

Which Route Carries User-Generated Content? Disentangling the Cognitive, Affective and Trust Mechanisms of Travellers' Information Adoption

Xiaxuan Qu

*Beijing Luhe International Academy, Beijing, China
AllisonQU@163.com*

Abstract. The three mechanisms of user-generated content affecting tourists' decision-making, namely cognition, emotion and trust, are often put forward side by side in existing studies, but rarely compare the relative weight on the same batch of data. Based on the S-O-R framework and source credibility theory, this study operationalises the three paths as observable content and source attributes and tests them on 161541 real TripAdvisor travel reviews, taking the intensity of information adoption as the response variable. The independent variance contribution of the cognitive path is 0.0326, about 4.5 times that of the emotional path, and the standardised coefficient of information depth, 0.166, is the largest of all predictors. The emotional path is composed of two components in opposite directions: the coefficient of emotional intensity is 0.025, and the emotional positivity is negative 0.071. Source credibility has no positive direct effect once content characteristics are controlled, but its indirect effect through content depth is 0.031 with a confidence interval excluding zero. Credibility operates mainly through the content the publisher writes, not through the identity label itself.

Keywords: user-generated content, information adoption, stimulus-organism-response, source credibility, tourism

1. Introduction

Social media is now the main channel through which tourists obtain destination information. Content published by ordinary users is more readily accepted than enterprise-produced professional content because it is close to real experience, and it substantially affects the choice of destination.

The explanation of this impact by existing studies roughly follows three paths: the cognitive path, in which content supplies destination information and reduces search cost; the emotional path, in which the narrative of other people's experiences evokes emotional reactions; and the trust path, in which the credibility of the publisher determines whether the content is believed. Each has a theoretical basis and empirical support.

These explanations are mostly put forward separately and rarely compared on the same data. When all three enter one model, it is unclear which really carries the influence of the content and

how much the other two independently contribute. The gap matters in practice: platform ranking rules and destination marketing strategies both need to know which attributes to prioritise.

This study integrates three paths with the S-O-R framework [1], and tests them on 161541 real TripAdvisor comments, operationalising cognition, emotion and trust as attributes measurable from the content and the publisher's record, with the intensity of information adoption as the reaction variable. It contributes the relative weight of the three paths on one large sample, the finding that the cognitive path dominates by an order of magnitude, and a mediation account showing that source credibility works by shaping content rather than independently of it.

2. Literature review and hypotheses

2.1. User-generated content and tourists' reactions

User-generated content is original content created and publicly published by ordinary users; in the travel context it changes the destination cognition and visit tendency of potential tourists [2, 3] and raises willingness to buy [4]. The S-O-R framework casts this as external stimulation converted into behavioural response through internal processing, and has been applied to consumption and adoption in tourism [5, 6]. The information adoption model adds that adoption depends on argument quality and source credibility [7], and on tourism platforms adoption is directly observable from how other tourists rate a review's usefulness [8, 9].

2.2. Cognitive path

The cognitive path holds that the information value of the content determines how far it is adopted: full, detailed and specific comments reduce uncertainty and are more diagnostic [9], while readability and distinctiveness also shape usefulness judgments [10, 11]. Information quantity and information load pull against each other, however: when a review touches on too many attributes without developing any, processing cost rises and adoption may fall [12, 13]. Accordingly:

H1: The information depth of the content positively predicts information adoption.

H5: Among the three paths, the independent variance of the cognitive path contributes the most.

2.3. Emotional path

The emotional path holds that emotions carried by the content affect the recipient's attitude. Existing studies disagree on direction: some find high-arousal negative emotions enhance usefulness [14, 15], others focus on the bipolar effect of extreme evaluation [16, 17], and evaluation valence itself relates to usefulness judgments [18]. Because intensity and direction are distinct dimensions, this study separates them and states a directional expectation for intensity only:

H2: The affective intensity of the content positively predicts information adoption.

2.4. Trust path

Source credibility theory splits credibility into professionalism and reliability [19], and travellers' trust in platform content is determined jointly by source and content characteristics [20]. On tourism platforms a publisher's contribution history and footprint breadth are observable signals of professionalism [21], while the co-presence of positive and negative content signals reliability, since a balanced account weakens the suspicion of bias [22, 23]. Publisher identity and content characteristics may also work together in usefulness judgments [24]. Accordingly:

H3: Source credibility positively predicts information adoption.

H4: The two-sidedness of the content positively predicts information adoption.

H6: Source credibility positively moderates the strength of the cognitive path.

3. Methodology

3.1. Data

This study uses the publicly released TripAdvisor comment data set [25]: 161541 English comments, each with the comment body and the publisher's historical contribution record. Publishers post a median of 16 comments covering a median of 13 cities; comments average 137.1 words, median 96. Only comments with at least one useful vote are retained, so this study measures the intensity of adoption rather than whether adoption occurs. The corpus is released for non-commercial research under a CC BY-NC-SA 4.0 licence (DOI 10.57967/hf/0613). TripAdvisor suits the question because a single record carries the review text, the contributor's accumulated posting history and the reaction of other travellers, so stimulus attributes and response are observed on the same unit without linking separate sources.

3.2. Variable measurement

The reaction variable is the intensity of information adoption, which is mapped into five ordered levels by the number of useful votes by logarithm [25], with values from 0 to 4, and the average value is 0.463.

The cognitive path has four indicators: information depth, the logarithm of comment words; topic breadth, the number of hotel service dimensions covered, judged against nine word lists (location, room, staff, catering, price, cleanliness, facilities, noise, booking) and valued 0 to 9; specificity, the share of numerical word examples; and vocabulary diversity, the mean segmental type-token ratio with a window of 25 to remove the mechanical effect of length, defined as

$$\text{MSTTR} = \frac{1}{K} \sum_{k=1}^K \frac{|V_k|}{w} \quad (1)$$

Among them, w is the window length, K is the number of windows, and $|V_k|$ is the number of different words in the k window.

The emotional path contains two indicators, both of which are calculated by the VADER emotional analysis tool [26]. Emotional intensity is taken from 1 minus the proportion of neutral words, which reflects the proportion of emotional load in the content; emotional positivity is taken from the comprehensive polarity score of the tool.

The trust path includes three indicators. The professionalism of the source and the breadth of the source experience are the logarithm of the cumulative number of comments of the publisher and the number of cities covered respectively; the two-sidedness measures the balance of positive and negative content, which is defined as

$$TS_i = \frac{2\min(p_i, n_i)}{p_i + n_i} \quad (2)$$

Among them, p_i and n_i are the ratio of positive and negative emotions in the i comment, and the value of 1 indicates that the positive and negative are completely balanced.

The data set also supplies the publisher's per capita and cumulative useful votes. Both share their source with the reaction variable, so including them would cause common-source contamination; they are excluded and only activity indicators are kept as credibility signals.

The four cognitive indicators are kept as separate regressors rather than averaged into a composite: their internal consistency is low (Cronbach's alpha 0.438), so a single cognitive score would blur constructs that behave differently. The same reasoning applies to the affective block, where intensity and valence are treated as distinct rather than combined.

3.3. Model setting

The main model regresses adoption intensity on the standardised indicators, controlling for comment time position:

$$\text{Adopt}_i = \beta_0 + \sum_j \beta_j^C \text{Cog}_{ij} + \sum_k \beta_k^A \text{Aff}_{ik} + \sum_l \beta_l^T \text{Tru}_{il} + \gamma \text{Age}_i + \varepsilon_i \quad (3)$$

All coefficients use heteroskedasticity-robust standard errors. To compare the relative weight of the three paths, the independent variance contribution of a block is defined as the difference between the goodness of fit of the complete model and that of a model from which every indicator belonging to that block has been removed. Because the comparison is made against the same complete model in each case, the quantity is directly comparable across blocks of unequal size:

This indicator is unaffected by differences in the number of indicators per block. Mediation uses 1000 bootstrap resamples to estimate the indirect path's confidence interval.

4. Results

4.1. Descriptive statistics and collinearity

The complete model reaches a goodness of fit of 0.0709 against 0.0147 with the control variable alone. The maximum variance inflation factor is 3.35, well below the usual criterion of 10. At a sample size of 161541 statistical significance is almost inevitable, so the discussion rests mainly on standardised coefficients and variance contributions. Adoption is heavily concentrated at the bottom of the scale: 101,403 reviews (62.8%) sit at the lowest level, 47,306 at the second, and only 230 reach the highest. The mean of 0.463 therefore describes a distribution in which most reviews attract a single helpful vote while a small minority accumulate many.

4.2. The relative contribution of the three paths

Table 1 reports the main model and Figure 1 the coefficient distribution. The standardised coefficient of information depth, 0.166, is the largest of all predictors; moving from the 10th to the

90th percentile raises adoption by 0.436, or 94.0% of the sample mean, supporting H1. Independent variance contributions are 0.0326 for cognition, 0.0073 for emotion and 0.0004 for trust, making the cognitive path about 4.5 times the emotional one and supporting H5.

Topic breadth carries a coefficient of negative 0.038: holding length constant, comments covering more dimensions are adopted less, consistent with an information-load account [13] in which a broad shallow list is less useful than a deep one.

Expressed on the same tenth-to-ninetieth percentile scale used for information depth, the remaining effects are modest: sentiment valence shifts adoption by negative 0.139, or 30.0% of the mean, topic breadth by negative 0.104 (22.4%), affective intensity by 0.063 (13.5%) and two-sidedness by 0.022 (4.7%). Only information depth moves adoption by an amount comparable to the mean itself.

The two components of the emotional path run in opposite directions: emotional intensity is 0.025, supporting H2, while emotional positiveness is negative 0.071. Negative comments average 0.678 adoption against 0.441 for positive ones, an effect size of 0.322. Split by positiveness, the most negative and most positive fifths reach 0.566 and 0.545 while the middle fifth falls to 0.392, a high-ends pattern. Neither a quadratic term nor absolute extremity is significant; both tests are exploratory and reported regardless.

The trust path behaves against expectation: source professionalism is negative 0.012 and experience breadth negative 0.0003 and not significant, so H3 is not supported, while two-sidedness is 0.008 and significant, supporting H4.

4.3. Mediation and moderation

Source credibility correlates positively with adoption at zero order, with a total effect of 0.008. Source professionalism raises content depth by 0.218 and content depth raises adoption by 0.142, giving an indirect effect of 0.031 with a bootstrap interval of 0.030 to 0.032, while the direct effect after controlling depth is negative 0.023. The opposing signs constitute a competitive mediation, so the proportion mediated is not reported. Experienced publishers are adopted more because they write more complete content; at equal content the resume itself adds nothing.

The interaction between information depth and source professionalism is negative 0.008, opposite to expectation and worth only 0.00014 in fit; depth's effect is 0.175 at low professionalism and 0.158 at high. H6 is not supported and the interaction is negligible.

4.4. Robustness

An ordered logit on 30,000 random sub-samples keeps every sign of the main model: odds ratios are 1.599 for information depth, 0.833 for emotional positiveness, 1.050 for emotional intensity and 0.932 for thematic breadth; source professionalism and experience breadth are not significant and two-sidedness falls to the edge level.

On the split supplied with the data set, 145,381 rows train and 8,080 test the model: test goodness of fit is 0.0709 for the linear model and 0.0820 for gradient boosting, with mean absolute errors of 0.542 and 0.538 against a mean baseline of 0.582. Explanatory power is stable out of sample but modest, so adoption intensity also depends on factors beyond content attributes. The validation split of 8,080 reviews supplied with the data set was left unused and no hyper-parameter was tuned, so the test figures are not optimistically biased.

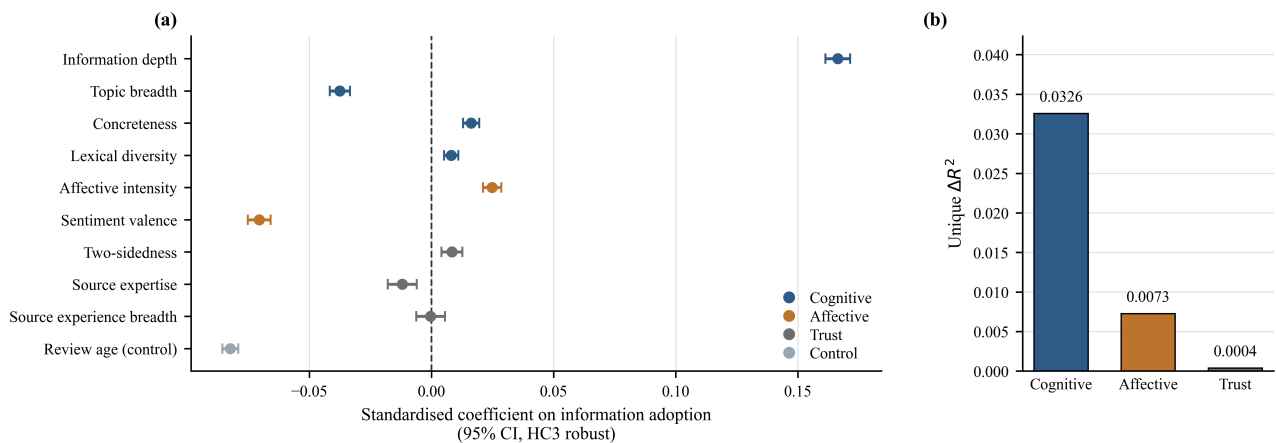


Figure 1. (a) Standardised coefficients on information adoption with 95% confidence intervals; (b) unique variance explained by each route

Table 1. Determinants of information adoption

Route	Predictor	beta	SE	95% CI	VIF
Cognitive	Information depth	+0.1664***	0.0026	[+0.161, +0.171]	2.16
	Topic breadth	-0.0375***	0.0021	[-0.042, -0.033]	1.67
	Concreteness	+0.0163***	0.0017	[+0.013, +0.020]	1.07
	Lexical diversity	+0.0081***	0.0015	[+0.005, +0.011]	1.02
Affective	Affective intensity	+0.0249***	0.0019	[+0.021, +0.029]	1.47
	Sentiment valence	-0.0705***	0.0024	[-0.075, -0.066]	1.51
Trust	Two-sidedness	+0.0084***	0.0022	[+0.004, +0.013]	1.59
	Source expertise	-0.0119***	0.0030	[-0.018, -0.006]	3.35
	Source experience breadth	-0.0003	0.0030	[-0.006, +0.006]	3.34
Control	Review age (control)	-0.0823***	0.0016	[-0.086, -0.079]	1.03

N = 161,541. OLS with HC3 robust standard errors; all predictors standardised. $R^2 = 0.0709$. *** $p < .001$, ** $p < .01$, * $p < .05$.

5. Discussion

5.1. Theoretical implications

Compared in one model, the three paths are not equal: the cognitive path carries most of the explainable variation, while the emotional and trust paths contribute more than an order of magnitude less. Work citing the S-O-R framework therefore needs to distinguish a path's existence from its relative weight.

The internal structure of the emotional path also matters. Intensity and direction carry opposite signs, so emotion does not work through pleasure: emotionally charged critical content is adopted more readily, consistent with a diagnosticity account [15, 17] and against equating the emotional mechanism with evoking longing.

The trust result is the most corrective. The publisher's record correlates positively with adoption at zero order, but the association disappears once content is controlled: its role passes entirely through content depth. Credibility acts through what the publisher writes, not through the identity label, which speaks to recent work on how publisher identity and content characteristics jointly matter [24].

Read together, the three results suggest that the organism stage in this setting is dominated by elaboration rather than by affect or source inference. Emotion and credibility are not absent, but they enter through what the contributor writes rather than as independent channels. A framework that treats the three as parallel and comparable therefore overstates two of them.

5.2. Practical implications

Platforms should raise content quality by encouraging fully developed narratives rather than broader attribute coverage: the negative thematic-breadth coefficient shows that prompting users to rate everything need not add practical value. For destination marketers, a contributor's posting history adds little once content is known; information density is the more direct criterion. For contributors, the advice is narrow but clear: length that carries substance, concrete detail, and a willingness to state drawbacks alongside strengths all correspond to higher adoption, whereas simply covering more of a property's attributes does not.

5.3. Research limitations

Three boundaries apply. First, the response variable is useful-voting intensity, reflecting how far other tourists adopt the content rather than the tourists' own travel intention; since the data set retains only comments with at least one vote, the conclusion concerns the intensity of adoption, not whether adoption occurs. Second, the data are cross-sectional, so the coefficients describe conditional associations and cannot exclude reverse causality or unobserved confounding. Third, the three paths are represented by observable attributes of content and source, which are the conditions that activate each path rather than direct measures of the recipient's internal state; testing that state requires experimental or survey designs.

6. Conclusion

Across 161,541 real travel reviews, the cognitive path contributes 0.0326 of independent variance, about 4.5 times the emotional path, with information depth the strongest single predictor; the emotional path splits into components of opposite sign, intensity raising adoption and positivity lowering it; and the trust path has no positive direct effect once content is controlled, acting entirely through content depth with an indirect effect of 0.031.

These results turn the side-by-side account of the three mechanisms into one with a clear primary and secondary: information content is the backbone through which user-generated content operates, and emotion and credibility act through it. Later work can extend the framework to audio-visual content such as short videos and measure the recipient's internal state directly.

Author contribution

Xiaxuan Qu: conceptualization, methodology, data curation, formal analysis, writing of the original draft, review and editing.

Declaration of interest

The author declares no competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

- [1] Mehrabian, A., & Russell, J. A. (1974). *An approach to environmental psychology*. Cambridge, MA: MIT Press.
- [2] Zain, N. A. M., et al. (2025). User generated content versus mainstream media influence on hot spring tourism destination image formation. *Tourism Review*, 80(6), 1261-1276.
- [3] Wang, L., et al. (2024). Show me the destination or show me the tourist? Effect of image-based user-generated advertisement type on tourists' destination interest. *Current Issues in Tourism*, 27(23), 4354-4373.
- [4] Mayrhofer, M., et al. (2020). User generated content presenting brands on social media increases young adults' purchase intention. *International Journal of Advertising*, 39(1), 166-186.
- [5] Erul, E., et al. (2026). Rethinking stimulus-organism-response theory for residents' behaviour in tourism. *Current Issues in Tourism*, 29(8), 1547-1563.
- [6] Hew, J. J., et al. (2018). Mobile social tourism shopping: A dual-stage analysis of a multi-mediation model. *Tourism Management*, 66, 121-139.
- [7] Sussman, S. W., & Siegal, W. S. (2003). Informational influence in organizations: An integrated approach to knowledge adoption. *Information Systems Research*, 14(1), 47-65.
- [8] Erlebach, S., et al. (2026). Beyond helpfulness votes: Examining the helpfulness of content in online customer review text. *Decision Support Systems*, 200, 114546.
- [9] Mudambi, S. M., & Schuff, D. (2010). What makes a helpful online review? A study of customer reviews on Amazon.com. *MIS Quarterly*, 34(1), 185-200.
- [10] Yhee, Y., & Koo, C. (2026). Seeing AI as human or machine? Effects of transparency, valence, and readability on review summary helpfulness. *Tourism Management*, 113, 105305.
- [11] Wang, S., et al. (2025). Content dissimilarity and online review helpfulness: Contextual insights. *Journal of Business Research*, 187, 115068.
- [12] Baek, H., Ko, C., & Lee, S. (2026). Visual and verbal fit-diagnostic contextual cues and review helpfulness in online apparel reviews. *Journal of Retailing and Consumer Services*, 93, 104887.
- [13] Wang, L., et al. (2024). Online review helpfulness and information overload: The roles of text, image, and video elements. *Journal of Theoretical and Applied Electronic Commerce Research*, 19(2), 1243-1266.
- [14] Ming, Y., et al. (2025). The effect of anger on online review helpfulness: Role of credibility. *Current Issues in Tourism*.
- [15] Yun, S., Jun, S., & Kim, J. W. (2024). The impact of high arousal and displeasure on online review helpfulness: Exploring the moderating role of product involvement. *Electronic Commerce Research and Applications*, 67, 101436.
- [16] George, M. (2026). The impact of negativity and positivity of extreme reviews on the helpfulness of online reviews. *Electronic Commerce Research*.
- [17] Roman, S., Riquelme, I. P., & Iacobucci, D. (2024). Unlocking the helpfulness of extreme and exaggerated hotel online reviews: Consumers and brand influences. *Tourism Management Perspectives*, 54, 101321.
- [18] Ulu, S., Usay, C., & Yenyurt, S. (2025). Is this review helpful? How product gender, verification, and valence shape perceived helpfulness. *Journal of Retailing and Consumer Services*, 87, 104356.
- [19] Ohanian, R. (1990). Construction and validation of a scale to measure celebrity endorsers' perceived expertise, trustworthiness, and attractiveness. *Journal of Advertising*, 19(3), 39-52.
- [20] Filieri, R., Alguezaui, S., & McLeay, F. (2015). Why do travelers trust TripAdvisor? Antecedents of trust towards consumer-generated media and its influence on recommendation adoption and word of mouth. *Tourism Management*, 51, 174-185.
- [21] Li, C., Liu, H., & Li, L. (2025). How to establish credibility? The influence of expression manner on tourist information adoption. *Journal of Travel Research*, 64(7), 1739-1765.
- [22] Wang, D., et al. (2025). Unravelling the effects of two inconsistencies on online review helpfulness: Evidence from TripAdvisor. *Decision Support Systems*, 193, 114450.
- [23] Li, J., Xu, X., & Ngai, E. W. (2024). How review content, sentiment and helpfulness votes jointly affect trust of reviews and attitude. *Internet Research*, 34(6), 2232-2256.

- [24] Kim, J. M., Mariani, M., & Hwang, K. (2026). Beyond the words: How reviewer status and review features jointly affect helpfulness in online employee reviews. *Journal of Business Research*, 207, 116008.
- [25] Nayeem, M. T., & Rafiei, D. (2023). On the role of reviewer expertise in temporal review helpfulness prediction. *Findings of the Association for Computational Linguistics: EACL 2023*.
- [26] Hutto, C., & Gilbert, E. (2014). VADER: A parsimonious rule-based model for sentiment analysis of social media text. *Proceedings of the International AAAI Conference on Web and Social Media*, 8(1), 216–225.