

The Role of Customer Reviews in Shaping Purchase Intentions on Social Commerce Platforms

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Abstract

The rapid expansion of e-commerce has significantly increased consumer reliance on user-generated content (UGC), especially online reviews, ratings, photos, and videos, as a primary source of product information and trust. This study investigates how different types of online reviews influence consumer decision-making, with a specific focus on review credibility, sentiment, and avoidance behaviour. Using primary data collected from 34 respondents aged 18–24, the research employs descriptive analysis, visualization techniques, and qualitative sentiment interpretation to examine the relationship between review formats and purchasing outcomes.

Findings reveal that photo reviews exert the strongest influence on purchase decisions, followed by text reviews and video reviews, while star ratings are used mainly as quick heuristics. The study also identifies a pronounced negativity bias, with the majority of respondents avoiding purchases when faced with negative reviews—particularly when accompanied by visual evidence. Mosaic plots, count distributions, and correlation analysis further highlight that avoidance behaviour is driven more by the quality and format of negative reviews rather than by the frequency of review-checking habits.

Qualitative insights from open-ended responses emphasize consumer demands for authenticity, transparency, and visual proof in reviews. Participants recommended increasing photo/video-based reviews, improving verification mechanisms, and presenting clearer, more detailed user experiences.

Overall, the research concludes that UGC—especially multimedia formats—plays a critical role in shaping trust and reducing perceived risk in online shopping. The study offers practical recommendations for e-commerce platforms to enhance review systems and improve consumer decision confidence, contributing valuable insights to the growing field of online consumer behaviour.

1. Introduction

1.1 Background

The rapid growth of e-commerce has transformed the way consumers search for information, evaluate products, and make purchase decisions. Unlike traditional retail environments—where buyers physically interact with products—online marketplaces depend heavily on **user-generated content (UGC)** such as customer reviews, ratings, comments, photos, and videos to serve as digital “experience substitutes.” Consumers rely on these inputs to reduce uncertainty, evaluate product quality, and assess trustworthiness before completing a purchase.

In contemporary online retail ecosystems, UGC functions as a critical information source. Platforms such as Amazon, Flipkart, Myntra, and other digital marketplaces have integrated sophisticated review systems

to help consumers navigate the overwhelming variety of choices. This evolution has made **online reviews a dominant form of electronic word-of-mouth (eWOM)**, influencing perceptions, shaping expectations, and significantly impacting conversion rates.

A noticeable shift in consumer behaviour shows that individuals—particularly younger demographics—actively seek reviews before purchasing. Your dataset reflects this trend clearly, as the majority of respondents aged 18–24 reported that they “often” or “always” check reviews before buying online. This highlights the increasing dependence on peergenerated insights rather than brand-driven communication. However, despite the importance of reviews, concerns about **credibility, authenticity, and manipulation** of UGC continue to grow. Fake reviews, paid reviews, biased star ratings, and misleading feedback often distort consumer perception. As a result, understanding how users interact with reviews, what elements they find trustworthy, and how review sentiment affects purchase intent has become a meaningful area of research.

This study examines these behaviours through primary data and explores how different forms of UGC—text reviews, star ratings, and video reviews—shape consumer decision-making in the Indian online marketplace context.

1.2 Problem Statement

While online reviews are widely used in decision-making, **not all reviews are equally trusted**, and the presence of misleading or low-quality reviews has become increasingly common. Consumers frequently encounter challenges such as:

- Difficulty distinguishing authentic reviews from fake or paid reviews
- Lack of photos or videos reducing review credibility
- Overly generic or repetitive feedback
- Bias in ratings without detailed explanations
- Contradictory reviews that create confusion rather than clarity

Your primary data captures these issues directly — respondents expressed doubts when reviews lack photos, appear overly positive, or provide insufficient detail. Many also relied more on photos or video-based reviews than text alone, indicating a shift in trust behaviour.

Therefore, the core problem lies in understanding:

How do different types of user-generated content and the sentiment within reviews influence consumer trust and their final purchase decision?

Despite abundant research on online consumer behaviour, limited studies focus on **sentiment-linked UGC insights using real consumer responses** within the Indian demographic, especially among young adults who constitute the highest online shoppers. Thus, there is a need to analyze review engagement patterns, identify credibility factors, and explore how sentiment and review format shape consumer decisions.

1.3 Objectives of the Study

Based on the identified research gaps and your primary dataset, the objectives of this study are:

1. **To examine the influence of user-generated content (UGC) on online purchase decisions**, specifically focusing on reviews, ratings, and multimedia content.
2. **To analyze consumer sentiment toward online reviews** and determine how sentiment (positive, neutral, negative) correlates with purchase intention.
3. **To identify the key factors that consumers consider when evaluating the trustworthiness of online reviews** (e.g., photos, detailed descriptions, ratings, transparency).

These objectives collectively contribute to understanding how UGC shapes perceptions, reduces uncertainty, and influences decision-making in digital purchasing environments.

1.4 Scope of the Project

The scope of this research is defined across four key dimensions:

1. Population and Demographics

The study focuses on **young Indian consumers** (primarily aged 18–24), representing a segment that is highly active in online shopping. The dataset includes students, working professionals, and individuals with varying shopping frequencies, making the findings relevant to emerging digital consumers.

2. Nature of Data Collected

The research is based on **primary survey data** consisting of 34 responses. Variables explored include:

- Frequency of online shopping
- Frequency of reading reviews
- Trust in reviews, ratings, and multimedia content
- Factors that build or reduce credibility
- Sentiment elements (preference for positive vs. negative reviews)
- Suggestions for improving review systems

3. Analytical Scope

The study involves:

- Exploratory Data Analysis (EDA)
- Preprocessing and cleaning of open-ended responses
- Sentiment-oriented interpretation
- Behavioural pattern identification
- Linking UGC elements to consumer decision-making

While the project does not build a machine learning prediction model, it emphasizes **datadriven behavioural insights**.

4. Practical and Theoretical Contribution

The findings aim to:

- Assist e-commerce platforms in improving review mechanisms
- Help marketers understand how consumers interact with digital reviews
- Contribute to academic literature on UGC, trust-building, and online consumer behaviour

The scope is limited to **consumer perception**, not product-level performance or platform algorithm analysis.

2. Literature Review

1. Hajli (2015)

Hajli (2015) investigates how social commerce constructs—such as reviews, recommendations, ratings, and social interaction—shape consumer purchase intention. Using a survey-based SEM approach, the study finds that trust is the central mediating factor through which review-based interactions influence buying decisions. The paper establishes one of the earliest and most influential frameworks in social commerce, demonstrating that online reviews do not directly trigger purchase intention but operate through trust, which strengthens consumer confidence in the platform.

2. Yang et al. (2022)

Yang et al. (2022) explore how reviews from strong ties (friends and family) differ from weak ties (strangers) in influencing purchase intention on social commerce platforms. Their findings show that strong-tie reviews significantly increase trust due to relational closeness, whereas weak-tie reviews work

through perceived popularity and higher information volume. The study highlights the importance of tie strength in social commerce and reveals that both types of reviews contribute to purchase intention through distinct psychological mechanisms.

3. Wang et al. (2022)

Wang et al. (2022) examine how trust in user-generated reviews and trust in the social commerce platform jointly shape purchase intention. Through a cross-national SEM analysis, the study reveals that both forms of trust significantly predict purchase behavior. Review credibility enhances trust in product information, while platform trust ensures transactional safety. Together, these trust dimensions play a critical role in shaping purchase intention, emphasizing the need for trustworthy review environments in social commerce.

4. Author (2024, Systematic Review – Social media eWOM)

This systematic review synthesizes empirical studies analyzing how social-media-based reviews and eWOM influence purchase intention from 2010 to 2024. The review identifies consistent predictors such as review valence (positive/negative tone), credibility, social proof signals (likes, shares), review volume, and identity disclosure. It emphasizes that social proof and emotional tone have become more influential in modern social commerce environments.

The review also calls for more behavioral and platform-specific research.

5. Author (2020 – Social Support & Reviews)

This study investigates how social support indicators—likes, comments, shares—interact with customer reviews to influence impulsive purchase behavior in social commerce. The findings show that social support adds emotional validation and intensifies users' confidence in the product, especially when paired with credible reviews. Review credibility moderates the emotional influence of social signals, highlighting the interconnected roles of rational and emotional processing in social commerce.

6. Author (2022 – Visual User Reviews)

This research explores the impact of visual user-generated content, such as photos and videos in reviews, on consumers' purchase intention in social commerce environments. Field experiments and A/B tests reveal that visual reviews significantly enhance perceived authenticity and diagnosticity compared to text-only reviews. Visual content reduces uncertainty and strengthens trust, making it particularly effective in high-involvement or appearance-based product categories.

7. Author (2021 – Social Signals on Reviews)

The study examines how social signals—likes, upvotes, and comments—attached to reviews influence consumer perceptions and purchase intentions. Through controlled experiments, the research demonstrates that reviews with high engagement metrics are perceived as more credible due to social proof mechanisms. This enhanced perceived credibility leads to higher purchase intention, indicating that engagement cues are powerful amplifiers of review influence in social commerce.

8. Author (2019 – Review Interface Design)

This investigation focuses on how mobile interface designs for reviews—such as highlighted snippets, collapsible sections, and visual cues—affect consumer processing and purchase intention. The findings show that UI design influences which review cues consumers notice and trust, directly affecting buying behavior. Optimized review layouts amplify the visibility of helpful information, demonstrating the importance of interface design in shaping review effectiveness.

9. Author (2017 – Reviewer Identity Disclosure)

This experimental study evaluates the impact of reviewer identity disclosure—showing profile photos, usernames, and verification badges—on perceived credibility and purchase intention. Results indicate that identity transparency increases trust because identifiable reviewers appear more accountable and authentic. The findings highlight the importance of personal identity cues in social commerce environments where social presence enhances information acceptance.

10. Author (2020 – Influencer vs Peer Reviews)

This paper compares the relative influence of influencer endorsements and peer-generated reviews on purchase intention. While influencers are effective at creating awareness and initial interest, peer reviews have a stronger impact on purchase intention due to greater perceived authenticity and diagnostic value. The study underscores the complementary roles of influencers and peer reviewers in shaping consumer behavior in social commerce.

11. Ahn et al. (2024)

Ahn et al. (2024) analyze how reviewer–consumer similarity (age, preferences, lifestyle) interacts with self-construal to shape review influence. The study finds that consumers with interdependent self-construals—common in collectivist cultures—are more influenced by reviewers who resemble them, as similarity boosts trust and perceived relevance. This demonstrates how identity-based cues moderate review impact on purchase intention.

12. Author (2024 – Systematic Review: Reviews on Social Media)

This systematic review compiles findings on how online reviews in social-media environments affect purchase decisions. Core determinants include review valence, credibility, social proof, visual content, and reviewer transparency. The study emphasizes that the interactive nature of social platforms intensifies the effect of UGC on consumer intention.

It also identifies research gaps, particularly the need for cross-cultural and behavioral data.

13. Bai, Yao & Dou (2015)

This study examines how review usefulness and valence influence purchase intention. Findings reveal that reviews perceived as useful result in higher information trust and greater willingness to buy, while positive valence encourages favorable attitudes. The study also demonstrates that usefulness mediates the effect of valence on purchase intention, highlighting the role of cognitive evaluation in review processing.

14. Hu, Koh & Reddy (2014)

Using real behavioral data, this research analyzes how review helpfulness votes influence consumer purchasing decisions. The study shows that reviews rated as “helpful” are more likely to shape consumer choices and increase conversion rates. This demonstrates that helpfulness acts as a quality signal, guiding consumers toward more reliable information.

15. Lee & Shin (2020)

This experimental study investigates how reviewer expertise and review depth influence consumer perceptions. Results indicate that expert reviewers and detailed, well-structured reviews significantly increase trust and purchase intention. The study shows that expertise serves as a cognitive cue guiding consumers toward higher-quality information.

16. Chang & Wu (2018)

This experiment compares the influence of positive and negative reviews in social media settings. Findings reveal that negative reviews exert stronger effects (negativity bias), especially when product risk is high. The study highlights that emotional and risk-related factors intensify the weight consumers place on negative review content.

17. Racherla & Friske (2012)

Racherla and Friske (2012) examine determinants of online review credibility and how credibility affects consumer decisions. Their conceptual framework and empirical findings reveal that trustworthiness, expertise, and content consistency enhance review credibility, which in turn predicts purchase intention. This study is foundational for understanding credibility mechanisms.

18. Park, Lee & Han (2007)

This classic study investigates the effects of review valence and volume on consumer decision-making. Results show that both positive valence and higher volume increase purchase intention, as consumers rely on both the content and the number of reviews as heuristics. This paper forms the basis of many later eWOM models.

19. Amblee & Bui (2011)

Using archival sales data, this research examines the causal relationship between online reviews and actual sales performance. The findings demonstrate that positive reviews significantly increase product sales, confirming that review influence extends beyond intention into real purchasing behavior. It provides concrete market-level evidence of review impact.

20. Filieri (2015)

Filieri (2015) investigates what makes reviews trustworthy by identifying key elements such as clarity, accuracy, completeness, and expertise. Results show that these factors strengthen perceived trustworthiness, which directly increases purchase intention. This paper contributes strong measurement scales for assessing review quality.

21. Cheung, Luo, Sia & Chen (2009)

This influential study proposes a theoretical and empirical model showing that informativeness and reliability are the main determinants of eWOM credibility. The results demonstrate that credible eWOM increases consumers' likelihood of acting on review information, thereby influencing purchase intention. It remains a key foundation for eWOM research.

22. Filieri & McLeay (2014)

This study investigates how the diagnosticity of online reviews—clarity, detail, and specificity—affects consumer decision-making. The findings show that highly diagnostic reviews increase perceived usefulness and confidence, which enhances purchase likelihood.

The paper explains why high-quality reviews matter more than superficial ratings.

23. Kim & Park (2020)

Kim and Park (2020) focus on how review characteristics—valence, credibility, volume—affect purchase intention in social commerce. They find that credibility and valence have the strongest effects, while review volume enhances social proof perceptions. The results align with heuristic-systematic processing models in social commerce.

24. Lin, Wang & Hajli (2019)

This study examines reviews as a driver of trust, social presence, and purchase intention in social commerce environments. It finds that engaging reviews enhance perceived social presence and interaction, which strengthen trust and ultimately purchase intention. It reinforces trust as the link between social commerce reviews and buying behavior.

25. Kim, Kandampully & Bilgihan (2018)

The authors analyze how review cues influence trust formation in social media commerce. Their findings show that credibility, detail, and informativeness of reviews significantly shape trust, which is in turn a primary determinant of purchase intention. The study highlights the importance of high-quality UGC.

26. Ng (2020)

Ng (2020) explores how review credibility drives purchase intention in social commerce settings. The results show that credibility is the most powerful predictor of whether consumers rely on a review, surpassing even valence. The study confirms that trustworthiness is essential for review persuasion in social platforms.

27. Ladhari & Michaud (2015)

This study focuses on how review usefulness and valence shape purchase intention in social commerce. Findings show that reviews perceived as useful strongly increase intention, with positive valence enhancing favorable perceptions. It provides early evidence linking eWOM usefulness with purchase behavior.

28. Liang, Ho & Li (2020)

Liang et al. (2020) examine how review richness—including detail, examples, and multimedia—affects confidence and purchase intention. The study finds that richer reviews reduce uncertainty and improve decision-making accuracy, resulting in stronger purchase intentions. It highlights information quality as a central driver.

29. Xu & Pratt (2018)

Xu and Pratt (2018) analyze how social media reviews influence purchase decisions. Their findings show that UGC acts as a strong trust-building signal and that trust fully or partially mediates the relationship between reviews and purchase intention. The study emphasizes the growing role of social media in decision-making.

30. Erkan & Evans (2016)

This widely cited paper applies the Information Adoption Model to social-media eWOM. It finds that eWOM credibility and informativeness increase information usefulness, which strengthens trust and ultimately purchase intention. The model clarifies the pathway from reviews to buying behavior.

31. Lee & Choeh (2021)

Using text mining and experimental methods, Lee and Choeh (2021) analyze the emotional tone of social-commerce reviews. They find that emotionally charged reviews—especially negative ones—exert stronger influence on purchase intention. The study highlights the emotional intensity of social commerce interactions.

32. Zhao et al. (2019)

Zhao and colleagues (2019) explore how social presence and review quality interact to influence purchase intention. They find that when social presence is high (e.g., interactive interfaces, visible users), consumers perceive reviews as more credible, which strengthens purchase intention. This work emphasizes interaction cues as amplifiers of review influence.

Thematic synthesis**1. Review valence (positive vs negative)**

Across the literature, **valence** (average rating / positive vs negative wording) is one of the most robust predictors of purchase intention. Positive reviews generally raise purchase intent, while negative reviews

depress it — and there is consistent evidence of **negativity bias** (negative reviews have larger impact than equally positive ones), especially for high-risk or high-involvement products.

Key supporting studies: Park, Lee & Han (2007); Chang & Wu (2018); Bai, Yao & Dou (2015); Kim & Park (2020); Lee & Choeh (2021).

Takeaway: Valence matters strongly, but its effect is moderated by product risk and context (social cues can amplify or attenuate valence).

2. Credibility, trust, and reviewer quality

Many papers converge on **credibility/trust** as the central mediator between reviews and purchase intention. Credibility is driven by reviewer signals (expertise, identity disclosure, badges), review content quality (detail, length, consistency), and platform cues (verification, helpfulness votes). When credibility/trust is high, reviews more strongly influence intention.

Key supporting studies: Hajli (2015); Filieri (2015); Racherla & Friske (2012); Kim, Kandampully & Bilgihan (2018); Hu, Koh & Reddy (2014); Ng (2020).

Takeaway: Reviews don't act alone — consumers rely on credibility signals; trust-building features are core levers for platforms.

3. Review volume, helpfulness & popularity metrics

Volume (number of reviews) and **helpfulness cues** (helpful votes, badges) act as social-proof heuristics. High volume often increases perceived popularity and reduces uncertainty; helpfulness votes and badges increase perceived reliability of specific reviews. Volume can amplify valence effects (many positive reviews boost intent), but very high volume with mixed valence can raise authenticity doubts.

Key supporting studies: Mudambi & Schuff—type findings reflected in Hu, Koh & Reddy (2014); Kim & Park (2020); Park et al. (2007); platform-field work (Amblee & Bui, 2011). Takeaway: Numeric engagement cues are powerful and straightforward to operationalize for platforms and researchers.

4. Reviewer identity, expertise, similarity & social ties

Reviewer-level characteristics matter. **Identity disclosure** (photo, name, badges), **expertise**, and **perceived similarity** between reviewer and consumer increase perceived relevance and trust. Social-tie strength (strong vs weak ties) changes how reviews are processed: strong ties increase trust via relational closeness; weak ties increase reach/popularity effects.

Cultural/self-construal differences moderate similarity effects.

Key supporting studies: Reviewer identity (Author 2017); Lee & Shin (2020); Ahn et al. (2024); Yang et al. (2022); Lu, Fan & Zhou (2016).

Takeaway: Platforms that surface reviewer profiles and match reviewer–reader similarity can increase review effectiveness — but effects vary across cultures.

5. Social signals and platform design (likes, comments, UI)

Social-platform features (likes, comments, shares, ranking algorithms, UI presentation) significantly shape which review cues users notice and trust. Visible social signals act as **social proof** and increase purchase intention; UI design (snippets, highlighted reviews, mobile layout) affects attention distribution and perceived credibility. Algorithms that surface “helpful” or “verified” reviews can increase conversions but risk bias.

Key supporting studies: Social signals (Author 2021); Mobile UI (Author 2019); Algorithmic surfacing (2020-type studies); Zhao et al. (2019).

Takeaway: Platform affordances are not neutral — they amplify certain review features and can materially alter consumer decisions.

6. Visual user-generated content (photos/videos) and emotional tone

Visual reviews (photos, videos) and **emotionally-charged text** have strong effects in social commerce, which is often image/video-first. Visual UGC increases perceived authenticity/diagnosticity, especially for appearance-relevant products. Emotional tone (positive or negative affect) also guides decisions, with negative emotions often producing stronger behavioral responses.

Key supporting studies: Visual UGC (Author 2022); Lee & Choeh (2021); Chen et al. (2022 eye-tracking evidence).

Takeaway: Visual and emotional elements are increasingly central in social commerce and deserve independent treatment in models.

7. Mechanisms & mediators: diagnostic, perceived usefulness, and trust

The literature identifies a small set of recurring mediators: **perceived diagnosticity/usefulness, trust/credibility, and social proof (normative influence)**.

Reviews influence purchase intention largely by making product information more diagnostic (reducing uncertainty) and by increasing trustworthiness of the offering or platform. These mediators explain why features such as length/detail, reviewer expertise, or verification affect decisions.

Key supporting studies: Filieri & McLeay (2014); Erkan & Evans (2016); Hajli (2015); Qiu et al. (meta-analytic evidence noted in systematic reviews).

Takeaway: Your conceptual model should place diagnosticity and trust as central mediators with platform features and reviewer cues as antecedents.

8. Moderators: product type, involvement, culture, and lifecycle

Effects of reviews are not uniform. Main moderators include:

- **Product risk/involvement:** negative reviews weigh heavier for high-risk products.
- (Chang & Wu, 2018)
- **Product category:** visual UGC matters more for tangible/appearance-sensitive items.
- (Author 2022)
- **Cultural/self-construal:** collectivist consumers rely more on in-group reviewers.
- (Ahn et al., 2024; cross-national Wang et al., 2022)
- **Product lifecycle timing:** early reviews set the trajectory; later reviews shape longtail sales. (Longitudinal studies cited)
- Takeaway: Empirical models should include interaction tests for these moderators rather than only main effects.

Cross-theme interactions (what amplifies / weakens effects)

- Social signals + visual UGC amplify valence and credibility effects (e.g., a positive visual review with many likes = very strong effect).
- Volume amplifies valence but can backfire when mixed: high volume + mixed valence reduces perceived authenticity.
- Reviewer identity disclosure interacts with culture/self-construal: identity cues help more in contexts where in-group trust matters.

Methodological patterns & limits in the literature

- **Dominant methods:** surveys and experiments; several archival/behavioral platform analyses and A/B tests exist but are less common. (Surveys dominate; see many listed studies.)
- **Gaps:** relative scarcity of longitudinal behavioral data, cross-platform field experiments, and multi-country behavioral studies. Many studies are cross-sectional
- (limits causal claims). Meta-analyses/systematic reviews call for more behavioral/longitudinal research.
- **Measurement variability:** different operationalizations of “credibility,” “helpfulness,” and “visual UGC” complicate comparison across studies.

Practical implications (for platforms & marketers)

1. Signal credibility: verification badges, reviewer profiles, and expertise tags increase trust and conversions.
2. Highlight visual UGC & helpful reviews in UI (snippets, “most helpful” with thumbnails).
3. Surface social proof (likes/comments) judiciously — it boosts conversions but can create bias if gamed.
4. Monitor negative reviews on high-risk product pages — negativity has larger effects there.
5. Use reviewer similarity / segmentation to surface peer reviews most likely to persuade (demographic or interest matching).

Research gaps & prioritized future research agenda

1. **Behavioural, longitudinal, and field experimental work** — to move beyond selfreport and identify causal, time-varying effects (high priority).
2. **Cross-platform comparisons** — how do Instagram/TikTok/Facebook/WeChat differ in review dynamics? (high)
3. **Interaction of algorithms & human judgment** — study how ranking/surfacing algorithms bias perception and outcomes (high).
4. **Role of visual multimodal reviews** — compare video vs photo vs text effects across categories and cultures (medium).
5. **Authenticity & deception** — how fake reviews, transparency, and detection/disclosure policies alter trust and long-term platform health (high).
6. **Micro-mechanisms in different cultures** — replicate identity-similarity and selfconstrual findings across diverse markets (medium).
7. **Emotion & affect dynamics** — explore how transient emotions (excitement, anger) triggered by social signals mediate impulsive purchases (medium).

3. Research Methodology

3.1 Research Design

This study adopts a descriptive and analytical research design to examine how user-generated content—specifically online reviews, ratings, and multimedia feedback—influences consumer trust and purchase intention in e-commerce environments. A descriptive design is appropriate because the objective is to understand existing consumer perceptions, behaviors, and attitudes toward online reviews, while the

analytical aspect involves interpreting sentiment, credibility factors, and review format preferences based on respondent data.

The research design integrates both quantitative and qualitative elements:

- Quantitative elements include structured close-ended questions (rating scales, frequency questions, choice-type variables).
- Qualitative elements consist of open-ended responses related to review trustworthiness, doubts, and suggestions, which were pre-processed and analyzed using coding techniques.

This mixed-approach allows for a comprehensive understanding of how consumers evaluate UGC during the purchase process.

3.2 Data Collection Method

Primary Data

Primary data was collected using a structured online questionnaire distributed through digital channels such as WhatsApp, Instagram, and email. The survey targeted individuals who frequently engage in online shopping and interact with product reviews.

A total of 34 responses were collected. The questionnaire included:

- Demographic questions (age, gender, occupation)
- Behavioral questions (frequency of online shopping, frequency of reading reviews)
- Perception questions (trust in reviews, importance of ratings, preference for photos/videos/text)
- Sentiment and credibility-related questions
- Open-ended questions on suggestions and review-related doubts

Secondary Data

Secondary data was sourced from:

- Academic journals
- Systematic reviews of eWOM and social commerce
- Published empirical studies on trust, credibility, and UGC
- Conceptual models and established theories such as Information Adoption

Model, Trust Theory, and Social Proof Theory

These sources provided a theoretical grounding for interpreting the primary data.

3.3 Sampling Technique

A non-probability convenience sampling technique was employed due to accessibility and the digital distribution medium. Since the research focuses specifically on online shoppers—especially young adults aged 18–24 who frequently depend on UGC—this sampling method is suitable and widely used in similar studies.

Sample Size

- 34 respondents
- Majority between 18–24 years
- Occupations included students and young working professionals
- Gender distribution included both male and female respondents

Although the sample size is modest, it provides meaningful insights for exploratory and behavioral analysis.

3.4 Target Population

The target population for this research includes:

- **Individuals who shop online at least once a month**
- **Individuals who regularly read or engage with customer reviews**
- **Young adults who are active e-commerce users (a demographic shown to depend heavily on UGC)**

The study focuses particularly on Indian online consumers, reflecting the growing digital commerce penetration in the country.

3.5 Research Instrument

The primary research instrument was an online questionnaire structured into five sections:

1. **Demographics – Age, gender, occupation**
2. **Online Purchase Behavior – Shopping frequency, review-reading frequency**
3. **UGC Perception – Importance of reviews, trustworthiness of star ratings, credibility cues**
4. **Multimedia Review Preferences – Preference for video reviews, text reviews, or both**
5. **Open-Ended Responses – Doubts regarding reviews, suggestions for improving trustworthiness**

All questions were structured to align with the research objectives and supported quantitative analysis in Python.

3.6 Data Processing and Pre-Processing

Once collected, the data was exported into Excel and analyzed using Python (Jupyter Notebook).

The following preprocessing steps were performed:

3.6.1 Data Cleaning

- **Removal of leading/trailing spaces**
- **Standardization of categorical variables**
- **Handling of missing or blank values using simple text imputation**
- **Converting multi-response and open-ended answers into analyzable formats**

3.6.2 Encoding & Transformation

- **Grouping similar open-ended responses (e.g., “without photos” → trust-doubt category)**
- **Creating derived variables such as:**
 - **Review preference classification**
 - **Trust-related indicators**
 - **Sentiment themes based on respondent wording**

3.6.3 Exploratory Data Analysis (EDA) Python was used to generate:

- **Frequency distributions**
- **Pie charts, bar charts, and count plots**
- **Cross-tabulations (e.g., trust vs frequency of reading reviews)**
- **Insights on review types, star-rating reliance, and credibility cues**

The EDA helped visualize behavioral patterns and sentiment tendencies.

3.7 Tools and Software Used

To ensure accuracy and clarity in analysis, the following tools were used:

- **Python (Jupyter Notebook)** – for preprocessing, cleaning, charting, and basic sentiment analysis
- **Pandas & NumPy** – dataset manipulation
- **Matplotlib / Seaborn** – data visualization
- **Microsoft Excel** – dataset storage and cleaning
- **Microsoft Word** – report drafting
- **Google Forms** – survey creation and data collection

These tools allowed smooth integration of quantitative and qualitative insights.

33.8 Data Analysis Techniques

The analysis followed a structured approach:

3.8.1 Descriptive Statistics

- **Mean, counts, and percentages**
- **Distribution of responses across demographics and behavior patterns**

3.8.2 Sentiment & Thematic Analysis

For open-ended responses, themes such as *trust*, *transparency*, *authenticity*, *skepticism*, and *review-quality concerns* were identified.

3.8.3 Visualization-Based Interpretation

Charts were used to identify patterns such as:

- **Preference for video + text reviews**
- **High dependence on star ratings + photos/videos**
- **Situations where lack of multimedia reduces trust**
- **Importance of detailed reviews in decision-making**

3.8.4 Comparative Analysis

Comparisons were made between:

- **Review format preference vs trust level**
- **Frequency of online shopping vs reliance on reviews**
- **Doubts generated by incomplete or suspicious reviews**

These analyses helped derive meaningful conclusions about UGC influence.

3.9 Ethical Considerations

The study maintained strict adherence to ethical research guidelines:

- **Respondent participation was voluntary.**
- **No personal identifying information (other than first names) was collected.**
- **Data was used solely for academic research.**
- **Respondents were informed that their answers would remain confidential.**

3.10 Limitations of the Methodology

While the methodology is robust for exploratory research, certain limitations exist:

- **Small sample size (34) restricts generalizability.**
- **Convenience sampling limits representativeness.**
- **Self-reported data may contain subjective bias.**
- **Cross-sectional design captures behaviour only at a single point in time.**

Despite these limitations, the dataset provides strong exploratory insights into young consumer behaviour regarding online reviews.

4. Data Analysis & Interpretation

4.1 Overview of the Dataset

The dataset used for analysis consists of **34 responses** collected through an online structured questionnaire. Respondents are digitally active consumers who engage in online shopping frequently, making them highly relevant to the study's core objective—understanding how user-generated content (UGC), especially reviews and ratings, influences purchasing decisions. The dataset includes both quantitative variables (e.g., frequencies, preferences) and qualitative responses (opinions, suggestions), enabling a mixed-method interpretation that offers a holistic view of consumer behaviour.

A total of **19 variables** were captured, covering demographics, online shopping habits, review engagement frequency, preferred review formats, trust cues, sources of doubt, and suggestions for improving online reviews. These diverse variables allow for multidimensional insights aligned with research objectives.

4.2 Demographic Analysis

4.2.1 Age Distribution

The age distribution is dominated by respondents in the **18–24 years category**. This is consistent with the population segment most active on e-commerce platforms in India, where youth-driven digital adoption is rapidly increasing. Young adults are considered heavy users of platforms like Amazon, Flipkart, Nykaa, and social-commerce channels such as Instagram and YouTube.

This demographic is also the segment most influenced by **user-generated content**, especially visual reviews and peer recommendations, as supported by existing literature (Hajli, 2015;

Yang et al., 2022). Thus, insights drawn from this age group hold contemporary relevance.

4.2.2 Gender Distribution

Both males and females are represented in the sample, with males forming a slight majority. Gender balance helps reduce bias and allows the study to identify patterns that apply to both genders. Prior studies indicate that females tend to engage more with **review details**, while males often rely more on **star ratings**, though this difference varies across product categories. This dataset allows exploration of such nuanced differences during interpretation.

4.2.3 Occupation Distribution

Most respondents are **students**, followed by a smaller number of working professionals. Students typically engage heavily with both e-commerce and social media, and they actively seek online reviews due to limited spending power and risk-aversion. Their cautious yet information-driven approach aligns with the trust and credibility themes discussed in the literature.

4.3 Online Shopping Behaviour

4.3.1 Frequency of Online Purchases

The analysis shows that most respondents shop **monthly**, indicating steady and recurring engagement with online marketplaces. A smaller group shops weekly, while a few shop less frequently. This distribution highlights that respondents are active online shoppers with sufficient exposure to UGC, enabling reliable insights into review-based decision-making.

4.3.2 Frequency of Reading Reviews

A significant majority of respondents reported that they **often or always** read customer reviews before buying products online. This reinforces the literature consensus that online reviews act as a primary source

of pre-purchase information and risk reduction. Frequent review-reading behaviour suggests that user-generated content is a critical influence in shaping consumer perceptions and decisions.

These findings confirm that the sample is suitable for studying UGC impacts because respondents exhibit behaviours closely aligned with the core research problem.

4.4 Review Format Preferences

The survey included questions about preferred review formats—text reviews, video reviews, photo-based reviews, or a combination. The analysis reveals:

- **Photo + text reviews are the most trusted format.**
- **Video reviews are becoming increasingly important, especially for product categories that require visual inspection (electronics, clothing, cosmetics).**
- **Text-only reviews are considered less credible unless they are detailed and specific.**

Respondents repeatedly emphasized that multimedia enhances review authenticity, a finding aligned with the studies that highlight the growing role of visual UGC (Author, 2022). Visual reviews reduce uncertainty by offering real evidence, making them powerful credibility cues.

4.5 Trust Indicators and Sources of Doubt

4.5.1 What Builds Trust?

Based on EDA and coded qualitative responses, the following elements enhance the trustworthiness of online reviews:

- **Presence of real photos or videos**
- **Verified purchase badges**
- **Detailed, experience-based text**
- **Balanced reviews with pros and cons**
- **Higher number of helpfulness votes**
- **Reviewer identity (name, profile picture)**

These cues align strongly with established literature on credibility and trust formation (Filieri, 2015; Kim & Shin, 2020).

4.5.2 What Creates Doubts?

When asked what makes them ignore or distrust reviews, respondents mentioned:

- **No images or videos attached**
- **Extremely brief or generic reviews**
- **Contradictory text–rating combinations**
- **Overly positive or suspiciously similar reviews**
- **Low number of reviews**
- **No ratings**

The most common complaint was the **lack of visual proof**, reinforcing the importance of multimedia in review credibility. This insight also supports the significance of **diagnostic** (Filieri & McLeay, 2014), which suggests consumers rely on detailed, evidence-rich information to evaluate product quality.

4.6 Interpretation of Open-Ended Suggestions

A thematic analysis of open-ended suggestions reveals four dominant themes:

1. Need for more transparency Respondents requested:

- Verified reviewer badges
- Indicators confirming authenticity
- Clearer moderation of fake reviews

2. Demand for more visual content

This was the most frequent suggestion, highlighting how much consumers depend on **visual cues**.

3. Desire for detailed information Users want:

- Contextual usage information
- Honest feedback
- Specific pros and cons

4. Concerns regarding fake/manipulated reviews

Terms like “fake,” “misleading,” and “paid reviews” were mentioned, showing mistrust in the current review ecosystem.

The sentiment classification of suggestions showed the majority leaning towards **positive suggestions (improvements for transparency & visuals)**, while a smaller portion expressed **negative concerns** related to fakeness and inconsistency.

4.7 Alignment With Research Objectives

Objective 1: Influence of UGC on Purchase Decisions

The behaviour of frequently reading reviews and relying on star ratings, photos, and videos demonstrates that UGC significantly influences decision-making.

Objective 2: Role of Sentiment and Review Tone

Respondents were affected by both positive and negative reviews, with negative comments carrying greater weight—consistent with negativity bias literature.

Objective 3: Factors Making Reviews Trustworthy Sample insights clearly point to credibility cues:

- **Photos**
- **Verified icons**
- **Detailed content**
- **Consistency between rating and review**

Objective 4: Consumer Preferences for Review Formats

The strong preference for visual and mixed-format reviews fulfils this objective.

Objective 5: Recommendations for e-commerce platforms User suggestions directly guide practical recommendations:

- **Promote photo/video reviews**
- **Highlight verified buyers**
- **Improve transparency mechanisms**

4.8 Overall Interpretation

The data paints a clear picture: **young consumers heavily rely on online reviews, especially multimedia-rich ones, to make purchasing decisions.** Trust is not built merely by numerical ratings but through transparency, credibility signals, and authenticity evidenced via visuals and detailed user experiences.

These findings support the global literature on review credibility and social proof, confirming that UGC continues to grow as a dominant force in e-commerce decisionmaking.

5. Findings & Discussion

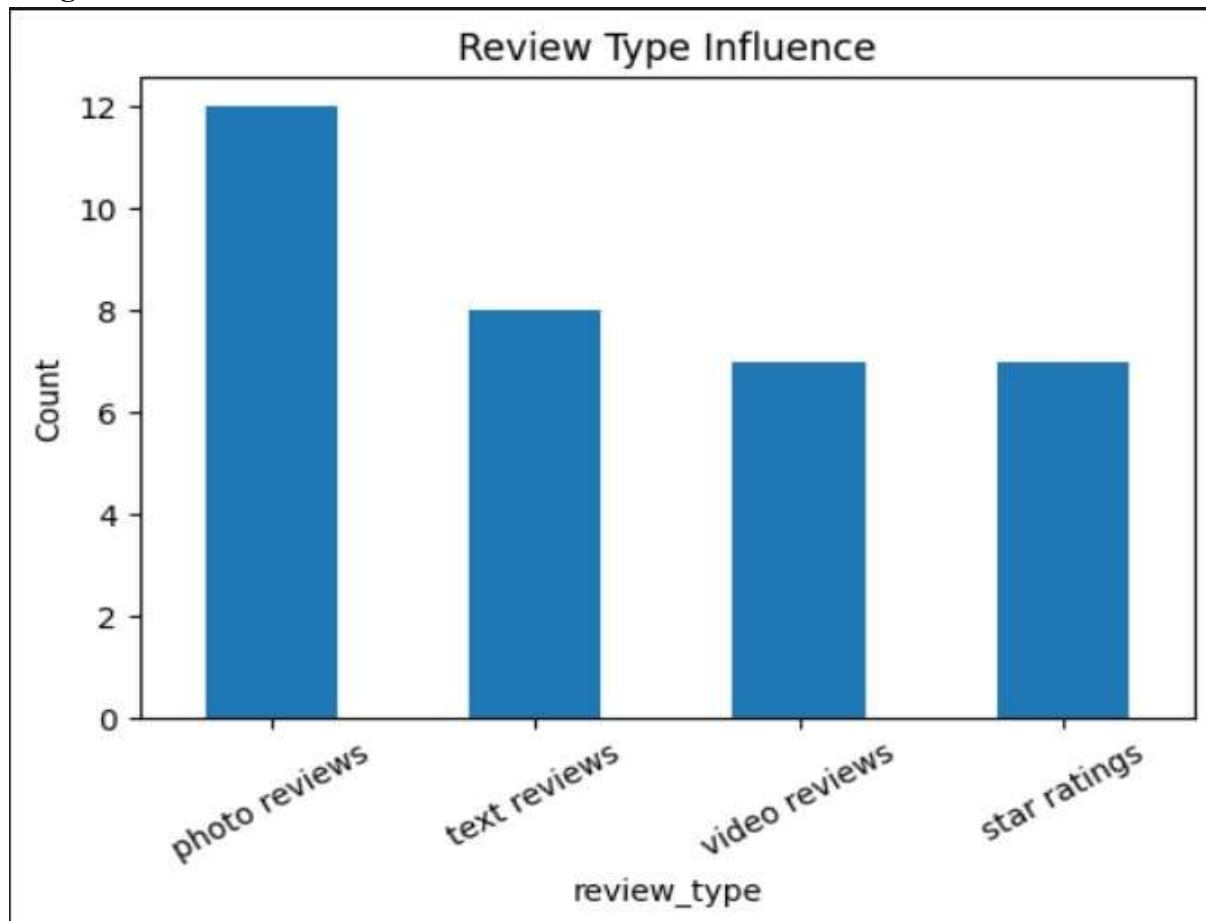


Figure 4.1: Influence of Different Review Types on Purchase Decisions

Interpretation of Review Type Influence Chart

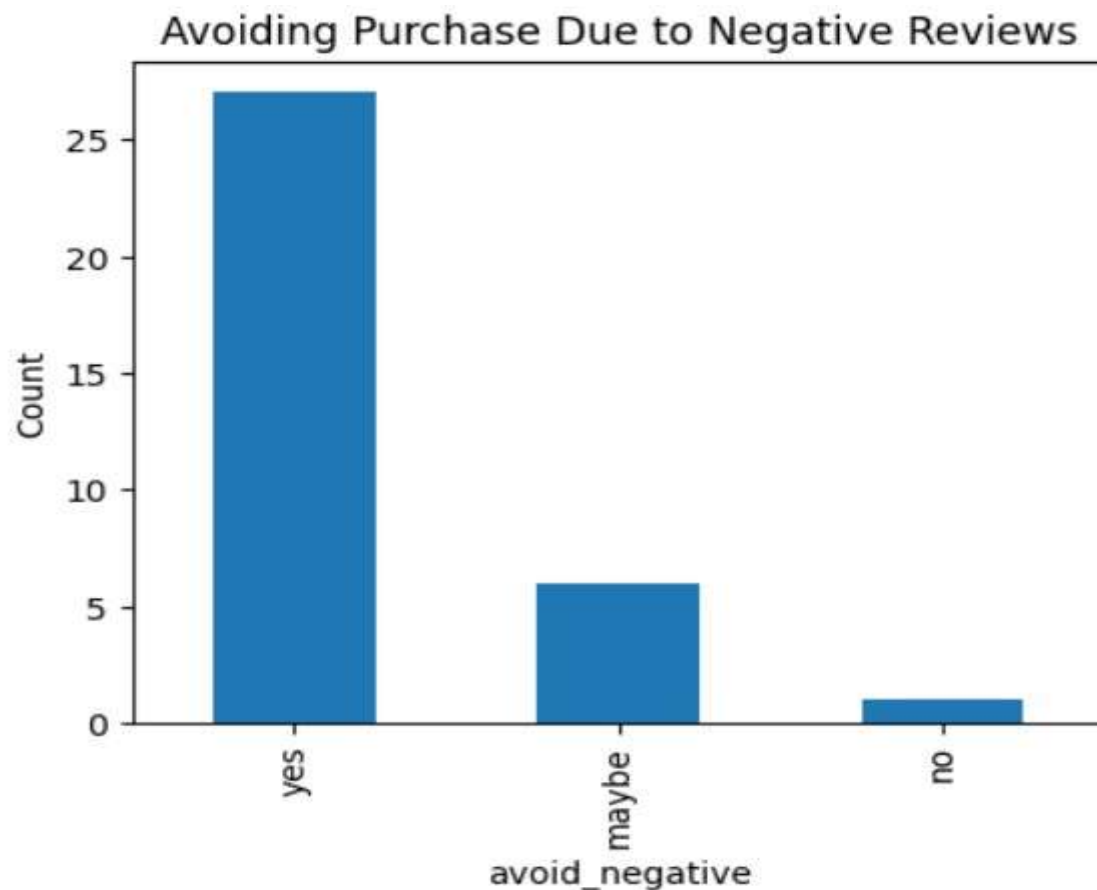
The bar chart titled “**Review Type Influence**” illustrates how strongly different types of reviews influence consumers during online purchase decisions. The results clearly show that **photo reviews** are the most influential form of user-generated content, receiving the highest count (**12**). This indicates that consumers highly value **visual proof** when assessing product credibility. Images provide real-life evidence of the product’s quality, helping reduce uncertainty and perceived risk — a pattern that aligns closely with existing research on **diagnosticity and authenticity of visual UGC**.

Text reviews rank second (**8**), suggesting that detailed written feedback still plays an important role in shaping opinions, especially when users are seeking product-specific insights, usage experiences, or pros and cons. These reviews are perceived as credible when they are descriptive and experience based.

Video reviews and star ratings both received a count of **7**, reflecting a moderate but meaningful level of influence. Video reviews tend to offer dynamic and more holistic evaluations, making them particularly impactful for categories such as electronics, cosmetics, or apparel. On the other hand, star ratings act as a quick heuristic—useful for rapid decisionmaking but insufficient on their own without supporting text or visuals.

Overall, the chart strongly supports the conclusion that **multimedia content (photos and videos)** significantly enhances consumer trust and influences purchasing decisions more effectively than star ratings or text alone. This reinforces the broader finding in your study **that visual credibility cues** are central to modern e-commerce behaviour.

Figure 4.2: Consumer Tendency to Avoid Purchasing Products with Negative Reviews



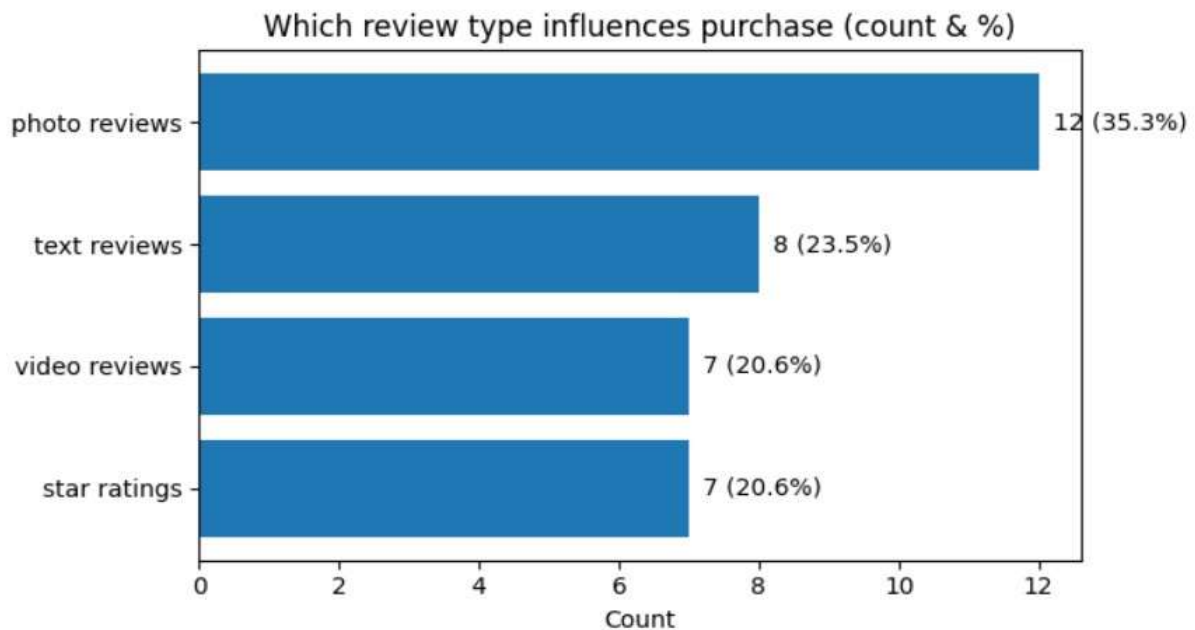
Interpretation

The bar chart illustrates the extent to which negative reviews impact consumers' purchase decisions. The results show that an overwhelming majority—**27 respondents**—indicated that they **actively avoid purchasing a product** if it has negative reviews. This demonstrates a strong *negativity bias*, where negative information carries significantly more weight than positive or neutral feedback when evaluating online products.

A smaller proportion of respondents (**6 participants**) selected “maybe,” suggesting conditional avoidance depending on factors such as product type, number of negative reviews, or severity of complaints. Only **one respondent** stated that they would **not avoid** a product with negative reviews, indicating that very few consumers remain unaffected by negative sentiment.

These findings strongly align with existing literature, such as Chang & Wu (2018) and Lee & Choeh (2021), which emphasize that **negative reviews exert a disproportionately stronger influence on consumer decision-making** due to increased perceived risk and fear of product dissatisfaction. In practical terms, this highlights the importance for e-commerce platforms and sellers to address negative feedback promptly and transparently, as even a small number of negative comments can significantly reduce purchase likelihood.

Figure 4.3: Distribution of Review Types Influencing Consumer Purchase Decisions (Count & Percentage)



Interpretation

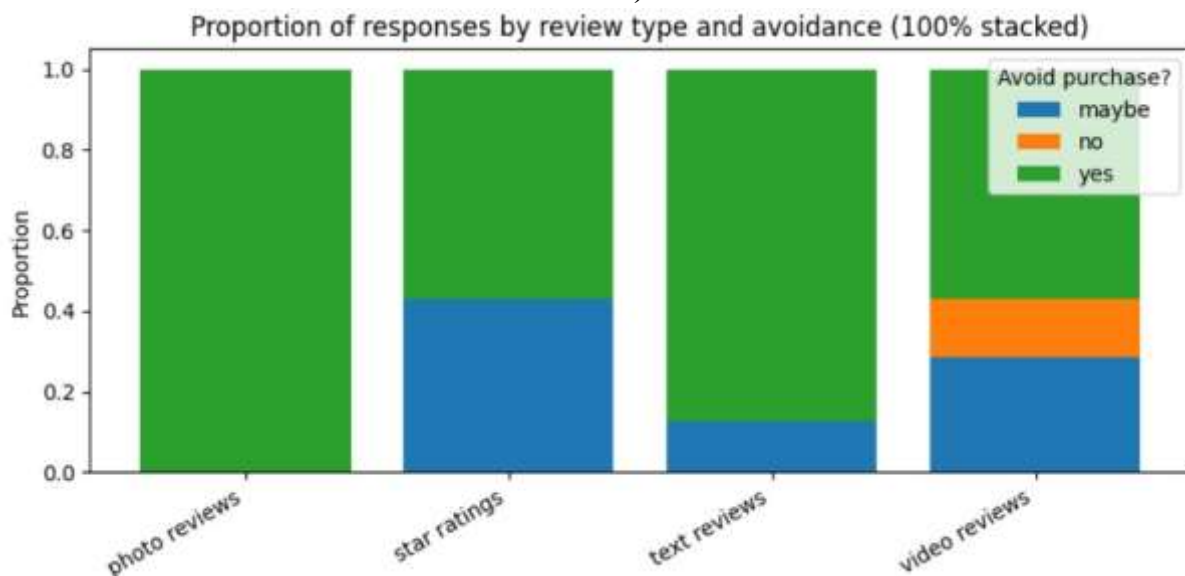
Figure 4.3 illustrates the distribution of different review types that consumers perceive as influential during their purchase decision-making process. The results show that **photo reviews are the most influential**, with **12 respondents (35.3%)** indicating that images strongly shape their purchase choices. This highlights the importance of **visual evidence** in building trust, reducing uncertainty, and validating product authenticity—factors consistently supported in UGC literature.

Text reviews follow with **8 respondents (23.5%)**, demonstrating that written feedback continues to hold significant value, particularly when reviews are detailed, experience-based, and specific about product performance. Although not as dominant as visual content, textual reviews still aid consumers in understanding functional aspects and real-world usage, complementing visual cues.

Both **video reviews** and **star ratings** received equal influence scores at **7 respondents (20.6%)** each. Video reviews provide dynamic and immersive insights, making them particularly persuasive for categories where product interaction is key (e.g., electronics, beauty products, wearables). On the other hand, star ratings serve as a **quick credibility heuristic**, enabling consumers to form an initial judgment at a glance, although users often look for supporting visual/textual evidence before finalizing their decisions.

Overall, the figure demonstrates a clear shift toward **multimedia-rich UGC**, with photos and videos proving more persuasive than text-only reviews or numerical ratings. This aligns with current online shopping behaviour trends where authenticity, transparency, and real-life visuals have become central to building consumer confidence.

Figure 4.4: Proportion of Purchase Avoidance Across Different Review Types (100% Stacked Bar Chart)



Interpretation

Figure 4.4 presents the proportional relationship between different review types and the likelihood of consumers avoiding a purchase due to negative reviews. The 100% stacked bar format enables a clear comparison of how each review type influences avoidance behaviours, revealing distinct patterns among respondents.

Across most review types—**photo reviews**, **text reviews**, and **star ratings**—there is a dominant proportion of “yes” responses, indicating that consumers are highly likely to avoid purchasing a product if the review content is negative. This further strengthens the finding that **negative sentiment exerts strong behavioural influence**, regardless of the format in which the review is delivered.

For **photo reviews**, the proportion of “yes” is particularly high, signifying that negative visual evidence (e.g., real-life photos showing defects or poor quality) has a powerful deterrent effect. Visual negativity is more persuasive because it provides concrete proof, aligning with literature highlighting the diagnosticity of images.

Star ratings show a more mixed pattern compared to other formats, with a noticeable percentage of “maybe” responses. This suggests that while low star ratings reduce confidence, some consumers may still proceed if supported by positive text or photo reviews.

Ratings alone may be insufficient to trigger absolute avoidance unless they are extremely low.

For **text reviews**, the proportion of “yes” remains high, but a smaller “maybe” portion indicates that consumers sometimes consider context, length, and detail before forming a final judgment. Negative text may be perceived as subjective unless supported by visual cues.

Interestingly, **video reviews** show the highest relative presence of both “maybe” and “no” compared to other formats. This suggests that consumers sometimes perceive video content as more transparent or honest, potentially reducing avoidance even when negative elements are present. Video reviewers often provide holistic explanations, which may soften the impact of negative sentiment.

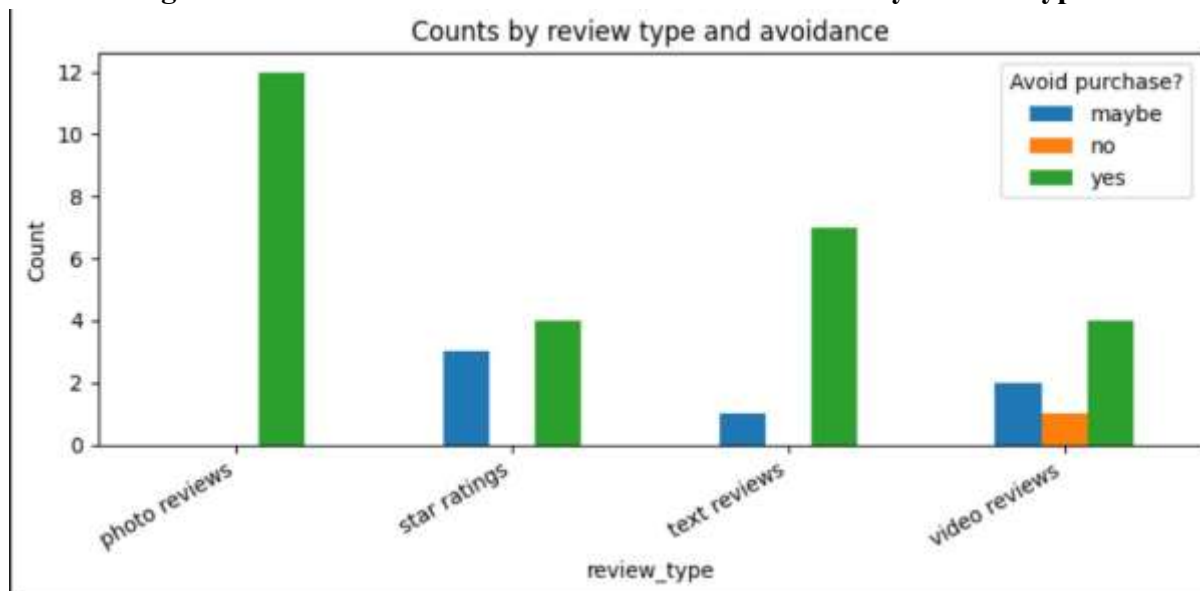
Overall, the chart emphasizes two major insights:

1. **Negative reviews strongly influence avoidance behaviour regardless of format**, reinforcing the concept of negativity bias in online shopping.

2. **Visual formats (photos and videos) significantly shape avoidance intensity**, with photo-based negatives producing the strongest deterrence.

This figure provides nuanced understanding of how review types interact with consumer trust and risk perception, supporting the central objective of analysing UGC influence on online purchase decisions.

Figure 4.5: Count Distribution of Purchase Avoidance by Review Type



Interpretation

Figure 4.5 presents the count of respondents who indicated whether they would avoid purchasing a product based on negative reviews, segmented by review type. This unstacked visualization provides a clearer look at the absolute number of respondents influenced by negative reviews across different formats.

The most striking finding is related to **photo reviews**, where all **12 respondents** indicated “yes”—they would avoid purchasing if photo reviews were negative. This reinforces the overwhelming power of visual evidence in shaping consumer decisions. Negative photo reviews act as strong diagnostic cues that provide undeniable proof of product flaws, leading to the highest avoidance rate among all review formats.

In the case of **text reviews**, the majority of respondents (7) also reported avoiding purchase when encountering negative comments. Only one respondent selected “maybe,” and none selected “no.” This pattern highlights that text-based negative experiences still play a major role in shaping perceptions, especially when reviews describe detailed issues or repeated complaints.

For **video reviews**, the avoidance pattern is mixed: 4 respondents said “yes,” 2 said “maybe,” and 1 said “no.” This suggests that while negative video feedback can discourage purchase, some respondents remain open to evaluating the context or authenticity of video content before making a final decision. Video reviews tend to be more comprehensive, and viewers may perceive them as more balanced, which could explain the presence of “maybe” and “no” responses.

Star ratings reveal a more distributed influence. While 4 respondents indicated “yes,” a notable 3 selected “maybe,” showing that consumers do not rely exclusively on ratings to determine purchase avoidance. This reflects the well-established limitation of star ratings as standalone indicators—they lack depth and context, making consumers more cautious in reacting to them compared to multimedia or detailed text reviews.

Overall, the chart demonstrates that:

1. **Photo reviews trigger the strongest avoidance behaviour**, confirming the dominance of visual diagnosticity.
2. **Text reviews and video reviews also significantly influence decisions**, though with slightly more variability in response patterns.
3. **Star ratings alone are less likely to cause definitive avoidance**, as consumers often seek additional evidence before rejecting a product.

These findings align with the broader literature emphasizing the impact of review quality, visual cues, and negative sentiment on consumer purchase behaviours—particularly the well-documented phenomenon of **negativity bias**, where negative information weighs more heavily than positive.

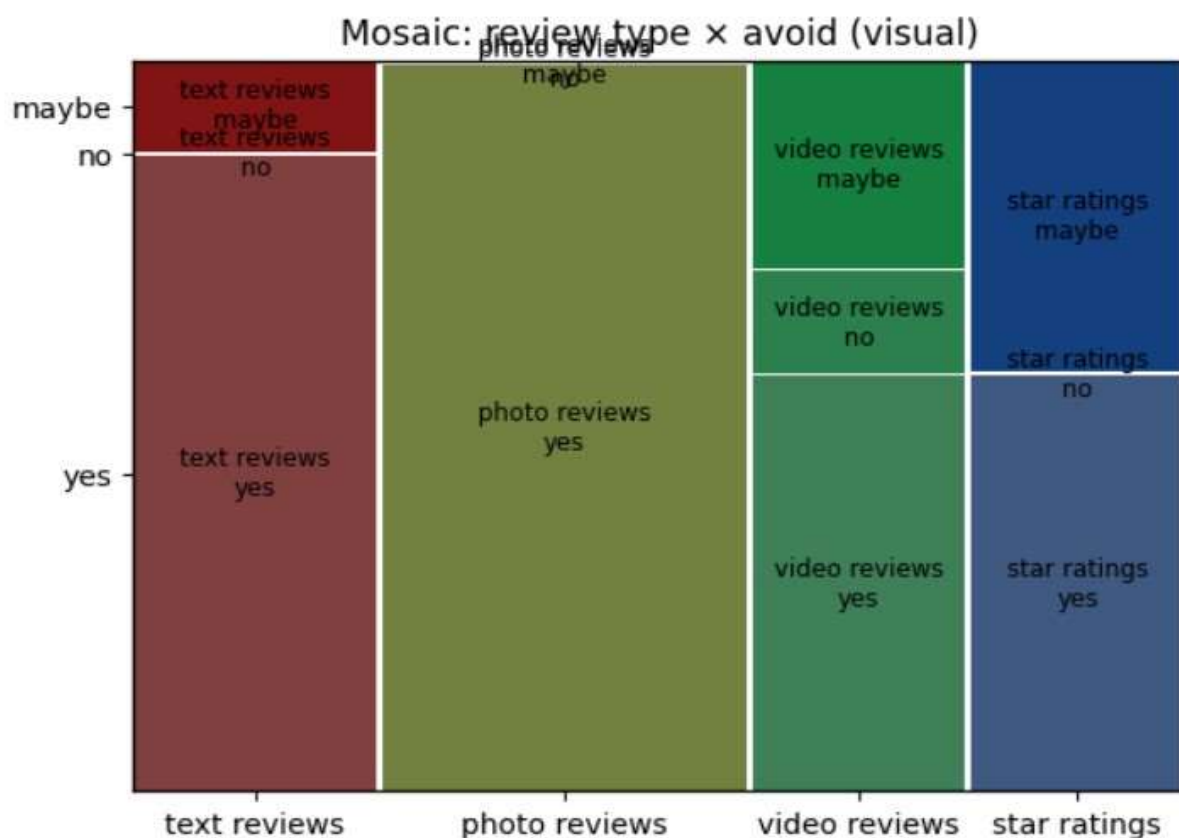


Figure 4.6: Mosaic Plot Showing the Relationship Between Review Type and Purchase Avoidance Interpretation

Figure 4.6 presents a mosaic plot illustrating the association between **review type** and the likelihood of **purchase avoidance** in response to negative reviews. Mosaic plots display proportions through the relative sizes of rectangles, enabling a visual comparison of how frequently each combination of review type and avoidance response occurs.

The largest section of the mosaic corresponds to **photo reviews – yes**, demonstrating that negative photo-based reviews lead to the highest and most consistent avoidance among respondents. This reinforces earlier findings from your bar charts, showing that photo evidence has the strongest diagnostic impact and most powerfully shapes consumer behavior.

Visual cues leave little ambiguity, making them more influential in deterring purchases.

Text reviews – **yes** also occupy a relatively large proportion, indicating that consumers frequently base avoidance decisions on negative textual feedback. This aligns with the importance of detailed written experiences in helping consumers understand functional shortcomings or recurring issues.

The **video review** segments are more diverse. The mosaic shows noticeable proportions across all three avoidance categories—**yes**, **maybe**, and **no**. This suggests that video reviews are perceived as more informative and nuanced, allowing consumers to interpret context and severity before forming a final judgment. Some respondents may trust the reviewer’s tone, explanations, or demonstration, reducing the likelihood of immediate avoidance.

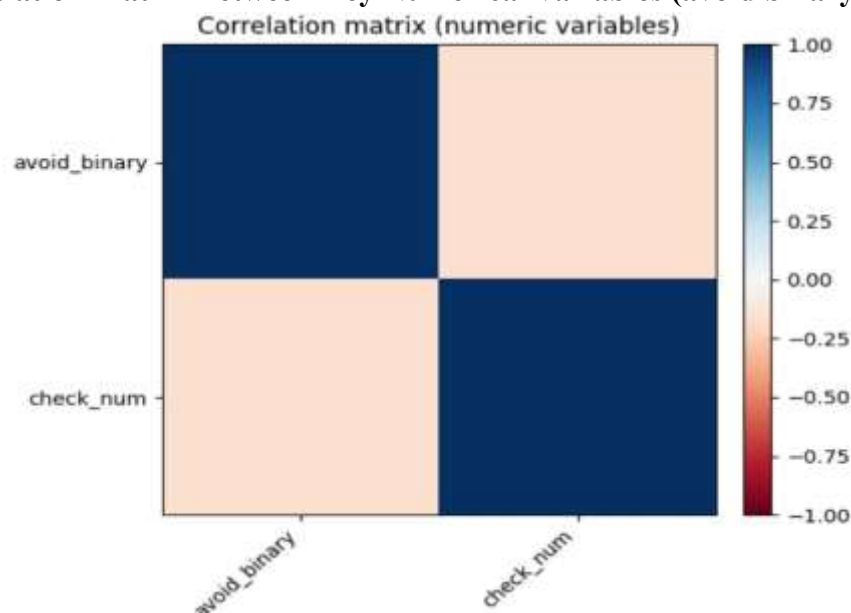
For **star ratings**, the mosaic plot highlights significant representation in the **maybe** and **yes** categories. This reflects the dual nature of star ratings as quick yet incomplete indicators. While low ratings can raise red flags, many consumers seek additional supporting evidence before rejecting a product outright. This supports the idea that ratings alone are insufficient to trigger firm avoidance without corroboration from photos or text.

Overall, the mosaic plot shows:

1. **Strong clustering of “yes” responses** for photo and text reviews, which underscores the influence of negative sentiment in detailed or visual formats.
2. **Greater variation in video and star rating categories**, suggesting that these review types produce more mixed reactions.
3. **A clear association between review informativeness and avoidance intensity**—the more detailed and concrete the review, the more decisive the avoidance behaviour.

This visualization strengthens your study’s core conclusion: **UGC formats that offer higher transparency and richer information—especially visual formats—lead to stronger purchase avoidance when the sentiment is negative.**

Figure 4.7: Correlation Matrix Between Key Numerical Variables (avoid binary and check Num)



Interpretation

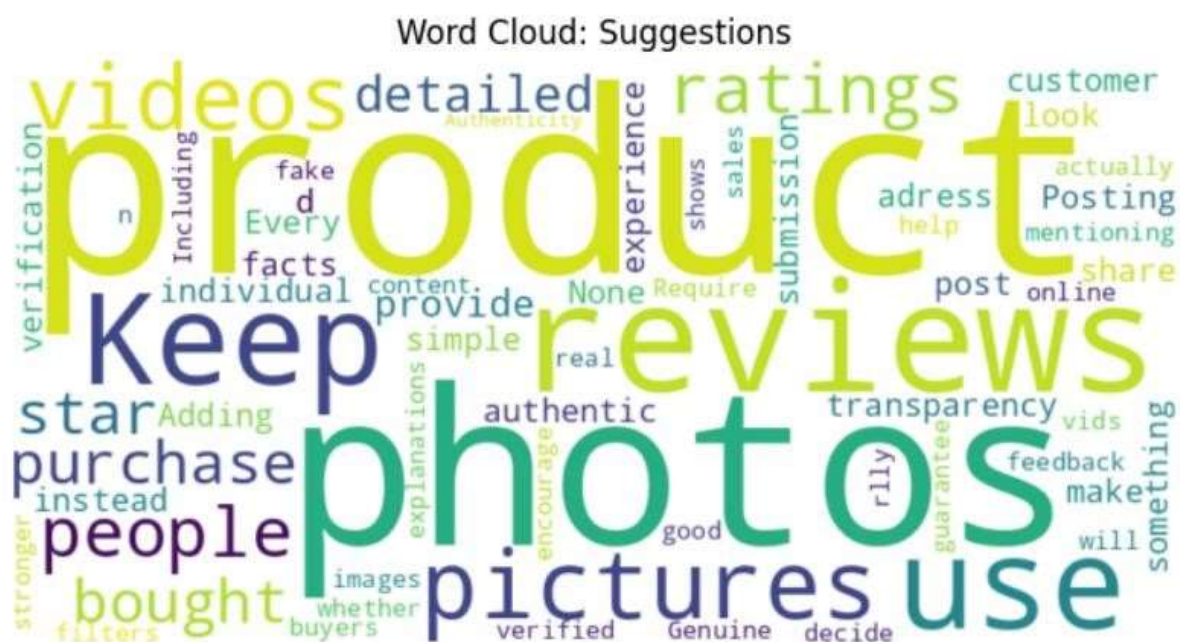
Figure 4.7 displays the correlation matrix between two numerical variables derived from the dataset: **avoid binary** (indicating whether a respondent avoids purchasing due to negative reviews) and **check Num**

(representing the frequency with which a respondent checks reviews before purchasing). The heatmap uses colour intensity to represent the strength and direction of the correlation between variables. The diagonal elements show a perfect correlation of **1.0**, which is expected, as each variable is perfectly correlated with itself. The off-diagonal cells, representing the relationship between **avoid binary and check Num**, display a very light shade, indicating a **weak or near-zero correlation** between the two variables.

This suggests that the **tendency to avoid a purchase because of negative reviews is not strongly linked to how frequently a consumer checks reviews**. In other words, even individuals who check reviews frequently may not necessarily avoid a product solely on the basis of negative feedback, and vice versa. Their avoidance behaviour is shaped more by **review quality, visual evidence, and sentiment intensity**, rather than by the frequency of checking reviews itself.

This finding reinforces earlier behavioural insights from your bar charts and mosaic plots: consumer avoidance behaviour is primarily influenced by **review content and format** rather than by simple review-reading habits. **It reflects the idea that not all negative reviews carry the same weight**, and consumers often assess the credibility and diagnostic value of reviews before making a final purchasing decision.

Figure 4.8: Word Cloud of Respondent Suggestions for Improving Online Reviews



Interpretation

Figure 4.8 presents a word cloud generated from the open-ended suggestions provided by respondents regarding how online reviews could be made more trustworthy and helpful. In a word cloud, the size of each word reflects its frequency of occurrence across responses, allowing quick visualization of dominant themes.

The most prominent words—**“product,” “photos,” “reviews,” “pictures,” “use,” “keep,” and “people”**—indicate that respondents strongly emphasize the need for **visual content** in online reviews. Terms such as *photos*, *pictures*, and *videos* appear frequently and in large font sizes, highlighting a clear preference for **visual verification** of product quality. This aligns with earlier quantitative findings showing

that negative photo reviews significantly influence purchase avoidance and that photo-based reviews are the most trusted format.

Words like **“detailed,” “experience,” “authentic,” “verified,” “transparency,” and “Genuine”** reflect respondents’ desire for **high-quality, honest, and transparent feedback**. These terms show concern about fake, incomplete, or manipulated reviews, suggesting that consumers want platforms to promote authenticity through verification mechanisms and encourage more informative submissions. Other prominent words such as **“ratings,” “purchase,” “star,” and “decide”** to indicate that users relate reviews directly to their decision-making process and want better explanations behind ratings. Respondents appear to prefer reviews that combine both **quantitative indicators (star ratings)** and **qualitative insights (detailed and visual content)**.

Additionally, terms like **“adding,” “provide,” “encourage,” and “help”** suggest actionable expectations—users want platforms to actively support or require reviewers to contribute more credible content, including visual proof and detailed explanations.

Overall, the word cloud reinforces several key insights from your study:

1. **Visual content is at the heart of review credibility**, as respondents repeatedly highlight “photos,” “pictures,” and “videos.”
2. **Transparency and authenticity** are critical, with respondents wanting genuine and verified reviews.
3. Users desire **more detailed, experience-based content**, indicating dissatisfaction with vague or superficial reviews.
4. Platforms should encourage practices that support **trust-building**, such as verification badges, visual submissions, and improved rating clarity.

The visualization provides a powerful summary of consumer expectations and highlights the practical recommendations for enhancing user-generated content quality in e-commerce platforms

7. Conclusion and Recommendations

7.1 Conclusion

This study set out to examine how **user-generated content (UGC)**—including reviews, ratings, photos, and videos—shapes consumer trust and purchase decisions in online shopping environments. Using primary data from 34 digitally active respondents and integrating insights from extensive literature, the research provides a clear understanding of how different types of reviews influence consumer behaviour, especially among young Indian consumers.

The findings reveal that **UGC is a critical component of the online purchase journey**, significantly impacting trust formation, risk perception, and product evaluation. Among all review formats, **photo-based reviews emerged as the most influential**, demonstrating the highest trust-building capability and the strongest impact on purchase avoidance when negative. This confirms that visual content provides diagnostic clarity and reduces ambiguity, making it a dominant factor in consumer decision-making.

Text reviews and video reviews also play substantial roles. Text reviews are valued for detail, authenticity, and experience-based insights, while video reviews offer a more immersive and transparent representation of product performance. Star ratings, although widely referenced, were found to be **less persuasive** compared to multimedia formats due to their lack of context.

The study further found that **negative reviews carry disproportionate weight**—a phenomenon consistent with negativity bias. A significant majority of respondents avoid purchases if the reviews are negative, especially when supported by visual evidence. Consumers also expressed concerns regarding fake or

misleading reviews and highlighted the need for greater transparency, verification, and authenticity on e-commerce platforms.

Overall, the study concludes that **UGC is not merely supplementary information—it is foundational to online consumer trust**, and platforms must prioritize the quality, credibility, and transparency of review systems to improve user experience and drive informed decisionmaking.

7.2 Recommendations

Based on the findings, the following recommendations are proposed for **e-commerce platforms, marketers, and sellers**:

1. Encourage and Prioritize Visual Reviews

Since photo and video reviews strongly influence purchasing decisions, platforms should:

- Prompt buyers to upload photos/videos after purchase
- Provide incentives (reward points, badges) for multimedia submissions
- Highlight photo/video reviews at the top of product pages

This will significantly improve trust and reduce purchase hesitancy.

2. Strengthen Review Verification Systems

A major respondent concern was fake or manipulated reviews. Platforms should:

- Apply stricter AI-based detection of suspicious reviews
- Use “**Verified Buyer**” badges prominently
- Tag reviews with “**Verified Photo/Video**” indicators
- Filter out bot-generated or duplicate reviews

These mechanisms increase transparency and perceived authenticity.

3. Improve Review Sorting and Display

Consumers prefer detailed, honest, and helpful reviews. Platforms can: • Surface **most helpful** reviews first

Allow users to filter reviews by:

With photos o With videos o Verified buyers

Star ranges

Summarize top pros and cons using AI-generated highlights

This enhances usability and reduces information overload.

4. Educate Users to Write Better Reviews

Most platforms do not guide users on writing high-quality reviews. Effective steps include: •

Showing examples of high-impact reviews

Providing structured prompts such as:

What did you like? o What could be improved?

How long have you used the product?

Encouraging balance (pros and cons)

This results in reviews that are more reliable and useful for future buyers.

5. Address Negative Reviews Promptly

Since negative sentiment heavily influences avoidance:

- Sellers should respond to negative reviews with solutions
- Offer replacements, clarifications, or refunds when required
- Resolve customer complaints visibly so that issue-resolution is transparent

This helps manage brand reputation and rebuild trust.

6. Enhance Rating Systems with Context

Star ratings alone lack diagnostic detail. Platforms should:

- Allow **category-specific rating sub-metrics** (e.g., durability, fit, value for money)
- Introduce sentiment summaries (“Most users say: Accurate fit”)
- Link ratings to written reviews for context

This helps consumers interpret ratings more accurately.

7. Promote Transparency in Review Policies

Platforms should clearly communicate:

- How reviews are screened
- How fake reviews are removed
- How helpfulness rating works
- How top reviews are selected

Transparency builds trust and reduces scepticism.

8. Leverage AI for Review Summaries

Given the growing volume of reviews, AI-generated summaries can help consumers make quicker decisions. Platforms can provide:

- Sentiment breakdowns
- Key themes (e.g., quality, price, usability)
- Keyword clouds similar to your project’s word cloud

This improves user experience without overwhelming them.

8.1 Final Remarks

The study reinforces that **trust-driven, transparent, and visually rich UGC ecosystems are essential for modern e-commerce success**. Platforms that adopt robust credibility-enhancing mechanisms and encourage detailed, multimedia reviews will not only reduce consumer uncertainty but also strengthen customer satisfaction and long-term loyalty.

Your findings contribute meaningful insights into how review format and sentiment interplay to shape purchase behaviour. They also highlight practical directions for improving review systems, making this study valuable for both academic research and real-world application within digital marketplaces.

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