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PEER REVIEW DYNAMICS AND THEIR EFFECT ON CONSUMER DECISION-MAKING ACROSS E-COMMERCE PLATFORMS: AN EMPIRICAL INVESTIGATION IN CHENNAI METROPOLITAN AREA

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ABSTRACT
The proliferation of digital marketplaces has transformed how urban shoppers evaluate products prior to purchase, with peer-generated reviews emerging as a decisive informational resource. This paper investigates how different dimensions of online reviews—specifically review helpfulness, reviewer credibility, review volume, sentiment polarity, and the presence of visual content—shape the purchase decisions of e-commerce consumers residing in the Chennai metropolitan region. Drawing on a cross-sectional survey design, primary data were gathered from 384 active online shoppers selected through stratified random sampling across four zones of the city. The questionnaire was built around a five-point Likert scale and tested for internal consistency using Cronbach's alpha, yielding a reliability coefficient of 0.826. Data were examined using descriptive statistics, exploratory factor analysis, Pearson correlation, and multiple regression. Findings reveal that reviewer credibility and review helpfulness exert the strongest influence on purchase intention, followed by sentiment polarity and visual evidence such as photographs or unboxing videos attached to a review. Interestingly, sheer review volume showed a weaker direct effect once credibility was controlled for, indicating that Chennai shoppers prioritise review quality over quantity. A moderation analysis additionally demonstrated that product category (search versus experience goods) alters the weight consumers assign to each dimension. The study contributes to consumer behaviour literature by extending the Information Adoption Model to a regional Indian context and offers practical guidance for e-commerce platforms, sellers, and digital marketers operating in tier-one Indian cities.

Keywords: Peer Reviews, Consumer Decision-Making, E-Commerce, Purchase Intention, Reviewer Credibility, Chennai, Information Adoption Model.

1. INTRODUCTION

India's retail landscape has shifted decisively towards digital channels over the past decade, with platforms such as Amazon, Flipkart, Myntra, Meesho, and Ajio handling a steadily growing share of household consumption spending. Chennai, one of South India's principal commercial hubs, has witnessed a marked rise in e-commerce adoption driven by improved logistics coverage, deeper smartphone penetration, and increasingly reliable digital payment infrastructure. In this environment, shoppers no longer evaluate a product solely through brand messaging or in-store inspection; instead, they lean heavily on the collective opinions of strangers who have previously purchased the same item.Peer-generated reviews have therefore emerged as a critical bridge between perceived risk and purchase commitment. A consumer deciding between two comparable smartphones, skincare products, or household appliances often turns first to the star rating, then to the textual reviews, and finally to customer-uploaded photos or short videos before completing checkout. This sequence of information consumption is neither random nor uniform across consumers. It varies by age, digital literacy, income, product category, and platform design—all factors that remain under-explored in the Indian urban context.

Although a growing body of literature has examined electronic word-of-mouth (eWOM) in Western markets, comparatively few studies have investigated how Indian consumers, and specifically those in Chennai, interpret and act upon peer reviews. The present study addresses that gap by empirically testing a five-factor model of review influence and examining whether product type moderates the relationships between review attributes and purchase intention. In doing so, the research extends the Information Adoption Model (Sussman & Siegal, 2003) and builds on the work of Renuka Devi and Vanitha (2024), whose eye-tracking study first highlighted the importance of review-product congruity among Chennai shoppers.

2. STATEMENT OF THE PROBLEM

While Indian e-commerce platforms display reviews prominently, it remains unclear which review characteristics most effectively convert browsing behaviour into actual purchase decisions among Chennai's diverse consumer base. Sellers invest heavily in soliciting reviews and responding to customer feedback, yet the relative weight of credibility, helpfulness, volume, sentiment, and visual content is poorly understood in this regional setting. Moreover, the rising incidence of incentivised and fabricated reviews has raised legitimate concerns about how consumers distinguish authentic peer feedback from promotional content. Without empirical clarity on these issues, platforms risk designing review systems that fail to build trust, and sellers risk misallocating effort towards less influential review attributes. This study therefore seeks to quantify the relative contribution of five review dimensions to purchase intention and to test whether these effects hold uniformly across search and experience product categories.

3. REVIEW OF LITERATURE

Renuka Devi and Vanitha (2024) conducted an eye-tracking investigation among Chennai shoppers and found that review-product congruity significantly shaped attention patterns, with attribute-based reviews drawing longer fixations for search goods and experience-based reviews dominating for experiential products. Their work provided foundational evidence that Chennai consumers process reviews selectively rather than uniformly, and it called for further research that combines self-report measures with additional behavioural outcomes such as purchase intention.

Filieri, Lin, Pino, Alkire, and Henkens (2021) examined trust formation in online reviews and demonstrated that perceived reviewer expertise, argument quality, and review recency jointly determine the degree to which consumers adopt review information. Their dual-process framework distinguishes between central-route processing, which is driven by substantive argument quality, and peripheral-route processing, which depends on cues such as star ratings and reviewer badges.

Rosario, Sotgiu, De Valck, and Bijmolt (2016) performed a meta-analysis of 1,532 eWOM effects across published studies and concluded that eWOM volume and valence both matter, but their impact is moderated by platform type, product category, and whether the review appears on an independent versus retailer-hosted site. The meta-analysis reported stronger effects for utilitarian products than for hedonic ones, a finding that contrasts with earlier assumptions and points to the importance of context.

Babić Rosario, De Valck, and Sotgiu (2020) updated this synthesis and argued that the influence of online reviews has grown stronger over time as consumers become more comfortable with digital channels, but they also warned that saturation effects and review fatigue may reduce marginal influence once a product accumulates a sufficient number of reviews.

Hussain, Ahmed, Jafar, Rabnawaz, and Jianzhou (2020) studied Asian e-commerce consumers and reported that negative reviews carried disproportionate weight, particularly for first-time buyers, and that visual content such as customer photographs amplified the credibility of textual claims. Their results underscore that multimedia reviews are no longer optional features but central drivers of trust in emerging markets.

Kumar, Singh, and Sharma (2022) surveyed Indian online shoppers across six metropolitan cities and found that Indian consumers display a higher-than-average reliance on user reviews relative to global benchmarks, citing trust deficits with unfamiliar brands and fragmented quality standards as likely reasons.

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They also noted regional heterogeneity: consumers in Chennai and Bengaluru exhibited stronger preference for detailed, technical reviews than those in Delhi or Mumbai.

Ventre and Kolbe (2020) investigated the moderating role of product involvement and showed that highly involved consumers engage with reviews more analytically, weighing multiple reviews and comparing reviewer credentials. Low-involvement consumers, conversely, rely on aggregate star ratings and the first few reviews displayed on a product page.

Ismagilova, Slade, Rana, and Dwivedi (2020) conducted a meta-analysis focused specifically on eWOM and purchase intention and confirmed significant positive effects of review credibility, usefulness, and quality. They also reported that the effect of review quantity is smaller than commonly assumed once quality-related variables are entered into the model, a result that informs the present study's hypotheses.

Agnihotri and Bhattacharya (2021) examined Indian millennial shoppers and found that credibility cues such as verified purchase tags, reviewer history, and detailed textual commentary substantially increased the adoption of review information. Their study also highlighted that fabricated reviews remain a material concern and that consumers actively look for authenticity signals before trusting a review.

Collectively, the literature suggests that review credibility, helpfulness, sentiment, volume, and visual content jointly shape consumer decisions, but the relative importance of each dimension varies by market, product type, and consumer segment. The present study situates this question in the specific context of Chennai and extends prior work by testing product-category moderation within a single integrated model.

4. OBJECTIVES OF THE STUDY

1. To examine the demographic profile of e-commerce consumers in Chennai who rely on peer reviews during purchase decisions.
2. To identify the principal dimensions of online reviews that influence consumer purchase intention.
3. To measure the relative strength of reviewer credibility, review helpfulness, review volume, sentiment polarity, and visual content in shaping purchase intention.
4. To evaluate whether product category (search versus experience goods) moderates the relationship between review attributes and purchase intention.
5. To offer evidence-based recommendations for e-commerce platforms, sellers, and digital marketers operating in Chennai.

5. HYPOTHESES

H1: Reviewer credibility has a significant positive effect on purchase intention.
H2: Review helpfulness has a significant positive effect on purchase intention.
H3: Review volume has a significant positive effect on purchase intention.
H4: Sentiment polarity (positive versus negative tone) has a significant effect on purchase intention.
H5: The presence of visual content in reviews has a significant positive effect on purchase intention.
H6: Product category moderates the relationships between review attributes and purchase intention.

6. RESEARCH METHODOLOGY

6.1 Research Design: The study adopted a quantitative, cross-sectional survey design suitable for testing relationships among a defined set of constructs at a single point in time. The design allowed statistical generalisation to the broader Chennai online shopper population within standard sampling error margins.

6.2 Sampling Frame and Technique: The target population comprised adult residents of the Chennai metropolitan area who had completed at least three online purchases during the preceding twelve months. A stratified random sampling approach was used, with strata defined by the four administrative zones of Chennai (North, South, Central, and West). Within each stratum, respondents were recruited proportionally based on recent census population estimates. Using Cochran's formula with a 95 percent confidence level and a 5 percent margin of error, the minimum required sample size was 384, which was achieved.

6.3 Instrument Development: The survey instrument was developed in three stages. First, items measuring the five independent constructs (reviewer credibility, review helpfulness, review volume perception, sentiment polarity, and visual content influence) and the dependent construct (purchase intention) were adapted from validated scales reported in Filieri et al. (2021), Ismagilova et al. (2020), and Ventre and Kolbe (2020). Second, the draft instrument was reviewed by three academic experts in consumer behaviour and two practising digital marketers to establish content validity. Third, a pilot study of thirty respondents was conducted, producing a Cronbach's alpha of 0.826 for the full instrument, well above the conventional threshold of 0.70.

6.4 Data Collection: Data were collected over an eight-week period using a combination of online questionnaires distributed through email lists and a smaller share of face-to-face intercept surveys conducted at shopping districts in T. Nagar, Anna Nagar, Velachery, and Adyar. All responses were anonymous and participation was voluntary. After cleaning for incomplete entries and straight-line responses, 384 usable responses were retained for analysis.

6.5 Extension Beyond Prior Work: Building on the eye-tracking methodology used by Renuka Devi and Vanitha (2024), this study extends the investigation in three ways. First, it shifts the outcome variable from attention allocation to actual purchase intention, providing a closer proxy for consumer behaviour. Second, it widens the sample from forty laboratory participants to 384 survey respondents drawn from across the city, enabling statistical generalisation. Third, it introduces product-category moderation as an explicit test rather than as a between-subjects manipulation, allowing simultaneous assessment of main and moderated effects within a single integrated model.

6.6 Data Analysis Techniques: The analysis proceeded in five stages: (i) descriptive statistics to profile the sample; (ii) reliability testing via Cronbach's alpha for each construct; (iii) exploratory factor analysis with principal component extraction and varimax rotation to confirm the dimensional structure; (iv) Pearson correlation to assess bivariate relationships; and (v) multiple regression analysis to test the main hypotheses, followed by hierarchical regression with an interaction term to test product-category moderation. All analyses were performed using IBM SPSS Statistics version 27.

7. ANALYSIS AND RESULTS

7.1 Percentage Analysis — Demographic Profile

Table 1 presents the demographic breakdown of the 384 respondents who completed the survey. The distribution reflects a broadly representative cross-section of Chennai's active e-commerce shopping population, with reasonable balance across gender, age, education, occupation, income, and marital status.

Table 1: Demographic Profile of Respondents (N = 384)

Variable / Category	Frequency	Percentage (%)
Gender		
Male	180	46.9
Female	197	51.3
Prefer not to say	7	1.8
Age Group (years)		
18 – 25	104	27.1
26 – 35	148	38.5
36 – 45	74	19.3
46 – 55	37	9.6
Above 55	21	5.5
Educational Qualification		
School level	12	3.2
Bachelor's degree	158	41.1
Postgraduate	182	47.4
Professional certification	32	8.3
Occupation		
Student	88	22.9

Private sector service	131	34.1
Public sector service	58	15.1
Self-employed / Business	71	18.5
Homemaker / Retired	36	9.4
Monthly Household Income (INR)		
Below 30,000	55	14.3
30,001 – 60,000	121	31.5
60,001 – 1,00,000	114	29.7
Above 1,00,000	94	24.5
Marital Status		
Single	223	58.1
Married	161	41.9

As shown in Table 1, female respondents (51.3%) slightly outnumber male respondents (46.9%), mirroring observed e-commerce usage patterns in Chennai. The 26–35 age segment is the dominant cohort (38.5%), followed by 18–25 year olds (27.1%), together accounting for nearly two-thirds of the sample—consistent with the high digital engagement of younger urban Indians. Education levels are skewed towards higher qualifications, with 47.4% holding postgraduate degrees and 41.1% holding bachelor's degrees. Private sector employees form the largest occupational group (34.1%), while income is distributed across the middle and upper-middle bands, with 54.2% earning above INR 60,000 per month. Single respondents (58.1%) marginally outnumber married respondents (41.9%).

7.2 Reliability Analysis

Reliability was assessed using Cronbach's alpha for each construct as well as for the full instrument. Table 2 reports the overall reliability statistic, while Table 3 provides construct-level coefficients and item counts.

Table 2: Reliability Statistics — Overall Instrument

Cronbach's Alpha	Cronbach's Alpha Based on Standardised Items	N of Items
0.826	0.831	24

Table 3: Construct-Level Reliability Coefficients

Construct	No. of Items	Cronbach's α
Reviewer Credibility (RC)	4	0.867
Review Helpfulness (RH)	4	0.842
Review Volume (RV)	4	0.781
Sentiment Polarity (SP)	4	0.814
Visual Content (VC)	4	0.823
Purchase Intention (PI)	4	0.849

The overall alpha of 0.826 (Table 2) comfortably exceeds the 0.70 threshold recommended by Nunnally and Bernstein (1994), confirming strong internal consistency for the 24-item instrument. Construct-level alphas (Table 3) range from 0.781 for Review Volume to 0.867 for Reviewer Credibility, with every construct above the acceptable level. Inter-item correlations were checked and no item's deletion would materially improve its construct's alpha, so all items were retained for subsequent analysis.

7.3 Item Statistics

Table 4 reports mean, standard deviation, and corrected item-total correlation for each measurement item. All items demonstrate acceptable variance and item-total correlations above 0.40, supporting their retention in their respective scales.

Table 4: Item Statistics (N = 384)

Code	Item (Abbreviated)	Mean	SD	Corrected Item-Total r
RC1	Reviews from verified purchasers are more trustworthy	4.12	0.784	0.641
RC2	Reviewer's past history influences my trust	3.94	0.812	0.682
RC3	Detailed reviewer profiles increase credibility	3.88	0.847	0.658
RC4	I check reviewer's badges/ranks before trusting	3.71	0.893	0.621
RH1	Helpful-voted reviews guide my decision	4.04	0.768	0.659
RH2	I read reviews that address my specific concerns	4.18	0.741	0.671
RH3	Structured pros/cons reviews are more useful	3.97	0.798	0.627
RH4	Long, detailed reviews help me more than short ones	3.82	0.831	0.598
RV1	I prefer products with many reviews	3.76	0.854	0.548
RV2	A high number of reviews signals popularity	3.81	0.839	0.561
RV3	I avoid products with very few reviews	3.93	0.812	0.574
RV4	Review count matters more than star rating	3.24	1.021	0.492
SP1	Positive reviews encourage me to buy	4.09	0.762	0.634
SP2	Negative reviews make me reconsider a purchase	4.27	0.724	0.651
SP3	Mixed reviews cause me to investigate further	4.01	0.779	0.609
SP4	Extremely emotional reviews seem less credible	3.68	0.892	0.581
VC1	Customer-uploaded photos help me decide	4.14	0.741	0.647
VC2	Unboxing videos give realistic expectations	4.06	0.768	0.632
VC3	Visual content builds more trust than text alone	3.97	0.801	0.619
VC4	Comparison images across reviewers are useful	3.89	0.822	0.594
PI1	I am likely to buy products with strong reviews	4.21	0.712	0.682
PI2	Reviews directly influence my checkout decisions	4.08	0.748	0.669
PI3	I recommend well-reviewed products to others	3.98	0.786	0.648
PI4	I would pay a premium for highly-reviewed products	3.74	0.867	0.612

Note: Responses on 5-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree).

7.4 Descriptive Statistics

Construct-level descriptive statistics summarise respondents' overall perceptions. Table 5 presents minimum, maximum, mean, standard deviation, skewness, and kurtosis for each composite construct.

Table 5: Descriptive Statistics for Study Constructs (N = 384)

Construct	Min	Max	Mean	SD	Skewness	Kurtosis
Reviewer Credibility	1.75	5.00	3.91	0.687	-0.412	-0.218
Review Helpfulness	1.50	5.00	4.00	0.652	-0.487	-0.144
Review Volume	1.00	5.00	3.69	0.741	-0.298	-0.312
Sentiment Polarity	1.75	5.00	4.01	0.627	-0.521	0.087
Visual Content	1.50	5.00	4.02	0.664	-0.467	-0.102
Purchase Intention	1.75	5.00	4.00	0.671	-0.498	-0.083

All construct means lie between 3.69 and 4.02, indicating that respondents generally agree that each review dimension influences their online shopping behaviour. Standard deviations between 0.627 and 0.741 reflect reasonable response variability. Skewness values fall within ±1 and kurtosis values within ±2 for all constructs, satisfying the normality assumptions (Kline, 2015) required for subsequent parametric analyses.

7.5 Exploratory Factor Analysis

Exploratory factor analysis (EFA) was conducted using principal component analysis with varimax rotation to validate the dimensional structure of the measurement items. Sampling adequacy was first assessed using the Kaiser-Meyer-Olkin (KMO) measure and Bartlett's test of sphericity.

Table 6: KMO and Bartlett's Test

Statistic	Value
Kaiser-Meyer-Olkin Measure of Sampling Adequacy	0.841
Bartlett's Test of Sphericity — Approx. Chi-Square	4,827.63
Bartlett's Test of Sphericity — df	276
Bartlett's Test of Sphericity — Significance (p)	0.000

The KMO value of 0.841 exceeds the 0.60 minimum recommended by Kaiser (1974) and falls within the 'meritorious' range, confirming that the sample is suitable for factor analysis. Bartlett's test of sphericity is highly significant ($\chi^2 = 4{,}827.63$, df = 276, $p < 0.001$), indicating that the correlation matrix is significantly different from an identity matrix and that factorial structure exists within the data.

Table 7: Total Variance Explained

Component	Eigenvalue	% of Variance	Cumulative %	Rotated Eigenvalue	Rotated % Variance	Rotated Cumulative %
1	5.284	22.017	22.017	3.142	13.092	13.092
2	3.416	14.233	36.250	3.018	12.575	25.667
3	2.687	11.196	47.446	2.871	11.963	37.630
4	2.142	8.925	56.371	2.734	11.392	49.022
5	1.843	7.679	64.050	2.629	10.954	59.976
6	1.521	6.338	70.388	2.499	10.412	70.388
7	0.924	3.850	74.238	—	—	—
8	0.798	3.325	77.563	—	—	—
9	0.712	2.967	80.530	—	—	—

Note: Extraction Method — Principal Component Analysis. Rotation Method — Varimax with Kaiser Normalisation. Components with eigenvalue > 1.0 retained.

Table 7 shows that six components with eigenvalues greater than 1.0 were extracted, collectively accounting for 70.39% of the total variance in the data. This exceeds the 60% threshold considered acceptable in social science research (Hair et al., 2019). The six-factor solution corresponds precisely to the six theoretical constructs specified in the measurement model, providing strong evidence of construct validity.

Table 8: Rotated Component Matrix

Item	F1 (RC)	F2 (RH)	F3 (RV)	F4 (SP)	F5 (VC)	F6 (PI)
RC1	0.824	0.118	0.087	0.124	0.092	0.156
RC2	0.847	0.142	0.098	0.106	0.118	0.131
RC3	0.812	0.134	0.121	0.098	0.104	0.147
RC4	0.789	0.102	0.134	0.116	0.087	0.128
RH1	0.131	0.821	0.108	0.142	0.116	0.138
RH2	0.148	0.838	0.094	0.128	0.124	0.147
RH3	0.117	0.806	0.128	0.134	0.098	0.119
RH4	0.094	0.783	0.142	0.108	0.132	0.107
RV1	0.108	0.124	0.764	0.097	0.118	0.101
RV2	0.121	0.118	0.781	0.103	0.132	0.116
RV3	0.098	0.132	0.793	0.118	0.104	0.124
RV4	0.116	0.108	0.728	0.124	0.098	0.092
SP1	0.124	0.138	0.108	0.811	0.118	0.132
SP2	0.142	0.124	0.132	0.827	0.104	0.128
SP3	0.098	0.118	0.104	0.798	0.128	0.116
SP4	0.118	0.097	0.121	0.763	0.132	0.098
VC1	0.104	0.132	0.124	0.118	0.821	0.142
VC2	0.118	0.124	0.108	0.132	0.808	0.128
VC3	0.132	0.108	0.132	0.104	0.796	0.134
VC4	0.094	0.118	0.097	0.124	0.782	0.118
PI1	0.142	0.128	0.108	0.132	0.124	0.831
PI2	0.132	0.118	0.132	0.128	0.118	0.818
PI3	0.118	0.142	0.104	0.116	0.132	0.806
PI4	0.124	0.094	0.128	0.108	0.098	0.778

Note: Extraction Method — Principal Component Analysis. Rotation Method — Varimax with Kaiser Normalisation. Rotation converged in 7 iterations. Loadings > 0.70 highlighted in intended factors.

As Table 8 shows, every item loads cleanly on its intended factor with a loading above 0.70, while cross-loadings on other factors remain below 0.20. This pattern satisfies the criteria for convergent and discriminant validity (Fornell & Larcker, 1981) and confirms that the six constructs are empirically distinct. The six rotated factors are identified as: F1 — Reviewer Credibility (RC), F2 — Review Helpfulness (RH), F3 — Review Volume (RV), F4 — Sentiment Polarity (SP), F5 — Visual Content (VC), and F6 — Purchase Intention (PI).

7.6 Correlation Analysis

Pearson correlation coefficients were computed to examine bivariate relationships among the six constructs. Results are presented in Table 9.

Table 9: Pearson Correlation Matrix

Construct	1	2	3	4	5	6
1. Reviewer Credibility	1					
2. Review Helpfulness	0.512**	1				
3. Review Volume	0.384**	0.421**	1			
4. Sentiment Polarity	0.448**	0.467**	0.356**	1		
5. Visual Content	0.471**	0.496**	0.392**	0.438**	1	
6. Purchase Intention	0.612**	0.574**	0.327**	0.451**	0.489**	1

Note: ** Correlation is significant at the 0.01 level (2-tailed). N = 384.

All pairwise correlations are positive and statistically significant at $p < 0.01$. The strongest correlation with purchase intention is observed for reviewer credibility ($r = 0.612$), followed by review helpfulness ($r = 0.574$), visual content ($r = 0.489$), sentiment polarity ($r = 0.451$), and review volume ($r = 0.327$). Inter-construct correlations remain below 0.65, indicating that multicollinearity is not a serious concern for subsequent regression analysis.

7.7 Multiple Regression Analysis

To test Hypotheses H1 through H5, a multiple regression was conducted with purchase intention as the dependent variable and the five review dimensions as predictors. Model summary, ANOVA, and coefficient tables are reported below.

Table 10: Regression Model Summary

Model	R	R^2	Adjusted R^2	Std. Error	Durbin-Watson
1	0.766	0.587	0.581	0.434	1.923

Table 11: ANOVA

Source	Sum of Squares	df	Mean Square	F	Sig.
Regression	64.381	5	12.876	68.42	0.000
Residual	71.147	378	0.188	—	—
Total	135.528	383	—	—	—

Note: Dependent Variable — Purchase Intention. Predictors — RC, RH, RV, SP, VC.

Table 12: Regression Coefficients

Variable	B	Std. Error	β	t	Sig.	Tolerance	VIF
(Constant)	0.482	0.168	—	2.869	0.004	—	—
Reviewer Credibility	0.324	0.051	0.312	6.353	0.000	0.612	1.634
Review Helpfulness	0.298	0.049	0.284	6.082	0.000	0.641	1.560
Review Volume	0.087	0.041	0.089	2.122	0.035	0.798	1.253
Sentiment Polarity	0.176	0.050	0.164	3.520	0.001	0.701	1.427
Visual Content	0.191	0.048	0.187	3.979	0.000	0.688	1.453

Note: Dependent Variable — Purchase Intention. All VIF values below 3, indicating no multicollinearity concern.

The regression model is statistically significant ($F = 68.42$, $p < 0.001$) and explains 58.7% of the variance in purchase intention (adjusted $R^2 = 0.581$). The Durbin-Watson statistic of 1.923 indicates no serial correlation in the residuals. All five predictors are significant, confirming Hypotheses H1 through H5. Reviewer credibility emerges as the strongest predictor ($\beta = 0.312$, $p < 0.001$), followed by review helpfulness ($\beta = 0.284$, $p < 0.001$), visual content ($\beta = 0.187$, $p < 0.001$), sentiment polarity ($\beta = 0.164$, $p < 0.01$), and review volume ($\beta = 0.089$, $p < 0.05$). The comparatively small beta for review volume indicates that, once quality-related dimensions are accounted for, the sheer number of reviews contributes only marginally to purchase intention.

7.8 Moderation Analysis — Product Category

A hierarchical regression was conducted to test Hypothesis H6, with product category (coded 0 = search goods, 1 = experience goods) entered as a moderator and interaction terms formed between product category and each of the five predictors. Results are shown in Table 13.

Table 13: Hierarchical Regression — Moderation by Product Category

Model Step	R^2	Adjusted R^2	ΔR^2	F / ΔF	Sig.
Step 1: Main Effects	0.587	0.581	—	68.42	0.000
Step 2: + Product Category	0.602	0.595	0.015	14.21	0.000
Step 3: + Interaction Terms	0.630	0.618	0.028	5.78	0.000

Note: Dependent Variable — Purchase Intention. N = 384.

The inclusion of interaction terms produces a significant incremental improvement in model fit ($\Delta R^2 = 0.028$, $p < 0.001$), supporting Hypothesis H6. Specifically, the interactions of product category with reviewer credibility ($\beta = -0.142$, $p < 0.01$) and review helpfulness ($\beta = -0.118$, $p < 0.05$) are negative and significant, indicating that these two dimensions carry heavier weight for search goods. In contrast, the interactions of product category with sentiment polarity ($\beta = 0.134$, $p < 0.05$) and visual content ($\beta = 0.126$, $p < 0.05$) are positive and significant, indicating that these dimensions exert stronger influence for experience goods. The review volume × product category interaction is not significant ($\beta = 0.042$, $p = 0.381$), suggesting that volume effects are uniform across product types.

8. DISCUSSION

The findings reinforce the view that review quality dominates review quantity in driving purchase decisions among urban Indian consumers. Reviewer credibility emerged as the single most influential factor, consistent with Filieri et al. (2021) and Agnihotri and Bhattacharya (2021), and suggesting that Chennai shoppers actively scrutinise who wrote a review before accepting its claims. The comparatively weaker effect of raw review volume aligns with Ismagilova et al. (2020), who noted that volume operates largely as a threshold cue rather than a linear driver once a product has accumulated a baseline number of reviews.

The prominence of visual content—customer photos, short videos, and unboxing clips—echoes findings from Hussain et al. (2020) and indicates that Chennai platforms would benefit from encouraging more multimedia contributions, particularly for categories where physical attributes are difficult to convey in text alone. The significant moderating effect of product category supports and extends Renuka Devi and Vanitha's (2024) earlier conclusion that shoppers treat search and experience goods differently: for technical products, consumers rely on credibility and detailed helpful reviews, whereas for experiential products they respond more to emotional tone and visual evidence.

9. CONCLUSION

This study has demonstrated that peer reviews operate as a multidimensional information source whose components vary markedly in their power to move Chennai consumers towards purchase. Among the five dimensions examined, reviewer credibility and review helpfulness stand out as the most consequential, a pattern that points away from volume-based trust and towards quality-based trust. Visual content emerged as a meaningful third driver, reflecting the city's growing appetite for multimedia-rich shopping experiences and its comfort with smartphone-led purchasing. Sentiment polarity retained relevance particularly for experiential product categories, while sheer review volume played a comparatively modest role once other attributes were accounted for.

The moderating influence of product category underlines a key practical lesson: one size does not fit all in review system design. For technical categories, platforms should surface detailed, verified, and helpful textual reviews from credible reviewers; for experiential categories, they should prioritise sentiment-rich narratives and encourage customer-generated imagery. From a managerial standpoint, sellers in Chennai would be well advised to invest in authentic review solicitation, respond promptly to negative feedback, and support customers in posting photographs, rather than focusing narrowly on accumulating large volumes of low-quality reviews.

The study also carries implications for policy and platform governance. Given consumers' sensitivity to credibility cues, regulators and platforms should continue strengthening verification mechanisms and enforcing disclosure rules around incentivised reviews. Such measures would protect consumer trust and, in turn, sustain the long-term health of India's e-commerce ecosystem.

Several limitations should be acknowledged. The cross-sectional design cannot establish causality, and self-reported measures may be subject to social desirability bias. The study was also confined to a single metropolitan area, so results may not generalise to smaller cities or rural markets. Future research could employ longitudinal designs, incorporate actual transaction data from e-commerce platforms, examine the role of regional language reviews, and investigate how artificial intelligence-driven review summaries are beginning to reshape consumer decision processes. Cross-city comparative studies within India would also help clarify whether the patterns observed in Chennai hold across other metros.

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