

WHAT MAKES ONLINE REVIEWS HELPFUL? REVIEWER AND CONTENT CUES, TRUST AND PURCHASE DECISIONS AMONG INDIAN CONSUMERS

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ABSTRACT

Online reviews shape digital purchase decisions, yet research often studies source cues, review-content cues and downstream consumer responses in separate models. This study integrates these stages by examining which reviewer-side and content-side cues retain unique associations with perceived review helpfulness and whether helpfulness is linked to purchase decision through consumer trust and purchase intention. Survey data from 379 adult online consumers in India were analysed using partial least squares structural equation modelling (PLS-SEM). The model jointly estimates four reviewer-side cues and five content-side cues within an integrated Elaboration Likelihood Model, Source Credibility Theory and Information Adoption Model framework. Reviewer trustworthiness ($\beta = 0.136$, $p = .021$), review depth ($\beta = 0.165$, $p = .002$) and review clarity ($\beta = 0.138$, $p = .010$) were positively associated with perceived helpfulness. Review extremity showed a small positive coefficient ($\beta = 0.106$, $p = .038$), contrary to the hypothesised negative direction. Perceived helpfulness was positively associated with consumer trust ($\beta = 0.243$, $p < .001$), trust with purchase intention ($\beta = 0.306$, $p < .001$), and purchase intention with purchase decision ($\beta = 0.127$, $p = .015$). The sequential indirect association was significant ($\beta = 0.030$, 95% bias-corrected CI [0.011, 0.059], $p = .001$). The findings show that content diagnosticity and source trustworthiness provide distinct incremental information when review cues are evaluated jointly, while the positive extremity coefficient identifies an important boundary condition for future research.

Keywords: Online Reviews; Review Helpfulness; Reviewer Trustworthiness; Consumer Trust; Purchase Intention; Purchase Decision

1. INTRODUCTION

Online reviews have become a routine input into digital purchasing because consumers often evaluate products and services without direct pre-purchase inspection. Reviews can reduce information asymmetry by providing peer-generated evidence about product attributes, usage experiences and perceived value. As review volumes expand, however, the decision problem

shifts from accessing information to selecting which reviews deserve attention. Perceived review helpfulness therefore represents an important evaluative judgement in electronic word-of-mouth research [1,2].

A substantial literature identifies determinants of review helpfulness, but two issues remain open. First, source-related and content-related cues are often examined separately even though consumers observe them simultaneously. Reviewer expertise, trustworthiness, identity disclosure and reputation can shape source evaluation, whereas depth, clarity, valence, extremity and language quality shape evaluation of the message itself. Meta-analytic evidence shows substantial heterogeneity in the effects of review characteristics across settings [3]. Joint estimation is therefore necessary to identify which cues provide incremental explanatory value once competing cues are considered together.

Second, many helpfulness studies stop at evaluation of the review or at purchase intention. The Information Adoption Model (IAM) links perceived usefulness to subsequent information adoption [4], and online-review research connects perceived helpfulness with purchase intention [5]. Yet intention is not equivalent to a decision and does not invariably translate into subsequent action [6,7]. A more complete account therefore requires a sequence that begins with review evaluation and continues through trust and intention to a decision-proximal outcome.

This study addresses both issues in one structural model. Four reviewer-side cues and five content-side cues are estimated jointly as antecedents of perceived review helpfulness. Helpfulness is then linked to consumer trust, purchase intention and purchase decision. The model is tested with data from 379 adult Indian online consumers using PLS-SEM. The study makes three contributions. First, it distinguishes incremental cue effects from isolated associations. Second, it integrates the Elaboration Likelihood Model (ELM), Source Credibility Theory (SCT) and IAM as complementary explanations of different stages of the same review-influence process. Third, it extends the downstream sequence beyond intention and tests whether helpfulness is associated with purchase decision sequentially through trust and purchase intention. Because the design is cross-sectional, these contributions concern theoretically ordered associations rather than causal effects.

2. THEORETICAL BACKGROUND AND HYPOTHESIS DEVELOPMENT

2.1. Perceived review helpfulness as an information-adoption judgement

Perceived review helpfulness is the reader's judgement that a review provides useful information for product evaluation and purchase-related decision-making [1]. It is conceptually distinct from objective text properties such as length, readability or grammatical correctness; those characteristics may influence helpfulness, but helpfulness itself is a reader-level evaluation [2].

In the present framework, helpfulness occupies a bridging position. Upstream, consumers evaluate who produced the review and what the review contains. Downstream, a helpfulness judgement indicates that the information is sufficiently useful to enter subsequent judgement. This position is consistent with the broader eWOM literature [8] and with IAM, in which information characteristics shape perceived usefulness and subsequent adoption [4].

2.2. Reviewer-side cues: source credibility and source evaluation

SCT proposes that message acceptance depends partly on perceived source credibility, particularly expertise and trustworthiness [9,10]. Online review environments add further source signals such as identity disclosure and accumulated reviewer reputation [11,12]. Within ELM, source information can operate as a heuristic or peripheral cue under some

processing conditions, although the same cue can be processed more carefully when involvement is high [13]. The present study therefore treats reviewer characteristics as source-related credibility signals rather than assuming a fixed processing route.

Reviewer expertise reflects perceived product knowledge and experience. Its unique effect may weaken when review content is entered simultaneously because knowledgeable reviewers often produce more informative content [3,14]. Reviewer trustworthiness captures perceived honesty, sincerity and freedom from self-interested bias. Empirical and meta-analytic evidence shows that reviewer trustworthiness is associated with eWOM usefulness, credibility and behavioural outcomes [15,16]. Identity disclosure can increase accountability, while reviewer reputation provides a platform-level signal based on prior contributions [11,12,17].

H1a: Reviewer expertise is positively associated with perceived review helpfulness.

H1b: Reviewer trustworthiness is positively associated with perceived review helpfulness.

H1c: Reviewer identity disclosure is positively associated with perceived review helpfulness.

H1d: Reviewer reputation is positively associated with perceived review helpfulness.

2.3. Review-content cues: message quality and elaboration

ELM distinguishes relatively effortful evaluation of message arguments from greater reliance on peripheral cues [13]. In the present model, review depth, clarity, balanced valence, extremity and language quality are treated as message-related characteristics because evaluating them requires engagement with what the review says and how it is expressed.

Review depth captures the amount of substantive information about product attributes, use conditions and reasons underlying an evaluation and is among the most consistent predictors of review helpfulness [1,3]. Review clarity concerns whether information is organised and easy to process; readable and coherent reviews can reduce processing effort [18,19]. Balanced valence reflects a two-sided account that includes positive and negative aspects and can increase diagnosticity in some settings [5]. Review extremity captures the intensity of evaluative expression. Prior evidence indicates that extremity can be nonlinear and context dependent rather than uniformly beneficial or harmful [20,21]. Language quality captures linguistic correctness and readability, which have been linked to perceived usefulness and economic outcomes [22].

H2a: Review depth is positively associated with perceived review helpfulness.

H2b: Review clarity is positively associated with perceived review helpfulness.

H2c: Balanced review valence is positively associated with perceived review helpfulness.

H2d: Review extremity is negatively associated with perceived review helpfulness.

H2e: Language quality is positively associated with perceived review helpfulness.

2.4. From helpfulness to trust, intention and decision

IAM explains how information quality and source credibility shape perceived usefulness and subsequent information adoption [4]. In the present study, perceived review helpfulness is aligned with perceived information usefulness. When a review is judged helpful, consumers may be more willing to rely on the review when forming confidence in product-related claims. Trust is, in turn, a well-established antecedent of online transaction intention [23,24].

Purchase intention reflects motivational readiness to buy, whereas purchase decision captures a more decision-proximal self-reported judgement. The distinction matters because intention is an imperfect predictor of subsequent behaviour [6,7]. The final link is therefore expected to be positive but modest because price, availability, promotions, alternatives and situational constraints can intervene between intention and decision.

H3: Perceived review helpfulness is positively associated with consumer trust.

H4: Consumer trust is positively associated with purchase intention.

H5: Purchase intention is positively associated with purchase decision.

H6: Perceived review helpfulness has a positive sequential indirect association with purchase decision through consumer trust and purchase intention.

Table 1. Summary of hypotheses.

Hypothesis	Relationship	Expected direction
H1a	Reviewer expertise → perceived helpfulness	Positive
H1b	Reviewer trustworthiness → perceived helpfulness	Positive
H1c	Identity disclosure → perceived helpfulness	Positive
H1d	Reviewer reputation → perceived helpfulness	Positive
H2a	Review depth → perceived helpfulness	Positive
H2b	Review clarity → perceived helpfulness	Positive
H2c	Balanced valence → perceived helpfulness	Positive
H2d	Review extremity → perceived helpfulness	Negative
H2e	Language quality → perceived helpfulness	Positive
H3	Perceived helpfulness → consumer trust	Positive
H4	Consumer trust → purchase intention	Positive
H5	Purchase intention → purchase decision	Positive
H6	Helpfulness → trust → intention → decision	Positive indirect

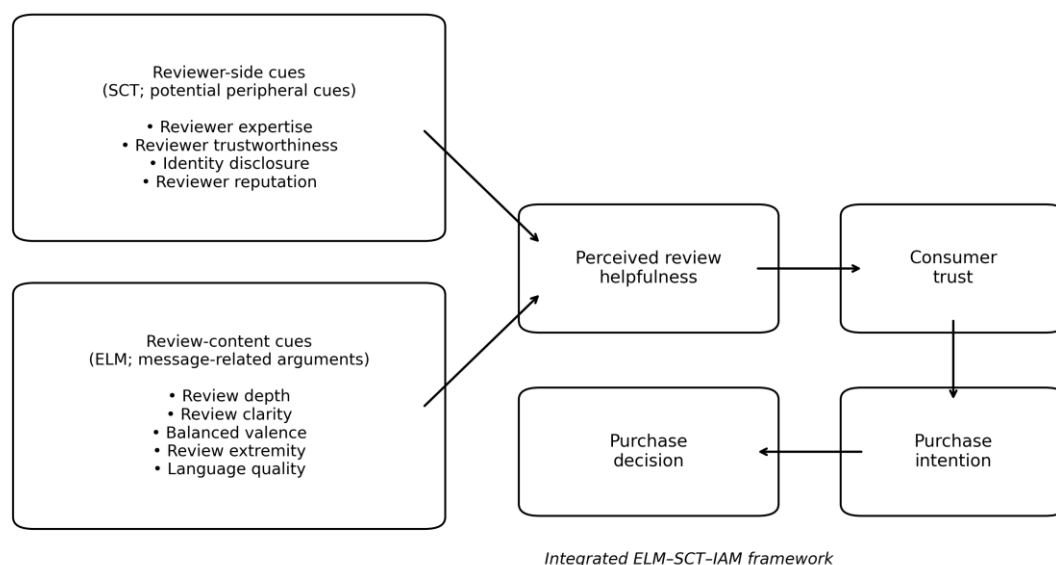


Figure 1. Integrated conceptual framework.

3. MATERIALS AND METHODS

3.1. Research design, population and sample

The study used a quantitative, cross-sectional survey design. The target population comprised adults in India who had prior online-shopping experience and had read at least one online product or service review before making a purchase-related decision. Participants were recruited through academic and professional networks, LinkedIn and other social-media channels. A screening question verified eligibility. The sampling approach was non-probability convenience sampling; consequently, the sample should not be interpreted as statistically representative of all Indian online consumers.

After incomplete submissions were removed, 379 usable responses remained. The sample was gender-balanced (50.1% female; 49.9% male), 71.2% of respondents were aged 21–40, and 65.5% reported postgraduate or doctoral-level education. Review use was frequent: 71.0% reported reading online reviews often or for nearly every purchase. Table 2 reports the sample profile.

Table 2. Sample profile (N = 379).

Variable	Category	n	%
Age	≤20 years	35	9.2
	21–30 years	160	42.2
	31–40 years	110	29.0
	41–50 years	40	10.6
	>50 years	34	9.0
Gender	Female	190	50.1
	Male	189	49.9
Education	School level	14	3.7
	Diploma/professional certification	51	13.5
	Undergraduate	63	16.6
	Postgraduate	117	30.9
	Doctoral/research level	131	34.6
Review reading frequency	Never/rarely	18	4.8
	Sometimes	92	24.3
	Often	174	45.9
	Always	95	25.1

3.2. Measures and questionnaire development

The questionnaire used reflective multi-item measures adapted from established scales. All items were rated on seven-point Likert-type scales ranging from 1 (strongly disagree) to 7 (strongly agree). Thirteen constructs were represented by 41 administered items: reviewer expertise, reviewer trustworthiness, identity disclosure, reviewer reputation, review depth, review clarity, balanced valence, review extremity, language quality, perceived review helpfulness, consumer trust, purchase intention and purchase decision. Principal scale sources are reported in Table 3.

Three subject specialists reviewed the instrument for face validity, construct coverage and wording, followed by a cognitive pretest with eight online consumers. The pretest identified hesitation around several negatively worded items, which were retained for field administration but scrutinised during measurement-model assessment. The questionnaire was administered online using Google Forms. Participation was voluntary and anonymous, informed consent was obtained before participation, respondents could discontinue at any point, and no personally identifiable information was collected.

Table 3. Construct operationalisation and principal scale sources.

Construct	Items retained	Principal source(s)
Reviewer expertise	4	Ohanian [10]; Dou et al. [12]
Reviewer trustworthiness	4	Ohanian [10]; Dou et al. [12]
Identity disclosure	3	Forman et al. [11]; Karimi and Wang [25]
Reviewer reputation	3	Dou et al. [12]; Kim et al. [17]
Review depth	4	Mudambi and Schuff [1]
Review clarity	2	Mudambi and Schuff [1]; Lantzy et al. [19]
Balanced valence	2	Filieri et al. [5]
Review extremity	3	Mudambi and Schuff [1]; Chou [21]
Language quality	2 retained	Ghose and Ipeiotis [22]
Perceived helpfulness	4	Filieri et al. [5]; Sussman and Siegal [4]
Consumer trust	2 retained	Gefen et al. [23]; Pavlou [24]
Purchase intention	2 retained	Filieri et al. [5]; Park et al. [26]
Purchase decision	3	Corbos et al. [27]; Hajli [28]

Note: *Three poorly performing reverse-worded indicators were removed during measurement-model refinement, as reported in Section 4.1.*

3.3. Analytical strategy

The model was estimated in SmartPLS 4 [29]. PLS-SEM was selected because the study estimates a relatively complex latent-variable model with multiple antecedents and evaluates both explanatory relationships and out-of-sample predictive relevance. Measurement assessment followed established guidance [30]. Indicator reliability was evaluated through outer loadings; internal consistency through Cronbach's alpha and composite reliability; convergent validity through average variance extracted (AVE); and discriminant validity through the heterotrait-monotrait ratio (HTMT) [31].

Structural paths were evaluated using 5,000 bootstrap subsamples. The analysis reports standardised path coefficients, t statistics, p values, Cohen's f^2 , R^2 and inner variance inflation factors (VIF). Sequential indirect effects were evaluated using bias-corrected bootstrap confidence intervals. Predictive relevance was assessed with PLSpredict [32] and the cross-validated predictive ability test (CVPAT) [33]. SRMR and NFI were treated as supplementary diagnostics rather than stand-alone global-fit criteria.

3.4. Common method and ethical considerations

Because predictor and outcome variables were collected in the same survey, procedural and statistical safeguards were used. Predictor and outcome sections were separated, anonymity was emphasised, and item wording was varied, consistent with established recommendations [34]. Post-hoc assessment included Harman's single-factor test and collinearity diagnostics. These checks can detect obvious warning signs but cannot demonstrate the absence of common method variance [35].

The study followed institutional research guidelines for anonymous social-science survey research at Devi Ahilya Vishwavidyalaya (DAVV), Indore. The opening survey page explained the research purpose, voluntary nature of participation, anonymity and academic use of data. Consent was obtained before respondents proceeded, no personally identifiable information was collected, and the final dataset contains anonymised responses only.

4. RESULTS AND DISCUSSION

4.1. Measurement model and common-method diagnostics

The first unrotated factor in Harman's test accounted for 28.4% of total variance, and inner VIF values ranged from 1.000 to 1.341. These diagnostics do not indicate severe method inflation, although residual common-method variance cannot be ruled out in a single-source design.

Three reverse-worded indicators performed poorly and were removed during measurement refinement: one language-quality item (loading = -0.375), one consumer-trust item (loading = -0.212) and one purchase-intention item (loading = 0.025). After removal, retained outer loadings ranged from 0.713 to 0.956. Cronbach's alpha ranged from 0.748 to 0.933, composite reliability from 0.859 to 0.952, and AVE from 0.672 to 0.894. All 78 HTMT values were below 0.85, with a maximum of 0.422. Table 4 therefore supports adequate reliability, convergent validity and discriminant validity for the retained measurement model. The need to delete three reverse-worded indicators is nevertheless substantively important because it reduces content coverage for several constructs and is treated as a limitation rather than as a purely technical refinement.

Table 4. Construct reliability and convergent validity.

Construct	k	Cronbach α	Composite reliability	AVE
Reviewer expertise	4	0.916	0.940	0.798
Reviewer trustworthiness	4	0.911	0.938	0.790
Identity disclosure	3	0.889	0.931	0.818
Reviewer reputation	3	0.885	0.927	0.810
Review depth	4	0.930	0.949	0.824
Review clarity	2	0.827	0.919	0.850
Balanced valence	2	0.847	0.927	0.865
Review extremity	3	0.838	0.901	0.753
Language quality	2	0.823	0.914	0.843
Perceived helpfulness	4	0.933	0.952	0.832
Consumer trust	2	0.882	0.944	0.894
Purchase intention	2	0.869	0.939	0.884
Purchase decision	3	0.748	0.859	0.672

4.2. Reviewer-side and content-side antecedents of helpfulness

Table 5 reports the direct structural paths. Among reviewer-side cues, trustworthiness was the only statistically significant predictor of perceived helpfulness ($\beta = 0.136$, $p = .021$). Expertise, identity disclosure and reviewer reputation did not retain significant unique associations when all reviewer and content cues were estimated simultaneously. This selective pattern is consistent with the idea that source characteristics share explanatory variance and should not be interpreted from isolated bivariate effects alone. It also adds nuance to prior work: Filieri et al. [5] found expertise and two-sidedness useful in a service-review context but did not find source trustworthiness helpful, whereas the present joint model identifies trustworthiness as the reviewer cue with incremental explanatory value. The contrast suggests that the relative importance of credibility dimensions is context and specification dependent rather than universal.

Among content-side cues, review depth had the largest antecedent coefficient ($\beta = 0.165$, $p = .002$), followed by review clarity ($\beta = 0.138$, $p = .010$). These findings align with prior evidence that detailed and readable review content improves perceived usefulness [1,3,18,36]. Depth and clarity remain significant together, indicating that informational richness and cognitive accessibility are not interchangeable. Balanced valence and language

quality did not retain significant unique effects, suggesting that their explanatory role may be absorbed by more diagnostic content characteristics in this sample.

Review extremity showed a small positive coefficient ($\beta = 0.106$, $p = .038$), opposite to the hypothesised negative direction; H2d was therefore not supported. This sign reversal should not be treated as evidence that extreme reviews are generally more helpful. Recent research shows that emotional arousal can exhibit nonlinear and valence-dependent relationships with review helpfulness [21]. The present result is better interpreted as a boundary-condition signal that warrants experimental testing across product categories and consumer goals.

Table 5. Structural model path coefficients.

Hyp.	Path	β	t	p	f ²	Decision
H1a	Expertise → Helpfulness	0.057	1.087	.277	0.003	Not supported
H1b	Trustworthiness → Helpfulness	0.136	2.318	.021	0.019	Supported
H1c	Identity disclosure → Helpfulness	0.061	1.171	.242	0.004	Not supported
H1d	Reputation → Helpfulness	0.055	1.040	.299	0.003	Not supported
H2a	Depth → Helpfulness	0.165	3.094	.002	0.029	Supported
H2b	Clarity → Helpfulness	0.138	2.587	.010	0.019	Supported
H2c	Balanced valence → Helpfulness	0.077	1.376	.169	0.006	Not supported
H2d	Extremity → Helpfulness	0.106	2.076	.038	0.013	Not supported (sign reversed)
H2e	Language quality → Helpfulness	0.037	0.733	.464	0.002	Not supported
H3	Helpfulness → Trust	0.243	4.563	<.001	0.063	Supported
H4	Trust → Purchase intention	0.306	6.024	<.001	0.103	Supported
H5	Purchase intention → Decision	0.127	2.443	.015	0.016	Supported

Note: H2d was statistically significant in the direction opposite to that hypothesised and is therefore classified as not supported.

4.3. Downstream sequence from helpfulness to purchase decision

Perceived helpfulness was positively associated with consumer trust ($\beta = 0.243$, $p < .001$), consumer trust with purchase intention ($\beta = 0.306$, $p < .001$), and purchase intention with purchase decision ($\beta = 0.127$, $p = .015$). These results are consistent with the role of trust in electronic commerce [23,24], while the modest intention-to-decision coefficient is compatible with the well-established gap between stated intention and subsequent behaviour [6,7].

The nine antecedents explained 25.8% of the variance in perceived helpfulness ($R^2 = 0.258$). R^2 values were 0.059 for consumer trust, 0.093 for purchase intention and 0.016 for purchase decision. The low terminal R^2 is informative rather than incidental: a review-centred model captures only a small portion of final purchase choice, which is also shaped by price, availability, promotions, competing alternatives and situational constraints. Accordingly, the model should not be presented as a comprehensive predictor of purchasing behaviour.

4.4. Indirect effects and predictive assessment

The complete sequential indirect association from perceived helpfulness to purchase decision through consumer trust and purchase intention was statistically significant ($\beta = 0.030$, 95% bias-corrected CI [0.011, 0.059], $p = .001$), supporting H6. The shorter helpfulness → trust → purchase-intention pathway was also significant ($\beta = 0.074$, 95% bias-corrected CI [0.032,

0.125], $p = .002$). Because the model is cross-sectional and does not include a direct helpfulness-to-purchase-intention path, these estimates are interpreted as statistically supported indirect associations in the prespecified sequence, not as proof of temporal or causal mediation.

All endogenous indicators had positive Q^2_{predict} values. Predictive relevance was strongest for perceived helpfulness, where Q^2_{predict} ranged from 0.098 to 0.218. CVPAT indicated statistically significant predictive improvement of the PLS model over the linear-model benchmark for all four perceived-helpfulness indicators. The saturated-model SRMR was 0.076; the estimated-model SRMR was 0.101 and NFI was 0.763. These mixed supplementary fit indices reinforce a cautious interpretation focused on measurement quality, structural estimates and predictive evidence rather than global-fit claims.

Table 6. Specific indirect effects.

Indirect path	β	LL 95% CI	UL 95% CI	p
Trustworthiness $\rightarrow$ Helpfulness $\rightarrow$ Trust	0.033	0.005	0.070	.047
Depth $\rightarrow$ Helpfulness $\rightarrow$ Trust	0.040	0.014	0.082	.018
Clarity $\rightarrow$ Helpfulness $\rightarrow$ Trust	0.034	0.009	0.072	.036
Helpfulness $\rightarrow$ Trust $\rightarrow$ Purchase intention	0.074	0.032	0.125	.002
Helpfulness $\rightarrow$ Trust $\rightarrow$ Intention $\rightarrow$ Decision	0.030	0.011	0.059	.001

4.5. Theoretical and managerial implications

The theoretical contribution is primarily integrative and comparative. ELM provides a processing architecture for distinguishing source-related cues from message-related arguments, SCT clarifies the credibility content of reviewer-side cues, and IAM connects perceived usefulness with subsequent adoption-related outcomes. Estimating these components in one model shows that variables supported in prior isolated studies do not necessarily retain unique explanatory power when competing cues are entered simultaneously. The finding that trustworthiness, depth and clarity survive joint estimation is therefore more informative than a simple list of significant antecedents.

The results also extend the IAM-oriented sequence to a self-reported purchase-decision construct through trust and purchase intention. The low R^2 for purchase decision constrains the claim appropriately: review evaluation is one component of a broader purchase process. Finally, the unexpected extremity coefficient identifies a specific boundary-condition problem for future theory, particularly because nonlinear arousal effects have been reported in large-scale review data [21].

For digital platforms, the most defensible design implication is to support diagnostic depth and clarity rather than review length alone. Structured prompts can encourage reviewers to describe product attributes, usage conditions, advantages and limitations, while interface design can make information easier to process. The reviewer-side result also suggests that authenticity-oriented signals, such as verified purchase, transparent incentive disclosure and reviewer history, may be more useful than status badges alone. Because the extremity result is small and contrary to prediction, platforms should not promote extreme reviews on the basis of this study; they should instead contextualise such reviews with rating distributions, verification status and neighbouring reviews.

4.6. Limitations and future research

Several limitations bound the conclusions. First, the cross-sectional design does not establish temporal ordering or causality. Longitudinal studies and experiments are required to test mechanisms. Second, convenience sampling limits population representativeness, and the

sample is relatively young, highly educated and digitally active. Third, purchase decision was measured through self-report rather than observed transaction data. Fourth, product category was not modelled as a moderator, although category heterogeneity may be important for extremity and other content effects.

Fifth, three reverse-worded indicators were removed and several constructs were therefore represented by two retained items. Although reliability and convergent-validity criteria were satisfied, future studies should use richer operationalisations and avoid unnecessary reverse wording when it creates comprehension problems. Finally, the single-source design leaves residual common-method concerns despite procedural safeguards and post-hoc diagnostics. Future research should combine survey data with behavioural or platform data and test whether the relative importance of source and content cues changes across product categories, cultures and levels of consumer involvement.

CONCLUSION

This study links antecedents and consequences of perceived online review helpfulness within one model. When reviewer-side and content-side cues were estimated jointly, reviewer trustworthiness, review depth and review clarity retained positive unique associations with helpfulness. Review extremity also showed a small positive coefficient, contrary to the hypothesised negative relationship. Downstream, helpfulness was associated with consumer trust, trust with purchase intention, and intention with purchase decision, with a statistically significant sequential indirect association. The findings therefore suggest that online review influence depends not only on informational richness but also on clarity and source trustworthiness. At the same time, the low explained variance in purchase decision, convenience sample and cross-sectional design place clear limits on causal, predictive and population-level claims. These limits are part of the contribution: review helpfulness is a meaningful component of digital consumer decision-making, but not a complete explanation of purchase choice.

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AUTHOR CONTRIBUTIONS

Kratika Yadav: conceptualisation, literature review, methodology, data collection, analysis and manuscript drafting. Dr. Piyush Kendurkar: supervision, research guidance, critical review and manuscript editing. Both authors approved the final manuscript.

COMPETING INTERESTS

The authors declare no competing interests.

ETHICS STATEMENT

Participation was voluntary and anonymous. Respondents received study information and provided informed consent before proceeding. No personally identifiable information was collected. The research was conducted in accordance with institutional research guidelines for anonymous social-science survey research at Devi Ahilya Vishwavidyalaya (DAVV), Indore.

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DATA AVAILABILITY

The study uses anonymised survey data. Data may be made available by the corresponding author subject to institutional and ethical considerations.

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