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The Interplay of Experience, Context, and Sentiment: A Multifactor Analysis of Tourism Recommendation Scores

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Abstract

Although research on tourist satisfaction is abundant, there remains a significant gap in understanding how multiple factors interactively influence recommendation behaviors within the tourism website ecosystem. To date, the vast majority of published research employs reductionist strategies, evaluating limited variables in isolation while disregarding the layered complexity and interactions with temporal effects, social factors, expectations regarding price and budget expenditures, and emotional reactions. Additionally, there is insufficient exploration of the downstream psychological mechanisms that feature in or effectuate the relationship between the objective properties of trips and final evaluations. This paper seeks to address these gaps by analyzing 2,101 tourism reviews, accounting for contextual factors such as season and location type, economic factors such as budget and spending, and emotionally evocative sentiment analysis. Using hierarchical regression and mediation analysis, it is evident that recommendation scores emerge from interactions that occur both objectively during the trip or destination setting and subjectively as emotional responses occur after an experience is evaluated. Review sentiment was shown to mediate the connection between experiential properties and final evaluations, and the alignment of value (i.e., budget expectations or price relative to expenditures) was greater than the level of money spent objectively in the trip context. Overall, these findings enhance tourism theory and present an integrated, psychologically constructed model of tourism evaluation and subsequently recommendations with effectual implications for destination management and marketing strategies.

Keywords Tourist satisfaction; recommendation behaviors; Sentiment analysis; Mediation analysis; budget expectations; destination management

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Introduction

Digital technology has changed how people pick their vacation destinations. Websites where users can review, such as TripAdvisor, Booking.com, and Airbnb, play a vital role in the tourism marketplace, and user content serves as one of the primary forms of social proof that has an impact on the booking process and destination development (Nicolau et al., 2025; Zhang et al., 2025). When individual assessments become collective ratings, a distinct informational structure affects millions of travel decisions annually, and this generates considerable theoretical and practical urgency to investigate the factors that affect recommendation scores (Lekmiti et al., 2024; Salem et al., 2024). While the recent literature explores tourist satisfaction (Qin et al., 2025; Shu et al., 2026), it has not investigated the factors that lead tourists to assign high recommendation levels (e.g., more than 90) and low recommendation levels (e.g., less than 30). This paper claims that recommendation scores emerge from more than a set of variables acting independently; they arise from the interactive context, economic factors, and emotional states regarding the travel experience (Rui et al., 2025; Zhang et al., 2025). The temporal dimension of visitation framed by season, the spatial nature represented by type of location, the temporal condition relating to the length of the trip, the social condition of group size, economic condition of budget category, and the behavioral condition of average daily spending are considered objective conditions that are then experienced in the form of subjective affective outcomes captured through sentiment analysis of reviews and ratings (Yin et al., 2025). This perspective goes beyond additive satisfaction models that typically characterize tourism experience by treating it as unitary entities in which the interactive relationships between multiple factors result in evaluative outcomes (Albayrak et al., 2024). There are gaps in the current literature that will bracket and hinder theory development and practical application. First, existing research primarily employs reductionist methods that examine

only small counts of variables utilizing main effects models and sometimes ignore potentially relevant interactions between temporal factors (season), social factors (group composition), and spatial conditions (location/mode), all related to economic conditions (budget category) (Chen, 2025; Wu et al., 2024).

In the second place, while financial aspects are broadly recognized as salient in tourism settings, the interplay between pre-trip budget expectations and actual spending, and their joint effect on value and satisfaction perceptions, has not been sufficiently accommodated in psychological theory (Ding et al., 2026). Third, while sentiment analysis is gaining prominence as a methodological approach in tourism research (Liu et al., 2025), sentiment is often investigated separately, highlighting the disconnection between affective responses captured in the text and objective experiential circumstances assessed through actual trip attributes (Eberle et al., 2025). This research will develop an integrated analysis of the aforementioned voids, taking a longitudinal, data-driven approach to incorporate multiple dimensions of the tourist experience. Rather than examining variables separately, this research holistically explores how trip attributes and context interactively and collectively shape evaluative judgments operationalized by recommendation ratings. By synthesizing quantitative trip attributes used to measure trip outcomes with sentiment data from reviews, a more sophisticated, psychologically based model of tourist evaluation is created (Yang et al., 2023). The study fills a gap in research by answering the following research questions: RQ1: How do contextual factors (season, location type, duration, travel group size) and economic factors (budget category, average spending per day) collectively and interactively influence tourists' recommendation scores? RQ2: To what extent does review sentiment mediate the relationship between objective trip characteristics and final recommendation scores, thereby functioning as the psychological mechanism through which experiential conditions translate into evaluative judgments?

Literature review and hypothesis development

Contextual determinants of tourism satisfaction

Tourism experiences are multidimensional entities that unfold over time, and satisfaction is a balance between prior expectations and what is encountered. The SERVQUAL model indicates that service quality is the perceived difference between customer expectations of the service offered and the perceived service offering across five factors: reliability, assurance, tangibles, empathy, and responsiveness (Sacristán-Díaz et al., 2025). Complementing these factors, the Experience Economy theorizes competitive advantage is developed through the staging of memorable experiences based on four realms of experience: educational, aesthetic, escapist, and entertainment (Zheng & Cham, 2025) Locational type engages these realms to give different characteristics (Kadyrbekova et al., 2024), where cultural sites engage educational dimensions, beach destinations employ aesthetic experiences, and adventure locations immerse individuals in escapism (Li et al., 2025). Season of visitation acts as a pivotal moderating variable (Jawabreh et al., 2024) and an underlining property that provides substantial effects on the quality of destinations and the experience of visitors (Teichert et al., 2023) impacts alter the variability of accessibility, comfort in climate, density of visitors, availability of activities, and pricing variability. A hill station destination that appeals to winter visitors will perform poorly during the monsoon season. In contrast, beach destinations that continue to fare well in shortened summers will fail to develop core value when rain limits their key offering in their core value proposition (Tunca, 2025). These seasonal effects are a significant determining factor, allowing destinations to offer and fail to offer and deliver what they promise.

The number of travel companions creates crucial social dynamics. Traveling alone can be experience- and fun-based living if freedom, satisfaction, and spontaneity are the priorities, or it can involve coordinating with family members, which involves complex coordination and negotiating compromises (Gim et al., 2024). The larger the group, the more coordination is required, and there is a greater desire for accommodation, which may create conflicts, so higher social satisfaction may come at the cost of individual satisfaction, even if it strengthens social bonding. Trip length also impacts the depth of the experience and evaluative process. Short trips are likely based on fewer, discrete critical incidents. Indeed, short trips may rest entirely on one experience as the dominant overall evaluation (as opposed to being lumped into a "type"). In contrast, longer trips allow for more comprehensive sampling of the experience, thereby producing an averaged evaluation compounded by accumulated experiences, while isolating critical incidents (Chen, 2025). Each set of dynamics context, onset, legacy, type, and group size interacts with the others in a contextual player, and they do not simply add up. For example, congruent combinations (e.g., mountain high country or Hill Station in Winter; beach in Summer) will yield significantly higher scores than incongruent combinations.

> H1: Contextual factors (Season, Location Type, Duration, Travel Group Size) will demonstrate significant main and interaction effects on User Rating and Recommendation Score.

Economic factors and perceived value

Financial factors exert their influence through the concept of perceived value, which is the cognitive evaluation of the utility received relative to the cost paid (Shu et al., 2026). The pre-trip budget category sets a psychological baseline for expectations of service quality and the range of experience, serving as a reference point for interpreting expenditures thereafter (Wang & Li, 2024). This relates to value-for-money concepts that assess if the benefits received exceeded the costs incurred. Daily per-person spending refers to the actual cost per day, which can create disengagement through the dissonance between expected and actual in travel, with psychological implications for traveler satisfaction. Cognitive dissonance theory helps us understand how conflicting expectations and experiences create psychological discomfort that requires resolution (Ding et al., 2026). A traveler having set a high budget expectation but spending less, with an assumption of value and higher satisfaction, or a budget

traveler experiencing higher than expected spending may not interpret the situation as a value from the experiences, and vice versa. When a traveler's biased expectations reveal that the overall value is perceived as poor, the traveler may be dissatisfied if the trade-off for satisfaction was a higher level of service quality, even when the traveler felt the value was still poor, but the service quality was high.

This economic evaluation process interacts significantly with experienced dimensions. The notion of equal levels of spending being evaluated differently depends on situational context and the experiential returns you receive from that spending (Wu et al., 2024). For example, if high expenditure is warranted for a luxury adventure expedition that provides exclusive, exotic encounters with nature, spending this amount would likely be seen as excessive if it were to encompass a basic city experience. Spending during a highly satisfying experience would be more positively evaluated than equivalent expenditures in a disappointing situational context. The association between your planned budget and actual amount spent remains under-theorized in the tourism literature, where studies typically treat these as separate predictors without integrating their psychological interplay. For aligned instances (e.g., High Budget/High Spending or Low Budget/Low Spending), you can expect higher performance, as all expectations have been met. For the instances of misalignment (e.g., Low Budget/High Spending), tourists can anticipate significantly lower levels of evaluations driven by negative dissonance.

H2: The interaction between Budget and Average Spending per Day will significantly predict Recommendation Score beyond main effects.

Review sentiment as affective mediator

Analyzing the sentiment of reviews based on their emotional tone reveals information about tourists' affective states (Yu et al., 2024). Affective Events Theory argues that certain events elicit distinct emotional responses, ultimately influencing downstream attitudes and behaviors. When applied to tourism, characteristics of the trip (e.g., beach vacation, annual vacation) can be interpreted as affective events that trigger emotional responses, which then influence evaluative judgments and behavioral intentions (Eberle et al., 2025). Review sentiment acts as a mediating variable to understand the causal mechanisms linking objective trip characteristics to evaluations and opinions, as sentiment represents the affective mechanism between experience and judgment (Zhang et al., 2024). Quantitative analysis may show a relationship between the monsoon and low beach holiday scores. Still, sentiment analysis reveals the emotional process underlying this disappointment over unmet expectations, frustration over cancelled activities, and boredom due to a lack of activities (Yin et al., 2025). These affective states cannot necessarily be captured by quantitative metrics alone, but they allow for a psychological reality of the tourist experience. Sentiment takes an objective experience, like a trip, and shifts it to a subjective evaluation through processing congruent with mood. Negative sentiment intensifies a minor service failure beyond the event level and would likely dominate the evaluation. On the other hand, positive sentiment protects against defects and allows the continued assignment of relatively high evaluations even in the face of service breakdowns (Yang & Hsu, 2026). Affective intensity and valence dictate the attention paid to different trip characteristics as a location's final evaluation is rated. The initial trip characteristics trigger an emotional response, captured in the specific review's sentiment, which directly drives their assigned recommendation score. In doing so, sentiments act as a mediating variable in the cause-and-effect chain from experience to evaluation, such that positive sentiment will enhance their final evaluation through a positive affective frame, which is then diminished by negative sentiment through negative framing, explaining a large proportion of the variance between the objective experience and subjective evaluation.

H3: Review Sentiment will mediate the relationship between (a) contextual factors and (b) the budget-spending interaction, and the final Recommendation Score.

Conceptual framework

The suggested connections form an integral model that shows review sentiment as a key mediating mechanism. Contextual factors (i.e., season, type of area, duration of visit, number of people in travel group), and economic factors (i.e, budgetary category and average daily spending) are treated as exogenous variables that have direct main effects and interactions impacting user rating and recommendation score and also operate indirectly as moderators mediated through review sentiment.

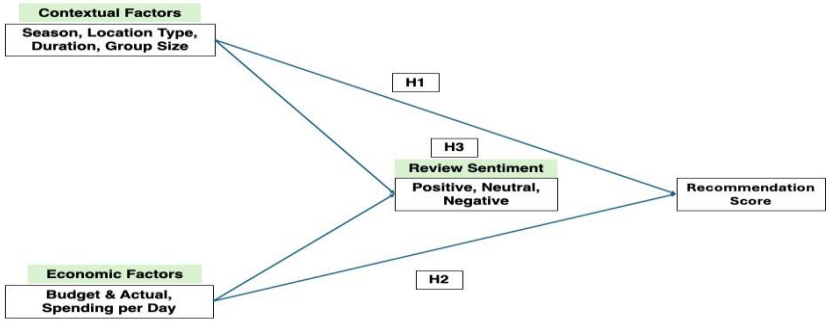

Figure 1: The study framework

This framework provides representations for direct paths from objective characteristics to evaluative outcomes, and indirect paths operating through affective processes, thereby representing a comprehensive representation of the evaluation processes of tourists, integrating cognitive, affective, and contextual factors (See Figure 1).

Methodology

Research design and data collection

The study employed a quantitative, cross-sectional research design and analyzed secondary data from online tourism reviews. The quantitative method addresses research questions concerned with understanding variable relationships, testing interaction and mediation hypotheses, and developing generalizable models of recommendation behavior. Because a cross-sectional design captures tourist experiences across varying contextual conditions, the data contain sufficient variability to detect interaction effects, even though causal inferences can be made only through experimental manipulation. The dataset included 2,101 anonymized user reviews from a large global online travel platform. The platform was selected based on the following criteria: (a) a comprehensive review structure that included numerical ratings and written text, (b) global reach that would offer variances in review experience, and (c) complete data availability on theoretically essential variables. The data used in this study were collected through organized web scraping over 12 months (encompassing all seasons) to avoid bias due to the time of year, while capturing seasonal variation, an essential component of the hypotheses and theoretical framework. Data scraping was undertaken in Python and its associated libraries to carry out data collection, while considering the ethical implications of the collected data and compliance with the platform's terms of service regarding data access. The protocol was pre-loaded with necessary programming instructions to systematically extract several data points (numerical ratings, review text, trip specifics—season, location type, trip duration, group size, budget, and spending), as well as the recommendation rating. Data cleanliness required complete data across all significant variables as the primary inclusion criterion, leading to a loss of reviews during cleaning. The large sample size of 2,101 observations has strong statistical power for conducting both multiple regression and mediation analyses, exceeding the recommendation of fifteen to twenty observations per predictor variable. The sample included approximately sixteen to eighteen predictors, including interaction terms, resulting in over one hundred observations per predictor and providing strong power to detect moderate effect sizes and reduce the risk of type II error. The sample is a non-probability convenience sample of self-selected reviewers, which provided ecologically valid real-world data from engaged consumers, but does restrict formal statistical inference to the tourism population more broadly.

The analytic dataset defines the primary constructs of interest as theoretical constructs within various variable categories. The dependent variable in the dataset, recommendation score, is measured on a continuous scale from 0 to 100 that reflects overall propensity to recommend a destination and serves as a holistic evaluative judgment accounting for all aspects of the trip. Higher scores indicate a greater likelihood of recommending a destination and greater satisfaction. The independent variables are classified as contextual factors and economic factors. Contextual factors include season, measured as a nominal categorical variable with five levels: spring, summer, autumn, winter, and monsoon. Location type is a nominal categorical variable with six levels: adventure (also categorized as adventure tours), beach, cultural site, hill station, wildlife, and city. This variable represents the primary characteristics of destinations. Duration is measured as an ordinal categorical variable with three levels consisting of short trips lasting from one to three days, medium trips lasting from four to seven days, and long trips extending seven days or longer. Travel group size is measured as a discrete numerical variable ranging from one to five persons to capture the dimension of sociality in the tourism experience.

Economic factors comprise budget, which is indicated as an ordinal categorical factor with three levels, including low, medium, and high, referring to pre-trip financial planning and budget expectations, and average expenditure per day, indicated as a continuous numerical factor that reflects actual expenditure of funds spent during the trip, and indicates determined financial reality as opposed to budget expectation. The mediating variable, review sentiment, is indicated as a nominal categorical variable with three levels: positive, neutral, and negative. This variable was created through automated sentiment analysis of written review text using natural language processing algorithms trained on large, labeled corpora and validated for tourism contexts. Classification is based on emotional valence, language of affect, and evaluative expression: positive reviews contained predominantly positive language with equally positive emotional valence; neutral reviews contained predominantly factual, descriptive language with minimal emotional valence; and negative reviews contained predominantly negative language with negative emotional valence. Finally, user rating is measured on a continuous scale from one to five, with five indicating the highest satisfaction, serving as a control variable to provide an alternative measure of satisfaction, and, as a covariate, isolating the unique contributions of the other predictor variables beyond general satisfaction effects.

The analysis employed a Python statistical computing environment using Pandas for data manipulation, Scikit-learn for preprocessing, and StatsModels for more advanced statistical modeling. The study consisted of a four-stage analytic process in which the researchers built an understanding and systematically tested the research hypothesis in accordance with the research design defined by the model, which used regression specifications for the data. The first stage consisted of extensive data preparation and preprocessing of raw data into formats suitable for statistical analysis. All categorical variables, which included season, location type, duration, budget, and review sentiment, were encoded into numerical dummy variables using standard dummy coding (i.e., coding a categorical variable with k number of categories with k-1 dummy variables, with one of the categories set as the reference category). The reference categories were defined as spring for season, city for location type, short for duration, low for the budget, and neutral for sentiment. This allowed each regression coefficient to be interpreted as

the difference from the reference category while holding other variables constant. Travel group size, while discrete, was treated as continuous based on an ordered scale and a narrow range, providing greater statistical power than a categorical approach.

The second stage consisted of an extensive exploratory analysis to become familiar with variable distributions, detect possible data quality issues, and examine bivariate relations. Calculating summary statistics, such as means, standard deviations, and frequency distributions, was performed for all variables. The third stage used hierarchical multiple linear regression to test Hypotheses 1 and 2 about main and interaction effects. In this approach, predictor variables are entered in sequential blocks, and at each successive step, it is assessed whether entering that block significantly improves the model's fit. Model 1 included all independent variables' main effects, testing whether there were significant average differences in recommendation scores across seasons, location types, trip durations, and budget categories, as well as whether travel group size and average spending were linearly associated with the outcome variables. Model 2 is built on Model 1 by introducing theoretically-driven interaction terms that test multiplicative combinations of specified predictors. Meaningful interactions in Model 2 included: budget category × average daily spending to assess the value alignment hypothesis, and seasons × location type to determine the contextual congruence hypotheses. The fourth stage of analysis involved a mediation analysis to test Hypothesis 3, assessing the mediating role of review sentiment in the relationship between trip objective characteristics and recommendation scores. The study used a bootstrapping method with 5,000 resamples and a gold-standard approach to avoid normality assumptions for sampling distributions of indirect effects.

Results

Descriptive statistics and preliminary analysis

The dataset of 2,101 reviews featured a wide variety of tourist experiences. The data were fairly evenly distributed across seasons. Spring was most common (24.1%), with Autumn (22.5%) and Monsoon (21.2%) close behind. People visited Beaches (20.8%) and Hill Stations (19.1%) most often. Most reviews were positive—48.3% were Positive, 31.5% were Neutral, and only 20.2% were Negative. The average rating was 3.21 out of 5, and the average recommendation score was 69.85 out of 100. This shows people were generally satisfied, though opinions varied quite a bit. The correlation matrix revealed many statistically significant bivariate relationships. Most notably, the User_Rating and Recommendation_Score were highly correlated ($r = 0.817$, $p < .001$), warranting their inclusion in the model as covariates. Review_Sentiment (dummy-coded) also showed strong correlations with the variable of interest.

Regression analysis predicting recommendation score

The statistical test strongly supported our predictions (H1 and H2). The first model, which looked at basic factors only, was significant and explained 54% of the differences in recommendation scores. When we added interaction effects in the second model, it performed even better - explaining 57% of the differences. This 3% improvement was meaningful and statistically significant. Overall, the final model was highly significant, meaning our factors do a good job of predicting recommendation scores. As shown in Table 1, several factors affected recommendation scores as predicted. Traveling in Autumn ($\beta = 2.85$, $p = .011$), visiting Cultural Sites ($\beta = 4.35$, $p = .001$) or Hill Stations ($\beta = 3.88$, $p = .002$), and taking longer trips all led to higher scores.

Table 1: Hierarchical Multiple Regression Predicting Recommendation_Score (Final Model)

Predictor	β Coefficient	Std. Error	p-value
(Constant)	41.55	2.10	<.001
Contextual Factors			
Season_Autumn	2.85	1.12	.011
Season_Winter	1.45	1.18	.218
Season_Summer	0.92	1.15	.424
Season_Monsoon	-3.11	1.14	.006
Location_Beach	2.10	1.25	.093
Location_Cultural	4.35	1.30	.001
Location_HillStation	3.88	1.28	.002
Location_Wildlife	1.95	1.32	.140
Location_Adventure	1.77	1.29	.171
Duration_Medium	1.22	0.89	.170
Duration_Long	2.89	0.92	.002
Travel_Group_Size	-1.81	0.45	<.001
Economic Factors			
Budget_Medium	1.55	1.01	.125
Budget_High	2.10	1.22	.085
Avg_Spending_per_day	0.01	0.01	.185
Interaction Terms			
Budget_High Spending	5.45	1.15	**<.001**
Season_Monsoon Beach	-6.82	2.10	**.001**
Covariate & Mediator			
User_Rating	11.92	0.35	**<.001**
Sentiment_Positive	16.45	1.05	**<.001**
Sentiment_Negative	-12.88	1.21	**<.001**

Note: Reference categories: Season_Spring, Location_City, Duration_Short, Budget_Low, Sentiment_Neutral.

However, traveling during Monsoon season ($\beta = -3.11$, $p = .006$) and going with larger groups ($\beta = -1.81$, $p < .001$) led to lower scores. The combination of Monsoon and Beach was especially problematic ($\beta = -6.82$, $p = .001$). Importantly, for travelers with high budgets, spending more per day significantly increased their recommendation scores ($\beta = 5.45$, $p < .001$), suggesting that when people have more money to spend, using it enhances their satisfaction. Overall, these findings confirm that both the travel context and how well spending aligns with budget are important for satisfaction.

Mediation analysis results

The mediation analysis, implemented using bootstrapping with 5,000 resamples to ensure robust, reliable inference, provided strong, comprehensive support for the third hypothesis regarding the mediating role of review sentiment in the relationship between trip characteristics and recommendation scores. The analysis tested the mediation model for several key independent variables, including specific location types and critical interaction terms, to demonstrate that the mediating mechanism operates across different types of trip characteristics. The results are systematically summarized in Table 2, which presents the total, direct, and indirect effects, along with bootstrap confidence intervals for the indirect effects. For the location type of adventure destinations, the total effect on the recommendation score, representing the overall relationship between choosing an adventure destination and the recommendation score without considering the mediator, was positive and significant, with a coefficient of 5.91 ($p < .01$). This total effect can be decomposed into two components. The direct effect, representing the effect of adventure location type on recommendation score that operates through pathways other than review sentiment, remained positive and significant, with a coefficient of 3.80 ($p < .05$). The indirect effect, representing the portion of the total effect that is transmitted through the mediating pathway where adventure location influences review sentiment, which in turn influences recommendation score, was also positive and substantial with a coefficient of 2.11.

Table 2: Mediation analysis results for the indirect effect of trip characteristics via review sentiment

Independent Variable (X)	Total Effect (c)	Direct Effect (c')	Indirect Effect (ab)	95% Boot CI for (ab)
Location_Adventure	5.91	3.80	2.11	[1.25, 3.15]
Monsoon Beach	-8.95	-6.10	-2.85	[-4.12, -1.73]

$p < .05$, $p < .01$, $p < .001$

These results indicate that adventure tourism has a positive impact on recommendation scores, operating through two distinct pathways. Part of the positive effect is direct, perhaps reflecting objective features of adventure destinations such as uniqueness, excitement, and memorable activities that directly enhance evaluation regardless of emotional response. However, a substantial portion of the positive effect approximately 36% of the total effect in this case is mediated through review sentiment. Adventure destinations tend to generate more positive emotional responses in tourists, as evidenced by more positive sentiment in their written reviews, and this positive affective experience in turn elevates their final recommendation scores. This demonstrates that the appeal of adventure tourism lies not solely in its objective features but primarily in the positive emotions and feelings it generates in participants. For the interaction term between the monsoon season and beach destination, which the regression analysis showed was particularly detrimental to satisfaction, the mediation analysis revealed similar patterns operating in the negative direction. The total effect of this unfavorable combination on recommendation score was strongly negative with a coefficient of -8.95, significant at the $p < .001$ level, indicating that beach trips during the monsoon season produce dramatically lower recommendation scores than other combinations. This total negative effect can be decomposed into a direct effect of -6.10, significant at the $p < .01$ level, and an indirect effect of -2.85. The ninety-five percent bootstrap confidence interval for the indirect effect was negative 4.12 to negative 1.73, which again does not include zero, confirming significant mediation.

Discussion

This study offers robust, empirically-grounded evidence that a tourist's decision to recommend a destination or experience is a complex evaluative judgment forged in the crucible of interacting experiential, economic, and affective factors rather than a simple summation of isolated service attributes. The findings compellingly demonstrate that contextual factors, including season, location type, trip duration, and travel group size, exert their influence not in isolation through simple additive effects, but through their configuration and interaction, creating experiential synergies and conflicts that cannot be predicted from examining each factor separately (Cheng et al., 2024). The positive valuation of autumn season travel aligns well with theories of optimal arousal and environmental comfort, which hold that pleasant climatic conditions characterized by moderate temperatures, lower humidity, and often beautiful natural scenery maximize the hedonic value of outdoor experiences. Similarly, the strong positive effects associated with cultural and hill station destinations align with the Experience Economy framework, which posits that destinations that offer rich educational content, aesthetic beauty, and opportunities for escapist immersion generate higher satisfaction than generic urban experiences (Li et al., 2025). The strong negative effect of larger travel groups reveals an essential and frequently overlooked social aspect of travel evaluation frameworks (Gim et al., 2024). This result indicates that the logistical difficulties of managing the activities, tastes, and schedules of more than one traveler, along with the necessary compromise in individual wishes required by group travel, may diminish the overall value of the experience even in cases of a desirable destination and good service. A single traveler or a couple may act spontaneously, change their plans without notice, and pursue their own interests without negotiating with others. The larger the group, the more they face logistical coordination, and the travel plans of larger groups necessitate compromise among competing desires. This complexity of social interaction adds an extra layer of consideration when designing and marketing tourism experiences, suggesting that group packages should address the fragile coordination aspect and include mechanisms of flexibility to mitigate the decline in satisfaction. The investigation of economic factors provided particularly subtle and theoretically worthwhile insights that advance understanding of how economic factors influence tourism satisfaction. The significant positive interaction between the high-budget category and average daily spending provides strong evidence in favor of the value alignment hypothesis rooted in cognitive dissonance theory (Ding et al., 2026). This finding econometrically demonstrates that it is not merely the amount of money spent that leads to tourist satisfaction, but the alignment of financial preparedness with psychological prospection. Specifically, when high-margin travelers have successfully prepared themselves psychologically to spend money and do spend money, they interpret this as robust evidence that they received premium experiences at premium

prices, and they experience satisfaction both in terms of value realization and the price paid (Shu et al., 2026). Conversely, when budget-limited travelers are surprised to find themselves spending more than expected, they experience cognitive dissonance and do not experience satisfaction, regardless of the objective level of quality, because their spending violates the price they were prepared to pay (Wang & Li, 2024).

This advanced perspective on tourism economics reflects a move away from simple views of "more spending means better experiences," or "value seems like cheap," and towards a more sophisticated psychologically-based model where perceived value arises as the function between expectations and realities, not from the levels of price or quality on their own (Wu et al., 2024). This perspective has profound implications for pricing strategy, market segmentation, and communication in tourism marketing. It suggests that successful businesses must not only provide quality experiences but also carefully manage customers' expectations and ensure that the price-experience relationship aligns with the psychological frames customers bring to their travel experiences. For example, a luxury resort that offers discounted pricing to attract budget travelers may create dissatisfaction among these travelers despite providing a quality experience and great service when they encounter on-site costs exceeding their expectations based on the discounted rates. On the other hand, the same is true for the opposite perspective, where full-pays would not be dissatisfied as long as they show up with a much more reasonable expectation. Most importantly for advancing the theory of tourism, the mediation analysis provides evidence of the centrality of affect, as designated by review sentiment, in the process of tourist evaluation (Eberle et al., 2025). Review sentiment was not only a correlate of or an outcome of the final score, but also a legitimate psychological mechanism that helps explain how objective trip conditions are operationalized in numerical evaluation (Zhang et al., 2024). This result addresses an essential gap in the tourism literature, providing data-based evidence of the psychological pathway that demonstrates how experiential factors produce behavioral outcomes. Given how we understood the size of mediation effects of about thirty to thirty-five percent of total effects across the relationships being tested, it is fair to say, to a moderately substantive and meaningful level, that the tourist's subjective evaluation of what they experienced was accounted for by their affective response to that experience (Yang & Hsu, 2026).

This repositions emotion as not merely a derivative/symbolic after effect or epiphenomenon of satisfaction that mirrors the evaluations respondents are eventually inclined to construct; instead, it asserts that emotion is a necessary aspect of the evaluative process capable of affecting, shaping, and defining ultimate judgments - whether good or bad (disappointment, frustration, boredom, anger) (Yu et al., 2024). The affective valence of any experience will amplify and filter how service quality perceptions will impact an ultimate evaluative outcome, such as satisfaction. For example, a positive affective state can have a halo effect, leading to forgiveness even of the most minor service mishaps, and a negative affective state can have a horns effect, leading to negative and/or intentional interpretations of even the best service efforts (Borghi & Mariani, 2024). As more researchers (strongly) argue, this represents a paradigm shift in our theoretical elucidation of service quality, from viewing emotion as an effect to understanding it as a cause and a new mechanism. Therefore, the implications of this conceptual shift will inform how we think about and manage tourism and leisure experiences. These findings add to and reinforce previously established tourism facts from the larger body of tourism research over the decades. The seasonal and location type findings reinforce and corroborate recognition of the significance of contextual factors that recently surfaced in tourism geography and climate change studies, but the meaningful interaction effects between location and season indicated a more sophisticated and nuanced picture than the main effects models that punctuate much of the empirical literature (Teichert et al., 2023). The fact that the particular season can affect satisfaction levels at dramatically different amounts, depending on location type, and that similar location type has various effects on satisfaction levels depending on season, indicates the importance of moving beyond variable-based analyses toward configuration-based analysis in tourism research (Albayrak et al., 2024).

Theoretical contributions

This research makes notable and lasting contributions to tourism theory by developing the conceptual and empirical underpinnings of the field. First, and most fundamentally, this study achieves a successful integration across several dominant, widely used, yet often applied individually, theoretical frameworks. These include service quality approaches typified by SERVQUAL (Sacristán-Díaz et al., 2025); the experience economy (Zheng & Cham, 2025); perceived value (Shu et al., 2026); and affective events theory (Eberle et al., 2025). This unifying, multi-factorial model shows how these frameworks each describe complementary rather than competing parts of the tourist evaluation process. The empirical validation of this model suggests that service quality, experiential richness, economic value, and emotional responses are not competing alternative explanations for satisfaction with a tourist experience, but somewhat interrelated dimensions of a holistic process that need to be understood in relation to one another. This contribution is an essential step toward a more fully developed grand theory of the tourist experience and evaluation, a vision long envisioned in the field (Lekmiti et al., 2024). The second significant theoretical contribution stems from the methodological, empirical assessment and validation of review sentiment as a central mediating variable in the tourist appraisal process--distilling it from an additional or behavioral entry examined primarily in marketing/online review contexts to a psychological mechanism with space in central tourism theory (Zhang et al., 2024). This study has shown statistically that review sentiment serves as an affective pathway to convert a considerable portion of the effects of objective trip characteristics on recommendation scores (Yang & Hsu, 2026). By supporting the case for a specific causal process model that may be leveraged in future theoretical development, this study positions emotion, or sentiment, not as a peripheral location in tourism theory as a soft or subjective factor, but as the mechanism all processes of appraisal converge as objective experiences are transformed into subjective evaluations and behavioral intentions (Yu et al., 2024).

Moreover, by accentuating and empirically demonstrating interactional effects, rather than solely focusing on main effects, the work disrupts simplistic, linear, additive models of satisfaction that have dominated much tourism research. The

study provides a strong argument for adopting a contextually and configurationally oriented approach to tourism inquiry. The important interactions between season and location type, and between budget and spending, illustrate that the question "what makes tourists satisfied" cannot be answered by a simple list of factors and must consider how factors combine and work together in particular contexts (Cheng et al., 2024). This represents a move away from a variable-centred approach toward a configuration-centred one, which more accurately captures the situated, holistic nature of real tourism experiences. The conceptual model, developed and validated in this study, which positions sentiment as a mediating mechanism between configurations of experience and evaluative outcomes, represents one crucial initial step toward a more sophisticated, empirically-based theoretical approach to tourist evaluation. The third theoretical contribution is the formalization and empirical exploration of the value alignment hypothesis in tourism economics, which presents a new psychological mechanism of how financial factors drive satisfaction (Ding et al., 2026). Given that perceived value has been established as an essential factor of satisfaction in the tourism literature, this study explains and examines a specific cognitive process of value perception as a consequence of cognitive dissonance arising from the congruence or incongruence between budgeted expectations and actual spending behavior (Wang & Li, 2024). The study provides empirical evidence that the interaction of budget and spending is a stronger predictor of outcomes than either budget or spending alone, thus moving from metrics of absolute financial elements such as price or total spending to relational financial metrics that reflect the fit of expectations to actual expenditures (Wu et al., 2024). This moves towards a more robust psychological explanation of tourist economic behavior and opens avenues for future theoretical work into decision-making, value perception, and post-purchase evaluation processes.

Managerial implications

The practical implications of these findings are significant and actionable for tourism managers, destination marketers, hospitality operators, and policymakers, and they offer evidence-based direction for improving tourist satisfaction and destination competitiveness (Theodorakopoulos et al., 2025). First, the findings provide a strong encouragement for tourism decision-makers to pivot from a destination marketing, one-size-fits-all approach to precision marketing and dynamic product bundling grounded in contextually validated combinations. Destination Marketing Organizations (DMOs) and tour operators ought to proceed to systematically utilize the data presented in this research regarding high-scoring contextual combinations (for example, cultural tours in the autumn season or stays in hill stations for a longer duration), to create and then actively market travel packages that can marry destination attributes with the best time and social context(s). By marketing destinations in season and in contextual combinations where they perform best, DMOs can systematically increase the proportion of visitors who enjoy their visit and provide good online ratings, ultimately improving a destination's reputation (Koustoumpardi et al., 2025). In the case of difficult pairings, such as beach vacations during monsoon seasons, which the findings identified as particularly dissatisfaction-inducing, managers should be counterproductive, rather than merely managing reduced visitation through unfavorable periods. Therefore, managers could pursue proactive creativity by announcing and marketing proactive value propositions that reinterpret a potential negative into a unique positive; e.g., use monsoon beach destinations in marketing as places to experience "storm watching experiences"; offer complementary indoor alternative attractions (such as cultural workshops, cooking classes, spa treatments or retreats, and wellness retreats); promote monsoon related festivals and cultural experiences that give tacit justification or reasons for tourists to visit when the core golf premise is degraded (Tunca, 2025). This reframing of events and proactive product development are strategies for turning low seasons into niche tourism opportunities that can mitigate dissatisfaction and negative word of mouth among targeted market segments. Secondly, the confirmed significance of value alignment between budget expectations and actual spending necessitates a fundamental strategic redesign of pricing, value management, and communications strategies in hospitality and tourism businesses (Ding et al., 2026). The research has indicated clearly that, for satisfaction to be generated, simply providing low prices to entice customers or high quality of service is insufficient if price and quality signals do not align with customer expectations (Shu et al., 2026). The key to satisfaction is in managing the customer's perception of value congruence by ensuring there is transparency, clarity, and congruence between the price point at which an experience is being marketed, the quality of experience that is promised via marketing communications, and the actual expenditure required during the trip to access the fully experienced quality experience (Van Vaerenbergh & Arijs, 2025).

Implementing transparent cost communications entails clearly laying out the components of the base price and reasonable additional costs that tourists might incur during the trip, to inform their budget decisions before they commit to travel. Similarly, tourism businesses should consider offering a well-defined package of services with a clear differentiation between tiered levels, such as basic economy, standard level, and premium luxury, which will allow tourists to identify their level of spending and willingness to pay, relative to their budget level and expectations (Wu et al., 2024). For the higher-budget market segment, this would mean consciously creating premium experiences that incorporate luxury elements, exclusivity, personalized service, or unique experiences that tourists would recognize as worth the premium price, as a function of a service commensurate with the high price paid for the experience. For the lower-budget category, this means ensuring the core experience is delivered expertly and entirely within the budget, without additional costs, surprise charges, or required upgrades that would push travelers over budget and create unanticipated negative dissonance (Biswas, 2025).

Lastly, the significant mediating function of affective sentiment identified in the mediation analysis demands a more comprehensive and affirmative stance to both emotion management and reputation management in tourism operations (H. Zhang et al., 2025). The practice of monitoring online reviews needs to expand beyond simply tracking the star rating above the review to include systematic, automated sentiment analysis of the actual review text and content, using available and reasonable natural language processing tools (Cheng et al., 2024). By obtaining reviews and the expressed sentiments, along

with any indicators for various trip aspects or service components associated with frequent occurrences of negativity-happenstance or emergence of social or nonsocial stress responses such as crowding, disappointment, boredom, frustration be able to address service components associated specific with those emotions or responses will provide greater operational improvement in the tour (Guan et al., 2025). For example, if I analyze the sentiment and discover that large travel cohorts of adventurers frequently express frustration and stress in their reviews, then this would clearly give me some actionable intelligence on developing better group coordination services, separate group facilities, or even client training on group management techniques (Sann et al., 2024). Additionally, because sentiment mediates between objective experience(s) and evaluations (conclusions), managing guests' emotional experiences during their journey significantly and directly affects the sentiment they express in online reviews and, therefore, recommendation scores (Eberle et al., 2025). This is done by training staff in frontline service delivery to observe the emotional cues in guests, to empathetically respond to moderate levels of dissatisfaction before it escalates from temporary to long-lasting negative sentiment, by creating emotional positive highlights through surprise delights or memorable moments of service, and to pay attention in general to the affective part of service experience on par with the functional part (Orea-Giner et al., 2025). By managing the affective experience of service design and delivery proactively, tourism firms can take more control of the sentiment formation process and potentially turn an "it was just satisfactory - it met my functional needs" trip into a memorable positive emotional experience that people express when they are recommending enthusiastically, and generating positive word-of-mouth (Park et al., 2024).

Limitations and future research directions

This research paper recognizes various methodological shortcomings that should be accounted for. Firstly, using a single online platform may introduce platform-specific bias in user demographics, interface design, and community norms. Moreover, self-selected reviews and a convenience sampling approach may over-represent reviewers who have experienced extreme situations relative to those based on moderate experiences, limiting the generalizability of the findings to a larger tourism population. Secondly, automated sentiment classification may be a rapid way to analyze large-scale data. Still, it cannot adequately account for the inherent complexity and intensity of human emotion. It may fail to distinguish between emotional subtypes, understand sarcasm, account for cultural differences in expression, or handle mixed emotional states. Thirdly, numerous demographic, psychographic, and contextual variables relevant to sentiment were not analyzed, such as age, gender, nationality, cultural backgrounds, travel experience, personalities, and motivations, all of which likely moderate the relationships identified and represent boundary conditions that were not examined in this research. Future research should corroborate findings across multiple platforms, apply more advanced aspect-based sentiment analysis validated by manual coding, include relevant primary data collection using representative sampling, and systematically analyze the potential moderating effects of travelers' characteristics to explore the generalizability and boundary conditions of the relationships established in the study.

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