



The Impact of Perceived Online Review Inauthenticity on Consumer Information Vigilance: Evidence from Regression, Correlation and Parallel Mediation Analysis

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ABSTRACT:

Online reviews are a dominant source of pre-purchase information, but fake, paid, exaggerated and AI-generated reviews have made review authenticity a central concern for consumers and platforms. Most research addresses the algorithmic detection of fake reviews, while few studies examine how a consumer's own perception of inauthenticity shapes information-search and verification behaviour. This study examines the impact of perceived online review inauthenticity (ORI) on consumer information vigilance (CIV), directly and through two proposed parallel mediators, review skepticism (RS) and perceived information uncertainty (PIU). A quantitative, cross-sectional survey was conducted with a structured five-point Likert questionnaire (four constructs, five items each), and 270 valid responses from online shoppers who read reviews before purchase were analysed in jamovi using Cronbach's alpha, descriptive statistics, Pearson and Spearman correlation, simple and multiple linear regression, and a parallel mediation model with 5,000 bootstrap resamples. The sample was young (72.6% aged 18–25), mostly male (68.5%) and habitual review readers (77.4% always or often). All scales were reliable ($\alpha = .704-.832$) and all construct means were well above neutral (3.93–4.14). ORI significantly predicted CIV ($B = 0.360$; $\beta = .394$; $R^2 = .156$; $F(1, 268) = 49.4$; $p < .001$) and correlated strongly with RS (Pearson $r = .507$; Spearman $\rho = .536$; $p < .001$). RS ($\beta = .251$) and PIU ($\beta = .424$) jointly explained 36.9% of the variance in CIV ($F(2, 267) = 78.1$; $p < .001$). Both indirect effects were significant (via RS = 0.0908; via PIU = 0.1481) and the direct effect

remained significant (0.1213; $p =$

.018), indicating partial mediation. All four hypotheses were supported. The study extends the Persuasion Knowledge Model to online reviews and supports visible authenticity signals and incentive-free reviews as ways of reducing consumers' verification burden. Because the design is cross-sectional and self-reported, the findings describe association and statistical pathways rather than causation.

KEYWORDS: Online review inauthenticity, Review skepticism, Perceived information uncertainty, Consumer information vigilance, Parallel mediation, Consumer behaviour.

INTRODUCTION:



Online reviews have become one of the most widely used sources of information in consumer decision-making. Before buying a phone, booking a hotel, ordering food or choosing a service provider, most consumers now read the ratings and comments left by earlier buyers. Reviews compress the experience of many customers into a form that can be read in minutes, and they let a prospective buyer judge quality, reliability and value without relying only on what the seller claims. For e-commerce platforms they are therefore part of the core mechanism through which trust is created between strangers who trade online.

The same importance makes reviews a target. Fake, paid, exaggerated and incentivised reviews can raise the apparent quality of a product, hide its weaknesses or damage a competitor, and advances in text generation have made convincing reviews easier to produce at scale^{1,2}. Evidence from the Amazon marketplace indicates that fake reviews raise seller sales by about 25% while cutting honest sellers' profit by about 4.7%², and research on real fake reviews shows that models trained on laboratory imitations generalise poorly to what is found on commercial platforms³. Consumers are aware of these risks. Many readers now ask not only what a review says but also whether it can be believed.

A consumer who doubts the authenticity of reviews can stop reading them, read them but discount them, or try to verify them by comparing platforms, reading reviewer profiles, looking for verified-purchase indicators and searching for independent sources. This study is concerned with the third response, termed consumer information vigilance (CIV). Two psychological states are proposed to lie between the perception of inauthenticity and vigilant behaviour: review skepticism (RS), the tendency to question the credibility of review content, and perceived information uncertainty (PIU), the feeling that the available review information is inaccurate, inconsistent or inadequate for a decision. Whether, and through which routes, perceived inauthenticity translates into vigilance is an open empirical question.

Three streams of theory frame the question. The Persuasion Knowledge Model proposes that consumers develop knowledge about marketers' influence tactics and draw on it when they suspect they are being persuaded⁴; paid or manipulated reviews are persuasion attempts disguised as independent opinion, so suspecting them should activate this knowledge. The trust–distrust literature separates low trust, which may only lead a consumer to ignore a source, from active distrust, which leads to critical examination of the source. Finally, uncertainty in information processing motivates further search: when information is incomplete, inconsistent or of doubtful accuracy, decision-makers are driven to collect more. Together these suggest a chain in which perceived inauthenticity raises skepticism and uncertainty, and these in turn are associated with greater effort to verify, compare and scrutinise information.

Despite the growth of research on fake reviews, three shortcomings remain. First, prior work overwhelmingly targets algorithmic detection or platform economics rather than the consumer's own psychological response^{2,3,5}. Second, skepticism and uncertainty have rarely been tested together as parallel mechanisms leading to a behavioural outcome. Third, the evidence reviewed is drawn largely from United States and other global platform settings such as Amazon and Yelp, with few domestic empirical studies linking perceived review inauthenticity to consumer verification behaviour in India. Against this background, the objectives of the present study are: (i) to examine the impact of perceived online review inauthenticity on consumer information vigilance; (ii) to assess the relationship between perceived online review inauthenticity and review skepticism; (iii) to examine the effect of review skepticism and perceived information uncertainty on consumer information vigilance; and (iv) to investigate the mediating roles of review skepticism and perceived information uncertainty in the relationship between perceived online review inauthenticity and consumer information vigilance.

LITERATURE REVIEW:

This section reviews ten studies published between 2013 and 2024 on fake reviews, review manipulation and their consequences for consumers, sellers and platforms, summarised in Table 1, together with the theoretical foundations of the study. The studies are grouped by what they examine rather than by country, and the review then asks what they leave unexplained.

Detection of Fake and Deceptive Reviews

The earliest study in the set compared reviews written by crowd workers to imitate fakes with real fake reviews identified on a commercial platform and found that models trained on the crowdsourced material generalise poorly to real data³. Fake reviews in the real marketplace are therefore not simply the same as laboratory imitations, and what consumers encounter is harder to recognise than experimental material suggests. Later work has tried to reduce the labelling burden: a semi-supervised positive-unlabelled learning approach reached a best F-score of 0.87 using only 100 labelled fake reviews⁵. At the other end of the threat spectrum, adversarial research found that



automatically generated reviews are harder to detect than conventional fakes¹. Together these studies indicate that detection is technically difficult and that neither platforms nor consumers can assume every fake review will be filtered out.

Machine Learning and Sentiment-Based Approaches

A second group applies machine learning to review classification. A web application for classifying and removing deceptive hotel reviews reported that a Random Forest classifier reached 90.6% sentiment accuracy⁶. Sentiment-based detection using classical machine learning found that a support vector machine (SVM) achieved the highest accuracy among five algorithms tested⁷, and an extended study confirmed the SVM's superior accuracy and reported that stop-word removal helps performance⁸. A tiered opinion-mining approach showed that multi-phase classification improves the granularity of detection⁹. These studies are valuable for platforms that wish to filter reviews, but they describe the problem from the algorithm's point of view and do not ask how a consumer comes to believe that reviews are inauthentic or how the consumer behaves as a result.

Economics of Fake Reviews and Platform Enforcement

A third group examines what fake reviews do to markets. Rating dispersion, the spread of ratings around the mean, helps consumers infer that reviews may be fake and lowers their willingness to pay¹⁰. A study of the Amazon marketplace found that fake reviews raise seller sales by about 25% and cut honest sellers' profit by about 4.7%², and an economic analysis of seller incentives concluded that platform enforcement, including mass delisting, reduces the inflow of fake reviews¹¹. The first of these is especially relevant here because it recognises that consumers draw inferences about authenticity from rating patterns and adjust their behaviour. It expresses that adjustment, however, as willingness to pay and not as the effort consumers devote to checking information.

Theoretical Foundations

The Persuasion Knowledge Model explains how consumers use their understanding of marketing tactics to cope with persuasion attempts⁴. In the review context, paid and manipulated reviews are persuasion attempts disguised as independent opinion; once consumers perceive the disguise, the model predicts closer scrutiny, which in this study is expected to appear as skepticism and as additional information-checking effort. Trust and distrust are not opposite ends of one scale: distrust implies active scrutiny, whereas low trust may only mean that reviews are ignored, so perceived inauthenticity should be associated with more, not less, information effort. Uncertainty, finally, motivates search: if reviews seem unreliable, consumers experience a gap in the information they need and are motivated to fill it. Skepticism (doubt about the source) and uncertainty (doubt about the sufficiency of the information) can co-occur but are not identical, which is why they are treated as separate, parallel mediators.

Table 1. Summary of reviewed literature on fake reviews and consumer response

No.	Author(s) (Year)	Focus & Context	Key Findings	Gap / Contribution to Study
1	Mukherjee et al. (2013)	Crowdsourced (AMT) pseudo fake reviews versus real fake reviews	Crowdsourced fake-review models generalise poorly to real data.	Real fakes are hard to recognise; consumers' own response not examined.
2	Huang, Villas-Boas & Zhao (2023)	Rating dispersion and demand	Dispersion helps consumers infer fake reviews and lowers willingness to pay.	Consumers infer fakes; response expressed as willingness to pay, not verification effort.
No.	Author(s) (Year)	Focus & Context	Key Findings	Gap / Contribution to Study
3	Gandhi, Hollenbeck & Li (2024)	Fake reviews and platform welfare (Amazon)	Fake reviews raise seller sales by about 25% and cut honest sellers' profit by about 4.7%.	Market effects documented; consumer-side response not modelled.
4	Alshehri (2024)	Positive-unlabelled (PU) learning detection	Best F-score of 0.87 using only 100 labelled fake reviews.	Detection is feasible with scarce labels; algorithm-side focus.
5	Bansode et al. (2021)	Machine-learning web application for hotel reviews	Random Forest reached 90.6% sentiment accuracy.	Platform-side filtering tool; no consumer behaviour.
6	Elmurngi & Gherbi (2017)	Sentiment-based fake-review detection	SVM achieved the highest accuracy among five algorithms tested.	Classifier comparison; no consumer cognition.
7	Hovy (2016)	Adversarial, NLP-generated reviews	AI-generated reviews are harder to detect than conventional fakes.	Makes consumer suspicion plausible; no consumer data.



8	Patel, Kapoor & Sonawane (2018)	Opinion mining with tiered classification	Multi-phase classification improves detection granularity.	Detection granularity; consumer response not studied.
9	Elmurngi & Gherbi (2018)	Extended sentiment-based detection study	Confirms SVM's superior accuracy; stop-word removal helps.	Extends detection work; algorithm-side focus.
10	Kiseleva (2022)	Economics of fake reviews; seller incentives	Platform enforcement (mass delisting) cuts fake-review inflow.	Enforcement can reduce fakes; consumers' reaction not modelled.

Source: Compiled by the authors from the reviewed literature.

RESEARCH GAPS:

- **Detection over cognition:** Prior work overwhelmingly targets algorithmic fake-review detection; the consumer's own psychological response to perceived inauthenticity is rarely modelled^{1,3,5}.
- **Missing mediating mechanisms:** Review skepticism and perceived information uncertainty are plausible responses to perceived inauthenticity but have not been jointly tested as parallel mediators leading to vigilance.
- **Limited behavioural outcome:** Existing studies stop at detection accuracy or platform welfare^{2,6}; few connect inauthenticity perceptions to consumer verification effort, termed information vigilance here.
- **Geographic gap:** Domestic empirical studies linking perceived review inauthenticity to consumer verification behaviour are limited; the most cited work is based on United States or global platform data such as Amazon and Yelp.

PROBLEM STATEMENT:

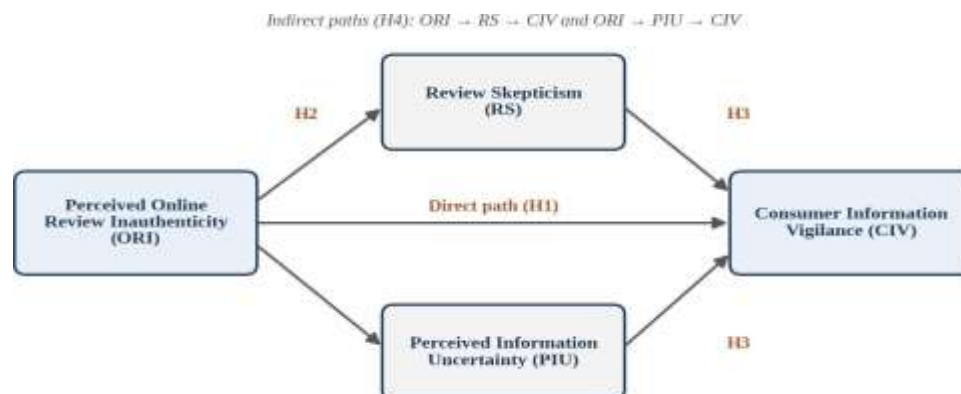
Online reviews influence consumer decisions, yet the growing presence of fake, paid, exaggerated and AI-generated reviews raises doubts about their authenticity. It is not clearly understood whether and how these doubts change the way consumers handle information: whether perceived inauthenticity is associated with greater information vigilance, whether review skepticism and perceived information uncertainty explain that association, and how strong these relationships are among online consumers in India. The study therefore addresses the following research questions:

- **RQ1:** Does perceived online review inauthenticity affect consumer information vigilance?
- **RQ2:** Is perceived online review inauthenticity related to review skepticism?
- **RQ3:** Do review skepticism and perceived information uncertainty jointly predict consumer information vigilance?
- **RQ4:** Do review skepticism and perceived information uncertainty mediate the relationship between perceived online review inauthenticity and consumer information vigilance?

CONCEPTUAL FRAMEWORK AND HYPOTHESES DEVELOPMENT:

The framework in Figure 1 positions perceived online review inauthenticity (ORI) as the independent variable and consumer information vigilance (CIV) as the dependent variable, with review skepticism (RS) and perceived information uncertainty (PIU) as parallel mediators. The direct path tests H1, the ORI–RS path tests H2, the two mediator-to-outcome paths test H3, and the combined indirect paths test H4.

Figure 1. Conceptual framework of the study





Source: Developed by the authors.

H1 follows the Persuasion Knowledge Model and the trust–distrust literature, which suggest that doubts about authenticity lead to closer scrutiny of information⁴. H2 draws on the same model: when persuasion knowledge is activated, consumers become more skeptical. H3 reflects the argument that skeptical consumers question the credibility of information and uncertain consumers seek to reduce their uncertainty. H4 follows from the chain itself: if perceived inauthenticity raises skepticism and uncertainty, and these raise vigilance, part of the ORI–CIV relationship should operate through them. Accordingly, the following hypotheses were formulated:

- **H1:** Perceived online review inauthenticity (ORI) has a significant positive effect on consumer information vigilance (CIV).
- **H2:** Perceived online review inauthenticity (ORI) is significantly and positively related to review skepticism (RS).
- **H3:** Review skepticism (RS) and perceived information uncertainty (PIU) have a significant positive effect on consumer information vigilance (CIV).
- **H4:** Review skepticism (RS) and perceived information uncertainty (PIU) mediate the relationship between perceived online review inauthenticity (ORI) and consumer information vigilance (CIV).

RESEARCH METHODOLOGY:

Research Design

The study adopts a quantitative, cross-sectional survey design. A structured questionnaire was administered once to each respondent and the responses were coded numerically. A quantitative design suits objectives that ask whether constructs are related and how strongly, because these questions are answered by estimating coefficients, confidence intervals and explained variance. Each objective is tied to a distinct procedure: Objective 1 is a bivariate prediction problem (simple linear regression), Objective 2 a bivariate association problem (Pearson correlation), Objective 3 a joint-effect problem (multiple linear regression) and Objective 4 a test of whether two variables transmit part of an effect (parallel mediation with bootstrap intervals). Because measurement occurs at a single point in time, the design supports statements about association and prediction, not causation¹².

Population, Sampling and Sample Size

The target population comprised consumers who shop online and read product or service reviews before purchase. The final dataset contains 270 valid responses, all of which were used in every analysis; the mediation model used listwise handling of missing data and still retained $N = 270$, so no case was lost. No probability sampling frame was used, so the sample is treated as a purposive sample of online review users¹³ and the results are interpreted as describing this sample, not as population estimates. With 270 cases the multiple regression has 267 residual degrees of freedom, and the sample can detect a correlation of about 0.17 at the 5% level with 80% power (a supplementary computation), well below the observed correlation of 0.507.

Measurement Instrument

The questionnaire recorded four respondent-profile variables (age group, gender, frequency of online shopping and frequency of checking reviews before purchase) and then presented statements on a five-point Likert scale (1 = strongly disagree; 5 = strongly agree) for four constructs, with five items per construct (20 items in all; Table 2). A composite score for each construct was computed as the arithmetic mean of its five items, so each composite lies between 1 and 5. Higher scores indicate stronger perceived inauthenticity (ORI), greater skepticism (RS), greater uncertainty (PIU) and greater effort to verify information (CIV).

Table 2. Operationalisation of the research constructs

Construct	Code	Role in model	Items	Content measured	Cronbach's α
Perceived Online Review Inauthenticity	ORI1–ORI5	Independent	5	Belief that reviews are fake, paid, exaggerated, manipulated or misleading	.704
Review Skepticism	RS1–RS5	Mediator / predictor	5	Tendency to doubt and question the credibility of review content	.801
Perceived Information Uncertainty	PIU1–PIU5	Mediator / predictor	5	Uncertainty about the accuracy, consistency or adequacy of review information	.832
Consumer Information Vigilance	CIV1–CIV5	Dependent	5	Effort to verify, compare and scrutinise information before purchase	.829



Source: Survey instrument developed by the authors (item-level wording is not reproduced; items are identified by construct and item code).

Tools of Analysis

All analyses were carried out in jamovi¹⁴. Internal consistency was judged with Cronbach's alpha¹⁵ against the conventional minimum of 0.70¹⁶. Descriptive statistics, Pearson correlation (with Spearman's rank correlation as a robustness check), simple and multiple linear regression (Objectives 1 to 3) and the jAMM GLM mediation module (Objective 4) were used. Because the sampling distribution of a product of coefficients is usually not normal, indirect effects were tested with 5,000 bootstrap resamples and 95% percentile confidence intervals, and an indirect effect is regarded as supported when its interval excludes zero¹⁷. Effect sizes follow Cohen's benchmarks¹⁸. One-sample *t* tests against the scale midpoint of 3.0, confidence intervals for means, Cohen's *d*, predicted values, variance-inflation estimates and effect shares were computed from the reported summary statistics and are labelled as supplementary. The decision rule was to reject the null hypothesis when $p < .05$. Construct validity was not tested with factor analysis.

Ethical Considerations

Participation was voluntary and the questionnaire did not ask for sensitive information. Respondent names were not required for the analysis and are not reproduced, results are reported only in aggregate, and the study follows the university's research-ethics and plagiarism requirements.

RESULTS:

Profile of Respondents

Table 3 shows that the sample is young, digitally active and experienced with reviews. Respondents aged 18–25 (72.6%) and 26–35 (23.3%) together make up 95.9% of the sample, and only 4.1% are aged 36–45 (2.6%) or below 18 (1.5%). Men outnumber women by about 2.2 to 1 (68.5% versus 31.1%); one respondent (0.4%) preferred not to say. Most respondents are regular online buyers (68.1% shop frequently or very frequently; none never shop online), and review checking is a habit: 65.2% always and 12.2% often check reviews before buying, so 77.4% do so always or often, while only 0.7% never do.

Table 3. Profile of respondents (N = 270)

Variable	Category: n (%)
Age group	Below 18: 4 (1.5); 18–25: 196 (72.6); 26–35: 63 (23.3); 36–45: 7 (2.6)
Gender	Male: 185 (68.5); Female: 84 (31.1); Prefer not to say: 1 (0.4)
Online shopping frequency	Rarely: 20 (7.4); Sometimes: 66 (24.4); Frequently: 77 (28.5); Very frequently: 107 (39.6)
Review-checking frequency	Never: 2 (0.7); Rarely: 23 (8.5); Sometimes: 35 (13.0); Often: 33 (12.2); Always: 176 (65.2)

Source: Primary survey data (N = 270), jamovi output.

Reliability and Descriptive Statistics of the Constructs

All four scales meet the conventional 0.70 threshold (Table 4): RS ($\alpha = .801$), PIU (.832) and CIV (.829) show good internal consistency and ORI (.704) is acceptable. ORI has the weakest reliability, so relationships involving it may be slightly attenuated by measurement error, which makes the significant ORI results more, not less, convincing. All four construct means lie well above the neutral midpoint (Figure 2), with CIV highest (4.139), followed by PIU (4.104), RS (4.071) and ORI (3.933). Each differs significantly from 3.0 with very large effects ($d = 1.13$ – 1.51 ; Table 5), and all fall in the “agree” band of the Likert scale. The ordering $ORI < RS < PIU < CIV$ is consistent with the proposed sequence of perception, psychological response and behavioural outcome, although adjacent differences are small. ORI has the widest observed range and the largest SD, so perceptions of inauthenticity vary more across respondents than the other constructs, which is useful for the regression analyses.

Table 4. Reliability and descriptive statistics of the constructs (N = 270)

Construct	Items	Cronbach's α	Verdict	Mean	SD	Min	Max
ORI	5	.704	Acceptable	3.933	0.828	1.200	5.000
RS	5	.801	Good	4.071	0.777	1.400	5.000
PIU	5	.832	Good	4.104	0.787	1.600	5.000
CIV	5	.829	Good	4.139	0.756	1.400	5.000

Thresholds: 0.70 acceptable; 0.80 good. Source: jamovi output.

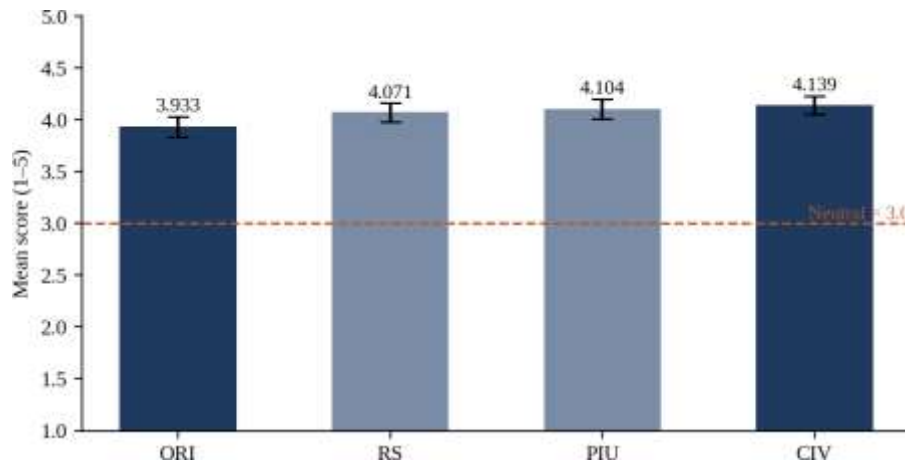


Table 5. Construct means compared with the neutral midpoint of 3.0 (supplementary)

Construct	Mean	95% CI	<i>t</i> (269)	<i>p</i>	Cohen's <i>d</i>	% of max.
ORI	3.933	3.83–4.03	18.52	< .001	1.13	78.7%
RS	4.071	3.98–4.16	22.65	< .001	1.38	81.4%
PIU	4.104	4.01–4.20	23.05	< .001	1.40	82.1%
CIV	4.139	4.05–4.23	24.76	< .001	1.51	82.8%

Source: computed from reported means and SDs (two-tailed); supplementary computations.

Figure 2. Mean construct scores with 95% confidence intervals



Source: jamovi output; confidence intervals computed; prepared by the authors.

Objective 1: Impact of Perceived Online Review Inauthenticity on Consumer Information Vigilance

A simple linear regression was estimated with CIV as the dependent variable and ORI as the predictor. The model is statistically significant, $F(1, 268) = 49.4$, $p < .001$, and ORI accounts for 15.6% of the variance in CIV ($R = .394$; $R^2 = .156$; adjusted $R^2 = .152$; RMSE = 0.693), a medium-to-large effect (Cohen's $f^2 \approx 0.18$). As Table 6 shows, ORI is a positive and significant predictor ($B = 0.360$; $\beta = 0.394$; $t = 7.03$; $p < .001$), so a one-point increase in ORI is associated with an estimated 0.360-point increase in CIV. The 95% confidence interval [0.259, 0.461] excludes zero and is fairly narrow, indicating a precisely estimated effect.

Table 6. Simple linear regression of CIV on ORI (N = 270)

Predictor	B	SE	β	<i>t</i>	<i>p</i>	95% CI for B
(Intercept)	2.722	0.206	—	13.21	< .001	[2.316, 3.127]
ORI	0.360	0.051	0.394	7.03	< .001	[0.259, 0.461]

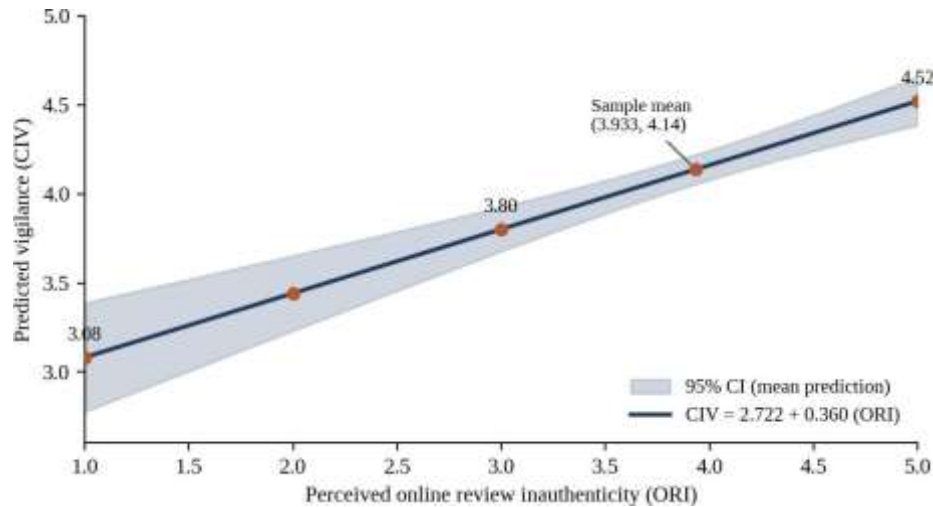
Model: $R = .394$; $R^2 = .156$; adjusted $R^2 = .152$; $F(1, 268) = 49.4$, $p < .001$. $CIV = 2.722 + 0.360 (ORI)$. Source: jamovi output.

Translated into predicted scores (Figure 3), respondents with the lowest possible ORI score (1.0) are predicted to have a CIV of about 3.08, which indicates a baseline level of vigilance regardless of perceived inauthenticity; predicted vigilance rises to 3.80 at the neutral ORI score of 3.0, 4.14 at the sample mean and about 4.52 at the maximum of 5.0. The jamovi diagnostic plots showed some tail deviation in the residuals and some outlying observations, so the residuals cannot be described as perfectly normal; with $N = 270$ the coefficient estimates remain usable. The remaining 84.4% of variance in CIV relates to factors not included in the model.

H1 is supported.



Figure 3. Fitted regression line for ORI and CIV with 95% confidence band



Source: jamovi regression equation; band computed from reported RMSE and descriptive statistics; prepared by the authors.

Objective 2: Relationship between Perceived Online Review Inauthenticity and Review Skepticism

ORI and RS are significantly and positively correlated (Pearson $r(268) = .507$; $p < .001$; 95% CI [.413, .591]; Table 7). Spearman's $\rho = .536$ ($p < .001$) leads to the same conclusion, so the result does not depend on the choice of method or on a few extreme points. By Cohen's benchmarks¹⁸ an r of .507 is a large association, and the interval lies entirely above the medium-effect value of .30. The coefficient of determination ($r^2 = .257$) shows that the two constructs share about 25.7% of their variance: they are clearly related but not the same, which supports treating perceived inauthenticity (a belief about the reviews) and skepticism (a disposition in reading them) as distinct. Respondents who see reviews as more inauthentic are therefore also more skeptical of what reviews say. This is an association, not proof that ORI causes RS. **H2 is supported.**

Table 7. Correlation between ORI and RS (N = 270)

Test	Coefficient	df	p	95% CI
Pearson r	.507	268	< .001	[.413, .591]
Spearman ρ (robustness check)	.536	—	< .001	[.445, .616] (approximate)

Source: jamovi output; the Spearman interval is an approximate Fisher-z computation (supplementary).

Objective 3: Effect of Review Skepticism and Perceived Information Uncertainty on Consumer Information Vigilance

A multiple linear regression with CIV as the dependent variable and RS and PIU as predictors is significant, $F(2, 267) = 78.1$, $p < .001$, and the two predictors together account for 36.9% of the variance in CIV ($R = .608$; $R^2 = .369$; adjusted $R^2 = .364$; $RMSE = 0.599$). This is a large effect (Cohen's $f^2 \approx 0.58$) and more than double the 15.6% explained by ORI alone in Objective 1. Both predictors are positive and significant while controlling for the other (Table 8; Figure 4): RS has $B = 0.244$ ($\beta = 0.251$; $p < .001$) and PIU has $B = 0.407$ ($\beta = 0.424$; $p < .001$), and both confidence intervals exclude zero.

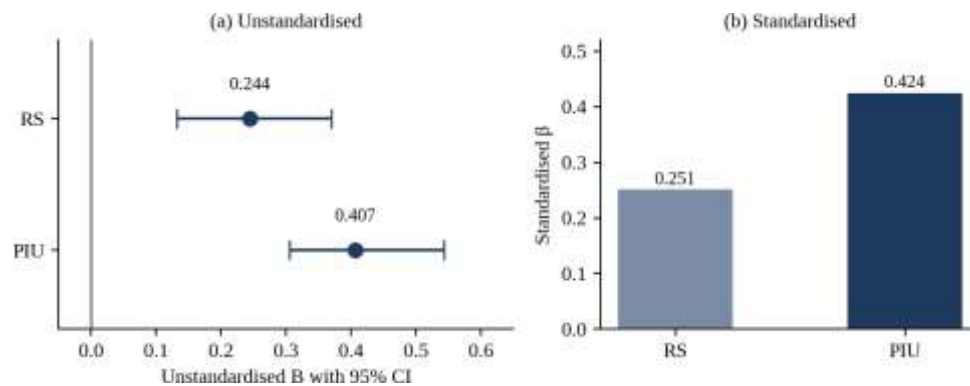
Table 8. Multiple linear regression of CIV on RS and PIU (N = 270)

Predictor	B	SE	β	t	p	95% CI for B
(Intercept)	1.473	0.218	—	6.75	< .001	[1.043, 1.903]
RS	0.244	0.059	0.251	4.16	< .001	[0.132, 0.370]
PIU	0.407	0.058	0.424	7.02	< .001	[0.305, 0.543]

Model: $R = .608$; $R^2 = .369$; adjusted $R^2 = .364$; $F(2, 267) = 78.1$, $p < .001$. $CIV = 1.473 + 0.244 (RS) + 0.407 (PIU)$. Source: jamovi output.



Figure 4. Regression coefficients for RS and PIU (dependent variable: CIV)



Source: jamovi output; prepared by the authors.

PIU is the stronger predictor: its standardised coefficient (0.424) is about 1.7 times that of RS (0.251). This comparison is descriptive, as no formal test of the difference was run. The correlation between RS and PIU was not part of the output but can be back-calculated from R^2 and the standardised coefficients as approximately .59, implying a variance inflation factor of about 1.54 (tolerance $\approx$ 0.65), well below the usual warning thresholds, so multicollinearity is unlikely to be a problem. On that basis about 21% of the variance in CIV is shared by RS and PIU, about 11.7% is uniquely associated with PIU and about 4.1% uniquely with RS (supplementary approximations). Consumers who are more skeptical, and consumers who are more uncertain about the adequacy of review information, report more vigilant verification; skepticism expresses doubt about the source and uncertainty a gap in the information. The residual 63.1% of variance indicates that other factors also contribute. **H3 is supported.**

Objective 4: Mediating Roles of Review Skepticism and Perceived Information Uncertainty

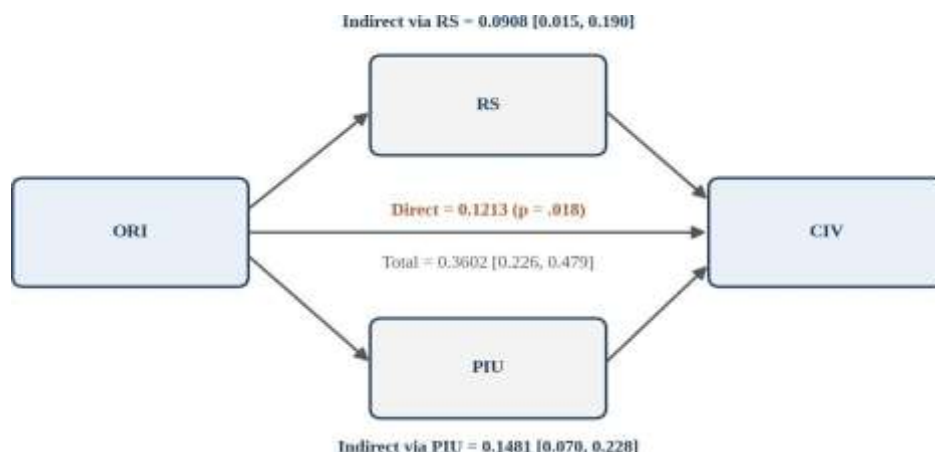
A parallel mediation model was estimated with the jAMM GLM mediation module, with ORI as the independent variable, RS and PIU as parallel mediators and CIV as the dependent variable ($N = 270$; listwise deletion; 5,000 bootstrap repetitions; 95% percentile intervals). Table 9 and Figures 5 and 6 report the effects. Both indirect effects are significant because their bootstrap intervals exclude zero: through RS the effect is 0.0908 [0.0151, 0.190] and through PIU it is 0.1481 [0.0699, 0.228]. The direct effect remains significant after both mediators are included ($B = 0.1213$; $p = .018$; 95% CI [0.0092, 0.234]), and the total effect is 0.3602 ($p < .001$; 95% CI [0.2261, 0.479]). The total effect equals the Objective 1 coefficient (0.360) and decomposes exactly into the direct effect plus the two indirect effects ($0.1213 + 0.0908 + 0.1481 = 0.3602$).

Table 9. Parallel mediation: indirect, direct and total effects of ORI on CIV ($N = 270$)

Effect	Path	Estimate	SE	95% CI lower	95% CI upper	β	z	p
Indirect	ORI $\rightarrow$ RS $\rightarrow$ CIV	0.0908	0.0310	0.0151	0.190	0.0994	2.93	.003
Indirect	ORI $\rightarrow$ PIU $\rightarrow$ CIV	0.1481	0.0301	0.0699	0.228	0.1621	4.91	< .001
Direct	ORI $\rightarrow$ CIV	0.1213	0.0512	0.0092	0.234	0.1329	2.37	.018
Total	ORI $\rightarrow$ CIV	0.3602	0.0512	0.2261	0.479	0.3944	7.04	< .001

Source: jamovi jAMM output (5,000 bootstrap resamples, 95% percentile CI).

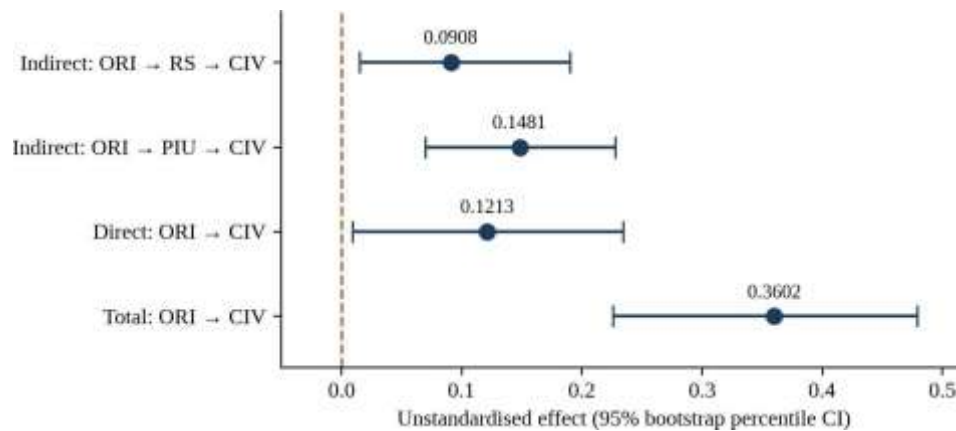
Figure 5. Parallel mediation model with estimated effects





Source: jamovi jAMM output; prepared by the authors.

Figure 6. Indirect, direct and total effects with 95% bootstrap confidence intervals



Source: jamovi jAMM output; prepared by the authors.

Expressed as shares of the total effect (descriptive ratios computed from the estimates), about 41.1% passes through PIU, 25.2% through RS and 33.7% remains direct, so the two indirect pathways together carry about 66.3%. The PIU route is about 1.6 times the RS route, but the confidence intervals overlap and no formal comparison was made, so the ordering is suggestive and not conclusive. The lower limit of the RS interval is close to zero, making that pathway the weaker and less precisely estimated of the two, and the direct effect is likewise estimated with limited precision (lower limit 0.0092). Because the direct effect remains significant, the pattern is one of partial and not full mediation. The data are consistent with significant indirect pathways under the specified model, but they do not prove that the mediators cause the outcome, because the design is cross-sectional and self-reported^{17,19}. **H4 is supported (partial mediation).**

Summary of Hypothesis Testing

Table 10. Summary of hypothesis testing

Hypothesis	Test and key result	Decision
H1	Simple regression: $B = 0.360$; $\beta = .394$; $R^2 = .156$; $F(1, 268) = 49.4$, $p < .001$	Supported
H2	Pearson $r = .507$, 95% CI [.413, .591], $p < .001$; Spearman $\rho = .536$	Supported
Hypothesis	Test and key result	Decision
H3	Multiple regression: RS $B = 0.244$, PIU $B = 0.407$ (both $p < .001$); $R^2 = .369$; $F(2, 267) = 78.1$	Supported
H4	Indirect via RS = 0.0908 [0.0151, 0.190]; via PIU = 0.1481 [0.0699, 0.228]; direct = 0.1213, $p = .018$	Supported (partial mediation)

Source: Compiled by the authors from the jamovi analyses.

DISCUSSION:

Suspicion intensifies, rather than switches off, information effort. ORI significantly predicts CIV ($\beta = .394$) and explains 15.6% of its variance: consumers who believe reviews may be fake, paid or manipulated report greater effort to verify, compare and scrutinise information. This fits the Persuasion Knowledge Model, in which suspicion that a communication is designed to persuade leads to closer scrutiny⁴, and it is consistent with the view of distrust as an active, effortful state and not simply low trust. It also adds a consumer-side counterpart to the economic literature, where consumers who infer fake reviews from rating dispersion lower their willingness to pay¹⁰: the present results suggest that suspicion shows itself not only in price but also in the effort spent on checking. The direction is notable, because perceived inauthenticity did not make respondents disengage from reviews.

Inauthenticity and skepticism are linked but distinct. The large correlation between ORI and RS ($r = .507$; $\rho = .536$) agrees with the expectation that activated persuasion knowledge makes consumers more skeptical⁴. The two constructs share only about a quarter of their variance, so the belief that reviews are inauthentic and the disposition to question what they say are related but separable, which justifies modelling skepticism as a mediator.

Uncertainty is the stronger psychological route. RS and PIU together explain 36.9% of the variance in CIV, more than twice what ORI explains alone, which suggests that vigilance is driven less by the bare perception of



inauthenticity than by the states it produces: doubt about the source (RS) and doubt about the adequacy of the information (PIU). PIU carries the larger coefficient ($\beta = .424$ versus $.251$) and about 41% of the total effect passes through it, in line with the idea that an information gap creates a need to search. This is also consistent with research showing that consumers read patterns such as rating dispersion as signals about review reliability¹⁰. Skepticism adds less unique information once uncertainty is accounted for, probably because the two are moderately correlated.

Partial mediation. Both indirect effects are significant and the direct effect remains, so about two thirds of the total effect (0.3602) is carried by RS and PIU and about one third remains direct. The direct component may reflect habitual cross-checking prompted by general awareness of fake reviews, without a conscious change in skepticism or uncertainty, or other mediating states that were not measured. Given the cross-sectional design, these readings are suggestions for future research and not conclusions.

Convergence across analyses. The four analyses form a coherent sequence in which all effects are positive and significant and none contradicts another: concerns about authenticity are connected with greater skepticism and uncertainty, and these psychological responses are in turn connected with greater vigilance in verifying information before purchase. This shifts the emphasis from detection alone, which dominates the reviewed literature^{3,5,7}, to how consumers feel about the information they read.

IMPLICATIONS:

Managerial Implications

- **E-commerce platforms:** Invest in visible authenticity signals such as verified-purchase tags, reviewer history and clear explanations of how reviews are moderated. Because uncertainty is the strongest route to vigilance, make the reliability of review information easier to judge, for example by showing rating distributions, the share of verified purchases and the recency of reviews.
- **Sellers and marketers:** Encourage genuine, incentive-free reviews. Manipulated reviews may raise short-term sales², but suspicion of inauthenticity raises skepticism, uncertainty and verification effort, which can erode trust and add to consumers' search costs over time.
- **Consumers:** The findings validate cross-checking reviews across platforms and reading reviewer profiles as rational responses when authenticity is in doubt; consumer education on simple verification habits can help people protect themselves.
- **Policymakers and regulators:** Because perceived inauthenticity measurably changes consumer behaviour and not only platform metrics, the findings support accountability measures such as platform enforcement and disclosure norms for incentivised reviews. Enforcement that reduces the inflow of fake reviews¹¹ is likely to lower consumer uncertainty as well.

Academic Implications

- The study extends the Persuasion Knowledge Model to online reviews and shows perceived inauthenticity linked to skepticism and, through it, to active information-verification behaviour.
- It empirically tests skepticism and uncertainty as parallel mediators between inauthenticity perceptions and vigilance, a pathway that detection-focused studies did not test.
- It shows distrust of reviews as an active and effortful state, since perceived inauthenticity is associated with more, not less, information effort.
- It demonstrates a compact, replicable analytical sequence for perception research: reliability, descriptives, correlation, simple and multiple regression, and a bootstrap parallel mediation model with decomposition of the total effect.

CONCLUSION:

This study examined how perceived online review inauthenticity relates to consumer information vigilance, directly and through review skepticism and perceived information uncertainty, using 270 valid responses from online shoppers who read reviews. All four objectives are supported: ORI significantly predicts CIV ($R^2 = .156$), ORI and RS are strongly and positively correlated ($r = .507$, $p < .001$), RS and PIU jointly explain 36.9% of the variance in CIV, and both partially mediate the ORI–CIV relationship (indirect effects 0.0908 and 0.1481; direct effect 0.1213). In short, when consumers doubt whether online reviews are



genuine they become more skeptical and more uncertain, and they work harder to verify information before buying. Authenticity is therefore not only a matter of detecting fake reviews but also of how consumers feel about the information they read. Because the design is cross-sectional and self-reported, the findings describe association and indirect statistical pathways, not proven causation.

LIMITATIONS OF THE STUDY:

- The cross-sectional design captures perceptions at one point in time; the relationships, including the mediation results, are associative and predictive and not proof of causality¹².
- The sample is skewed towards younger adults (72.6% aged 18–25) and male respondents (68.5%), no probability sampling frame was used¹³, and city of residence was not among the recorded profile variables, which limits generalisability.
- Single-source, self-reported perceptions raise the possibility of common-method bias²⁰.
- The residual diagnostics for the Objective 1 model showed some deviation from normality, with tail deviation and some outlying observations.
- The ORI scale has the lowest reliability ($\alpha = .704$), construct validity was not tested with factor analysis, and several supplementary statistics were computed from reported summary values and therefore carry rounding error.
- The study did not examine specific platforms, product categories or actual verification behaviour, and the difference between the two indirect effects was not formally tested.

FUTURE SCOPE:

- Use longitudinal or experimental designs to test the causal direction between inauthenticity perception and vigilance.
- Collect broader and more balanced samples across age, gender and geography, including older consumers and respondents from several cities.
- Add moderators such as platform trust, product category and consumer expertise, and further mediators that might explain the remaining direct effect.
- Test the measurement model with confirmatory factor analysis and compare the two indirect effects formally.
- Combine survey measures with observed behaviour, such as actual cross-platform checking of reviews.

CONFLICT OF INTEREST:

The authors declare no conflicts of interest regarding this investigation.

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REFERENCES:

1. Hovy D. Adversarial detection of automatically or NLP/statistically generated fake reviews. 2016.
2. Gandhi A, Hollenbeck B, Li D. Equilibrium effects of fake reviews on Amazon marketplace welfare. 2024.
3. Mukherjee A, Venkataraman V, Liu B, Glance N. Comparing crowdsourced (AMT) pseudo fake reviews vs. real fake reviews. 2013.
4. Friestad M, Wright P. The persuasion knowledge model: How people cope with persuasion attempts. *Journal of Consumer Research*. 1994; 21(1):1–31.
5. Alshehri M. Semi-supervised (PU-learning) detection of fake reviews. 2024.
6. Bansode S, Pardeshi A, Okhal S, Shinde P, Birajdar S. An end-to-end web application to classify and remove deceptive hotel reviews. 2021.
7. Elmurngi E, Gherbi A. Sentiment-analysis based fake review detection using classical machine learning. 2017.



8. Elmurngi E, Gherbi A. Extended study on sentiment-based fake review detection. 2018.
9. Patel R, Kapoor R, Sonawane S. Fake review detection using opinion mining and tiered classification. 2018.
10. Huang N, Villas-Boas JM, Zhao Y. Fake reviews, rating dispersion, and consumer demand. 2023.
11. Kiseleva D. Economics of fake reviews: Seller incentives and platform enforcement effects. 2022.
12. Setia MS. Methodology series module 3: Cross-sectional studies. *Indian Journal of Dermatology*. 2016; 61(3):261–264. doi.org/10.4103/0019-5154.182410
13. Etikan I, Musa SA, Alkassim RS. Comparison of convenience sampling and purposive sampling. *American Journal of Theoretical and Applied Statistics*. 2016; 5(1):1–4. doi.org/10.11648/j.ajtas.20160501.11
14. The jamovi project. jamovi [Computer software]. <https://www.jamovi.org>
15. Cronbach LJ. Coefficient alpha and the internal structure of tests. *Psychometrika*. 1951; 16(3):297–334.
16. Nunnally JC. *Psychometric theory*. 2nd ed. New York: McGraw-Hill; 1978.
17. Preacher KJ, Hayes AF. Asymptotic and resampling strategies for assessing and comparing indirect effects in multiple mediator models. *Behavior Research Methods*. 2008; 40(3):879–891.
18. Cohen J. *Statistical power analysis for the behavioral sciences*. 2nd ed. Hillsdale, NJ: Lawrence Erlbaum Associates; 1988.
19. Baron RM, Kenny DA. The moderator–mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. *Journal of Personality and Social Psychology*. 1986; 51(6):1173–1182.
20. Podsakoff PM, MacKenzie SB, Lee JY, Podsakoff NP. Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology*. 2003; 88(5):879–903. doi.org/10.1037/0021-9010.88.5.879