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Collaborative Policy Modeling for Ecotourism Conservation and Development: A Multi-Case Empirical Study Based on Policy Instrument Taxonomy

Jundi Chen¹, Junhua Chen², Zijian Li³, Yicong Bin^{1,*}

¹Guangdong Lingnan Institute of Technology, Guangzhou 510663, China

²Guangdong Ocean University, Zhanjiang 524088, China

³Guangzhou Vocational and Technical University of Science and Technology, Guangzhou 510550,

*China Corresponding author: Yicong Bin, 3560868644@qq.com

Abstract

The synergistic imbalance between conservation and development remains a core constraint on the sustainable development of ecotourism. Grounded in externality theory, this study constructs a three-dimensional modeling framework that integrates the quantification of positive externalities from ecological conservation, the pricing of negative externalities from tourism development, and the adaptation of policy instruments. Employing a dual-case design contrasting Bijiaoshan Mountain (karst-type) with the Qinghe Yungeng project (hilly-type), the study adopts a sequential mixed-methods approach combining natural language processing (NLP) sentiment analysis, household questionnaires, in-depth interviews, policy-text coding, and ecological spatial analysis. The empirical results show that a persistent “ticket-experience” gap constitutes a systematic structural contradiction across ecotypes; community participation incentives exhibit a markedly gradual and marginally diminishing trajectory; transparent benefit distribution is more fundamental than the absolute amount of economic compensation; and the complementarity of mandatory, market-based, and voluntary instruments is the institutional basis for balancing conservation and development. The study contributes an extended externality framework incorporating carbon-reduction ecosystem-service value, a temporal estimation model of community participation, and a transferable full-chain analytical path from quantitative analysis to policy implementation.

Keywords

Community participation, Ecotourism sustainable development, Externality theory, Multi-case empirical study, Qinghe Yungeng

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1. Introduction

Ecotourism is widely regarded as an ideal pathway for reconciling ecological conservation with regional economic development. Since Ceballos-Lascuráin first proposed the concept of “ecotourism” in 1983, the field has undergone more than four decades of theoretical evolution and practical exploration, progressing from an initial “responsible travel in nature” to a multidimensional policy instrument encompassing community development, biodiversity conservation, and green economic transition. At the practical level, however, the synergy between “conservation” and “development” remains far from realized—the public-goods attribute of ecological resources leads to a systematic undervaluation of their positive externalities, while the environmental negative externalities of tourism development lack effective pricing and internalization mechanisms.

From a macro perspective, the synergistic dilemma facing China’s ecotourism has deep institutional roots. On the one hand, since the launch of the national park system pilot in 2015, the first batch of five national parks was officially established in 2021; yet under the “conservation first” orientation, community development space has been compressed, and a closed-loop institutional mechanism for community benefit compensation has yet to take shape [1]. On the other hand, rural tourism poverty-alleviation policies have driven the launch of numerous ecotourism projects, yet most have fallen into the predicament of “emphasizing construction while neglecting operation”—in 2023, national rural tourism received over 3 billion visits, but per-capita consumption was only about RMB 180, far below the RMB 620 of urban tourism in the same period. This “high-traffic, low-conversion” phenomenon reflects the homogenization of ecotourism product supply and the dilution of experiential value [2].

This paper aims to answer the following core research question: at the level of policy design, how can the synergy between ecotourism conservation and development be achieved? Unlike existing studies, this paper introduces the Qinghe Yungeng project as a second empirical case, forming a “karst-type vs. hilly-type” dual-case comparison with Bijiashan Mountain. The Qinghe Yungeng project contributes NLP sentiment analysis of 3,357 scenic-area reviews, 600 household questionnaires (582 valid returns, 97% validity rate), over 50 in-depth resident interviews, 18-month longitudinal tracking data of 16 households, and carbon-reduction data independently estimated based on GB/T 32150, effectively filling the gap left by single-case studies in the micro-mechanisms of communities and the quantification of ecosystem service values.

The structure of this paper is arranged as follows: Section 2 reviews the theoretical foundations and constructs the analytical framework; Section 3 elaborates the mixed-methods design and multi-source data system; Section 4 presents the dual-case empirical analysis results; Section 5 discusses the principal findings, theoretical contributions, and practical and policy implications; Section 6 presents limitations and future research directions; and Section 7 concludes with the core problem, principal empirical insight, and overall contribution.

2. Theoretical Foundation and Analytical Framework

2.1 Externality Theory and Community Participation Incentives

The positive externalities of ecotourism—biodiversity conservation, water-source conservation, and carbon-sink increments—are characterized by non-excludability and non-rivalry, so their supply is inevitably insufficient under spontaneous market allocation. Pigou (1920) advocated correcting externalities through taxation or subsidies, while Coase (1960) argued that, given well-defined property rights, a Pareto optimum could be reached through negotiation; yet both paths face operational obstacles in ecotourism: the former is constrained by the monetization difficulty of ecosystem service values, and the latter by the ambiguity of community property-rights delineation [3,4].

From a spatial perspective, the positive externalities of ecotourism exhibit significant cross-regional spillover effects. Research on the eco-economic-social coupled coordinated development of China’s national park regions shows that the enhancement of ecosystem service values within protected areas often benefits surrounding counties and cities, while the county where the protected area is located bears the principal opportunity cost of development, forming a spatial mismatch of “localized conservation costs and externalized ecological benefits” [5]. The natural-landscape quality assessment of the Sanjiangyuan National Park further reveals that the spatial heterogeneity of ecosystem services makes it difficult for a uniform compensation standard to fit diverse conservation scenarios [6], requiring policy design to transcend administrative boundaries and establish a cross-regional ecological-compensation transfer-payment mechanism.

From an international comparative perspective, Costa Rica returns 30% of national park revenue to community conservation areas, raising rainforest coverage by 8 percentage points and achieving an average annual tourism-revenue growth of 12% [7,8]; Zhangjiajie, through ticket-price reform, raised per-capita consumption from RMB 800 to RMB 1,500, suggesting the guiding effect of pricing-mechanism adjustment on consumption structure. None of these cases, however, examines the micro-transmission mechanism of community participation incentives.

At the level of theoretical depth, the applicability of externality theory in ecotourism faces three challenges. First, the time-discount problem of ecosystem service values—an intertemporal trade-off between short-term development gains and long-term conservation gains—combined with community farmers’ generally higher discount rates than the social

optimum, leads to insufficient conservation investment. Second, adverse selection induced by information asymmetry—in ecological-compensation contracts, farmers hold an informational advantage regarding the true cost of their own conservation behaviors, which may induce the moral hazard of “low-quality conservation” to capture compensation. Third, the collective-action dilemma—conservation behavior at the community level constitutes a public-goods provision game, and free-rider motives weaken individuals’ participation incentives.

From a broader theoretical perspective, the effectiveness of community participation incentives can be formalized through a principal-agent framework. The scenic-area management (principal) delegates conservation behaviors to community farmers (agents), whose effort level is private information. An effective incentive contract must simultaneously satisfy the “participation constraint” (farmers’ expected benefit from participating is no less than the reservation utility of non-participation) and the “incentive compatibility constraint” (farmers’ expected benefit from high-effort conservation is no less than that from low-effort conservation). The Qinghe Yungeng data provide an empirical basis for parameter estimation: the minimum-price guarantee procurement price must at least cover farmers’ opportunity cost (the participation-constraint threshold is approximately RMB 8,000 annual income increase), and the marginal intensity of carbon-credit incentives must reach the level that “for each one-standard-deviation increase in conservation effort, the carbon-credit benefit increases by no less than 5%” (the incentive-compatibility-constraint threshold), so as to achieve self-reinforcement of conservation behavior.

2.2 Challenges in Policy Instrument Adaptation

Building on related tourism and rural-governance research [9,10] and the classical three-way classification of policy instruments in environmental governance, ecotourism policy instruments can be divided into three categories: mandatory (emission standards, visitor-capacity ceilings), market-based (emission-trading rights, ecological compensation), and voluntary (environmental certification, community covenants). Tourism-governance research shows that the governance paradigm is undergoing a transition from “government-led” to “pluralistic co-governance,” but this transition faces unique institutional frictions in ecotourism—the state-owned attribute of ecological resources limits the depth of market-mechanism intervention, while weak community organizations constrain the implementation effect of voluntary instruments [11].

The typical predicament of mandatory instruments in Bijiaoshan Mountain lies in high implementation costs: real-time monitoring of visitor-capacity ceilings relies on IoT infrastructure investment, yet most scenic areas lack corresponding resource allocation. Research on agricultural ecological compensation provides a useful reference—practices at home and abroad show that precise monitoring technology is a key mediating variable between compensation standards and effects, and compensation schemes lacking technical support often fall into a “data black box,” leading to low capital-use efficiency [12].

At the level of domestic policy practice, the national park system pilot has accumulated rich experience in policy instruments. Research on the Hainan Tropical Rainforest National Park shows that spatial spillover is a key link connecting ecotourism with rural industrial revitalization—ecotourism activities in the core conservation zone radiate to surrounding villages through industry-chain spillover, employment spillover, and brand spillover; yet the spatiotemporal decay of the spillover effect requires policy design to allocate investment priorities to the inflection-point region of the spillover-decay curve.

Table 1 presents the classification of ecotourism policy instruments, together with their typical implementation means and theoretical bases.

Table 1. Comparison of ecotourism policy instrument classification.

Instrument Type	Typical Means	Performance in This Study’s Cases	Theoretical Basis
Mandatory (command-and-control)	Emission standards, visitor-capacity ceilings	Bijiaoshan capacity ceiling relies on IoT investment, with high implementation cost	Policy instrument classification framework
Market-based	Emission-trading rights, ecological compensation	Qinghe Yungeng introduces third-party auditing and blockchain traceability, achieving closed-loop fund supervision	Community co-management equilibrium
Voluntary	Environmental certification, community covenants	Farmers’ environmental behavior yields dispersed benefits but self-borne costs, with insufficient participation motivation	Ticket-economy transition

Note: Data sources are the project practice records and policy documents of the two case areas (2020-2025); compiled by the authors.

The three types of instruments exhibit a complementary relationship in this study’s dual cases: mandatory instruments are constrained by implementation costs, market-based instruments depend on transparency building, and voluntary instruments are constrained by individual-incentive dilemmas; only the synergy of the three can support the dynamic balance between conservation and development.

This complementary relationship can be formalized through a “policy mix matrix,” whose horizontal axis is the “degree of coercion” of instruments (from voluntary to mandatory) and vertical axis the “implementation complexity” (from simple to complex). Based on the dual cases, this paper proposes a suggested, conceptual combination—market-based instruments as the main body (weight about 50%), mandatory instruments as the supplement (about 30%), and voluntary instruments as the complement (about 20%). It should be emphasized that these weights derive from qualitative reasoning based on case evidence rather than from statistical estimation or formal optimization, and should therefore be interpreted as a conceptual heuristic for policy design. The economic logic is: market-based instruments guide resource allocation through price signals, theoretically closest to the Pigou optimum; mandatory instruments serve as a “bottom-line guarantee” to prevent irreversible ecological damage caused by market failure; and voluntary instruments serve as “flexible space” to absorb heterogeneous needs at the community level.

2.3 The Double-Edged-Sword Effect of Digital Technology

The rise of short-video platforms has brought significant traffic dividends to ecotourism, yet it has also spawned a structural imbalance between “traffic and quality,” as illustrated by the contrast between Bijiaoshan Mountain’s 5.409 million Douyin views and its 3.2/5 satisfaction. A deeper risk lies in the “internet-celebrity-ization” marketing tendency driven by traffic logic: when scenic areas prioritize “photogenic-rate” and “check-in-spot” construction while neglecting infrastructure and service quality, short-term traffic growth instead overdraws long-term brand equity.

At the same time, digital technology opens new possibilities for policy-instrument innovation: the Qinghe Yungeng project uses a natural language processing (NLP) sentiment-analysis system to monitor scenic-area reviews in real time, with the classification accuracy reported in Section 3.3. Building on network-text-based destination-image research [13,14], the system provides a high-precision visitor-experience feedback channel for policymakers, reducing the cost of information asymmetry and enhancing the responsiveness and precision of governance. At a more macro level, digital technology is reshaping tourism-destination governance from “top-down” administrative control to “data-driven” pluralistic consultation, imposing new capability thresholds on the digital literacy of governance subjects (especially grassroots communities).

2.4 Economic-Policy Modeling Framework

Based on the above theoretical deduction, this paper constructs a three-dimensional analytical framework of “positive-externality quantification—negative-externality pricing—policy-instrument adaptation.” The positive-externality quantification module, beyond the traditional vegetation-coverage indicator, adds a carbon-reduction ecosystem-service-value dimension—the carbon reduction of the Qinghe Yungeng project is independently estimated based on GB/T 32150, providing an alternative quantification path for the elasticity relationship between carbon-sink increments and tourists’ willingness to pay. The negative-externality pricing module aims to internalize the environmental-restoration cost of visitor overload and the social cost of community-cultural erosion into the scenic-area pricing model. The policy-instrument adaptation module introduces the temporal parameter of community participation rate (estimated from the longitudinal tracking data; see Section 4.3), extending static policy design into dynamic implementation-path planning.

The core feature distinguishing this framework from existing studies lies in the “feedback coupling” among the three dimensions: the positive-externality quantification result provides a benchmark reference for negative-externality pricing (e.g., carbon-sink increments can inversely offset part of the environmental-restoration cost), while the adaptation effect of policy instruments feeds back to the positive-externality quantification module through indicators such as community participation rate and visitor satisfaction, forming a closed-loop iterative mechanism of “quantification—pricing—adaptation—feedback.”

The operation logic of this closed loop is as follows. In the first loop, the positive-externality quantification module, based on carbon-reduction accounting, remote-sensing inversion of vegetation coverage, and ecosystem-service-value assessment, outputs an “ecosystem-service-value equivalent.” In the second loop, the negative-externality pricing module converts the environmental-restoration cost of visitor overload (vegetation-trampling recovery, water eutrophication control, solid-waste treatment) and the socio-cultural erosion cost (commercialization impact on traditional lifestyles and over-consumption of cultural symbols) into monetary equivalents, and performs a net-difference calculation with the positive-externality equivalent to determine the benchmark amount of ecological compensation. In the third loop, the policy-instrument adaptation module dynamically selects the instrument combination based on the net difference and the temporal parameter of community participation rate—when the net difference is positive and the participation rate is below 10%, market-based and community-incentive instruments are prioritized; when the net difference is negative, mandatory instruments and ecological-restoration investment are prioritized. In the fourth loop, the implementation effect feeds back to the first and second loops through NLP sentiment monitoring and the ArcGIS ecological-pressure index [15], triggering iterative calibration.

3. Research Methods

3.1 Overall Design

This paper adopts a mixed-methods design, with triangulation as the core strategy, integrating three methodological paths—NLP text mining, policy-text coding, and ecological spatial analysis—so that conclusions are cross-validated by multi-source data. The rationale is that the “conservation-development” synergy problem involves four heterogeneous data domains: tourist experience (subjective-perception dimension), community participation (social-behavior dimension), ecological indicators (objective-environment dimension), and policy texts (institutional dimension), which cannot be effectively covered by a single methodological path. The triangulation design, through the “convergence-divergence” judgment among data sources and methods, both enhances the reliability of conclusions and reveals tensions that a single method cannot detect.

The specific architecture is a “sequential mixed-methods design,” implemented in three time-ordered phases: an exploratory phase (online-review mining and policy-text coding), a verification phase (household questionnaires and in-depth interviews), and a spatial-corroboration phase (ArcGIS ecological spatial analysis), so that each phase informs the design of the subsequent one while the three paths remain cross-referenced at the interpretation stage. Temporally, the design follows a three-stage logic of “exploration–validation–deepening”: Stage 1 (March–June 2024) conducted exploratory analysis through NLP text mining and policy-text coding to identify key variables and hypotheses; Stage 2 (July–December 2024) tested these hypotheses through household questionnaires, supplemented by in-depth interviews for mechanistic explanations; Stage 3 (January–March 2025) conducted spatial corroboration through ArcGIS analysis to complete the evidence chain. The databases of the three stages were stored and constructed independently, to reduce the impact of researchers’ confirmation bias on subsequent data collection.

3.2 Data Sources

Online review data. Reviews from three platforms—Meituan, Douyin, and Ctrip—for Bijiaoshan Mountain scenic area from 2020 to 2025, with 12,630 valid reviews retained after deduplication and invalid-filtering. The Qinghe Yungeng project collected 3,357 reviews from six scenic areas in the same period as an independent validation dataset. Network text analysis has formed a mature methodological path in tourism-destination image-perception research [16]. The platform selection is based on channel complementarity: Meituan focuses on consumption-decision evaluation, Douyin on short-video traffic-generation effects, and Ctrip on in-depth experience sharing; the three sources combined reduce the selection bias of a single platform. Raw reviews were deduplicated and filtered through automated and manual checks (duplicate detection, spam and non-tourist review removal, and language filtering); a detailed selection flow is provided in the supplementary materials.

Questionnaire and interview data. The Qinghe Yungeng project distributed 600 household questionnaires in total, recovering 582 valid questionnaires (97% validity rate); the questionnaire dimensions cover benefit-distribution perception, participation willingness, environmental behavior, and community trust, following the ecotourism community-resident perception scale developed by Lu Xiaoli (2006) with localized revisions. Households were selected through purposive sampling based on their involvement in the two demonstration areas and their willingness to participate in repeated surveys; the 16-household longitudinal subsample covered both participating and non-participating households to track within-household variation over the 18-month observation window. More than 50 in-depth resident semi-structured interviews were conducted, each lasting 45–90 minutes, covering scenic-area management (8 persons), village cadres (6 persons), participating farmers (22 persons), non-participating farmers (9 persons), and tourist representatives (5 persons). The sample-selection procedure and representativeness discussion are reported in the supplementary materials.

Policy-text data. Fifteen ecotourism-related policy documents at the national and local levels were collected, spanning 2018–2025 and covering three administrative levels: national, provincial, and scenic-area. The coding framework integrates the issue-classification system of tourism-governance research and the policy dimensions of community co-management evolutionary-game analysis.

Ecological-monitoring data. Landsat 30 m-resolution satellite remote-sensing images from 2020 to 2024, used for vegetation-coverage and land-use-change analysis; monthly water-quality monitoring data of the rafting area (12 indicators); visitor-flow monitoring data (15-minute sampling interval).

3.3 Analytical Methods

NLP sentiment and topic analysis. Sentiment classification adopts an improved supervised NLP algorithm based on a fine-tuned pre-trained language model (BERT-based, Chinese), trained on manually annotated reviews from the Qinghe Yungeng project and evaluated on an independent test set. On the independent test set of 3,357 reviews, the model achieves 99.1% classification accuracy, significantly outperforming a TF-IDF combined with a latent Dirichlet allocation (LDA) baseline (about 78%–85% on the same test set). The policy value of high-precision sentiment analysis lies in: when the classification error drops from 15%–22% to less than 1%, the visitor-satisfaction early-warning system based on review data can achieve the leap from “qualitative reference” to “quantitative decision-making,” providing

credible data support for real-time policy adjustment. Topic modeling adopts the LDA algorithm to identify potential topic dimensions in tourist reviews.

Policy-text coding. NVivo 12 was used to perform three-level coding (open coding–axial coding–selective coding) on the 15 policy documents, extracting core categories such as policy-instrument types, implementing subjects, and constraint conditions.

Ecological spatial analysis. Based on ArcGIS 10.8, an Ecological Pressure Index (EPI) was constructed to generate a spatiotemporal dynamic map of ecological pressure, integrating three indicator dimensions: vegetation-coverage change, water-quality indicators, and visitor density. Indicator definitions and data sources are provided in the supplementary materials.

To further enhance topic interpretability, grid search based on perplexity was used to determine the optimal number of topics ($k = 8$), and topic semantic consistency was verified through manual annotation, finally retaining six core topics directly related to the “conservation-development” synergy. The policy-text coding was independently executed by two researchers, with inter-coder reliability tested by the Kappa coefficient ($Kappa = 0.82, p < 0.01$); divergent entries were arbitrated by a third person after discussion. The EPI calculation adopts the entropy method to determine dimension weights, avoiding subjective weighting bias; spatial interpolation adopts ordinary Kriging with a fitted variogram model to generate a $100\text{ m} \times 100\text{ m}$ grid-scale pressure-distribution map, providing spatialized data support for the model calibration of the “ecological-vulnerability coefficient.” The weighting method, interpolation method, and output grid resolution are reported in the supplementary materials.

4. Empirical Analysis

4.1 Overview of Empirical Design

The empirical design is centered on the logic of “cross-ecotype comparison.” The rationale for selecting Bijiaoshan Mountain (karst-type) and Qinghe Yungeng (hilly-type in the Greater Bay Area) as dual cases lies in: (1) ecotype differences—karst and hilly landforms differ essentially in ecological vulnerability, vegetation-recovery cycles, and landscape carrying capacity, constituting a natural laboratory for testing policy-instrument adaptability; (2) development-stage differences—Bijiaoshan Mountain has entered a mature operation period (350,000 annual visits), while Qinghe Yungeng is in its start-up growth period (RMB 800,000 first-year revenue), jointly covering the key life-cycle nodes of ecotourism development; and (3) governance-model differences—Bijiaoshan adopts the traditional ticket-dependence model, while Qinghe Yungeng explores a “cooperative + minimum-price guarantee procurement” community co-construction model. The empirical analysis proceeds through three progressive levels—tourist experience (4.2), policy-instrument implementation effectiveness (4.3), and the eco-economic-cultural system (4.4)—each examined across the two cases, forming a complete empirical chain of “problem diagnosis—mechanism analysis—system reconstruction.”

Table 2 summarizes the key characteristics of the two cases, including their development models, main contradictions, governance instruments, and core evaluation data.

Table 2. Comparison of dual-case characteristics: Bijiaoshan Mountain and Qinghe Yungeng.

Comparison Dimension	Bijiaoshan Mountain (Karst-Type)	Qinghe Yungeng (Hilly-Type in Greater Bay Area)
Project Location	Guangdong (National Ecotourism Demonstration Zone)	Greater Bay Area (six-scenic-area coordinated operation)
Development Model	Ticket-dependent, short-video traffic generation	Cooperative + minimum-price guarantee procurement, diversified experience
Main Contradiction	Traffic-quality imbalance, satisfaction 3.2/5	Low community participation rate (2.1% initially)
Governance Instruments	Capacity ceiling, pricing-mechanism adjustment	Blockchain traceability, real-time NLP monitoring
Core Data	350,000 annual visits, RMB 120 per-capita consumption	42% non-ticket revenue share, RMB 18,000 average annual household income increase

Note: Data are from project records, questionnaire surveys, and field interviews in the two case areas (2020-2025); compiled by the authors.

Although the two cases differ in ecotype and development stage, they jointly point to two structural contradictions—the “ticket-experience” gap and insufficient community participation. We acknowledge that data depth and availability differ between the two cases; the comparison therefore emphasizes structural similarities in the policy process rather than data symmetry.

4.2 Structural Contradictions in Tourist Experience

Taking Bijiashan Mountain in Guangdong as an example, the scenic area was selected as a “National Ecotourism Demonstration Zone” in 2023, with cumulative short-video platform views reaching 5.409 million and annual visitor volume of 350,000; however, per-capita consumption was only RMB 120 and visitor satisfaction merely 3.2/5, highlighting the structural gap between traffic dividends and experiential quality. Similar structural problems appeared in the coordinated operation of six scenic areas under the Qinghe Yungeng project: a low community participation rate (only 2.1% initially) and an insufficient share of non-ticket revenue, with first-year revenue of RMB 800,000 far from covering ecological maintenance costs. Zhangjiajie, a benchmark case of domestic ecotourism, likewise reveals the “ticket economy” contradiction: although per-capita consumption rose from RMB 800 to RMB 1,500 after the 2018 ticket-price reform, the share of secondary consumption remained below 20% [17,18]; research on its modern tourism development history shows that this path dependence traces back to excessive reliance on ticket revenue in the early stage of scenic-area development [19].

The NLP topic analysis of Bijiashan Mountain’s 12,630 reviews shows that tourists’ negative evaluations concentrate on three dimensions: cost-performance anxiety (72% of negative reviews mention “not worth the ticket price”), experience homogenization (lack of differentiated cultural-tourism product supply), and insufficient infrastructure. An assessment of the spatiotemporal evolution of China’s ecotourism high-quality-development level provides a macro background—although the ecotourism development index rose overall from 2010 to 2022, the growth rate of “development quality” (2.3% annually) was far lower than that of “development scale” (11.7% annually).

The independent NLP analysis of 3,357 reviews from six scenic areas of the Qinghe Yungeng project presents a highly consistent pattern: comments of the “ticket-experience” gap type account for 31.2%, echoing the finding of Bijiashan Mountain across cases. This indicates that the gap is not a management defect of individual scenic areas but a systematic structural contradiction faced by the ecotourism industry in the stage of rapid traffic growth—tourists are attracted by low ticket prices and short-video marketing, yet the actual experience significantly lags expectations; this gap, amplified by the network-text effect, in turn suppresses secondary consumption and word-of-mouth dissemination, forming a vicious cycle of “traffic can be attracted, but experience cannot be retained.”

Further analysis reveals that the deep root of tourist-experience homogenization lies in the insufficient development depth of eco-cultural resources. The practice of Gannan Tibetan Autonomous Prefecture shows that organically embedding ethnic-cultural experiences (such as Tibetan traditional handicrafts and grassland nomadic life) into the ecotourism product system can significantly increase the average stay duration (from 1.2 days to 2.8 days) and revisit willingness (from 23% to 47%) [20]. Similarly, research on the integrated development of ecotourism and eco-culture points out that the product life cycle of ecotourism relying solely on natural landscapes is only about 5-8 years, while it can be extended to over 15 years after incorporating local cultural elements [21]. The preliminary practice of the Qinghe Yungeng project in farming experience (22% of non-ticket revenue) and study-tour courses (12%) supports the logic that cultural integration enhances experience depth and consumption depth.

Table 3 reports the tourist perception dimensions identified from the review data, together with representative review examples and their sentiment tendencies.

Table 3. Tourist perception dimensions and typical review examples.

Perception Dimension	Sentiment Tendency	Typical Review Example	Share / Source
Ticket-Experience Gap	Negative	“Not worth the ticket price,” “expensive ticket but nothing to play”	31.2% (Qinghe Yungeng)
Experience Homogenization	Negative	“All the same everywhere, lacking differentiated cultural-tourism products”	Concentrated dimension of Bijiashan negative reviews
Insufficient Infrastructure	Negative	“Hard to park, unclear signs, few restrooms”	Concentrated dimension of Bijiashan negative reviews
Eco-Cultural Integration	Positive	“Parent-child farming experience is very meaningful”	22% (Qinghe Yungeng farming income)

Note: Review examples are from the Meituan, Douyin, and Ctrip platforms (2020-2025); shares are calculated based on the Qinghe Yungeng project data.

These dimensions are highly consistent with the resident and tourist impact-perception framework summarized by Lu Xiaoli (2006), and support the effectiveness of network text analysis in tourism-destination image diagnosis. China’s long-term dependence on a ticket economy has become an academic consensus—Kang Xiaoqing’s (2015) review points out that the share of ticket revenue in the total revenue of domestic ecotourism scenic areas has long remained between 55% and 75%, far higher than the 30%-40% average of international peers [22]; this structural deviation is one of the institutional roots that makes the experience-homogenization problem difficult to break through.

It is worth noting that the “double-edged-sword” effect of digital technology has an amplification mechanism in ecotourism—the algorithmic recommendation of short-video platforms naturally prefers “visual spectacles” while

neglecting “cultural depth,” which is intrinsically tense with the “responsible in-depth experience” advocated by ecotourism. In the practice of the Qinghe Yungeng project, managers observed a significant differentiation in behavioral patterns between the “internet-celebrity check-in” tourist group and the “ecological study-tour” tourist group: the former had an average stay of only 1.8 hours, per-capita consumption of RMB 65, and a negative-review rate as high as 28%, while the latter had an average stay of 4.2 hours, per-capita consumption of RMB 180, and a negative-review rate of 6%. These data reveal that it is the quality rather than the quantity of traffic that is key to sustainable ecotourism—policy design should shift from “traffic assessment” to “experience-quality assessment,” incorporating an “experience-quality index” into the performance appraisal system of scenic-area management through real-time NLP monitoring.

4.3 Implementation Effectiveness of Policy Instruments

The Bijiashan Mountain case reveals the “last-mile” fault from institutional design to terminal implementation of policy instruments—mandatory instruments (capacity ceilings) are constrained by insufficient monitoring infrastructure, market-based instruments by the pricing difficulty of ecosystem service values, and voluntary instruments by the deviation between farmers’ individual and collective rationality. The Qinghe Yungeng project provides an improvement reference: in the early six-scenic-area coordinated operation stage, information asymmetry in fund use led to low allocation efficiency; later, the introduction of third-party auditing and blockchain traceability mechanisms achieved closed-loop supervision of ecological-compensation funds (project practice data), strongly suggesting the decisive role of transparency building in policy-instrument implementation effectiveness.

The core bottleneck of market-based instruments lies in the reliable monetization of ecosystem service values, which the Qinghe Yungeng experience above shows can be mitigated through transparency infrastructure. Voluntary instruments, meanwhile, face the classic “tragedy of the commons” dilemma: the benefits of an individual farmer’s environmental behavior are highly dispersed while the costs are entirely self-borne, resulting in naturally insufficient participation motivation [23].

In the exploration of paths to escape the “ticket economy,” the academic community has accumulated relatively rich countermeasures. Zhou Qiuning and Chen Deguang (2023) systematically reviewed four development paths—product diversification, service value-adding, industry-chain extension, and digital empowerment—and pointed out that ticket-price-reduction policies do not necessarily lead to revenue-structure transformation; the key lies in whether the supporting secondary-consumption product supply is sufficient [24]. Wang Hongyan (2018) demonstrated the urgency of transformation from a policy-timetable perspective—by then, over 60% of the nation’s 5A-level scenic areas had implemented ticket-price reductions, but the lag effect of revenue-structure adjustment would take at least 3-5 years to manifest [25]. Lin Yuxiang (2013) earlier proposed the necessity of transitioning from a “ticket economy” to an “industrial economy,” pointing out that the greatest resistance comes from scenic-area management’s risk aversion to short-term revenue fluctuations [26]. Geng Songtao (2012) analyzed the transformation predicament from the perspective of price theory and practice—the institutional bundling between ticket-pricing power and fiscal subsidies leaves scenic areas lacking endogenous motivation for diversified transformation [27].

In the dimension of community participation, the trial-and-error case of Dajiao Hecang provides valuable temporal parameters. Based on the empirical benchmark derived from the tracking data presented below, if Bijiashan Mountain were to raise its community participation rate to a target value of 30%, it would take about 6 years of continuous investment. The staged trajectory—a relatively lower growth rate in Years 1-2, an acceleration period in Years 3-5, and a flattening tendency after Year 6—should be understood as a hypothesized scenario based on project historical records and model-based extrapolation, rather than as an empirically observed multi-year trajectory, because the household panel data cover only 18 months. This temporal-estimation model provides policymakers with an operational staged reference, distinguishing it from static policy recommendations lacking a temporal dimension.

The longitudinal household data of the Qinghe Yungeng project provide direct empirical evidence on this mechanism. Data from 16 tracked households show that the share of tourism-related income in total household income was below 5% before participation and rose to about 18% after participation [28]; participating households achieved an average annual income increase of about RMB 18,000 over the 18-month tracking window, with the fastest growth observed in the early participation stage. Yet the income-increase effect is not linear: the trial-and-error case of Dajiao Hecang shows that raising the community participation rate from 2.1% to 8.7% took 18 months, with an average annual increase of about 4.4 percentage points, revealing that community participation incentives have a markedly gradual and marginally diminishing characteristic. The household questionnaires further reveal that 83.5% of farmers regard the opacity of the benefit-distribution mechanism as the primary reason for low participation enthusiasm (project survey data). This indicates that the clarity of property-rights delineation and the transparency of benefit distribution are more fundamental than mere economic compensation—the effectiveness of community participation incentives depends not only on the “compensation amount” but also on the “credible commitment of distribution rules.”

4.4 Eco-Economic-Cultural System Analysis

Bijiashan Mountain’s revenue structure exhibits a typical “ticket-dependence” characteristic, leading to a break in the positive-feedback loop between the economic system and the ecosystem. The Qinghe Yungeng project provides a

differentiated reference: in the first-year revenue of RMB 800,000, the share of non-ticket revenue had reached 42%, with a specific composition of farming experience (22%), study-tour courses (12%), and agricultural-product derivatives (8%). This revenue structure suggests the feasibility of the diversification transition path: when a scenic area extends its value chain from a single “ticket” node to an “experience-education-product” composite chain, tourist stay time is prolonged, per-capita consumption significantly increases, and path dependence on ticket revenue is effectively reduced.

The carbon-reduction dimension provides a new quantification link for the eco-economic coupling. The carbon reduction of the Qinghe Yungeng project is independently estimated based on GB/T 32150; carbon accounting parameters are provided in the supplementary materials. Carbon-sink increments can be converted into tradable carbon credits, providing a market-based pricing basis for ecological compensation. If the carbon-reduction amount is incorporated into Bijiaoshan Mountain’s positive-externality accounting system, the ecological-compensation standard could, on the basis of these preliminary estimates, be expected to gradually upgrade from the current “cost-compensation” model to a “value-compensation” model, effectively narrowing the scissors gap between conservation costs and development benefits.

Community-level collaborative governance is the micro-foundation of the eco-economic-cultural system coupling. Research on community-participation problems in China’s ecotourism shows that “lack of participation channels” and “unfair benefit distribution” are the two core obstacles constraining community participation. The Dajiao Hecang trial-and-error of the Qinghe Yungeng project provides a specific solution path—through the “cooperative + minimum-price guarantee procurement” model, farmers are transformed from passive “resource providers” to active “operating partners,” an identity transformation whose effect on participation-willingness enhancement even exceeds the economic incentive itself. From the theoretical perspective of collaborative governance, the governance performance of rural-tourism relational networks is influenced by the interaction of network structural characteristics (connection density, centrality) and governance mechanisms (trust, reciprocity, reputation) [29,30]. In the practice of Qinghe Yungeng, the establishment of the cooperative substantially enhanced the connection density of the community network, while blockchain traceability provided technical assurance for the trust mechanism; together they constitute the institutional infrastructure of collaborative governance.

Further eco-economic coupling analysis reveals a noteworthy non-linear pattern: after the non-ticket revenue share breaks through the 30% level, the positive association between the non-ticket revenue share and the community participation rate appears to strengthen at an accelerating pace. In the stage where Qinghe Yungeng’s non-ticket revenue share rose from 12% to 30%, the participation rate increased only from 2.1% to 4.3% (1.5 percentage points annually); but after the 30% level was crossed, the participation rate grew about 4.4 percentage points annually (from 4.3% to 8.7%). Given the limited number of observation points, the 30% value should be interpreted as an observed empirical turning point in the project data rather than as a statistically established threshold. The policy implication is that the input-output ratio in the early stage of diversification transformation may not be attractive, but once the critical value is crossed, the transformation benefits enter an accelerated release period; policy design should therefore set up a transitional subsidy mechanism to help scenic areas survive the “low-return plateau period.”

5. Discussion

5.1 Interpretation of Major Findings and Dialogue with Previous Research

When placed in a broader academic context, this study contributes to several strands of the literature on ecotourism governance.

First, in the application of externality theory, this paper, by introducing the carbon-reduction ecosystem-service-value indicator, concretizes and operationalizes the extension of Pigou’s tax-subsidy path and the community-participation incentive mechanism. Unlike traditional externality research that focuses on the “pricing” problem, this paper focuses on the “distribution” problem—how the monetized benefits of positive externalities can be fairly, transparently, and sustainably distributed at the community level. The finding reported in Section 4.3 that benefit-distribution opacity is regarded by most farmers as the primary obstacle echoes Ostrom’s core argument on the priority of “procedural justice” over “distribution outcomes” in common-pool-resource governance.

From the perspective of tourist experience, the essence of the “ticket-experience” gap is the cognitive dissonance between “price expectation” and “value perception.” When tourists enter a scenic area at a low ticket price, if the actual experience fails to meet expectations formed through short-video marketing, they experience a psychological sense of loss at being “deceived” and vent their emotions through negative reviews. The Qinghe Yungeng practice shows that incorporating “experience-expectation management” into the operation system—such as clearly informing tourists at the ticket-purchasing stage that “this scenic area focuses on farming experience and ecological study tours, not a traditional sightseeing-type scenic area”—can effectively reduce cognitive dissonance, and the negative-review rate thus dropped by about 11 percentage points. This provides a new idea beyond price adjustment for governing the “ticket-experience” contradiction.

Second, in the field of policy-instrument research, the “complementary relationship” revealed by this paper’s dual-case comparison—mandatory, market-based, and voluntary instruments are not substitutes but exhibit differentiated effectiveness under different spatiotemporal conditions—challenges the implicit “optimal-instrument-selection” assumption in existing literature. Specifically, this paper finds that policy-instrument effectiveness is highly dependent on the completeness of “institutional infrastructure”: market-based instruments require transparency infrastructure (third-party auditing, blockchain traceability), voluntary instruments require social-capital infrastructure (community trust, cooperative organizations), and mandatory instruments require technical infrastructure (IoT monitoring). The absence of institutional infrastructure—rather than the wrong choice of instrument type—is the more fundamental cause of policy failure.

Third, in the field of community-participation research, the temporal-estimation model constructed in this paper (see Section 4.3) provides a longitudinal quantitative reference that is extremely scarce in existing literature. Although research on the influence mechanism of rural-tourism relational-network collaborative governance has identified key variables such as trust, reciprocity, and reputation, it lacks empirical characterization of how these variables evolve over time. The longitudinal tracking data of 16 households reported in Section 4.3 preliminarily fill this gap, suggesting staged characteristics of community participation—a “start-up period” (Years 1-2), an “acceleration period” (Years 3-5), and a “plateau period” (after Year 6)—interpreted, however, as a hypothesized scenario based on project historical records and model-based extrapolation, given that the household panel data cover only 18 months.

Finally, at the methodological level, this paper provides an exemplar of a “dual-case embedded mixed-methods” design for ecotourism research. Traditional ecotourism research either emphasizes quantification (macro statistics, spatial analysis) or qualitative methods (in-depth interviews, ethnography), and the methodological divide makes it difficult to form a complete explanatory chain. This paper achieves a multi-dimensional understanding of the community-participation incentive problem through triangulation among NLP mining, questionnaire statistics, and in-depth interviews—for example, the questionnaire finding that benefit-distribution opacity is the primary obstacle obtains the qualitative explanation that “farmers’ lack of trust in the cooperative’s financial-disclosure system stems from several historical distribution disputes.” Regarding convergence and divergence, the NLP review analysis, questionnaire statistics, interviews, policy-text coding, and ecological indicators converged on the central finding that institutional transparency—especially benefit-distribution opacity and trust in financial disclosure—is a key constraint on community participation; they diverged mainly in emphasis, with questionnaire and interview data highlighting distributional and trust mechanisms and NLP and ecological-spatial data highlighting visitor-experience and ecological-pressure channels, and are interpreted jointly here as complementary rather than contradictory.

As a cross-case validation exercise, this study places the modeling framework in four ecotype settings for comparative interpretation: the Costa Rican tropical-rainforest type, the Zhangjiajie sandstone-peak-forest type (87.5% per-capita-consumption increase), the Bijiashan karst type (traffic-quality imbalance), and the Qinghe Yungeng Greater-Bay-Area hilly type. It should be clarified that primary data were collected only for the two empirical cases; the Costa Rican and Zhangjiajie settings serve as secondary benchmark cases drawn from published literature and are used for qualitative adaptability comparison rather than as first-hand survey cases. As the fourth setting, Qinghe Yungeng supports the cross-ecotype adaptability of the “ecological-indicator-economic-benefit” elasticity coefficient: the carbon-sink-value transformation efficiency of hilly-type scenic areas is preliminarily estimated at about 0.7 times that of karst-type, based on the project’s carbon-accounting data. Given the limited sample and the preliminary nature of the carbon accounting, this coefficient should be regarded as a preliminary estimate rather than a fully validated parameter, providing a new empirical data point for the calibration of the ecological-vulnerability coefficient in the model.

The multi-setting adaptability comparison also reveals a pattern with policy-implication significance: the higher the ecological vulnerability of the scenic-area type (e.g., karst-type), the stronger the positive-feedback effect between “community participation” and “ecological conservation,” because in highly vulnerable ecosystems the dependence between community livelihoods and ecological quality is closer, farmers’ perception of ecological degradation is more acute, and the marginal benefit of conservation behavior is higher. This finding guides the differentiated design of policy instruments—in highly vulnerable ecotypes, community-participation incentives should be given high priority; in relatively stable ecotypes, market mechanisms can be appropriately used to share conservation costs.

5.2 Theoretical Contributions

The research contributions of this paper can be summarized into four dimensions. First, theoretical contribution: incorporating the carbon-reduction ecosystem-service value into the positive-externality quantification module extends the indicator-dimension boundary of the traditional externality framework. Second, methodological contribution: the improved NLP algorithm, whose classification accuracy is reported in Section 3.3, provides a high-precision analytical tool for tourism-review sentiment analysis. Third, empirical contribution: based on the longitudinal tracking data reported in Section 4.3, this paper constructs a temporal-estimation model of community participation rate, providing an operational quantitative reference system for policy planning. Fourth, practical contribution: the coordinated operation of six scenic areas of Qinghe Yungeng demonstrates the operability of the full-chain analytical path of “quantitative analysis → policy instruments → implementation effects.” Overall, these contributions are systematic (elevating the “conservation-development” synergy problem to a framework covering theory, methods, and evidence), operable (all

core findings carry quantitative parameters), and reproducible (the dual-case design and mixed-methods path are fully documented for testing in other ecotype scenic areas).

5.3 Practical and Policy Implications

Based on the dual-case empirical findings, this paper proposes a three-tier progressive policy-instrument optimization scheme. The first tier is a negative-list system: explicitly prohibiting high-density development activities in ecologically sensitive areas, with a credit-point deduction mechanism for violations; the design needs to refer to the carrying-capacity thresholds of each ecotype, since the ecotourism carrying capacity of different provinces varies significantly and a one-size-fits-all negative list cannot fit regional heterogeneity. The second tier is the transparency upgrade of market-based instruments: drawing on the third-party auditing and blockchain-traceability governance practice of Qinghe Yungeng, establish a full-process traceable mechanism for ecological-compensation funds, ensuring a complete closed loop from “allocation” to “implementation”—the decentralized-ledger characteristic of blockchain is naturally suited to the multi-party supervision needs of ecological-compensation funds and can effectively resolve the moral hazard induced by information asymmetry. The third tier is community-participation incentives: implement the “cooperative + minimum-price guarantee procurement” model—the longitudinal tracking data reported in Section 4.3 show that income growth was fastest in the early participation stage with a subsequent slowing trend, consistent with the law of marginal diminishing returns; it is recommended that policy design concentrate incentive intensity in the early participation stage. In a broader context, ecotourism development and the construction of beautiful countryside interact profoundly—the former provides infrastructure and human capital for the latter, while the latter provides industrial support and income-increase channels for the former.

Escaping the “ticket economy” should be a medium- and long-term goal of policy-instrument optimization. Successful transformation cases all follow a three-stage path of “product first—institutional support—cultural sedimentation,” rather than simple administrative price reduction. Policy design should shorten the transformation painful period, hedge short-term revenue fluctuations through transitional fiscal subsidies, and gain a time window for product iteration and market cultivation.

Unlike existing policy-recommendation literature, this paper emphasizes that policy-instrument optimization should be elevated from the “technical-solution” level to the “institutional-design” level. Most current policy recommendations remain at the technical level of “should increase X, should reduce Y,” neglecting the deep institutional roots of policy-instrument failure—such as the multi-layer information asymmetry in the “allocation—use—audit” chain of ecological-compensation funds, the fiscal-system constraints behind scenic-area management’s “ticket dependence,” and the lack of legal-person status behind communities’ “nominal existence.” This paper’s three-tier progressive scheme therefore takes the construction of “institutional infrastructure” (transparency mechanisms, corporatization reform, performance-appraisal reform) as the prerequisite for policy-instrument optimization, rather than simplifying policy recommendations into a rearrangement of instrument types.

It should be pointed out that the effect of policy-instrument optimization is highly dependent on the execution capacity and administrative inertia of local governments. The dual-case comparison reveals a noteworthy phenomenon: the Qinghe Yungeng project, due to its small scale (RMB 800,000 first-year revenue) and flat organizational hierarchy, adopted new instruments significantly faster than Bijiashan Mountain—the latter, due to institutional frictions such as multi-department coordination and existing-interest-pattern adjustment, has a policy-instrument iteration cycle about three times that of the former. This suggests that the promotion strategy should follow a gradual path of “small-scale pilot → medium-scale validation → large-scale rollout,” and only after fully grinding the institutional friction points in the pilot stage can it enter large-scale promotion.

A trinity digital foundation of “IoT monitoring—NLP sentiment analysis—AR guidance” should also be built. The IoT layer is responsible for real-time monitoring and threshold early-warning of visitor capacity and ecological indicators; the improved NLP algorithm (see Section 3.3) undertakes comment-sentiment monitoring, achieving early warning and dynamic response to tourist-experience problems; the AR-guidance layer enhances tourists’ cultural-perception depth through immersive experiences, directly responding to the structural problem of “experience homogenization.”

Beyond the empirical scope of this study, digital-technology empowerment of ecotourism suggests three frontier directions for future research, rather than direct policy implications of the present evidence: first, digital-twin technology in national-park ecological monitoring, building a virtual mirror of protected areas to simulate environmental-change preview and policy-effect deduction; second, AI large models in tourist-behavior prediction, building tourist profiles from multi-source data (reviews, consumption, trajectories) to support personalized product recommendation and dynamic pricing; and third, Web3.0 and token economics in community-participation incentives, quantifying farmers’ environmental behaviors into tradable “eco-tokens” to build a green incentive mechanism within the community.

The core obstacle to community participation lies not in the insufficiency of the total amount of economic incentives, but in the opacity of the benefit-distribution mechanism and the institutional ambiguity of property-rights delineation. Policy design should be driven by the “twin wheels” of “transparency” and “participatory governance”: the former relies on blockchain traceability to make benefit distribution fully verifiable; the latter realizes the institutionalized

sharing of governance power through the substantial participation of community representatives in the decision-making of the scenic-area management committee.

At the level of institutional design, the effectiveness of the community-participation mechanism depends on three key parameters: the participation threshold (the minimum resource input required for participation), the benefit elasticity (the marginal relationship between participation degree and benefits), and the exit cost (the penalty intensity for exiting participation). The data of the Dajiao Hecang trial-and-error case reported in Section 4.3 show that the current design has achieved initial results in lowering the participation threshold, but there is still much room for improving benefit elasticity—farmers’ perception of opacity in the benefit-distribution mechanism suggests that even if the absolute value of income increase is considerable, the uncertainty of rules still suppresses the further release of participation willingness.

In the carbon-reduction dimension, the carbon-reduction data independently estimated by the Qinghe Yungeng project based on GB/T 32150 provide an accounting basis for incorporating carbon credits into farmers’ benefit distribution. Although the absolute amount of the estimated carbon-credit revenue (Section 4.4) is limited, the “marginal increment” characteristic of carbon-credit revenue gives it a unique incentive effect—compared with the “stock guarantee” of minimum-price guarantee procurement, carbon credits provide farmers with a “direct price signal of conservation behavior,” forming a positive-feedback loop of “conservation → carbon sink → revenue → more active conservation.” The core advantage lies in achieving incentive compatibility between ecological-conservation incentives and community-income-increase goals: farmers do not need to make an either-or choice between “conservation” and “income increase”; the two become dual returns of the same behavior.

6. Limitations and Future Research

6.1 Research Limitations

This paper has the following limitations: the tracking sample of 16 households is relatively small, and coverage needs expansion to enhance the robustness of statistical inference; the carbon-reduction accounting is a preliminary estimate based on GB/T 32150 and has not yet been certified by a third-party verification agency; the temporal model of community participation rate is constructed from a single trial-and-error case, and cross-context extrapolation should be treated with caution; and although the dual-case design enhances internal validity, external validity is limited by the number of cases—generalizability to other ecotypes (plateau-lake-type, island-type, grassland-type, etc.) remains to be verified. The data-collection time span also constrains the analysis: review data cover 2020-2025, but interview and questionnaire data are concentrated in 2024, and the time-series length is insufficient for more refined econometric analyses such as panel regression. In addition, the NLP classification accuracy and the entropy-based EPI weights are subject to measurement uncertainty, although the core findings are robust to the sensitivity checks (available from the corresponding author upon reasonable request). Finally, the three-tier policy-instrument scheme, though derived from dual-case evidence, has not been validated by field policy-intervention experiments; future research should cooperate with local governments to conduct quasi-experimental designs and perform causal inference on implementation effects.

6.2 Future Research

Future research can advance in three directions. First, expand the farmer-tracking sample to over 100 households and conduct panel-data analysis to control individual heterogeneity, and introduce third-party carbon-verification agencies to independently certify carbon-reduction data, enhancing the reliability of ecosystem-service-value accounting. Second, test the cross-context generalizability of the framework in more ecotype scenic areas (plateau-lake-type, island-type, etc.), and incorporate new-media data (short videos, live streaming) into the NLP analysis framework, following the deepening impact of emerging digital media on tourist behavior. Third, at the policy level, pay attention to the synergy-effect evaluation of ecotourism policy instruments: although this paper has revealed the complementary relationship among the three instrument types, it has not yet quantitatively modeled the optimal combination ratio and implementation sequence; a System Dynamics-based policy-simulation model, simulating the eco-economic-social synergy effects of different instrument combinations over a 10-20-year time span, could provide more precise combination schemes and timetables. Furthermore, with the deepening of the “dual-carbon” goal, the maturation of the carbon-credit trading mechanism will provide a new channel for monetizing positive externalities in ecotourism—through the closed loop of “conservation → carbon sink → carbon credit → market transaction → community feedback,” contributing, subject to market maturation, to the financial sustainability of ecological conservation, which is the most dynamic extension of the three-dimensional framework.

7. Conclusion

Addressing the synergy between conservation and development remains the central challenge of sustainable ecotourism. This study shows that transparent benefit distribution, complementary policy instruments, and experience-quality-oriented governance jointly determine whether conservation and community development reinforce each other, and its

extended externality framework, temporal participation model, and full-chain analytical path offer transferable tools for both research and policy practice.

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Ethics Statement

Ethical review and approval were not required for this study. The empirical analysis relied on publicly available online consumer reviews and on anonymized household surveys and semi-structured interviews conducted with informed consent. No sensitive personal information was collected, and all data were anonymized prior to analysis.

Informed Consent

Informed consent was obtained from all survey and interview participants prior to data collection, and all data were anonymized prior to analysis.

Data Availability Statement

Data supporting this study are available upon reasonable request from the corresponding author.

Author Contributions

Jundi Chen served as the primary and leading contributor, undertaking the overwhelming majority of the overall content, including conceptualization, methodology, data collection, formal analysis, data optimization, original draft writing, translation, and final manuscript polishing. Junhua Chen assisted Jundi Chen with Chinese version polishing and translation, as well as visualization and manuscript review. Zijian Li assisted with the investigation and formal analysis. Yicong Bin, as the corresponding author, provided academic guidance and supervision, project administration (YB), and manuscript review and editing. All authors have read and agreed to the published version of the manuscript.

Conflicts of Interest

The authors declare no conflict of interest.

Generative AI Statement

During the preparation of this work, the authors did not use any generative AI tools or AI-assisted technologies in the writing or editing of the manuscript. The authors take full responsibility for the content of this publication.

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