}} \tag{2}$$

3. Relative value of the largest connected component: The relative value of the largest connected component is another important indicator for measuring network resilience, describing the proportion of the largest connected subgraph in the total graph. The core purpose of this indicator is to evaluate the connectivity and stability of the tourism network under external shocks. If the largest connected component in a tourism network is relatively large, it indicates that even if some nodes are disrupted, other nodes in the network can still maintain certain connectivity and functionality. This suggests that the tourism industry has strong shock resistance and can quickly recover and continue operations during emergencies. Conversely, a small largest connected component indicates that the structure of the tourism network is relatively fragile, susceptible to impacts from individual nodes or groups, thereby affecting the stability and sustainability of the overall consumption pattern. Assuming the current number of nodes in the

largest connected subgraph is V', the total number of initial network nodes is V, and the node deletion ratio is o, the calculation formula is:

$$H(o) = \frac{V'}{V} \tag{3}$$

4. Network connectivity integral: The network connectivity integral is a comprehensive indicator considering the connectivity and robustness of the entire tourism network. It measures the network's response capability to shocks by calculating the connectivity level between all nodes. A high network connectivity integral indicates that the tourism network can quickly adjust and reallocate resources when facing external disturbances, ensuring smooth information flow and rapid response to consumer demand. The specific calculation formula is:

$$U = \int_0^1 H(o) fo \tag{4}$$

Adaptive capacity refers to the ability of the tourism network to adjust strategies, optimize resource allocation, and quickly resume operations after encountering shocks. This ability reflects the flexibility and response speed of the tourism industry in a complex network environment. For example, tourism service providers can quickly adjust products or services through mobile interaction technology, making personalized recommendations based on tourists' preference data and real-time feedback, thereby recovering and attracting tourist consumption intentions. Tourism consumption patterns with strong adaptive capacity can rapidly adjust tourism products and services through information flow and intelligent decision-making mechanisms, enhancing the overall network's recovery capability in a short period. Therefore, this study selects four core evaluation indicators for adaptive capacity: robustness R value, total industry sales, number of core enterprises, and number of core enterprise product categories.

1. Robustness R value: The robustness R value is an important indicator for measuring the stability of the entire tourism network. It represents the ability of tourism consumption patterns to maintain normal operations under external disturbances such as natural disasters, economic crises, or social events. The R value is typically calculated by simulating the loss of certain nodes or connections within the network, reflecting the extent to which the network can continue operating despite partial node failures or external disruptions. A tourism consumption pattern with high robustness can maintain network stability through self-adjustment and resource reallocation, even in the face of external shocks. Assuming the total number of nodes in the network is V, and the proportion of nodes in the largest connected subgraph after the removal of O nodes is represented by $H(O)$, the calculation formula is:

$$E = \frac{1}{V} \sum_{O=1}^{V} H(O) \tag{5}$$

2. Total industry sales: Total industry sales refer to the total revenue generated by the entire tourism industry through various channels over a specific period. It not only reflects the economic scale of the industry but also serves as an indirect indicator of the resilience of tourism consumption patterns. When total industry

sales are high, it indicates robust consumer demand, high market activity, and more frequent and concentrated consumption activities within the network. In the face of external shocks, if total industry sales remain at a high level, it suggests that consumer willingness to spend has not been significantly affected, and the liquidity within the network is strong, effectively supporting the resilience of the overall tourism consumption pattern. Assuming the transaction amount between nodes is q_{uk}, the calculation formula is:

$$B = \sum\nolimits_{r_{uk} \in R} q_{uk} \tag{6}$$

3. Number of core enterprises: The number of core enterprises is another critical resilience indicator that measures the quantity of key enterprises or nodes supporting the stability of the entire consumption pattern in the tourism industry. These core enterprises are typically the most influential companies or organizations in the market, such as large travel agencies, well-known scenic spots, airlines, and online travel platforms. They occupy crucial positions within the tourism consumption network. Core enterprises attract a large number of consumers and maintain significant market shares by offering unique products and services. A higher number of core enterprises indicates the presence of multiple strong players within the tourism network, which are mutually dependent and collectively sustain the stability of consumption patterns. The proposed number of core enterprises is primarily determined by $J(n_u)$ and $Y(n_u)$, which are standardized to obtain $J(n_u)'$ and $Y(n_u)'$. The calculation formulas are as follows:

$$J(n_u)' = \frac{J(n_u)}{MAX\left(J(n_u)\right)} \tag{7}$$

$$Y(n_u)' = \frac{Y(n_u)}{MAX\left(Y(n_u)\right)} \tag{8}$$

4. Number of product categories offered by core enterprises: The number of product categories offered by core enterprises reflects the diversity of products and services that these enterprises can provide, serving as an important dimension for assessing the resilience of tourism consumption patterns. Core enterprises often attract diverse consumer groups by offering a wide range of tourism products, such as different types of travel routes, service packages, and transportation options. An increase in the number of product categories not only helps attract a broader spectrum of consumers but also effectively enhances the network's adaptive capacity. Assuming the set of core enterprises is represented by N_G, and the set of product categories associated with n_u is represented by $\omega(n_u)$, the calculation formula for the number of product categories β is:

$$\beta = \sum\nolimits_{n_u \in N_G} \left|\omega(n_u)\right| \tag{9}$$

4 COMPREHENSIVE EVALUATION OF RESILIENCE IN TOURISM CONSUMPTION PATTERNS

This paper utilizes the entropy-weighted TOPSIS Model to perform a comprehensive evaluation of the resilience of tourism consumption patterns. By combining the objectivity of the entropy weighting method and the integrative nature of TOPSIS, this approach provides a multidimensional assessment of the tourism industry's ability to resist and adapt to shocks. The following six steps outline the evaluation process:

Step 1: Data standardization: Due to the possible differences in the dimensionality and value range of different indicators, directly comparing the indicators may lead to bias. To address this issue, a data standardization method is used to process the raw data so that all indicators have the same dimensionality and can be compared on the same scale. This paper adopts the linear standardization method, assuming that the standardized value of the u-th evaluation object for the k-th indicator is denoted by e_{uk}, and the raw data is denoted by t_{uk}. The calculation formula is as follows.

$$e_{uk} = \frac{t_{uk} - MIN(t_k)}{MAX(t_k) - MIN(t_k)} \tag{10}$$

Step 2: Calculation of indicator weights: Indicator weights reflect the relative importance of each evaluation criterion in assessing the resilience of tourism consumption patterns. To ensure objectivity, the Entropy Weight Method is adopted. This method calculates weights based on the information entropy of each indicator, where greater information entropy implies higher weight. The entropy value of each indicator is computed as follows:

$$r_k = -m\sum_{u=1}^{l} d_{uk} \times \ln d_{uk} \tag{11}$$

$$d_{uk} = \frac{e_{uk}}{\sum_{u=1}^{l} e_{uk}} \tag{12}$$

$$m = \frac{1}{\ln l} \tag{13}$$

The weight of each indicator is then determined using the formula:

$$q_k = \frac{1 - r_k}{v - \sum_{k=1}^{v} r_k} = \frac{f_k}{\sum_{k=1}^{v} f_k} \tag{14}$$

Step 3: Construct positive and negative ideal solutions: In resilience evaluation, the positive ideal solution (PIS) represents the scenario where all indicators exhibit the highest resilience, such as maximum total industry sales, the strongest core enterprise network, and the highest robustness RRR value. Conversely, the negative ideal solution (NIS) reflects the weakest resilience across all indicators. The formulas for constructing these solutions are:

$$e_k^+ = MAX_u e_{uk} \tag{15}$$

$$e_k^- = MIN_u e_{uk} \tag{16}$$

Step 4: Calculate the optimal distance: The optimal distance measures how far each tourism consumption pattern deviates from the positive ideal solution, with smaller distances indicating closer alignment with the ideal state. Similarly, the distance from the negative ideal solution helps evaluate the pattern's worst-case performance. These distances are calculated using the following formulas:

$$F_u^+ = \sqrt{\sum_{k=1}^{v} q_k \left(e_{uk} - e_k^+\right)^2} \tag{17}$$

$$F_u^- = \sqrt{\sum_{k=1}^{v} q_k \left(e_{uk} - e_k^-\right)^2} \tag{18}$$

Step 5: Determine the relative closeness: Relative closeness is used to measure the degree of closeness of each consumption model to the positive ideal solution, reflecting the overall quality of the model. The higher the relative closeness, the stronger the resilience of the tourism consumption model, indicating stronger pressure resistance and adaptability. The specific calculation formula is:

$$Z_u = \frac{F_u^-}{F_u^+ + F_u^-} \tag{19}$$

Step 6: Analyze results and make decisions: The analysis of comprehensive evaluation results is based on the ranking of relative closeness. By determining the relative resilience of various consumption patterns, it is possible to classify their performance levels and evaluate their responses to different types of shocks. These results provide quantitative insights for industry decision-makers, supporting adjustments to enhance the robustness and recovery capacity of tourism consumption patterns. This systematic approach not only enables precise resilience assessments but also offers practical guidance for optimizing the tourism industry's adaptive strategies in dynamic environments.

5 EXPERIMENTAL RESULTS AND ANALYSIS

By analyzing the experimental data of the resilience of tourism mobile interaction network consumption modes under different disturbance forms in Figures 3–5, it can be observed that the change trends of the relative values of the largest connected component under internal disturbances (including degree centrality and betweenness centrality) and external disturbances. First, the impact of internal disturbance on the resilience of the tourism network consumption mode gradually becomes evident as the proportion of deleted nodes increases. Taking degree centrality as an example, when the node deletion ratio increases from zero to one, the impact of internal disturbance on the upstream network consumption mode resilience is greatest, with the relative value of the largest connected component decreasing from one to close to zero (0.005), while the changes in midstream and downstream are relatively small. For betweenness centrality, although the impact of internal disturbance is relatively stable, the connectivity also decreases in extreme node deletion cases.

The situation of external disturbances is more complex, especially in the downstream network consumption mode, where external disturbances show greater volatility. The largest connected component gradually decreases to near zero when a high proportion of nodes are deleted, indicating that external shocks have a stronger destructive effect on the resilience of the downstream network consumption mode. From the experimental data, it can be concluded that the resilience of the tourism consumption mode exhibits significant regional differences when facing internal and external disturbances. For the upstream network consumption mode, due to its core position in the overall network structure, its resilience is significantly affected by high internal disturbances (especially degree centrality), indicating that the core nodes in this area are crucial for maintaining the stability of the network consumption mode. However, when the node deletion ratio is high, even the upstream network consumption mode shows a significant decline in resilience, especially when degree centrality is high, and the connectivity of the network decreases significantly. The midstream network consumption mode shows relatively strong adaptability, especially when facing internal disturbances of degree centrality and betweenness centrality, with the changes in the largest connected component being relatively stable, indicating that its adaptability to the network structure is strong and can effectively withstand a certain proportion of node deletions. In contrast, the downstream network consumption mode shows more fragile resilience under external disturbances; especially when external disturbances intensify, the decline of the largest connected component is more significant, indicating that the downstream network consumption mode is highly sensitive to external shocks and lacks sufficient self-recovery ability.

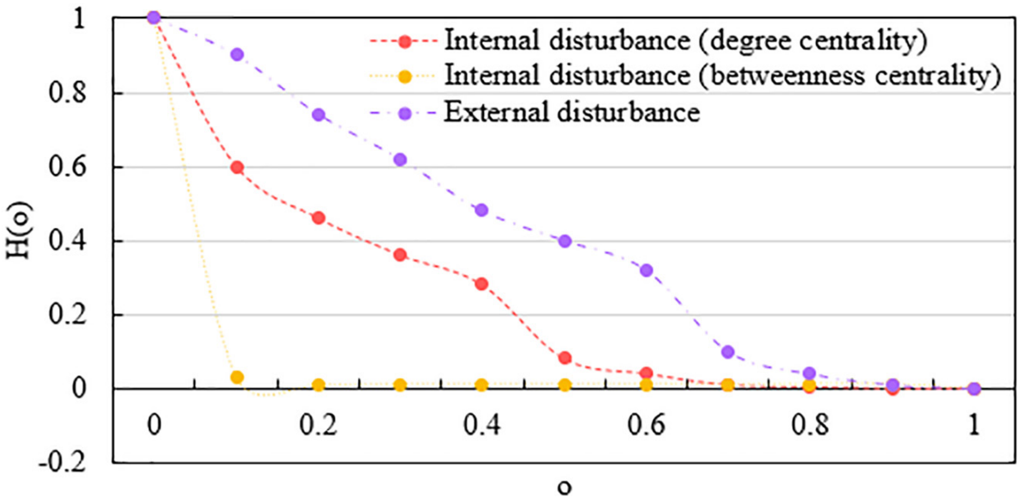

Fig. 3. Results of the relative values of the largest connected component of the tourism mobile interaction network upstream under different disturbance forms

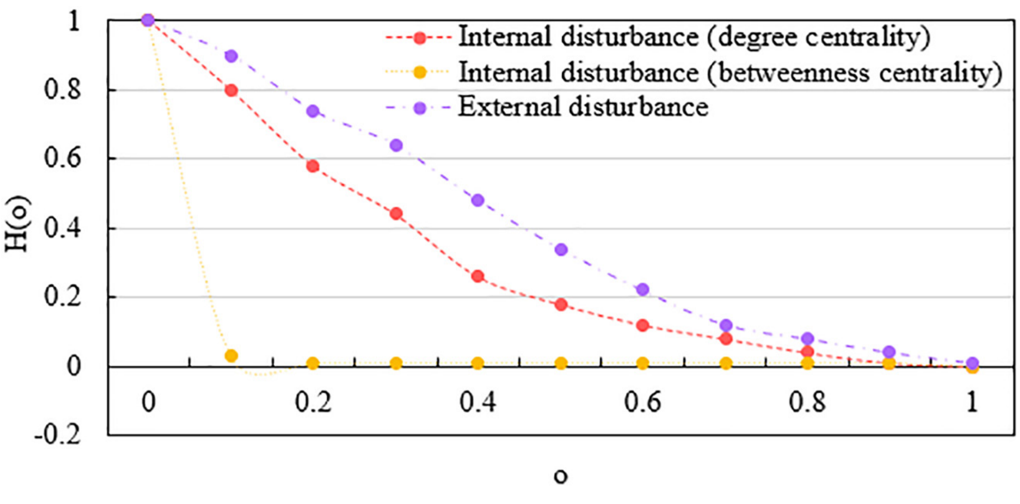

Fig. 4. Results of the relative values of the largest connected component of the tourism mobile interaction network midstream under different disturbance forms

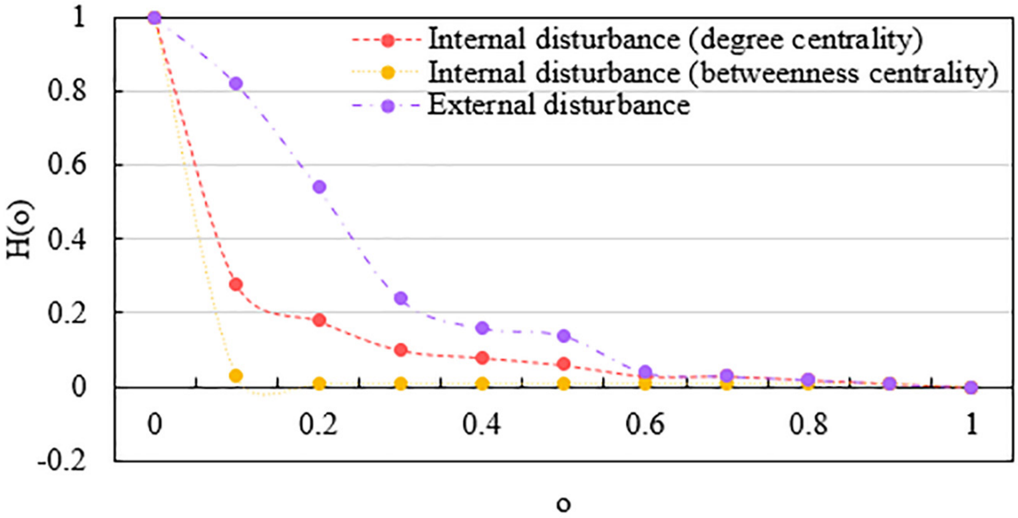

Fig. 5. Results of the relative values of the largest connected component of the tourism mobile interaction network downstream under different disturbance forms

Table 1. Entropy weight method results for indicator weights

Indicator	Information Entropy	Information Utility	Weight Coefficient
Internal Network Connectivity (Degree Centrality)	0.6125	0.3845	11.25%
Internal Network Connectivity (Betweenness Centrality)	0.5236	0.4781	13.21%
External Network Connectivity	0.6389	0.3625	9.23%
Robustness RRR under External Disturbances	0.5548	0.4216	12.35%
Total Industry Sales	0.6125	0.3698	9.58%
Number of Core Enterprises	0.3895	0.6154	16.25%
Number of Core Enterprise Products	0.3152	0.6685	16.48%

According to the results of the entropy weight method in Table 1, the indicators of the resilience of tourism consumption modes have different weight coefficients, reflecting the contribution of each indicator to the overall result in the assessment of resilience. First, the number of core enterprises (16.25%) and the number of product types of core enterprises (16.48%) have relatively high weights, indicating that the scale and diversification of core enterprises are crucial for the adaptability and risk resistance of the consumption mode in assessing the resilience of the tourism industry. Secondly, under internal disturbances, the network connectivity indices (degree centrality and betweenness centrality) have a more significant impact on the network structure, especially the weight coefficients of degree centrality (11.25%) and betweenness centrality (13.21%), which reveal the importance of the tight connections and the role of key nodes within the tourism industry. In addition, under external disturbances, the robustness R value (12.35%) and the network connectivity indices (9.23%) indicate that external shocks also have a significant impact on the tourism consumption mode. The total industry sales (9.58%) reflect the support of the tourism industry's economic foundation for the resilience performance.

The positive and negative ideal solution indicators in Table 2 provide benchmark references for evaluating the resilience of tourism consumption patterns. By comparing the positive and negative ideal solutions of each indicator, the impact of various factors on the resilience of tourism consumption patterns can be revealed. Firstly, the positive ideal solutions of the network connectivity integral (degree centrality and betweenness centrality) under internal interference are 0.215 and 0.236, respectively, while the negative ideal solution is 0.001 for both, indicating the importance of degree centrality and betweenness centrality to the stability of network structures. A higher degree of centrality reflects greater node connectivity density, which helps enhance overall network resilience. Secondly, the positive ideal solutions for the network connectivity integral and the robustness R-value under external interference are 0.158 and 0.214, respectively, indicating that network connectivity and robustness are crucial indicators of the risk resistance of tourism consumption patterns when facing external shocks. The number of core enterprises (positive ideal solution of 0.289) and the number of product categories of core enterprises (positive ideal solution of 0.325) are also key factors, playing a decisive role in the market adaptability and risk management capabilities of the tourism industry. Among all indicators, the stability and diversity of core enterprises exhibit a strong impact on resilience.

Table 2. Positive and negative ideal solutions

Indicator	Positive Ideal Solution	Negative Ideal Solution
Network connectivity integral (degree centrality) under internal interference	0.215	0.001
Network connectivity integral (betweenness centrality) under internal interference	0.236	0.001
Network connectivity integral under external interference	0.158	0.001
Robustness R-value under external interference	0.214	0.001
Total industry sales	0.189	0.001
Number of core enterprises	0.289	0.002
Number of product categories of core enterprises	0.325	0.002

The TOPSIS evaluation results in Table 3 reveal the relative performance of different network levels (upstream, midstream, and downstream) regarding the resilience of tourism consumption patterns. By calculating the distances of each network level from the positive and negative ideal solutions, relative closeness indicators are obtained, providing a comprehensive evaluation of the resilience of different levels. According to the results, the relative closeness of the upstream network is 0.623, ranking first, indicating that the upstream network has strong resilience and high adaptability when facing disturbances. Following closely is the midstream network with a relative closeness of 0.432, ranking second; though its resilience is weaker than that of the upstream network, it still exhibits a certain degree of risk resistance. The downstream network has a relative closeness of 0.278, ranking third, indicating that it is relatively fragile in response to disturbances and has lower resilience, likely being more susceptible to external market changes.

Table 3. TOPSIS evaluation results

Industry Level	Positive Ideal Distance	Negative Ideal Distance	Relative Closeness	Rank
Network Upstream	0.325	0.578	0.623	1
Network Midstream	0.458	0.365	0.432	2
Network Downstream	0.612	0.248	0.278	3

Based on the TOPSIS evaluation results, it can be concluded that the resilience of tourism consumption patterns exhibits significant hierarchical differences. When facing market fluctuations and environmental changes, the upstream network demonstrates the best resilience due to its relatively strong adaptability and disturbance resistance, making it a leader in the industry. Upstream enterprises typically control critical resources and technologies, enabling them to recover more quickly during crises. The midstream network displays moderate resilience; though it has relatively strong adaptability, it faces more external challenges than the upstream network. The downstream network is the most fragile in terms of resilience, showing the lowest relative closeness. This may be attributed to slower responses to market changes and a higher dependency on resources and support from the upstream and midstream.

6 CONCLUSION

This study focuses on the resilience of tourism consumption patterns, adopting a mobile interaction network model, resilience indicator construction, and the entropy weight-TOPSIS comprehensive evaluation method. The proposed mobile interaction network model aims to reveal how interaction technology enhances adaptability and risk resistance by reconstructing the network structure of the tourism industry. Through an analysis of different levels of networks within the tourism industry, the study reveals the stability of network structures and changes in adaptability under different disturbance scenarios. Secondly, the study defines and establishes resilience indicators for tourism consumption patterns to evaluate their performance when facing market fluctuations and environmental changes. Based on these resilience indicators, the study calculates the weights of each indicator using the entropy weight method and combined with the positive and negative ideal solutions, evaluates the performance of different network levels under interference conditions. Finally, the TOPSIS evaluation method is used to comprehensively analyze the resilience of tourism consumption patterns at different levels, concluding that the upstream network has high resilience while the downstream network has low resilience.

Experimental results indicate significant differences in the performance of resilience among different levels of tourism consumption patterns within the mobile interaction network. In the comparison of positive and negative ideal solution distances, the upstream network consumption pattern demonstrates the best resilience, exhibiting strong risk resistance, reflecting the advantages of upstream enterprises in resource control and market adaptation. Meanwhile, the midstream network consumption pattern shows moderate resilience; though it has certain risk resistance, its resilience is weaker compared to the upstream network. The downstream network consumption pattern exhibits the weakest resilience, with poorer adaptability and a greater susceptibility to external market fluctuations. Additionally, the calculation results of the entropy weight method play a crucial role in assessing the resilience of consumption patterns at different levels, further confirming the application value and differences of mobile interaction technology across various network levels.

7 ACKNOWLEDGMENT

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