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Multidimensional Emotional Structures and Intention-Expression Signals in Online Tourism Reviews

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Abstract

Tourism analytics has traditionally relied on sentiment polarity to explain behavioral outcomes, yet emotional expression in online reviews is inherently multidimensional. This study examines how four theoretically grounded emotional dimensions-valence, intensity, authenticity, and affective complexity-are associated with the explicit articulation of revisit intention in review text. Drawing on 7,500 English-language Trip.com reviews (2020-2024), emotional features were extracted using a hybrid NLP pipeline combining fine-tuned BERT classification with lexicon-based arousal scoring and linguistic indices. Revisit intention was operationalized as an explicit intention-expression signal within textual narratives, rather than as a survey-derived attitudinal construct. Logistic regression tested dimensional associations, while K-means clustering identified latent emotional profile types across the corpus. Results indicate that positive valence, greater emotional intensity, and higher affective complexity are each significantly associated with revisit intention expression, whereas emotional authenticity shows no significant direct association. Cluster analysis further reveals distinct emotional configurations that differ systematically in intention-expression prevalence. By reconceptualizing revisit intention as a communicative signal and modeling emotion as a multidimensional structure, this study advances emotion-aware computational analysis in tourism research. The integration of supervised and unsupervised analytics offers a scalable framework for examining how emotional structure shapes behavioral signaling in digital review environments.

Keyword : affective complexity, emotional authenticity, emotional expression, online tourism reviews, sentiment valence

1. Introduction

The COVID-19 pandemic has significantly reshaped the global tourism environment, intensifying uncertainty in travelers' decision-making and driving greater reliance on peer-generated online reviews as primary sources of evaluative information [1]. Within contemporary digital tourism ecosystems, review platforms have evolved beyond simple information repositories into technologically mediated environments where trust, safety perceptions and destination attractiveness are socially constructed and algorithmically filtered. Notably, reviews have grown increasingly emotionally expressive, with vivid experiential

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narratives enabling prospective tourists to mentally simulate travel experiences-a function particularly salient in post-pandemic contexts characterized by heightened affective sensitivity [2].

Despite this emotional richness, much of the existing literature continues to rely on reductive indicators such as star ratings or binary sentiment polarity [3][4], which insufficiently capture the multidimensional structure of emotion emphasized in Appraisal Theory [5] and the Affect-as-Information framework [6]. While recent hospitality and tourism technology research has highlighted the value of advanced analytics and emotion-aware systems [7], existing computational approaches often prioritize predictive accuracy over theoretical grounding, resulting in models that are technically efficient but psychologically simplistic.

To address this gap, this study conceptualizes emotional expression in online tourism reviews as a four-dimensional construct comprising valence, intensity, authenticity and complexity, and examines two research questions: (1) How are multidimensional emotional features associated with revisit intention signals in user-generated reviews? (2) Do emotion-based clusters reveal differentiated behavioral signaling patterns within digital tourism platforms? By integrating appraisal-informed emotion theory with scalable NLP methods, this study advances tourism sentiment analytics beyond polarity-based models, contributing a theoretically grounded framework for emotion-aware recommendation and engagement optimization in intelligent tourism systems.

2. Theoretical Background and Hypotheses Development

2.1 Theoretical Background

Appraisal theory provides a conceptual lens for understanding how emotional expressions in reviews may shape perception and behavioral signaling. Rooted in cognitive theories of emotion, appraisal perspectives suggest that emotional responses emerge from individuals' evaluations of how events relate to their goals, values and situational context [8], generating motivational orientations such as approach, avoidance and information-seeking.

In tourism contexts, which are inherently experiential and hedonic [9], emotions play an important role in shaping expectations, satisfaction and post-consumption expressions such as review writing and recommendation [10]. Online reviews function not only as informational signals but also as affective simulations enabling prospective tourists to anticipate how they might feel in similar situations [11]. Crucially, appraisal theory implies that readers actively re-evaluate emotional narratives through their own cognitive schemas rather than passively absorbing them [8], a process that may shape how behavioral intentions are articulated in digital review environments.

Despite this theoretical richness, empirical eWOM research in tourism has largely relied on simplified metrics such as sentiment polarity or average star ratings [3][4], which capture evaluative direction but overlook the structural complexity of emotional expression. Recent work in affective computing and psychological linguistics suggests that emotion can be more fully represented along four distinct dimensions: valence (positive-negative orientation), intensity (arousal strength), authenticity (perceived sincerity) and complexity (co-occurrence of mixed emotions) [12][13]. These dimensions capture distinct aspects of emotional communication and may operate differently within review narratives-authenticity has been linked to credibility in online contexts [14], while complexity has been associated with narrative realism and cognitive elaboration [15].

Accordingly, this study examines how these four theoretically informed dimensions are associated with revisit intention signals in user-generated tourism reviews, integrating appraisal-informed theory with computational text analysis to offer a structured framework for analyzing emotional expression in digital tourism environments.

2.2 Hypotheses Development

2.2.1 Sentiment Valence

Sentiment valence represents the evaluative direction of emotional expression, indicating whether an experience is appraised as favorable or unfavorable. Within appraisal theory, positive appraisals are associated with goal congruence and approach-oriented motivational tendencies, whereas negative appraisals signal goal incongruence and withdrawal. Prior empirical research consistently shows that positive review tone is associated with favorable destination image, satisfaction and behavioral intentions such as revisit and recommendation [16]. In digital review settings, positive valence may therefore increase the likelihood that revisit-related signals are explicitly articulated within the narrative.

H1. Greater positive sentiment valence in an online tourism review is positively associated with revisit intention signals.

2.2.2 Emotional Intensity

Emotional intensity refers to the magnitude or arousal level of emotional expression. Unlike valence, intensity is evaluatively neutral-both strongly positive and strongly negative experiences may be expressed intensely. High-arousal messages tend to attract attention and enhance cognitive elaboration [17], and contemporary affective computing research suggests that arousal amplifies evaluative signals rather than replacing them. In digital tourism reviews, emotionally intense narratives may increase expressive vividness, making behavioral signals more likely to be explicitly verbalized.

H2. Higher emotional intensity in an online tourism review is positively associated with revisit intention signals.

2.2.3 Emotional Authenticity

Emotional authenticity refers to the perceived sincerity and genuineness of emotional expression, and has been linked to credibility and message diagnosticity in online environments [14]. Importantly, authenticity does not imply positivity-a sincerely expressed negative experience may be highly authentic yet discourage revisit. This study therefore conceptualizes authenticity as a credibility-enhancing dimension associated with the communicative explicitness of behavioral signals, without presupposing directional positivity.

H3. Greater emotional authenticity in an online tourism review is associated with revisit intention signals.

2.2.4 Affective Complexity

Affective complexity refers to the co-occurrence of multiple emotional states within a single narrative, reflecting the multidimensional and ambivalent nature of tourism experiences [15]. Emotionally nuanced reviews acknowledging both positive and negative aspects are perceived as more diagnostic and credible, and may prompt elaborative cognitive processing that increases the likelihood of behavioral positions being explicitly articulated [5].

H4. Greater affective complexity in an online tourism review is associated with revisit intention signals.

2.2.5 Emotional Clustering

Emotional dimensions in online reviews rarely operate in isolation but tend to co-occur in structured patterns that collectively shape communicative styles [18]. This study applies K-means clustering to the four standardized emotional dimensions to identify latent emotional profiles, examining whether distinct emotional configurations correspond to differentiated patterns of intention-expression signaling within digital review environments.

H5. Emotion-based clusters of online tourism reviews exhibit significant differences in revisit intention signals.

3. Material and Methods

This study adopts a mixed-methods research design integrating natural language processing, machine learning and statistical modeling to examine how emotional expressions in online reviews are associated with tourists' revisit intentions. The analytical framework unfolds across three stages: systematic data collection, multidimensional emotion feature extraction, and the application of regression-based hypothesis testing alongside unsupervised clustering.

A stratified sampling approach was used to collect 7,500 English-language reviews from Trip.com, evenly distributed across five globally recognized landmarks-the Eiffel Tower, Colosseum, Central Park, Tokyo Tower and Gyeongbokgung Palace-with 300 reviews per location per year spanning 2020 to 2024. Reviews were retained only if originally written in English and containing at least seven meaningful words, with duplicates removed via text similarity algorithms. Descriptive statistics for the final dataset are presented in [Table 1].

[Table 1] Descriptive Statistics of Trip.com Reviews

place	year	avg_rating	std_rating	avg_word_count	N
Eiffel Tower (France)	2020	4.005	0.811	11.33	300
	2021	3.997	0.800	12.09	300
	2022	4.010	0.802	9.44	300
	2023	3.967	0.820	10.23	300
	2024	3.976	0.812	11.45	300
Colosseum (Italy)	2020	4.005	0.811	12.01	300
	2021	4.006	0.812	10.04	300
	2022	4.005	0.811	13.23	300
	2023	4.033	0.824	12.88	300
	2024	3.953	0.830	12.26	300
Central Park (USA)	2020	4.005	0.785	11.29	300
	2021	4.003	0.795	9.53	300
	2022	4.000	0.826	12.97	300
	2023	3.985	0.809	9.75	300
	2024	4.003	0.822	11.49	300

Tokyo Tower (Japan)	2020	3.943	0.787	12.34	300
	2021	4.023	0.802	10.7	300
	2022	3.993	0.837	12.27	300
	2023	4.020	0.791	12.83	300
	2024	3.943	0.812	12.7	300
Gyeongbokgung Palace (South Korea)	2020	4.053	0.790	11.49	300
	2021	4.037	0.784	12.88	300
	2022	4.030	0.854	10.71	300
	2023	4.023	0.793	11.74	300
	2024	3.993	0.804	10.95	300

Following data preparation, four emotional dimensions were operationalized from review text. Sentiment valence was computed using a fine-tuned mBERT model achieving 91.3% accuracy and a macro F1-score of 0.91, with inter-annotator reliability of Cohen's $\kappa = 0.89$. Emotional intensity was derived from the absolute polarity score complemented by an NRC Lexicon-based arousal index. Emotional authenticity was constructed as a composite linguistic index capturing first-person pronoun frequency, affective adjectives and syntactic elaboration markers. Affective complexity was measured using entropy-based sentiment co-occurrence metrics reflecting the degree to which positive and negative cues co-occur within a single review. The dependent variable, revisit intention, was identified through rule-based pattern matching of explicit intention expressions, validated through manual coding of a 10% subsample with 92% inter-coder agreement and coded dichotomously.

The analytical framework consists of two sequential phases. In Phase I, multiple logistic regression was employed to test the associations between the four emotional dimensions and revisit intention, controlling for review length via log-transformed word count. Model robustness was evaluated using VIF diagnostics, AUC and pseudo-R^2. In Phase II, K-means clustering was applied to the four standardized emotional features to identify latent emotional profiles, with the optimal solution of $k = 3$ confirmed by both the Elbow method and Silhouette coefficient. Cluster robustness was validated through hierarchical agglomerative clustering and DBSCAN, both yielding consistent three-cluster structures. Group differences in revisit intention across clusters were subsequently tested using one-way ANOVA with Tukey's HSD post-hoc comparisons.

3. Results

The logistic regression results revealed that three of the four emotional dimensions significantly predicted revisit intention. Sentiment valence ($\beta = 0.316$, $p < 0.001$) and emotional intensity ($\beta = 0.213$, $p < 0.001$) were both positively associated with revisit intention, supporting H1 and H2 respectively. Positive emotional tone may foster psychological affinity toward a destination, consistent with appraisal theory's notion that positive evaluations trigger approach-oriented behaviors (Scherer, 2005), while emotional intensity amplifies message salience and cognitive engagement regardless of polarity (Berger, 2011). Affective complexity was also positively associated with revisit intention ($\beta = 0.147$, $p < 0.001$), supporting H4, suggesting that emotionally layered narratives are perceived as more realistic and persuasive, thereby enhancing behavioral signaling. Emotional authenticity, however, returned a negative but non-significant coefficient ($\beta = -2.725$, $p = 0.103$), leaving H3 unsupported. Although authentic expression is generally linked to trustworthiness, it may simultaneously surface problem-focused or mixed content that dampens revisit motivation. The overall model demonstrated strong fit, with a pseudo-R^2 of 0.227 and an AUC of 0.81. Results are summarized in [Table 2].

[Table 2] Impact of Emotional Dimensions on Revisit Intention

Hypothesis	Independent Variable	Coefficient (β)	SE	p-value	Support
H1	Sentiment Valence	0.316	0.045	< 0.001	Supported
H2	Sentiment Intensity	0.213	0.038	< 0.001	Supported
H3	Emotional Authenticity	-2.725	1.820	.103	Not Supported
H4	Affective Complexity	0.147	0.030	< 0.001	Supported

K-means clustering further revealed three distinct emotional profiles that differed systematically in revisit intention. High-Intensity Complex Emoters (Cluster 2), characterized by strong positive sentiment and high emotional intensity, exhibited the highest mean revisit intention ($M = 0.298$). Sincere Negatives (Cluster 1), despite high authenticity, showed the lowest revisit intention ($M = 0.031$), reflecting how emotionally subdued or problem-oriented narratives inhibit approach behaviors even when perceived as sincere. Low-Affect Neutralists (Cluster 0) occupied an intermediate position ($M = 0.113$), representing emotionally neutral or ambiguous expressions. One-way ANOVA with Tukey's HSD post-hoc tests confirmed that all pairwise differences were statistically significant ($p < .001$), underscoring that emotional profiles-rather than individual dimensions alone-shape behavioral signaling in distinct and meaningful ways. Results are presented in [Table 3].

[Table 3] Mean Revisit Intention by Emotion-Based Cluster

Cluster	Mean Revisit Intention	Interpretation	Post-hoc Comparison (Tukey HSD, $p < .001$)
High-Intensity Complex Emoters (2)	0.298	High revisit intention; characterized by strong positive sentiment and intensity	Significantly higher than Clusters 0 and 1
Sincere Negatives (1)	0.031	Lowest revisit intention; associated with low or negative sentiment and weak expression, despite high authenticity	Significantly lower than Clusters 0 and 2
Low-Affect Neutralists (0)	0.113	Moderate revisit intention; emotionally neutral or ambiguous group	Significantly different from Clusters 1 and 2

4. Conclusion

The findings extend sentiment-based tourism research by demonstrating that emotional intensity and affective complexity exhibit independent associations with revisit intention signals, beyond the well-established role of sentiment valence, supporting a multidimensional interpretation of emotion grounded in appraisal theory [5]. The non-significant effect of emotional authenticity suggests it may operate as a credibility amplifier rather than a direct predictor of favorable behavioral signaling. The integration of clustering alongside regression modelling further demonstrates that emotional dimensions co-occur in structured configurations that differentiate communicative styles of behavioral articulation in ways that linear analysis alone cannot reveal.

For digital tourism platforms, review-ranking algorithms relying solely on star ratings or binary sentiment classification may overlook emotionally salient narratives carrying higher communicative impact, and incorporating multidimensional emotional metadata-particularly intensity and complexity-into filtering mechanisms may improve content personalization. Destination marketers are similarly advised to encourage emotionally vivid and evaluatively clear storytelling, while exercising caution around authenticity-focused strategies.

Several limitations should be noted. Revisit intention was operationalized as a textual signal rather than observed post-visit behavior, the dataset is restricted to English-language reviews from a single platform, and the exclusive focus on textual features overlooks multimodal affective cues prevalent in digital tourism communication. Future research should integrate behavioral outcome data, pursue cross-cultural analyses, expand emotion modelling to multimodal contexts, and explore the transferability of the proposed framework to other cultural media-including digital games, films, and animation-where affective stimuli similarly shape audience perceptions and behavioral orientations [19].

References

[1] S. Y. Bae and P. J. Chang, "The effect of coronavirus disease-19 (COVID-19) risk perception on behavioural intention towards 'untact' tourism in South Korea," *Current Issues in Tourism*, vol. 24, no. 7, pp. 1017-1035, Jul. 2021, doi: 10.1080/13683500.2020.1798895.

[2] S. Gössling, D. Scott, and C. M. Hall, "Pandemics, tourism and global change: a rapid assessment of COVID-19," *Journal of Sustainable Tourism*, vol. 29, no. 1, pp. 1-20, Apr. 2021, doi: 10.1080/09669582.2020.1758708.

[3] Z. Zhang, X. Fu, L. A. Cai, and L. Lu, "Destination image and tourist loyalty: A meta-analysis," *Tourism Management*, vol. 40, pp. 213-223, Feb. 2014, doi: 10.1016/j.tourman.2013.06.006.

[4] K. L. Xie, K. K. F. So, and W. Wang, "Joint effects of management responses and online reviews on hotel performance," *International Journal of Hospitality Management*, vol. 62, pp. 101-110, Apr. 2017.

[5] K. R. Scherer, "What are emotions? And how can they be measured?," *Social Science Information*, vol. 44, no. 4, pp. 695-729, Dec. 2005, doi: 10.1177/0539018405058216.

[6] N. Schwarz and G. L. Clore, "Feelings and phenomenal experiences," in *Social Psychology: Handbook of Basic Principles*, 2nd ed., E. T. Higgins and A. W. Kruglanski, Eds. New York: Guilford Press, 2007, pp. 385-407.

[7] M. M. Mariani, R. Baggio, M. Fuchs, and W. Höepken, "Artificial intelligence and big data in tourism: A systematic review and research agenda," *Journal of Hospitality and Tourism Technology*, vol. 14, no. 1, pp. 1-23, Jun. 2023, doi: 10.1108/JHTT-12-2018-0118.

[8] K. R. Scherer and A. Moors, "The emotion process: Event appraisal and component differentiation," *Annual Review of Psychology*, vol. 70, pp. 719-745, Jan. 2019, doi: 10.1146/annurev-psych-122216-011854.

[9] J. Gnoth, "Tourism motivation and expectation formation," *Annals of Tourism Research*, vol. 24, no. 2, pp. 283-304, May 1997, doi: 10.1016/S0160-7383(97)80002-3.

[10] S. Hosany and D. Gilbert, "Measuring tourists' emotional experiences toward hedonic holiday destinations," *Journal of Travel Research*, vol. 49, no. 4, pp. 513-526, Oct. 2010, doi: 10.1177/0047287509349267.

[11] D. T. Gilbert and T. D. Wilson, "Prospection: Experiencing the future," *Science*, vol. 317, no. 5843, pp. 1351-1354, Sep. 2007, doi: 10.1126/science.1144161.

[12] J. A. Russell and L. F. Barrett, "Core affect, prototypical emotional episodes, and other things called emotion: Dissecting the elephant," *Journal of Personality and Social Psychology*, vol. 76, no. 5, pp. 805-819, [Month] 1999, doi: 10.1037/0022-3514.76.5.805.

[13] R. P. Bagozzi, M. Gopinath, and P. U. Nyer, "The role of emotions in marketing," *Journal of the Academy of Marketing Science*, vol. 27, no. 2, pp. 184-206, Spring 1999, doi: 10.1177/0092070399272005.

[14] T. Hennig-Thurau, K. P. Gwinner, G. Walsh, and D. D. Gremler, "Electronic word-of-mouth via consumer-opinion platforms," *Journal of Interactive Marketing*, vol. 18, no. 1, pp. 38-52, Winter 2004, doi: 10.1002/dir.10073.

[15] S. Ramanathan and A. L. McGill, "Consuming with Others: Social Influences on Moment-to-Moment and Retrospective Evaluations of an Experience," *Journal of Consumer Research*, vol. 34, no. 4, pp. 506-524, Jul. 2007, doi: 10.1086/520074.

[16] M. Jeong and S. Jang, "Restaurant experiences triggering positive electronic word-of-mouth (eWOM) motivations," *International Journal of Hospitality Management*, vol. 30, no. 2, pp. 356-366, Jun. 2011, doi: 10.1016/j.ijhm.2010.08.005.

[17] J. Berger, "Arousal increases social transmission of information," *Psychological Science*, vol. 22, no. 7, pp. 891-893, Apr. 2011, doi: 10.1177/0956797611413294.

[18] E. Cambria, B. Schuller, Y. Xia, and C. Havasi, "New avenues in opinion mining and sentiment analysis," *IEEE Intelligent Systems*, vol. 28, no. 2, pp. 15-21, Feb. 2013, doi: 10.1109/MIS.2013.30.

[19] H. Park and D. Kim, "Subliminal Priming in Cultural Content: Strategic Applications in Digital Games, Films, and National Soft Power," *Journal of Digital Media & Culture Technology*, vol. 4, no. 2, pp. 147-161, Dec. 2024, doi: 10.29056/jdmct.2024.12.06.