Research Square

Preprints are preliminary reports that have not undergone peer review.
They should not be considered conclusive, used to inform clinical practice,
or referenced by the media as validated information.

Electronic Word of Mouth, Tourist Mobility Networks, and Attraction Node Position: Evidence from 2019 Ctrip Reviews and Online Travel Blog Networks in China

Zhen Guo

guozhen@kangwon.ac.kr

Kangwon National University

Research Article

Keywords: electronic word of mouth, tourist mobility network, online reviews, network centrality, attraction type, seasonal heterogeneity

Posted Date: May 20th, 2026

DOI: https://doi.org/10.21203/rs.3.rs-9523377/v1

License: This work is licensed under a Creative Commons Attribution 4.0 International License. Read Full License

Additional Declarations: No competing interests reported.

Abstract

Online reviews are central to tourism decision making, yet research has rarely examined whether review text is associated with the structural position of attractions in tourist mobility networks. This study matches 2019 Ctrip attraction reviews with a seasonal scenic-spot mobility network in China derived from online travel blogs. After cleaning and attraction-season aggregation, the baseline sample contains 786 attraction-by-season observations. The analysis estimates how pure-text sentiment, review volume, attribute diversity, and negative service evaluation relate to three centrality indicators: in-strength, PageRank, and betweenness.

Pure-text sentiment is negatively associated with centrality, whereas review volume is positively associated with centrality across the baseline models. Negative service evaluation is generally negatively related to node position, although its stability is weaker for betweenness. Interaction models show that review volume strengthens the negative marginal association between sentiment and centrality. Seasonal analyses indicate that the negative sentiment effect is concentrated in spring, while the positive role of review volume is strongest in summer and autumn. Type heterogeneity shows the clearest joint role of review volume, review length, and attribute diversity among ancient-architecture attractions.

The paper extends eWOM research from conventional performance outcomes to attraction position in mobility networks. It shows that evaluative valence and engagement volume carry distinct and partly opposing implications for network position, and that these relationships vary by season and attraction type.

1. Introduction

Tourism products are characterized by high experiential intensity, strong information asymmetry, and limited pre-consumption verifiability. Travelers therefore rely heavily on publicly available experience-based information when evaluating destinations and attractions before a trip. Within this informational environment, electronic word of mouth has long been recognized as a central mechanism shaping tourist judgment, comparison, and decision-making. Early work established that eWOM in tourism and hospitality is not merely an online extension of traditional word of mouth, but a structural transformation in how travelers search for, interpret, and circulate market information (Litvin et al. 2008). Subsequent reviews further showed that the eWOM literature had expanded from platform characteristics and review attributes to consumer behavior, managerial response, and methodological development more broadly (Chen and Law 2016).

Despite this rich literature, the dominant outcomes in tourism eWOM research remain relatively conventional. Most studies examine how reviews affect hotel sales, review helpfulness, booking-related outcomes, destination choice, or downstream performance. Prior research has shown that online reviews can influence room sales, and meta-analytic evidence indicates that review volume and valence are both associated with market outcomes, although not always with equal magnitude or stability (Ye et al. 2009; Yang et al. 2018). More recent work has also shown that review expression is shaped by expectation confirmation, affective experience, review diagnosticity, and information-processing conditions rather than by a single linear satisfaction mechanism (Nam et al. 2020; Bigne et al. 2024; Islam et al. 2025; Qiu et al. 2026). These studies collectively suggest that review text cannot be reduced to a straightforward popularity signal. Nevertheless, the main empirical focus of the literature still lies in the review-performance or review-choice framework.

What remains underexplored is whether online review text is systematically related to the structural position of attractions in tourist mobility systems. That question matters because attractions are not consumed in isolation. They are embedded in multi-stop itineraries, transition paths, and destination networks that shape how tourists move, connect places, and allocate attention during a trip. Research on attraction and destination networks has shown that network position captures more than simple popularity. Centrality reflects route importance, inter-attraction connectivity, and the structural role a node plays within the broader tourism space (Gao et al. 2022; Xu et al. 2021; Xu et al. 2025). Other work has further demonstrated that tourist mobility networks are dynamic across scales, times, and movement contexts, and that destinations may be better understood through actual travel patterns than through administrative boundaries alone (Jin et al. 2018; Park et al. 2022; Paulino et al. 2021; Jung and Nam 2026).

This network perspective creates a theoretical tension with conventional eWOM expectations. A structurally central attraction is not merely an attraction with better reputation. It is also more exposed to tourist overlap, denser flows, stronger route dependence, and more intense public scrutiny. Such attractions may accumulate higher visibility and more online discussion, but they may also accumulate crowding, waiting, service friction, and harsher evaluation standards. Tourism crowding research consistently shows that dense visitor settings can weaken emotional responses, satisfaction, and behavioral outcomes, while studies on negative tourist-to-tourist interaction indicate that interactional friction can directly impair recommendation-related responses (Luo et al. 2025; Koç et al. 2022; Yin et al. 2024; Xu et al. 2024; Zhang et al. 2025). From this perspective, there is no strong reason to assume that the most central attractions in a tourist mobility network should also receive the most favorable review text.

At the same time, the methodological conditions for examining this question are now available. Tourist mobility datasets constructed from online travel diaries and blogs allow researchers to model attraction networks at scale, while platform review data make it possible to derive attraction-level textual indicators such as sentiment, review volume, and service-related negativity. Yet the two streams of research are still rarely combined. Text-based tourism studies typically treat reviews as proxies for satisfaction or market response, whereas mobility-network studies tend to focus on structural patterns, flow formation, and community structure without incorporating review text as an explanatory layer. As a result, the field still lacks a clear answer to several related questions: Do sentiment, review volume, negative service evaluation, and attribute diversity correspond systematically to attraction centrality? Does review volume alter the meaning of sentiment? And are these relationships stable across seasons and attraction types?

This study addresses these questions by matching attraction-level online review data with a seasonal tourist mobility network of scenic spots in China. Specifically, 2019 Ctrip reviews are aggregated to the attraction-by-season level and linked to a seasonal network derived from online travel blogs. Three classes of network centrality indicators are used as dependent variables. The empirical design then tests the roles of pure-text sentiment, review volume,

attribute diversity, and negative service evaluation, while also examining a review-volume interaction effect, seasonal heterogeneity, and attraction-type heterogeneity.

The study contributes to the literature in three ways. First, it extends tourism eWOM research from traditional performance-oriented outcomes to the structural position of attractions in a tourist mobility network. Second, it identifies a counterintuitive empirical pattern in which text sentiment is negatively associated with centrality while review volume is positively associated with centrality, thereby demonstrating that evaluative valence and engagement volume carry distinct and partially opposing implications for network position. Third, it shows that these relationships vary across seasonal and attraction-type contexts, which turns the pooled model into a boundary-condition test rather than a universal average claim. Taken together, the paper advances a more network-sensitive understanding of how online textual evaluations and tourism space interact.

2. Theoretical Background and Hypothesis Development

2.1 eWOM as a conditional expression of tourism experience

Electronic word of mouth has become a core informational mechanism in tourism because destinations and attractions are high-experience, high-uncertainty products. Travelers often cannot verify experiential quality before arrival, so they rely on publicly available reviews to infer what a place may offer and whether the experience is worth the effort, time, and cost. However, for the purposes of this study, reviews should not be treated only as inputs into destination choice. They should also be understood as outputs of tourists' own evaluative processes. This distinction is important because the present study explains attraction position in a tourist mobility network rather than purchase intention, revisit intention, or hotel performance.

Existing review research suggests that online review expression is not a simple translation of satisfaction into praise. Nam et al. (2020) show that positive and negative eWOM are shaped by different expectation-confirmation mechanisms, which means that review generation is already conditioned by the way tourists compare actual performance with prior expectations. This point is highly relevant in attraction settings, where highly visible attractions tend to attract not only more visitors but also more heterogeneous expectations. A tourist who visits a famous node in a travel network may apply stricter standards than a tourist who visits a peripheral node, even when both experiences are objectively acceptable. Under these conditions, review sentiment becomes a conditional expression of evaluation rather than a direct proxy for attraction quality.

Emotion-based studies reinforce this argument. Stylos et al. (2024) demonstrate, through Affective Events Theory, that affective states during sightseeing experiences spill over into eWOM-related outcomes. This finding indicates that online commentary is partly an affective response to the experiential situations tourists encounter. Yet affect does not operate in a vacuum. Bigne et al. (2024) find that review persuasiveness, informativeness, and diagnosticity vary with review type and destination familiarity, while Islam et al. (2025) show that review usefulness, quality, credibility, and diagnosticity shape review adoption in destination choice contexts. These findings imply that review text is both produced and interpreted under contextual conditions. In other words, what tourists write and how other tourists process that writing depend on expectations, familiarity, content structure, and the perceived value of the information.

This literature has two implications for the present study. First, text sentiment should not be interpreted as a pure quality signal. Second, a positive experiential variable does not necessarily generate a positive downstream review outcome. Qiu et al. (2026) show that tourist satisfaction can even be negatively related to review helpfulness because affective and cognitive expressions mediate how experience is translated into public review value. This counterintuitive result matters because it demonstrates that review-related outcomes can move in directions that differ from naive market expectations. In attraction networks, this means that more central nodes may not receive more favorable text simply because they are more visited or more important. Publicly expressed sentiment may instead reflect stronger evaluative pressure, denser exposure, and more intense comparison processes at highly visible attractions.

Taken together, the eWOM literature suggests that online reviews in tourism are conditional behavioral expressions shaped by expectation, affect, and information-processing logic. Once the outcome of interest moves from booking or advocacy to structural network position, there is no strong theoretical reason to assume that more central attractions should systematically receive more positive text. On the contrary, the literature leaves open the possibility that centrality and text sentiment may diverge.

Accordingly, this study advances the following hypothesis:

H1. In a tourist mobility network, attraction-level text sentiment is negatively associated with network centrality.

2.2 Attraction centrality as a structural property of tourism space

The second theoretical step is to clarify what attraction centrality represents. In many tourism studies, attraction importance is proxied by counts, rankings, ratings, or market share. Such indicators are useful, but they do not capture how attractions are positioned within the wider movement system through which tourists organize multi-stop trips. A tourism network perspective treats attractions not as isolated destinations but as interdependent nodes embedded in routes, transitions, and relational structures. Under this view, centrality does not merely indicate popularity. It reflects the structural role an attraction plays in connecting, receiving, and organizing tourist movement.

Recent mobility-network studies provide strong support for this perspective. Gao et al. (2022) show that attraction networks across China exhibit multi-scale structural patterns, including core-periphery arrangements and differentiated attraction functions. Xu et al. (2021) similarly demonstrate that mobility traces can be used to characterize destination networks and reveal collective movement dynamics and cross-group differences. These studies are important

because they shift attention from isolated destination performance to the architecture of movement systems. A highly central node is not simply a place that many people like. It is a place that occupies an important structural position in routing, transition, and inter-attraction connectivity.

This structural interpretation is strengthened by more specific work on movement patterns. Liu et al. (2023) show that tourist flow structures differ across transportation layers, suggesting that attraction centrality is partly shaped by infrastructure-linked movement opportunities. Ding et al. (2024) further show that attractions occupy different connection patterns within local movement systems, which means that attractions can play heterogeneous relational roles even within the same destination. Zheng et al. (2025) argue that tourism space should not be treated as fixed and administratively bounded, but as emergent, overlapping, and networked. This point directly supports the present study, which does not interpret attractions through city-level administrative categories alone.

A related contribution comes from research that rethinks the very definition of destinations. Paulino et al. (2021) argue that destinations should be identified through tourists' travel patterns rather than through fixed administrative boundaries. That claim is highly relevant here because the current paper studies scenic spots as movement nodes whose meaning is partly constituted by how tourists connect them in actual trips. Wang et al. (2021) provide a Chinese attraction-level precedent by showing that degree, closeness, and betweenness can differentiate tourism functions in an attraction cooperation network. Although that study is not the main conceptual anchor, it supports the empirical plausibility of interpreting centrality measures as functionally meaningful in attraction systems.

The network literature also makes clear that tourist movement structures are dynamic rather than static. Park et al. (2022) show that destination networks vary across seasons and times of day, while Jin et al. (2018) demonstrate temporal heterogeneity in tourist mobility using user-generated content. Jung and Nam (2026) further show that attraction-level movement patterns in Jeju Island shift across seasons and under pandemic conditions, with some attraction types gaining or losing centrality as tourist preferences adapt to safety and crowding concerns. Xu et al. (2025) synthesize these perspectives through a multi-scale analytical framework, emphasizing that destination networks must be understood across macro, meso, and micro levels rather than through a single summary statistic.

Taken together, this literature supports a crucial theoretical distinction: centrality is a structural property of tourism space, not a direct measure of satisfaction or textual favorability. A central attraction is one that occupies a meaningful relational position in how tourists move, connect places, and organize itineraries. Once this distinction is made clear, it becomes theoretically legitimate to ask whether online review text and structural network position move together, diverge, or interact in more complex ways.

The same network logic also provides the theoretical basis for review volume. Attractions that occupy central positions in tourist itineraries are more likely to be repeatedly visited, noticed, discussed, and reviewed. Review volume therefore reflects the public visibility and itinerary exposure attached to a node rather than only the average favorability of the experience. This mechanism is conceptually distinct from text sentiment: a central attraction can be widely discussed even when the tone of that discussion is not uniformly positive.

H2. Review volume is positively associated with attraction centrality in the tourist mobility network.

2.3 Why central attractions may generate less positive text

If centrality is not equivalent to popularity or quality, the next question is why structurally important attractions may produce less positive textual evaluations. The answer lies in crowding, friction, and interactional pressure. Central attractions typically receive more visitors, more route overlap, and more public exposure. These conditions can improve visibility, but they also increase the likelihood of waiting, congestion, service pressure, and unpleasant visitor encounters. In other words, centrality may intensify both desirability and experiential stress.

The crowding literature provides the clearest theoretical foundation for this claim. Luo et al. (2025) synthesize 45 empirical studies and show that perceived crowding has negative effects on satisfaction, emotional responses, experience quality, and behavioral outcomes. This meta-analytic evidence is especially useful because it demonstrates that crowding is not a marginal issue; it is a robust determinant of how tourists feel and how they evaluate destinations. If highly central attractions systematically expose visitors to denser social and spatial conditions, then they also expose them to stronger crowding-related dissatisfaction.

More specific mechanism studies deepen this argument. Koç et al. (2022) show that negative tourist-to-tourist interactions damage emotions and weaken recommendation intentions. Yin et al. (2024) further explain that crowding perception affects adaptive behavior through tourist fatigue and negative emotion, while peer emotional contagion shapes how those effects unfold. Xu et al. (2024) likewise show that crowding influences emotional reactions, experience quality, and satisfaction through a Stimulus-Organism-Response pathway. Zhang et al. (2025) provide attraction-level evidence that scenic-area congestion affects tourist satisfaction through spatial management and environmental conditions. Together, these studies indicate that dense visitor environments increase the probability of fatigue, emotional strain, dissatisfaction, and negative evaluation.

This mechanism is especially relevant when online reviews are used as the observable outcome of evaluation. A tourist who visits a core attraction may be more impressed by its importance, but also more frustrated by queues, lack of space, low control, crowding, or service inefficiency. Because online reviews are public expressions of interpreted experience rather than raw observations, the text may become more critical precisely where structural importance is highest. Qiu et al. (2026) indirectly support this possibility by showing that positive experiential states do not always translate into favorable downstream review outcomes. The tourism review process can invert expected relationships when exposure, cognition, and information value intervene.

The implication for the present study is straightforward. Attraction centrality may increase the likelihood of negative text not because central attractions are unimportant, but because they accumulate the experiential frictions associated with high exposure. This mechanism is consistent with the empirical

expectation that text sentiment and centrality may be negatively related once reviews are understood as public evaluations shaped by crowding and interactional stress.

Accordingly, the following hypothesis is proposed:

H3. The share of negative service evaluations is negatively associated with attraction centrality in the tourist mobility network.

2.4 Review volume as a conditioning mechanism and attribute diversity as an exploratory extension

Review volume is often treated as a control variable, but in this study it should be understood as a conditional mechanism. On tourism platforms, review volume reflects more than information supply. It also captures public visibility, participation intensity, and the scale of collective evaluation. A low-volume attraction may receive only scattered comments from a narrow visitor group, whereas a high-volume attraction is subject to repeated and heterogeneous public assessment. Under such conditions, the meaning of text sentiment changes.

This logic is consistent with research on review usefulness, diagnosticity, and information adoption. Islam et al. (2025) show that review quality, diagnosticity, and credibility shape adoption of online travel reviews in destination-choice settings. Verma et al. (2023) conceptualize eWOM usefulness as a multidimensional construct rather than a one-dimensional signal. Bigne et al. (2024) further show that review interpretation depends on destination familiarity and review format. These studies all suggest that the effect of textual content depends on the informational context in which it is generated and processed.

Qiu et al. (2026) extend this logic by showing that satisfaction can be negatively related to perceived review helpfulness, precisely because review value is filtered through affective and cognitive expression. Stylos et al. (2024) also show that eWOM outcomes are conditioned by experiential states rather than mechanically produced. The common implication is that online expression is context-sensitive. Its meaning changes with the evaluative environment.

Applied to attraction networks, this means that review volume may amplify the negative association between text sentiment and centrality. At low review volumes, textual sentiment may largely reflect idiosyncratic satisfaction from a small number of reviewers. At high review volumes, however, the text is more likely to capture collective evaluative pressure at highly exposed nodes. In these contexts, even mildly positive text may carry a weaker quality signal than expected because it is generated under more demanding comparison standards, more social congestion, and greater service friction.

The final hypothesis therefore concerns moderation rather than a simple additive effect:

H4. Review volume strengthens the negative association between text sentiment and attraction centrality, such that the marginal effect of text sentiment becomes more negative as review volume increases.

The final textual dimension in this study is attribute diversity. Unlike sentiment, review volume, or negative service content, attribute diversity does not yet have a sufficiently stable theoretical direction in the attraction-network literature. A review set that covers many attributes may indicate a rich and multifunctional experience environment. However, it may also indicate fragmented evaluative focus, heterogeneous visitor expectations, or the absence of a dominant experiential narrative. For this reason, attribute diversity is included as an exploratory explanatory variable rather than as the basis for a directional hypothesis.

This decision is methodologically preferable to forcing a prediction that the current literature cannot support convincingly. The empirical role of attribute diversity is therefore assessed in the results section and in heterogeneity analysis rather than built into the formal hypothesis structure.

[Insert Fig. 1 about here]

3. Research Design

3.1 Data Sources and Sample Construction

The review data come from a Ctrip attraction-review corpus compiled for this project. The raw review pool was first deduplicated, cleaned, and filtered by date. Only reviews strictly belonging to the 2019 calendar year were retained. This produced 102,026 valid reviews covering 417 attractions. The review data were then aggregated to the attraction-by-season level, yielding 1,631 attraction-season units.

The network data come from the national tourist mobility network dataset released by Zheng et al. (2026) and archived in the figshare repository as a reusable public dataset (Zheng et al. 2025). The dataset was constructed from sequential attraction visits extracted from Qunar travel blogs and provides directed weighted tourist mobility networks across China, including season-specific subnetworks. Following the data descriptor and the repository record, the current study uses the seasonal attraction network and matches it to the seasonally aggregated review sample. After attraction matching, 1,500 valid attraction-by-season observations remained, covering 381 attractions.

To reduce noise associated with very low-volume review units, the baseline regressions retain only observations with ReviewVol_is > = 30. The resulting baseline sample contains 786 attraction-by-season observations across 273 attractions. A stricter threshold of ReviewVol_is > = 50 is used in robustness checks.

3.2 Variable Definitions

The dependent variables are three measures of attraction centrality in the seasonal tourist mobility network. The first is ln(1+InStrength_is), which captures the logged weighted in-strength of each attraction and reflects its ability to absorb incoming tourist flows. The second is ln(PageRank_is), which measures the relative structural importance of the attraction in the network. The third is ln(1 + 1000*Betweenness_is_approx), which represents a transformed approximation of betweenness centrality and is used to capture the bridging role of attractions in route connectivity. Betweenness was computed as an approximate weighted betweenness centrality measure using NetworkX's sampling-based betweenness centrality procedure. Edge distance was defined as the inverse of flow weight, the sampling parameter was set to k = min(200, number of nodes) for each seasonal network, and the random seed was fixed at 42. This approximation was used because exact weighted betweenness is computationally intensive for large directed seasonal networks. Accordingly, the betweenness models are interpreted as evidence about route-bridging roles rather than as the sole basis for the paper's main claims. The robustness checks also re-estimate the betweenness specification using an asinh transformation of the same approximate measure.

The core explanatory variables are three text-derived indicators and one review-scale indicator. Sentiment_is is a pure-text sentiment measure constructed only from review text and explicitly excludes rating information. The coding procedure includes additional weighting for contrastive markers so that the final evaluative part of a sentence receives greater emphasis. NegService_is is the share of reviews containing explicit negative service-related expressions, including complaints related to waiting, crowding, management, hygiene, pricing, or service quality. AttrDiv_is captures attribute diversity by mapping review text into eight attribute groups — scenic aesthetics, cultural experience, family friendliness, convenience, crowding, price, hygiene, and service — and then calculating a smoothed normalized entropy score based on attribute mention intensity. ln_ReviewVol_is is the logged number of reviews in each attraction-season unit.

The control variables include AvgRating_is, ImageShare_is, and AvgReviewLength_is. AvgRating_is captures the mean star rating, ImageShare_is captures the share of image-containing reviews, and AvgReviewLength_is captures textual information density. City fixed effects are used to absorb cross-city unobserved heterogeneity, and seasonal fixed effects are included in pooled models unless season-specific subsamples are estimated.

3.3 Model Specification

The baseline model is specified as follows:

$$Y_{is} = \beta_0 + \beta_1 Sentiment_{is} + \beta_2 ln_ReviewVol_{is} + \beta_3 AttrDiv_{is} + \beta_4 NegService_{is} + \beta_5 AvgRating_{is} + \beta_6 ImageShare_{is} + \beta_7 A$$

where Y_is alternatively denotes ln(1+InStrength_is), ln(PageRank_is), and ln(1 + 1000*Betweenness_is_approx). The baseline models include season fixed effects and city fixed effects, with standard errors clustered at the attraction level. This clustering choice allows residual dependence across seasonal observations from the same attraction. In the seasonal heterogeneity models, each attraction appears at most once within a given seasonal subsample. For that reason, the seasonal regressions cluster standard errors at the city level, which is the next higher grouping level shared by attractions in the same seasonal subsample. This change in clustering level is a design choice rather than a change in the substantive model, and the seasonal results should be interpreted as heterogeneity evidence rather than as separate causal estimates.

To test the conditional role of review volume, the following interaction model is estimated:

$$Y_{is} = \beta_0 + \beta_1 Sentiment_{is} + \beta_2 ln_ReviewVol_{is} + \beta_3 (Sentiment_{is} \times ln_ReviewVol_{is}) + \beta_4 AttrDiv_{is} + \beta_5 NegService_{is} + Cont$$

Across the hypothesis tests, support is evaluated using a common standard: the coefficient direction must align with the hypothesis, conventional statistical significance is required in the relevant main specification, and consistency across the three centrality outcomes is treated as stronger evidence than significance in a single outcome. Results that satisfy the expected direction and significance in only part of the centrality set are reported as partial support. Robustness and heterogeneity models are used to assess stability rather than to redefine the hypotheses.

The empirical specification uses text-side variables as predictors of independently measured network position for expositional convenience, but the paper does not interpret this ordering as evidence that review text causally determines centrality. Instead, the matched cross-platform design uses attraction-season review conditions to identify systematic covariance with attraction-season network position. The theoretical mechanism in Section 2 and the empirical models therefore align at the level of association rather than directional causal identification.

In addition, the analysis includes two heterogeneity designs. Seasonal heterogeneity is examined through separate regressions for spring, summer, autumn, and winter. Attraction-type heterogeneity is examined using a mutually exclusive attraction classification that assigns attractions to five categories — museum, ancient architecture, mountain-and-water, park, and other — and estimates subgroup regressions for the four main types.

[Insert Fig. 2 about here]

4. Empirical Results

[Insert Fig. 3 about here]

4.1 Descriptive Statistics

Descriptive statistics are reported in Table 1. The baseline regression sample contains 786 attraction-by-season observations, indicating that the analysis is not driven only by a small number of superstar attractions. The three dependent variables all display substantial dispersion, which suggests meaningful variation in the structural positions of attractions across the mobility network. The core explanatory variables also show sufficient variation, including both

text sentiment and negative service content, making it possible to identify systematic patterns rather than isolated outliers. Review volume and review length are right-skewed, which is consistent with the typical distribution of online review data and justifies the use of log transformations.

[Insert Table 1 *about here]*

4.2 Baseline Results

The baseline estimates are reported in the first three columns of Table 2. Sentiment_is is significantly negative in all three centrality models. The estimated coefficients are − 1.7811 for InStrength, -1.6974 for PageRank, and − 2.3147 for Betweenness. These results support H1 and indicate that attractions with more positive textual sentiment tend to occupy less central positions in the tourist mobility network.

ln_ReviewVol_is is significantly positive in all three models, with coefficients of 0.3444, 0.2822, and 0.5203, respectively. This supports H2 and suggests that structurally central attractions also accumulate larger public review volumes. NegService_is is significantly negative in the InStrength and PageRank models and remains directionally consistent, though less stable, in the Betweenness model. Under this common evaluation standard, H3 receives partial rather than full support. By contrast, AttrDiv_is is not statistically significant in the pooled baseline sample, implying that attribute diversity does not provide a stable overall explanation for centrality differences at this stage.

Among the control variables, AvgReviewLength_is is consistently positive and significant across all three models, indicating that more central attraction-season units are associated with longer, more information-dense reviews. After switching to the pure-text version of Sentiment_is, AvgRating_is no longer remains significant, which suggests that the mechanical overlap between rating information and sentiment measurement has been substantially reduced.

4.3 Interaction Results

The last three columns of Table 2 report the interaction models. The coefficient on Sentiment_is × ln_ReviewVol_is is negative in all three cases and reaches conventional significance in the PageRank and Betweenness models, while remaining marginally significant in the InStrength model. The estimated interaction coefficients are − 1.2883, -1.4714, and − 2.1838, respectively. These results support H4 and indicate that the negative marginal effect of sentiment becomes stronger as review volume increases.

The positive main-effect coefficients on Sentiment_is in columns (4)-(6) do not indicate a substantive sign reversal. In an interaction model, those coefficients represent the estimated effect of sentiment when ln_ReviewVol_is = 0, which corresponds to one review and lies well outside the observed data range because the baseline sample begins at 30 reviews. For that reason, the sign on the main effect should not be interpreted independently of the negative interaction term.

The marginal-effect calculations are conducted on the log review-volume scale. The approximate thresholds are ln(ReviewVol) = 2.84, 3.07, and 3.17 for the InStrength, PageRank, and Betweenness models, respectively; these correspond to about 17.17, 21.58, and 23.70 reviews on the original count scale. Because the baseline sample restricts the data to units with at least 30 reviews, and ln(30) is approximately 3.40, most observations lie to the right of these thresholds. As a result, the average marginal effect of sentiment in the main sample is negative. Figure 3 visualizes this threshold logic.

The substantive implication is that sentiment does not have a constant meaning across attraction-season units. In low-volume settings, positive sentiment may still reflect localized satisfaction. In high-volume, high-exposure settings, however, sentiment appears to be embedded in stronger expectations, denser comparison environments, and more visible experiential pressure. Under those conditions, the marginal meaning of positive text weakens and can even turn negative in relation to structural centrality.

[Insert Table 2 *about here]*

4.4 Seasonal Heterogeneity

Seasonal heterogeneity results are reported in Table 3. The overall relationship is not evenly distributed across the four seasons but instead exhibits a clear seasonal structure.

First, the negative effect of Sentiment_is is driven mainly by the spring subsample. In spring, Sentiment_is is significantly negative in the InStrength model and marginally significant in the PageRank and Betweenness models. Autumn shows only a weaker and less stable pattern, whereas summer and winter do not produce consistent significance for sentiment.

Second, the positive effect of ln_ReviewVol_is is concentrated in summer and autumn. In those two seasons, review volume is stably and positively associated with all three network indicators. In spring the effect is weaker, and in winter it survives only marginally in the betweenness-related specification. This suggests that the positive association between visibility and centrality is especially characteristic of the high and shoulder travel seasons.

Third, the negative role of NegService_is appears mainly in spring and summer, especially in the InStrength and PageRank models. AttrDiv_is does not generate a stable pattern in any season. Overall, the pooled finding of “negative sentiment and positive review volume” is therefore not a smooth annual average; it is structured by meaningful seasonal variation.

[Insert Table 3 *about here]*

4.5 Attraction-Type Heterogeneity

Appendix Table A2 reports the mutually exclusive attraction-type heterogeneity results. After applying the exclusive classification, the baseline sample contains 46 museum observations, 250 ancient-architecture observations, 184 mountain-and-water observations, and 112 park observations. Compared with

the earlier overlapping classification, the mutually exclusive strategy is closer to the primary identity of each attraction, although it also reduces sample sizes in some groups, especially museums.

The ancient-architecture group produces the most stable pattern. ln_ReviewVol_is is significantly positive in all three centrality models, and AvgReviewLength_is is also consistently positive. In addition, AttrDiv_is becomes significantly positive in the InStrength and PageRank models. This implies that, for ancient-architecture attractions, network position is jointly shaped by review scale, textual information density, and the breadth of reviewable attributes.

The mountain-and-water group displays a more typical visibility-driven pattern. ln_ReviewVol_is and AvgReviewLength_is are relatively stable across all three models, whereas Sentiment_is, AttrDiv_is, and NegService_is do not form significant effects. This suggests that the structural role of mountain-and-water attractions is explained more by flow intensity and information density than by emotional tone or negative service evaluation.

By contrast, the park and museum groups do not generate stable net effects. Most core variables are insignificant in the park subsample, and the museum group loses the stronger significance pattern that had appeared under the earlier overlapping classification. This indicates that some of the museum-related effects in the looser classification may have been driven by attractions with overlapping museum, architecture, or park labels rather than by museums as a clearly distinct structural type.

5. Discussion

5.1 Theoretical Implications

This study contributes to tourism eWOM research by shifting the outcome of interest from traditional market or platform metrics to the structural position of attractions in a tourist mobility network. Most prior studies examine how reviews influence sales, booking behavior, review helpfulness, or destination choice. By contrast, this paper asks whether online review text helps explain how attractions are embedded in movement systems. That shift matters because it reframes eWOM from a demand-side performance predictor to a public evaluative layer that may reveal how attractions function within the tourism space. In doing so, the study moves the literature beyond the review-performance framework and toward a review-structure framework.

The findings also refine how review-related signals should be interpreted. Review volume and text sentiment do not play the same theoretical role. The results show that review volume is positively associated with network centrality, which is consistent with the argument that structurally central attractions accumulate more public visibility, more itineraries, and greater discussion intensity. At the same time, pure-text sentiment is negatively associated with network centrality under the main specifications. This pattern suggests that online positivity is not equivalent to structural importance. Instead, central attractions appear to attract stronger evaluative pressure, which is consistent with the idea that visibility, expectation, congestion, and service friction may jointly depress public textual tone.

The interaction effect further strengthens this interpretation. Review volume does not simply add explanatory power; it changes the meaning of sentiment. Under low-volume conditions, text sentiment can be interpreted more as a localized experiential expression. Under high-volume conditions, however, sentiment appears to reflect collective evaluation under heavier exposure and more demanding comparison standards. This result adds an important qualification to the broader eWOM literature: more reviews do not merely enhance credibility, they may also alter the substantive meaning of evaluative text.

Another contribution of the study is to demonstrate that heterogeneity is not secondary to the main relationship. The seasonal analyses show that the negative sentiment-centrality relationship is driven mainly by spring, whereas the positive role of review volume is concentrated in summer and autumn. The type-based analyses further suggest that not all attraction categories operate through the same mechanism. In the mutually exclusive classification, ancient-architecture attractions show the clearest joint role of review volume, review length, and attribute diversity, whereas mountain-and-water attractions are driven more by visibility and information density than by sentiment or negative service content. These findings suggest that a single pooled interpretation of eWOM and network position is inadequate.

Finally, the paper contributes to the interpretation of negative text in tourism settings. A common reading of negative textual tone is that it simply signals poor destination quality. The current results imply a more complex interpretation. At highly central attractions, negative text may reflect structural exposure to crowding, dense visitor overlap, waiting, fatigue, and service friction rather than simple unattractiveness. In this sense, negative sentiment can coexist with structural importance. That insight helps reconcile why core attractions remain essential nodes in travel itineraries even when their online text is not especially favorable.

5.2 Managerial Implications

For destination managers, the most immediate implication is that high review volume should not be interpreted as evidence of high experiential quality. Structurally central attractions naturally accumulate more visibility and more comments, but they do not necessarily accumulate more favorable text. Managers of core attractions should therefore focus less on review counts alone and more on the underlying friction points that depress textual evaluations, such as queuing, congestion, circulation bottlenecks, price dissatisfaction, spatial management, and frontline service quality.

The seasonal results also indicate that management interventions should not be uniform across the year. Because the negative association between sentiment and centrality is most pronounced in spring, managers may need to pay particular attention to expectation management, route coordination, crowd control, and service consistency during that season. By contrast, the stronger positive role of review volume in summer and autumn suggests that high-traffic periods intensify visibility effects. During those seasons, operational planning should prioritize throughput, signage, flow dispersion, and communication strategies that reduce the mismatch between attraction prominence and on-site experience.

The type heterogeneity results imply that different attraction categories require different response logics. For ancient-architecture attractions, centrality is not driven by exposure alone; it is also related to review length and attribute diversity. This suggests that managers in these sites should enhance the breadth and clarity of the experience, for example through interpretation systems, path organization, layered cultural presentation, and better articulation of experiential attributes that visitors can recognize and describe. For mountain-and-water attractions, the results suggest a stronger visibility-and-information mechanism. In those cases, capacity management, flow organization, and content clarity may be more important than trying to improve generalized emotional tone.

The results also carry implications for platform-facing review management. If central attractions attract harsher text partly because of structural exposure, then managers should not overreact to raw negativity without diagnosing its source. Negative service-related content may be especially informative because it signals friction that is actionable. Review monitoring systems should therefore distinguish among general sentiment, negative service expressions, and traffic-related signals rather than collapsing them into a single reputation score.

5.3 Limitations and Future Research

This study has several limitations that should be acknowledged. First, the empirical design is observational. Although the review data and mobility network are aligned to the same annual window and linked at the attraction-by-season level, the analysis does not establish strict causality. The results identify systematic associations between online text and structural network position, but they cannot fully separate causal influence from co-evolution, omitted variables, or shared exposure conditions. More specifically, the positive association between review volume and centrality may reflect bidirectional processes: central attractions attract more visitors and reviews, while accumulated platform engagement may also reinforce visibility and subsequent itinerary inclusion.

Second, one of the network indicators is approximate. The bridge-role measure uses an approximation of betweenness rather than an exact calculation. Although this is acceptable for the present exploratory structure, future work should validate whether the same findings hold under exact betweenness or alternative measures of brokerage and intermediation.

Third, the text variables remain measurement constructs rather than direct observations. Pure-text sentiment, negative service share, and attribute diversity were built from review text through rule-based and aggregated procedures. These variables are appropriate for the present design, but they inevitably compress linguistic nuance. Future work could combine manual annotation, stronger domain-adapted classifiers, or multilingual comparison to improve construct precision.

Fourth, the main analysis is restricted to the 2019 sample. This decision strengthens temporal alignment between review text and network structure, but it also limits historical generalizability. Future studies could build matched panel designs using comparable mobility networks from multiple years, or explicitly compare pre-pandemic and post-pandemic structures once network and review data can be aligned under the same temporal logic.

An additional limitation is that the network data come from Qunar travel blogs whereas the review data come from Ctrip. The matched design therefore links two user populations that may differ in travel experience, trip purpose, and reviewing norms. This cross-platform heterogeneity may attenuate internal validity even when the attraction-season matching is accurate.

Fifth, attraction-type heterogeneity remains sensitive to classification strategy. The mutually exclusive classification used here is more conservative than the overlapping alternative, but it still relies on attraction names and text-based type labels rather than on an official universal classification system. Future research could improve this aspect by integrating standardized attraction categories, administrative classifications, or expert-coded cultural and natural attraction taxonomies.

Taken together, these limitations do not weaken the core contribution of the paper, but they do clarify its scope. The current study provides evidence that eWOM and tourist mobility networks are meaningfully related at the attraction level, and that the relationship is conditional, seasonal, and type-sensitive. Future work can build on this foundation by improving causal identification, refining text measures, and extending the network-review linkage to broader temporal and spatial settings.

Declarations

Funding

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

Author Contribution

Zhen Guo: Conceptualization, data collection, data cleaning, formal analysis, methodology, visualization, writing - original draft, writing - review and editing.

Data Availability

The public tourist mobility network dataset analyzed in this study is available in figshare and is cited in the reference list. The derived dataset and replication code are available from the corresponding author upon reasonable request.

References

1. Bigné E., Ruiz C., Currás-Pérez R. (2024) How consumers process online review types in familiar versus unfamiliar destinations: A self-reported and neuroscientific study. Technological Forecasting and Social Change 199:123067. https://doi.org/10.1016/j.techfore.2023.123067
2. Chen Y.-F., Law R. (2016) A review of research on electronic word-of-mouth in hospitality and tourism management. International Journal of Hospitality & Tourism Administration 17(4):347–372. https://doi.org/10.1080/15256480.2016.1226150
3. Ding D., Zheng Y., Zhang Y., Liu Y. (2024) Understanding attractions' connection patterns based on intra-destination tourist mobility: A network motif approach. Humanities & Social Sciences Communications 11(1):636. https://doi.org/10.1057/s41599-024-03093-3
4. Gao J., Peng P., Lu F., Claramunt C. (2022) A multi-scale comparison of tourism attraction networks across China. Tourism Management 90:104489. https://doi.org/10.1016/j.tourman.2022.104489
5. Islam M. T., Herjanto H., Kumar J., Amin M. (2025) Online travel reviews and tourist destination choices: An extension of the information adoption model. Tourism Review International 29(1):17–32. https://doi.org/10.3727/194344225X17315216888907
6. Jin C., Cheng J., Xu J. (2018) Using user-generated content to explore the temporal heterogeneity in tourist mobility. Journal of Travel Research 57(6):779–791. https://doi.org/10.1177/0047287517714906
7. Jung K., Nam Y. (2026) Seasonal shifts and pandemic effects on tourist mobility: A study of attraction-level movement patterns in Jeju Island. Electronic Markets 36(1):28. https://doi.org/10.1007/s12525-026-00875-2
8. Koç B., Küçükergin K. G., Dimanche F. (2022) How destructive are negative tourist-to-tourist interactions despite the mitigating effect of optimism?. Journal of Destination Marketing & Management 23:100693. https://doi.org/10.1016/j.jdmm.2022.100693
9. Litvin S. W., Goldsmith R. E., Pan B. (2008) Electronic word-of-mouth in hospitality and tourism management. Tourism Management 29(3):458–468. https://doi.org/10.1016/j.tourman.2007.05.011
10. Liu S., Zhang J., Liu P., Xu Y., Xu L., Zhang H. (2023) Discovering spatial patterns of tourist flow with multi-layer transport networks. Tourism Geographies 25(1):113–135. https://doi.org/10.1080/14616688.2020.1850849
11. Luo L., Zhao X., Zhang Y., So K. K. F., Hua N. (2025) Crowding paradoxes in tourism: A meta-analysis of behavioral intentions, emotional responses, and boundary conditions. Journal of Hospitality and Tourism Management 65:101346. https://doi.org/10.1016/j.jhtm.2025.101346
12. Nam K., Baker J., Ahmad N., Goo J. (2020) Determinants of writing positive and negative electronic word-of-mouth: Empirical evidence for two types of expectation confirmation. Decision Support Systems 129:113168. https://doi.org/10.1016/j.dss.2019.113168
13. Park S., Zhong R., Xu Y. (2022) Understanding seasonal and diurnal variations of inter-city tourism destination network. Journal of Travel & Tourism Marketing 39(4):432–447. https://doi.org/10.1080/10548408.2022.2116626
14. Paulino I., Lozano S., Prats L. (2021) Identifying tourism destinations from tourists' travel patterns. Journal of Destination Marketing & Management 19:100508. https://doi.org/10.1016/j.jdmm.2020.100508
15. Qiu Y., Yang Y., Wang X., Guo L. (2026) Tourist satisfaction and review helpfulness: Examining the primary effects, mediating mechanisms, and moderating influences. Tourism Management 112:105252. https://doi.org/10.1016/j.tourman.2025.105252
16. Stylos N., Bigné E., Bellou V. (2024) The affective impact of sightseeing bus tour experiences: Using Affective Events Theory (AET) to examine length-of-stay and electronic word-of-mouth. Tourism Recreation Research 49(4):740–756. https://doi.org/10.1080/02508281.2022.2101273
17. Verma S., Yadav N., Chikhalkar R. (2023) An integrated measure of eWOM usefulness in leisure travel: Conceptualization, scale development, and validation. Journal of Marketing Communications 29(3):211–237. https://doi.org/10.1080/13527266.2021.2004442
18. Wang Y., Chen H., Wu X. (2021) Spatial structure characteristics of tourist attraction cooperation networks in the Yangtze River Delta based on tourism flow. Sustainability 13(21):12036. https://doi.org/10.3390/su132112036
19. Xu F., Zhan C., Li J., Li S. (2024) Tourists' approach or avoidance reaction to crowding in wellness tourism. Journal of Travel & Tourism Marketing 41(6):880–900. https://doi.org/10.1080/10548408.2024.2349814
20. Xu J., Su T., Cheng X., Chen H. (2025) Exploring the destination network in the context of tourism mobility: A multi-scale analytical framework. Current Issues in Tourism 28(8):1197–1219. https://doi.org/10.1080/13683500.2024.2334830
21. Xu Y., Li J., Belyi A., Park S. (2021) Characterizing destination networks through mobility traces of international tourists: A case study using a nationwide mobile positioning dataset. Tourism Management 82:104195. https://doi.org/10.1016/j.tourman.2020.104195
22. Yang Y., Park S., Hu X. (2018) Electronic word of mouth and hotel performance: A meta-analysis. Tourism Management 67:248–260. https://doi.org/10.1016/j.tourman.2018.01.015
23. Ye Q., Law R., Gu B. (2009) The impact of online user reviews on hotel room sales. International Journal of Hospitality Management 28(1):180–182. https://doi.org/10.1016/j.ijhm.2008.06.011
24. Yin J., Cheng Y., Ni Y. (2024) Staging a comeback? The influencing mechanism of tourist crowding perception on adaptive behavior. Tourism Management 100:104827. https://doi.org/10.1016/j.tourman.2023.104827
25. Zhang C., Li L. (2025) Impacts of urban scenic area congestion on tourist satisfaction. Anatolia. https://doi.org/10.1080/13032917.2025.2512792
26. Zheng Y., Wang J., Zhang Y., Mou N., Liu Y. (2025) A dataset of tourist mobility networks across China derived from online travel blogs [Data set]. Figshare. https://doi.org/10.6084/m9.figshare.30184726
27. Zheng Y., Wang J., Zhang Y., Mou N., Liu Y. (2026) A dataset of tourist mobility networks across China derived from online travel blogs. Scientific Data 13(1):443. https://doi.org/10.1038/s41597-026-06780-9

28. Zheng Y., Zhang Y., Makkonen T., Li M., Mou N., Liu Y. (2025) Rethinking the community detection for tourist mobility networks: Special structures and their implications for tourism. Information Technology & Tourism 28(1):12. https://doi.org/10.1007/s40558-025-00357-9

Tables

Table 1. Descriptive statistics for the baseline regression sample.

Variable	N	Mean	SD	Min	Median	Max
ln(1+InStrength)	786	4.5338	0.8724	0.6931	4.6001	6.7202
ln(PageRank)	786	-7.2995	0.6941	-10.8649	-7.2772	-5.5686
ln(1+1000*Betweenness)	786	1.9819	1.1397	0	1.9859	4.8378
Text sentiment	786	0.2047	0.0731	-0.0894	0.2083	0.4392
Log review volume	786	4.4597	0.6701	3.434	4.382	6.4394
Attribute diversity	786	0.7325	0.0968	0.3519	0.7434	0.9432
Negative service share	786	0.0931	0.0608	0	0.0833	0.3846
Average rating	786	4.6586	0.2105	3.2436	4.7005	5
Image review share	786	0.6607	0.2564	0	0.6133	1
Average review length	786	73.0637	24.8388	26.16	68.49	204.52

Note. The sample is the baseline regression sample (ReviewVol_is >= 30), including 786 attraction-by-season observations across 273 attractions. Dependent variables follow the transformed specifications used in the regressions.

Table 2. Baseline and interaction regressions of review-based variables on attraction centrality.

Variable	(1) InStrength	(2) PageRank	(3) Betweenness	(4) InStrength + interaction	(5) PageRank + interaction	(6) Betweenness + interaction
Text sentiment	-1.7811**	-1.6974**	-2.3147**	3.6625	4.5198*	6.9126*
	(0.7714)	(0.7055)	(1.0349)	(2.9282)	(2.5383)	(3.9725)
Log review volume	0.3444***	0.2822***	0.5203***	0.6196***	0.5965***	0.9867***
	(0.0802)	(0.0720)	(0.1044)	(0.1600)	(0.1421)	(0.2364)
Text sentiment x log review volume				-1.2883*	-1.4714**	-2.1838**
				(0.7352)	(0.6478)	(1.0222)
Attribute diversity	0.2212	0.1769	0.0143	0.2079	0.1617	-0.0083
	(0.4465)	(0.4195)	(0.6991)	(0.4366)	(0.4080)	(0.6909)
Negative service share	-1.8772**	-1.8962**	-2.2459*	-2.0878**	-2.1367***	-2.6028**
	(0.9187)	(0.8144)	(1.3018)	(0.9331)	(0.8292)	(1.3108)
Average rating	-0.3380	-0.2122	0.1329	-0.3590	-0.2363	0.0971
	(0.2472)	(0.2222)	(0.3483)	(0.2455)	(0.2202)	(0.3454)
Image review share	0.0873	0.0543	-0.2327	0.1314	0.1046	-0.1579
	(0.2802)	(0.2516)	(0.3929)	(0.2835)	(0.2528)	(0.3898)
Average review length	0.0100***	0.0100***	0.0213***	0.0096***	0.0095***	0.0207***
	(0.0031)	(0.0027)	(0.0036)	(0.0031)	(0.0027)	(0.0037)
Season fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Clustering level	Attraction	Attraction	Attraction	Attraction	Attraction	Attraction
N	786	786	786	786	786	786
R^2	0.5060	0.3812	0.3305	0.5102	0.3898	0.3375

Note. Cluster-robust standard errors at the attraction level are reported in parentheses. Columns (4)-(6) add the interaction term between Sentiment_is and ln_ReviewVol_is. Betweenness is measured using the transformed approximation of betweenness centrality. One-, two-, and three-asterisk markers indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 3. Seasonal heterogeneity in the relationship between review-based variables and attraction centrality.

Panel A. Dependent variable: ln(1+InStrength_is)

Variable	Spring	Summer	Autumn	Winter
Text sentiment	-3.2536**	-1.4749	-2.4171	-2.9880
(1.5839)	(1.2789)	(1.5377)	(2.1594)	
Log review volume	0.1087	0.3337***	0.2348**	0.4494
(0.1585)	(0.1179)	(0.1013)	(0.3770)	
Attribute diversity	1.1222	0.1051	-0.1431	-1.0896
(1.1886)	(0.6922)	(0.7761)	(1.7292)	
Negative service share	-4.2683**	-2.8068**	-2.7786	-2.1224
(2.1392)	(1.4098)	(2.3601)	(1.8948)	
Average review length	0.0121***	0.0143***	0.0093**	0.0074
(0.0045)	(0.0039)	(0.0040)	(0.0061)	
N	175	259	253	99
Number of cities	65	83	83	39

Panel B. Dependent variable: ln(PageRank_is)

Variable	Spring	Summer	Autumn	Winter
Text sentiment	-2.9743*	-1.6050	-2.1578	-3.0209
(1.5833)	(1.2975)	(1.3797)	(2.0214)	
Log review volume	0.0981	0.3140***	0.2397**	0.3824
(0.1683)	(0.1160)	(0.0946)	(0.3480)	
Attribute diversity	1.0371	0.1416	-0.1607	-0.8246
(1.1280)	(0.6569)	(0.7731)	(1.5969)	
Negative service share	-3.8706*	-2.7296**	-2.4631	-2.1596
(2.0417)	(1.3728)	(2.1018)	(1.8255)	
Average review length	0.0125***	0.0136***	0.0107***	0.0079
(0.0044)	(0.0039)	(0.0041)	(0.0060)	
N	175	259	253	99
Number of cities	65	83	83	39

Panel C. Dependent variable: ln(1+1000*Betweenness_is_approx)

Variable	Spring	Summer	Autumn	Winter
Text sentiment	-5.3855*	-1.1126	-3.3643*	-3.6889
(2.7649)	(2.0215)	(1.9524)	(3.8559)	
Log review volume	0.2721	0.4963***	0.5041***	0.8920*
(0.2907)	(0.1497)	(0.1644)	(0.5159)	
Attribute diversity	0.8295	0.4615	-0.5754	-1.4261
(1.8832)	(0.8913)	(1.4572)	(2.8172)	
Negative service share	-5.8251	-2.8946	-2.7484	-0.4874
(3.5863)	(2.3314)	(3.4558)	(3.0126)	
Average review length	0.0266***	0.0248***	0.0233***	0.0169
(0.0075)	(0.0067)	(0.0076)	(0.0118)	
N	175	259	253	99
Number of cities	65	83	83	39

Note. Seasonal regressions are estimated separately by season, retain city fixed effects, and report cluster-robust standard errors at the city level. AvgRating_is and ImageShare_is are included in the seasonal regressions but omitted from the displayed rows to conserve space. One-, two-, and three-asterisk markers indicate significance at the 10%, 5%, and 1% levels, respectively.

Figures

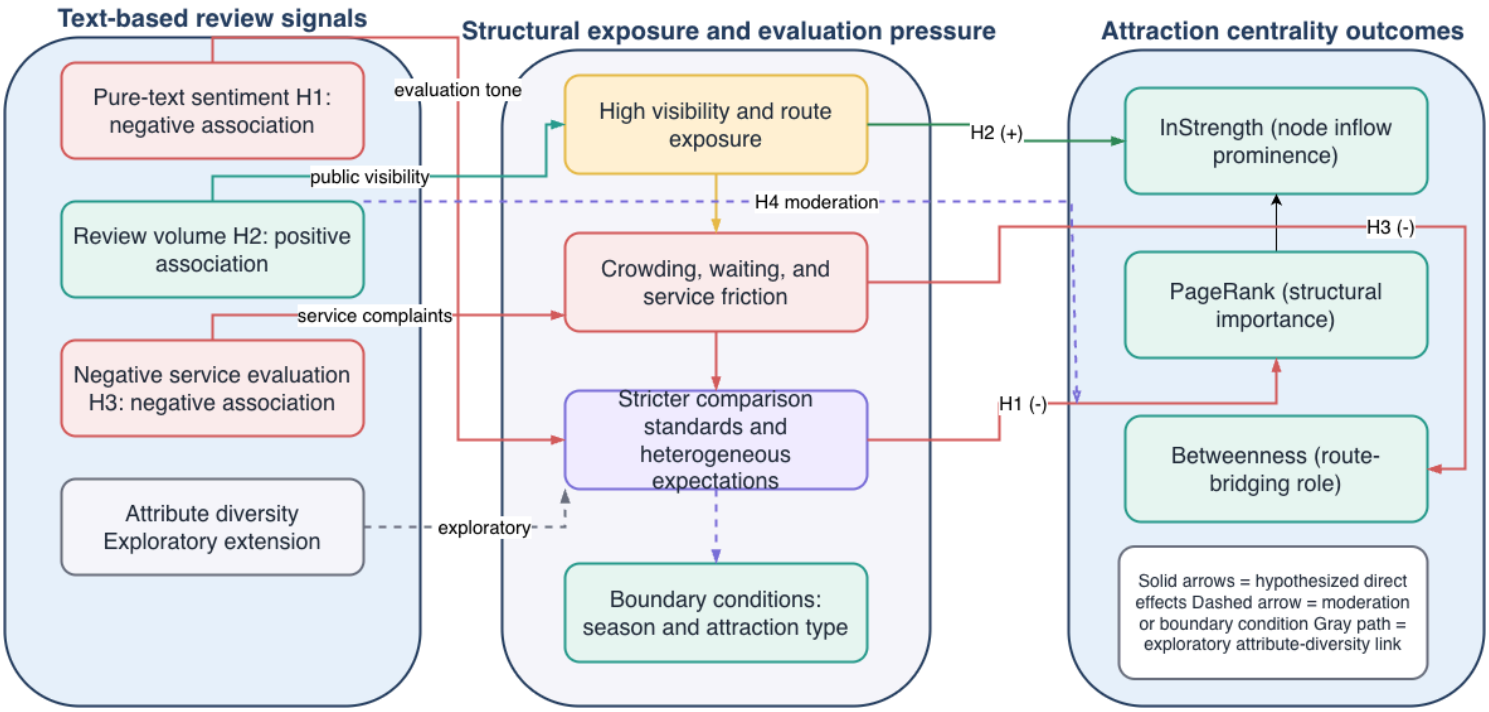

Figure 1

Theoretical mechanism linking review-based signals to attraction centrality

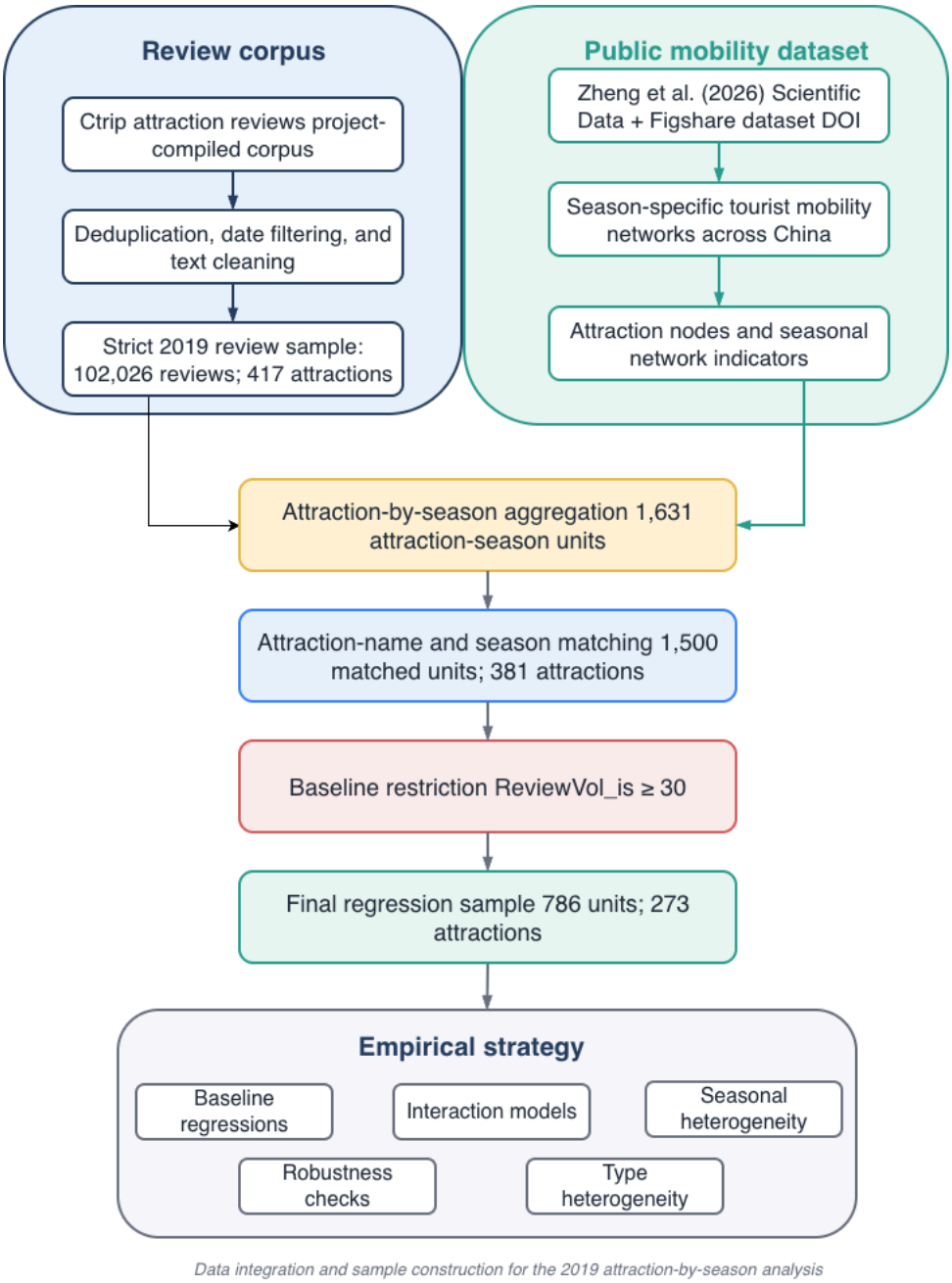

Figure 2

Research design workflow

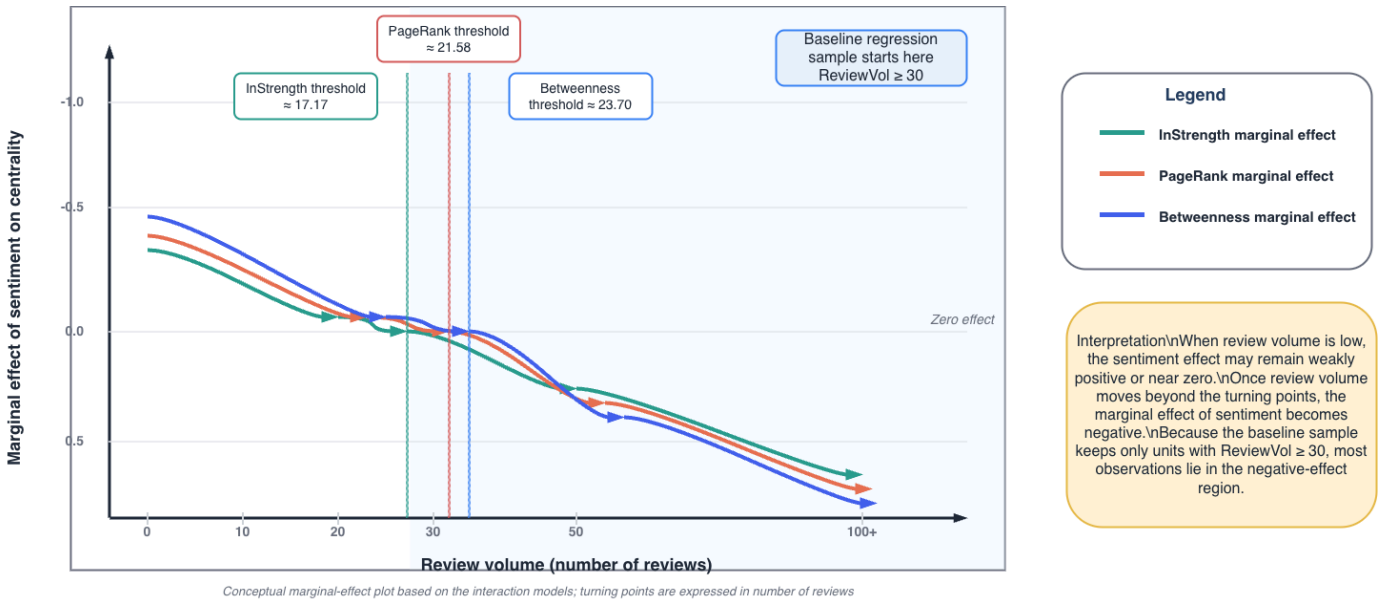

Figure 3

Review volume moderates the sentiment-centrality relationship

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- AppendixTables.docx