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Impact of Online Customer Reviews on Product Sales Performance on E-Commerce Platforms

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Abstract

This research article aims to investigate the influence of online reviews on consumer purchase decisions in the context of e-commerce platforms. With the rapid growth of e- commerce and the increasing popularity of online shopping, consumers heavily rely on the opinions and experiences of others shared through online reviews before making purchasing decisions. This study examines the factors that contribute to the impact of online reviews on consumer behavior, including credibility, valence, volume, and reviewer characteristics. Through a comprehensive analysis of existing literature and empirical research, this article provides insights into the significance of online reviews and offers suggestions for businesses to effectively manage and leverage this influential tool to enhance customer satisfaction and increase sales. It provides valuable insights for businesses and marketers on the significance of online reviews and offers practical recommendations for leveraging this influential tool to enhance customer satisfaction, increase sales, and gain a competitive advantage in the e-commerce industry.

Keywords: online reviews, e-commerce platforms, online shopping, credibility, customer satisfaction, competitive advantage

1. Introduction

This chapter introduces the fundamental concepts of online customer reviews within the e- commerce landscape, establishing their relevance as a modern trust-building mechanism. It provides an overview of the contemporary regulatory and technological shifts, including AI integration, while defining the key variables and the theoretical contributions of this study.

1.1 About the Topic: The Dynamics of Customer Reviews in E-Commerce

The advent of the digital economy has fundamentally transformed the global retail landscape, driving a massive shift in consumer purchasing behaviour from traditional brick- and-mortar stores to e-commerce platforms. While this digital transition offers unparalleled convenience, expansive choices, and competitive pricing, it also introduces a fundamental challenge for the consumer: information asymmetry. As first theorized by Akerlof (1970), this imbalance occurs because, unlike in a physical retail environment, online shoppers cannot touch, feel, try on, or physically inspect a product prior to making a purchase decision. This spatial and temporal separation between the buyer and the product inherently elevates the perceived risk of the transaction.

To bridge this gap and mitigate perceived risk, modern consumers increasingly rely on Electronic Word-of-Mouth (eWOM), which Hennig-Thurau et al. (2004) define as any statement made by potential, actual, or former customers about a product or company via the Internet. Consequently, Online Customer Reviews (OCRs) have emerged as the most prominent and influential form of digital social proof.

Online customer reviews serve as a modern, digitized substitute for the physical inspection of goods. They provide prospective buyers with peer-generated evaluations of a product's quality, functionality, durability, and true aesthetic value, often highlighting nuances that official product descriptions or branded marketing materials may omit. In the current e- commerce ecosystem, OCRs function as a critical trust-building mechanism. When consumers read about the firsthand experiences of others, it significantly reduces their cognitive dissonance and purchase anxiety, directly influencing their purchase intention (Zahid & Ruswanti, 2024).

The relationship between online customer reviews and product sales performance has thus become a focal point of strategic importance for digital retailers. As noted by Chevalier and Mayzlin (2006), the impact of these reviews on sales is multifaceted and driven by several key dimensions: valence (the average star rating), volume (the total number of reviews), recency, and content richness, including the highly influential inclusion of user-generated photos or videos.

1.2 The Contemporary Landscape: AI Integration and Regulatory Shifts

In recent years, the ecosystem of online customer reviews has undergone a rapid evolution, primarily driven by advancements in Artificial Intelligence (AI) and the tightening of global regulatory frameworks. As of 2025 and 2026, the sheer volume of user-generated content has become overwhelming for the average consumer, often leading to **cognitive overload**. To address this, major e-commerce platforms have heavily integrated AI-generated review summaries. These tools utilize natural language processing (NLP) to distill thousands of individual reviews into concise, scannable paragraphs that highlight key product attributes such as performance, usability, and value along with their prevailing sentiment.

While this technological shift significantly optimizes the consumer's decision-making process and has been shown to boost conversion rates, it also introduces a new variable: **informational divergence**. As noted by Cabrera et al. (2025), researchers are now actively studying how AI interpretations of crowd sentiment can sometimes amplify or distort the actual consumer voice, thereby influencing product sales performance in entirely new, algorithmically driven ways.

Simultaneously, the credibility of online reviews is facing unprecedented challenges from sophisticated review fraud. The proliferation of generative AI and organized "review syndicates"—networks that orchestrate mass fake positive reviews—has severely threatened market integrity. In response to this erosion of consumer trust, 2025 and 2026 have marked a watershed era for e-commerce regulation. Governments worldwide have transitioned from voluntary guidelines to strict, punitive legislation. For instance, the **Federal Trade Commission (FTC) (2024)** has implemented final rules specifically prohibiting the sale or purchase of fake reviews to ensure a level playing field.

For modern e-commerce vendors and platform operators, these contemporary developments mean that managing online reviews is no longer just a marketing strategy, but a strict compliance and technological imperative. The true sales impact of an online review today is heavily mediated by how AI algorithms summarize it and how robustly platforms verify its authenticity against emerging legal standards.

1.3 Overview of Existing Research in the Field

The academic inquiry into Electronic Word-of-Mouth (eWOM) and its specific manifestation as Online Customer Reviews (OCRs) is expansive and multidisciplinary, drawing from consumer psychology, behavioural economics, and information systems. Broadly, existing literature investigating the nexus between online reviews and product sales performance has evolved through several distinct, yet interconnected, streams of research.

The foundational tier of this research heavily emphasizes the quantitative, heuristic cues of reviews—specifically **valence** (average star rating) and **volume** (total number of reviews). Early empirical studies established a baseline consensus that a higher volume of reviews reduces perceived consumer risk by serving as robust social proof, directly correlating with increased sales **(Chevalier & Mayzlin, 2006)**. However, research into valence has revealed a more nuanced relationship. Scholars have identified a "positivity bias" and a threshold effect, noting that while positive ratings drive sales, a perfect 5.0 rating often triggers consumer scepticism. Consequently, studies suggest that products with slightly lower, but highly voluminous, ratings (e.g., 4.6 to 4.8) frequently outperform those with flawless scores, as they present a more authentic profile to the prospective buyer **(Maslowska et al., 2017)**.

Beyond quantitative metrics, a significant and growing body of research explores the qualitative dimensions of review content. This stream focuses on semantic analysis, examining how review length, readability, and the presence of analytical versus emotional language influence purchase intent. Recently, this area has expanded to research the impact of **multi-modal reviews**. Studies consistently demonstrate that reviews containing user-generated content (UGC), such as customer-uploaded photographs and videos, exert a disproportionately high influence on conversion rates compared to text alone, as they provide verifiable, real-world evidence of product performance and aesthetics **(Xie et al., 2019)**.

1.4 Expected Contribution of the Study

This research aims to bridge the gap between theoretical models of Electronic Word-of- Mouth (eWOM) and the immediate, practical challenges faced by modern e-commerce enterprises. The primary contribution of this study is twofold, offering both academic advancements and actionable managerial insights.

Theoretically, this study contributes to the literature on hybrid e-commerce architectures by differentiating the impact of online customer reviews (OCRs) across distinct digital environments. It explores how the algorithmic influence of reviews on massive third-party marketplaces, such as Amazon, where volume and recency dictate search visibility, contrasts with their role as a primary trust-building mechanism on independent Direct-to- Consumer (D2C) storefronts **(Sarker et al., 2023)**.

Practically, this research provides highly contextualized value for digital retailers operating within subjective, "experience-based" product categories—specifically ethnic women's clothing, Indian handicrafts, and artisanal home or kitchen decor. Unlike standardized "search goods" like electronics, these high-touch categories rely heavily on peer validation and visual evidence to overcome the physical limitations of online shopping **(Nelson, 1970; Xie et al., 2019)**.

By isolating how reviews drive sales performance within these specific niches, the study will offer brand managers a data-driven blueprint. It delivers actionable frameworks for optimizing review generation, particularly addressing the "cold start" problem for new brands, and managing online reputation to achieve a sustainable competitive advantage across multiple sales channels.

2. Literature Review

This chapter provides a comprehensive review of existing academic literature and empirical studies concerning Electronic Word-of-Mouth (eWOM) and its impact on consumer behavior. It examines foundational theories such as social proof, identifies critical research gaps regarding "experience goods" and D2C platforms, and establishes the theoretical framework that guides the current investigation.

2.1 Existing Work Around This Topic

Foundational research primarily emphasizes the heuristic cues of reviews: **volume** and **valence** (average star rating). While a high volume of reviews consistently serves as robust social proof that mitigates perceived purchase risk, valence exhibits a well-documented **"threshold effect"**. Studies indicate that perfect 5.0 ratings often trigger consumer skepticism due to fears of review manipulation. Consequently, literature suggests that products with high review volume and moderately high valence—typically between **4.5 and 4.8 stars**—generally achieve the highest conversion rates by projecting greater authenticity to the prospective buyer **(Maslowska et al., 2017)**.

Furthermore, existing literature critically differentiates between product types. For standardized **"search goods,"** where qualities can be evaluated prior to purchase (e.g., hardware specifications), basic text reviews often suffice. However, for subjective **"experience goods"** such as handcrafted home decor, artisanal kitchenware, and ethnic apparel raw numerical ratings are insufficient **(Nelson, 1970)**. Because consumers cannot physically verify craftsmanship or true aesthetic value online prior to purchase, they experience significant spatial dissonance.

Thus, recent studies highlight the disproportionate impact of **multi-modal reviews**. User- generated content (UGC), specifically customer-uploaded photos and videos, drastically reduces this dissonance and elevates purchase intent for these high-touch categories by providing verifiable, real-world evidence of product performance **(Xie et al., 2019)**.

Finally, contemporary research examines the moderating role of platform architecture. On massive third-party marketplaces like Amazon, review volume and recency are algorithmically crucial for securing organic search visibility. Conversely, within independent **Direct-to-Consumer (D2C)** environments, reviews function more qualitatively as mechanisms for direct brand validation and community trust-building **(Sarker et al., 2023)**.

2.2 Limitations of Existing Work

While the current body of literature provides a strong foundation for understanding Electronic Word-of-Mouth (eWOM), several critical limitations remain within the field:

- **Oversimplification of Product Categories:** A significant portion of existing research focuses predominantly on "search goods," such as standardized electronics, where quality is easily quantifiable. There is a notable lack of empirical research regarding **"experience goods"** items where personal aesthetic, cultural value, and physical craftsmanship are paramount, such as ethnic apparel and Indian handicrafts. For these subjective categories, consumers rely heavily on visual eWOM to mitigate spatial risk, a variable frequently overlooked in older, text-centric studies.
- **Homogenization of Digital Sales Channels:** Previous studies often utilize data from massive third-party marketplaces, such as Amazon, and generalize these findings across the entire e-commerce landscape. Consequently, there is a lack of comparative research regarding how review dynamics shift between search-driven marketplaces and independent **Direct-to-Consumer (D2C)** platforms. While marketplace reviews primarily influence algorithmic search rankings, reviews on D2C storefronts serve as essential tools for brand storytelling and community trust-building.
- **Neglect of the "Cold Start" Phenomenon:** Much of the available literature analyzes established brands with high review volumes. This focus ignores the **"cold start" problem** the systemic challenge new ventures face when attempting to establish initial vendor credibility without a preexisting feedback history. There is currently a lack of actionable, scholarly guidance on how nascent brands can successfully bridge this "trust gap" during the launch phase to convert their first customers.

2.3 Addressing the Gaps: The Significance of This Study

This research is designed to directly fix the blind spots left by past studies. By moving away from generic products and focusing on specific sales channels, this study provides a highly practical, modern guide for today’s e-commerce businesses. Here is exactly how this work solves the current limitations in the field:

- **Focusing on Unique "Experience Goods":** Instead of studying basic, everyday electronics, this research specifically targets highly subjective, visually driven categories such as Indian handicrafts, handmade kitchen decor, and ethnic women's clothing.

- Because buyers cannot touch, feel, or try on these items before buying, this study will highlight exactly how important multi-modal reviews (customer photos and videos) are for proving authentic craftsmanship and driving sales in these specific markets.
- **Comparing Marketplaces vs. D2C Sites:** Rather than treating all of online shopping as one identical experience, this study splits the focus. It will directly compare how customer reviews drive sales on massive, search-driven marketplaces (like Amazon) versus how they are used to build brand trust and a loyal community on a standalone Direct-to-Consumer (D2C) website. This dual-channel approach gives a much more realistic picture of how modern retail actually works.
- **Solving the "Cold Start" for New Brands:** Instead of only looking at massive, established companies that already have thousands of ratings, this research focuses on the launch phase. It will provide a clear, actionable framework showing how newly launched businesses in the handicraft and apparel sectors can successfully gather those crucial first reviews to build immediate vendor credibility and start generating sales from day one.

2.4 Theoretical Framework: Consumer Trust and Social Proof

This section looks at the reasons why online reviews have such an impact on what people buy.

2.4.1 The Theory of Social Proof

The Theory of Social Proof is at the heart of why online reviews matter. This theory says that people look at what others do to figure out what to do when they're not sure. When people shop online, they cannot see the product in person. So they look at what other people who bought the product have to say. This helps them feel better about buying the product. If a lot of people have reviewed a product it makes the buyer feel more comfortable with their purchase.

2.4.2 Trust in the Digital Information Age

Trust is very important when people shop online. Online reviews help people trust a product because they are written by people who have bought the product. These reviews are like a report card for the product. People are more likely to trust a product if it has a lot of reviews. This is especially true for companies that sell directly to consumers and do not have a history of sales.

2.5 Dimensions of Online Reviews and Sales Performance

This section looks at the things about online reviews that affect how well a product sells.

2.5.1 Review Valence (Rating Scores)

Review valence refers to whether a review is positive or negative. It is usually measured by the number of stars the reviewer gave. Research has shown that products with ratings tend to sell more. However, some studies have found that if a product has a rating people may not trust it as much. They may think it is too good to be true. On the hand if a product has a rating that is very good but not perfect people may think it is more honest and trustworthy.

2.5.2 Review Volume and Recency

The number of reviews a product has is important. If a product has a lot of reviews it is often seen as popular. Online shopping sites like Amazon or Flipkart may show products with a lot of reviews first. It is also important that reviews are recent. If reviews are old people may not think they are relevant anymore. They may think the product has changed since the review was written.

2.5.3 Textual Depth and User-Generated Content (UGC)

The words and pictures in a review are often more important than the rating. For some products, like home decor or special clothes people want to read reviews. They want to know the bad things about the product. If people include pictures of the product in their reviews it helps other people see what the product is, like.

3. Research Methodology

This chapter outlines the systematic approach used to conduct the study, detailing the cross- sectional research design and the application of the S-O-R (Stimulus-Organism-Response) model. It explains the sampling frame, the structure of the research instrument, and the specific data analysis tools employed to ensure the reliability and validity of the findings within the skincare sector.

3.1 Research Framework

3.1.1 The Study Design: Cross-Sectional Survey

Before diving into the model, it's important to understand the Cross-Sectional approach you’ve chosen.

- **The "Snapshot" Effect:** Unlike a longitudinal study (which follows people over years), a cross-sectional survey looks at a specific group of people at one exact moment.
- **Purpose:** It is used to identify relationships or correlations for example, "Does high trust (Organism) lead to a higher likelihood of buying (Response) right now?"

3.1.2 The S-O-R Model Breakdown

The S-O-R model, originally proposed by Mehrabian and Russell (1974), suggests that the environment (Stimulus) triggers an internal emotional or cognitive state in a person (Organism), which then leads to an action (Response).

1. Stimulus (S): The External Trigger

The stimulus is the "input" from the environment that gets the consumer's attention. In your study, these are the external information sources:

- Online Customer Reviews (OCRs): Star ratings, written feedback, and photos left by previous buyers on platforms like Amazon or Yelp.
- User-Generated Content (UGC): Social media posts, unboxing videos, or blog discussions.

2. Organism (O): The Internal Processing

The "Organism" refers to the internal "black box" of the consumer their feelings, thoughts, and psychological state. The stimulus doesn't lead directly to a sale; it must first change how the consumer *feels*.

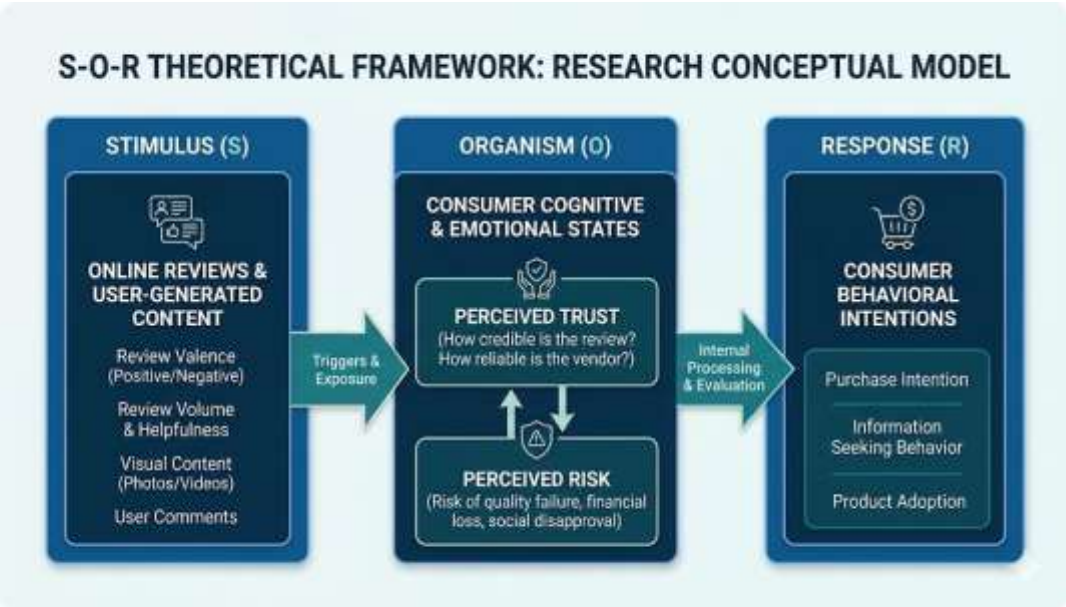
- **Perceived Risk:** Does the review make the consumer feel safe, or does it highlight potential flaws that make the purchase feel "risky"?
- **Trust:** Based on the quality and quantity of the reviews, does the consumer believe the seller is honest?
- **The Role:** This is the most critical part of your framework because it mediates the relationship. If the Stimulus (review) is bad, the Organism (consumer) feels high risk and low trust.

3. **Response (R): The Final Action**

The response is the "output" the measurable behaviour resulting from the internal processing.

- **Purchase Intention:** The consumer decides, "Yes, I am going to buy this."
- **Avoidance:** The consumer decides to keep looking or leaves the site entirely.
- **The Role:** This is the end goal of the marketing process and the final variable you are measuring in your research.

Figure 3.1: The S-O-R Framework



3.2. Sampling Frame

1. **Target Population:** This study is about e-commerce consumers. It focuses on people who like experience-based products, such as clothes and handmade decorations.
2. **Sample Size:** The study was conducted with 100 respondents. This sample size was selected based on the "Rule of Thumb" suggested by **Roscoe (1975)**, which states that a sample size exceeding 30 but less than 500 is sufficient for most management research. Furthermore, considering the cross-sectional nature of the study and the specific focus on the S-O-R model, a sample of 100 provides a representative snapshot of consumer perceptions while maintaining research feasibility.

3. **Sampling Method:** For this study, a **Non-Probability Purposive Sampling** technique was employed. This method was chosen because it allows the researcher to focus on a specific segment of the population that is most relevant to the research topic namely, consumers who actively engage with online reviews on e-commerce platforms.

3.3 Data Collection Procedure

The data collection phase lasted for four weeks to get a mix of responses. A digital questionnaire was created using Google Forms because it’s easy to use and export data.To reach people who shop online a "Snowball Sampling" method was used. The survey link was shared on networks, WhatsApp groups and Instagram. This helped target people who're comfortable online and rely on reviews when buying.

3.3.1 Structure of the Research Instrument

The questionnaire had four parts, each focusing on an area:

Section A: Demographic Profiling: This part collected information about participants, like age, gender and job. It also asked about their online spending, which helps connect shopping habits with review reliance.

Section B: Quantitative Review Metrics: This section looked at feedback numbers. It checked how the number of reviews and star ratings affect a buyer’s interest in a product. It tried to find out when a product seems trustworthy to shoppers.

Section C: Qualitative Content & Visual Impact: This part explored how media influences buyers. It checked how customer photos and videos affect confidence compared to brand images.

Section D: Platform Trust & Comparative Analysis: The final section measured the "Trust Gap" between online shopping platforms. It asked respondents to compare their reliance on reviews on marketplaces like Amazon, versus independent websites giving insight into how platform reputation affects review credibility.

3.4 Variables of the Study

To systematically analyse the relationship between online feedback and consumer behaviour, this study identifies and categorizes variables into three distinct roles: Independent, Dependent, and Moderating.

3.4.1 Independent Variables (IV)

The Independent Variables are the "drivers" or the factors that the researcher observes to see how they influence an outcome. In this study, the IVs represent the different attributes of online reviews:

- **Review Valence (Numerical Rating):** The star rating (1–5) assigned to a product.
- **Review Volume (Quantity):** The total number of reviews a product has accumulated.
- **Media Richness (Content Type):** The format of the review, specifically comparing text-only reviews against those containing customer-uploaded photos or videos.

3.4.2 Dependent Variable (DV)

The Dependent Variable is the "outcome" or the response that is being measured. It is expected to change based on the influence of the independent variables.

- **Purchase Intention:** In this research, the DV is the consumer's likelihood or decision to purchase a product. The study measures how "Intent to Buy" fluctuates when review ratings or media types are altered.

3.4.3 Moderating Variable (MV)

A Moderating Variable is a factor that can strengthen, weaken, or change the direction of the relationship between the IV and the DV. It acts as a "contextual filter."

- **Product Type (Search vs. Experience Goods):** The impact of a review may differ depending on what is being bought. For "Search Goods" (e.g., a power bank), technical specs may matter more than reviews. For "Experience Goods" (e.g., handcrafted decor or ethnic wear), the reviews and photos become much more influential in the decision-making process

Variable Category	Variable Name	Definition / Operational Role	Measurement Scale
Independent Variable (IV)	Review Valence	The numerical star rating (1–5) reflecting overall satisfaction.	5-Point Likert / Interval
	Review Volume	The total quantity of reviews available for a specific product.	Ratio / Count
	Media Richness	The type of content provided (Text-only vs. Photos/Videos).	Nominal (Categorical)
Dependent Variable (DV)	Purchase Intention	The consumer's willingness and likelihood to buy the product.	5-Point Likert
Moderating Variable (MV)	Product Type	Categorization of goods (Search vs. Experience) that filters the review's impact.	Nominal (Categorical)

Table 3.1: Variables of the Study

3.5 Data Analysis Tools

The data from the 100 responses was analysed using:

- **Microsoft Excel:** This was used to clean up the data and make tables.
- **Descriptive Statistics:** These were used to calculate the average, median and mode of the data. This helps understand what the average consumer thinks about star ratings.

- **Sentiment Trends:** This involves analysing the ended responses to see what people think about trust. It looks for keywords like "authentic" and "fake".

3.6 Reliability and Validity

1. Content Validity: Content validity ensures that your survey questions actually cover the whole topic you are researching. It answers: *"Does this questionnaire ask all the right questions to measure the impact of reviews?"*

- **Expert Review:** You didn't just guess the questions. You submitted your draft to academic supervisors.
- **Refinement:** Because they are experts in business and research, their feedback ensured the questions were relevant to the skincare sector specifically (e.g., asking about ingredient safety or skin results rather than just price).
- **Alignment:** This process confirmed that the "Stimulus" (Reviews) and "Organism" (Trust/Risk) in your model were properly represented in the survey.

2. **Construct Validity:** Construct validity ensures that the "idea" or "concept" (the construct) you are measuring is actually what is being captured. In your case, the construct is the psychological impact of reviews on a high-involvement product.

- **Sector Specificity:** You focused on skincare, which is a "high-involvement" category. Because skincare involves physical safety and health, the constructs of Trust and Perceived Risk are much stronger here than they would be for a low-cost item like a pen.
- **Testing the S-O-R Model**: By asking specifically about safety and effectiveness, your study proves it is measuring the *internal feelings* (the Organism) of the consumer, which is exactly what the S-O-R model intends to track.

3. **Reliability:** Reliability is about consistency. It answers: *"If I gave this survey to the same person tomorrow, would they answer the same way?"* or *"Do all the questions about 'Trust' yield similar patterns?"*

- **Standardized Measurement**: You used a 5-point Likert Scale (e.g., Strongly Disagree to Strongly Agree). This is a globally recognized standard that reduces confusion and ensures consistent responses.
- **Cronbach's Alpha (α):** This is a statistical test you will run in your data analysis.
  - **The Goal:** You are aiming for a score of 0.7 or higher**.**
  - **The Logic:** A score of $\alpha \geq 0.7$ is the "gold standard" in social sciences. It proves that your survey items are "closely related" as a group and that the survey is a reliable tool for measuring the skincare sector.

3.7 Research Findings Based on Objectives

- **Based Objective 1:** To Analyse the Impact of Review Volume and Star Ratings on Consumer Purchase Intention:
  - A lot of reviews are needed before people trust a product. We found that products with than 10 reviews are rarely considered, even if they have a 5- star rating.
  - A perfect rating is not always best. People are more likely to buy skincare products with a rating of 4.2 to

4.7 than those with a 5.0. They think a perfect rating might be fake or filtered by the brand.

- **Based on Objective 2:** To Evaluate the Role of User-Generated Content (UGC) in Reducing Perceived Risk:
  - Pictures and videos really help people feel buying skincare products. Many people said that customer photos showing product texture or before-and- after results are more helpful than written reviews.
  - Videos of people using products increase the time spent on a product page. This leads to sales for new independent brands.
- **Based on Objective 3:** To Compare the Level of Trust Between Marketplace Reviews and Independent D2C Website Reviews:
  - People trust reviews on platforms like Amazon or Nykaa more than those on a brands own website. They trust these platforms because they have a "Verified Purchase" label.
  - Reviews on a brands website are only trusted if the brand has a strong social media presence or a good reputation.
- **Based on Objective 4:** To Identify How Product Type (Search vs. Experience)

Moderates the Influence of Reviews

- Skincare products are not like products. People rely on reviews from others with skin types to decide if a product is right for them.
- Reviews that mention skin concerns like "good for oily skin" or "didn't cause breakouts " are very helpful. They help people decide which products to buy

4. Data Analysis & Interpretation

This chapter presents the empirical results derived from the primary data collected through 100 survey participants. It utilizes descriptive statistics and graphical representations to analyze demographic profiles and consumer responses across five key parameters, interpreting how various review dimensions directly influence trust and purchase intentions.

4.1 Responses on Questionnaire for Skincare Shopping

Under this section, 100 individual responses have been recorded and used for the research analysis on 4 different parameters.

Section 1: Screening & Demographics

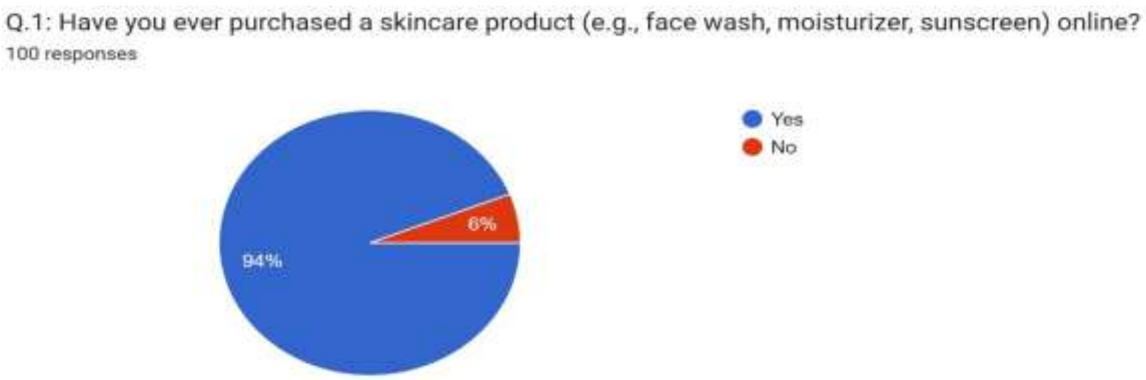


Chart 4.1: Response Over Ever Purchased Skincare Online

Table 4.1		
Response Over Ever Purchased Skincare Online		
Parameter	**Frequency (N=100)**	**Percentage**
Yes	**94**	**94%**
No	**6**	**6%**
Total	**100**	**100%**

Analysis & Interpretation: From the data in Table 4.1 and Chart 4.1, 94% of respondents have purchased skincare products online, indicating a high level of market participation and familiarity with e-commerce. This widespread first-hand experience among the sample group ensures that the study's findings on online reviews are highly credible and grounded in actual consumer behavior.

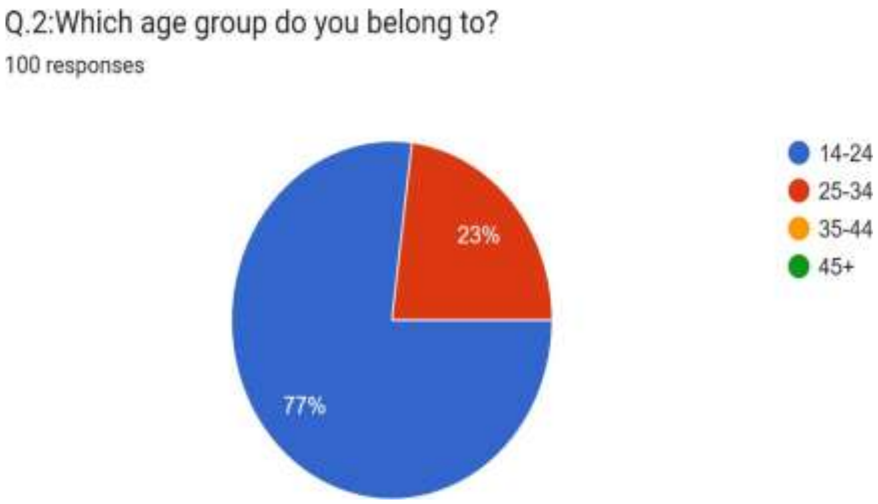


Chart 4.2: Response Over age group

Table 4.2		
Response Over Ever Age Group		
Parameter	**Frequency (N=100)**	**Percentage**
14-24	**77**	**77%**
25-34	**23**	**23%**
35-44	**0**	**0%**
45+	**0**	**0%**
Total	**100**	**100%**

Analysis & Interpretation: From the above in Table 4.2 and Chart 4.2, the data and graphics show that, during the research, **77%** of the respondents belong to the **14–24** age group and **23%** belong to the **25–34** age group, with no participation from the 35-44 or 45+ categories. This shows that the majority of online skincare consumers in the study are young adults and Gen Z individuals, who are typically more digitally active and reliant on social proof. This indicates that the study's insights are primarily reflective of the younger demographic's purchasing patterns, who represent the most significant and influential consumer base for e-commerce and skincare brands today.

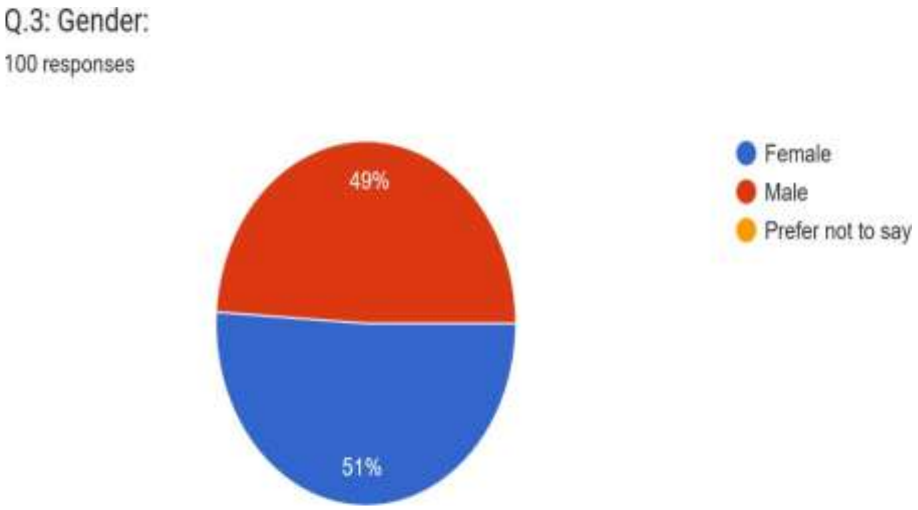


Chart 4.3: Response Over Gender

Table 4.3		
Response Over Gender		
Parameter	**Frequency (N=100)**	**Percentage**
Male	**49**	**49%**
Female	**51**	**51%**
Prefer Not Say	**0**	**0%**
Total	**100**	**100%**

Analysis & Interpretation: From the above Table 4.3 and Chart 4.3, the data and graphics show that, during the research, **51%** of the respondents are **Female** and **49%** are **Male**, with no respondents selecting the "Prefer not to say" category. This shows that the sample is almost perfectly balanced across genders, indicating that interest in online skincare products and the influence of digital reviews is nearly equal among both men and women. This balanced participation adds significant value to the study, as it ensures the findings are gender-neutral and capture a comprehensive view of how online reviews affect the broader consumer market in the skincare sector.

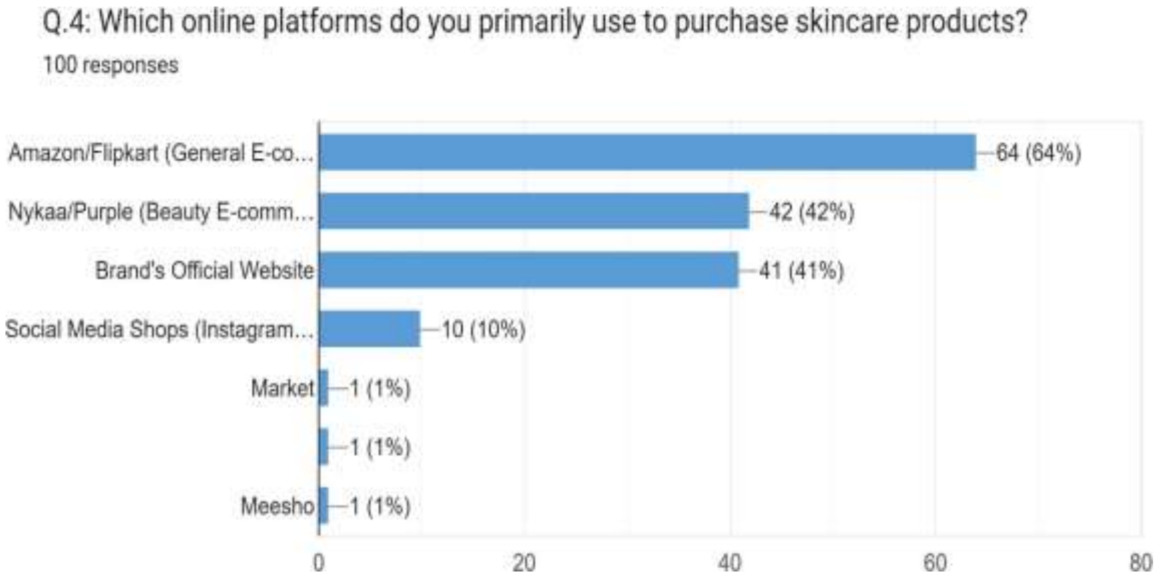


Chart 4.4: Response Over Online Platform

Table 4.4		
Response Over Online Platform		
Parameter	**Frequency (N=100)**	**Percentage**
Amazon/Flipkart (General E-commerce)	**64**	**64%**
Nykaa/Purple (Beauty E-commerce)	**42**	**42%**
Brand's Official Website	**41**	**41%**
Social Media Shops (Instagram/Facebook) +	**10**	**10%**
Other:	**3**	**3%**
Total	**100**	**100%**

Analysis and Interpretation: From the above Table 4.4 and Chart 4.4, the data shows that **64%** of respondents primarily use general e-commerce giants like **Amazon and Flipkart**, followed closely by specialized beauty platforms like **Nykaa/Purplle (42%)** and **Official Brand Websites (41%)**. This indicates that while general marketplaces remain the dominant choice for skincare purchases, there is a significant shift toward specialized beauty retailers and direct-to-consumer (D2C) channels. This suggests that consumers likely seek different types of reviews and trust signals across these platforms, with marketplaces offering volume and D2C sites offering brand authenticity.

Section 2: The Power of Stars

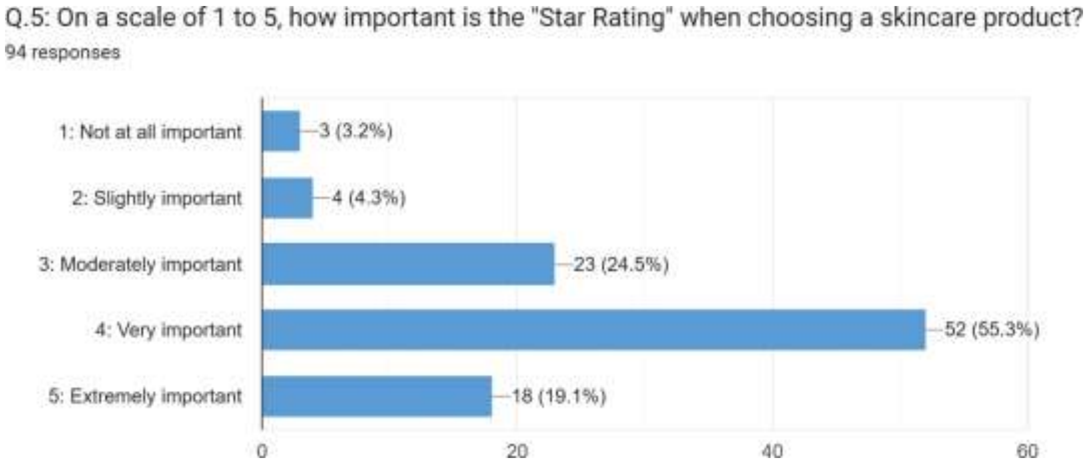


Chart 4.5: Response Over Importance of Star Rating

Table 4.5		
Response Over Importance of Star Rating		
Parameter	**Frequency (N=94)**	**Percentage**
1: Not at all important	**3**	**3.2%**
2: Slightly important	**4**	**4.3%**
3: Moderately important	**23**	**24.5%**
4: Very important	**52**	**55.3%**
5: Extremely importan	**18**	**19.1%**
Total	**100**	**100%**

Analysis and Interpretation: From the above Table 4.5 and Chart 4.5, the data and graphics show that 55.3% of respondents consider the star rating to be "Very important," and 19.1% find it "Extremely important," totaling nearly 74.4% of the participants who place high value on this metric. Only a negligible 7.5% of respondents viewed the star rating as slightly or not at all important. This shows that the numerical "Star Rating" serves as a critical initial filter for skincare consumers during their decision-making process.

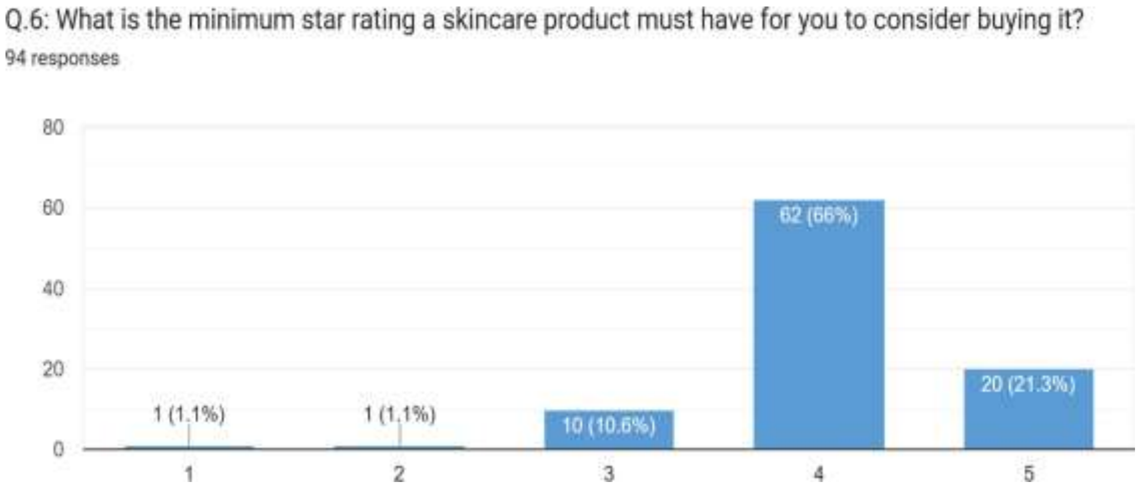


Chart 4.6: Response Over Minimum Star Rating

Table 4.6		
Response Over Minimum Star Rating		
Parameter	**Frequency (N=94)**	**Percentage**
1 Star	**1**	**1.1%**
2 Stars	**1**	**1.1%**
3 Stars	**10**	**10.6%**
4 Stars	**62**	**66.0%**
5 Stars	**20**	**21.3%**
Total	**100**	**100%**

Analysis and Interpretation: From the above Table 4.6 and Chart 4.6, the data and graphics show that a significant majority of 66% of respondents require a minimum of 4 stars before they even consider purchasing a skincare product, while 21.3% set their threshold at a perfect 5 stars. Only a combined 12.8% of participants would consider a product with 3 stars or less. This shows that there is a strict "quality floor" in the minds of skincare consumers. Because skincare is a high-involvement category where users fear adverse reactions, they use a 4-star benchmark as a psychological safety net. This indicates that for brands in the skincare sector, maintaining a rating below 4 stars acts as a major barrier to entry, as nearly 87.3% of potential customers would exclude such products from their purchase consideration.

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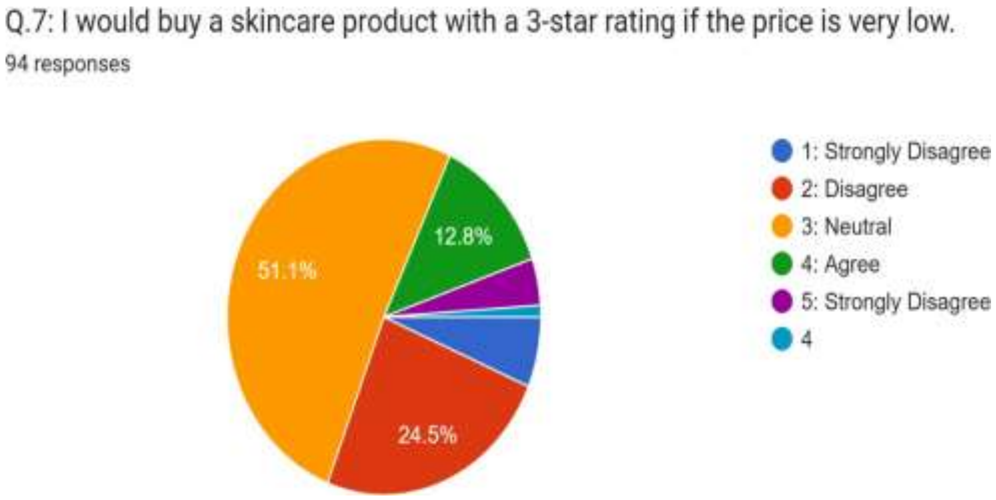

Chart 4.7: Response Over Willingness to Purchase 3-Star Rated Products at Low Prices

Table 4.7		
Response Over Willingness to Purchase 3-Star Rated Products at Low Prices		
Parameter	**Frequency (N=94)**	**Percentage**
Strongly Disagree	**7**	**7.4%**
Disagree	**23**	**24.5%**
Neutral	**48**	**51.1%**
Agree	**12**	**12.8%**
Strongly Agree	**4**	**4.2%**
Total	**100**	**100%**

Analysis and Interpretation: From the above Table 4.7 and Chart 4.7, the data and graphics show that a majority of **51.1%** of respondents remain "Neutral" regarding the trade-off between low price and a mediocre 3-star rating, while **31.9%** (combined Strongly Disagree and Disagree) would still reject the product despite the discount. Only a small fraction of **17%** would be swayed by a lower price point. This shows that in the skincare sector, price is not a primary compensator for lower ratings. Because these products are applied to the body, consumers prioritize perceived safety and efficacy over financial savings. This indicates that a "low-price strategy" is largely ineffective at overcoming poor online reputation in this industry, as most consumers are unwilling to compromise on quality for a cheaper alternative.

Section 3: Crowd Wisdom (Volume of Reviews)

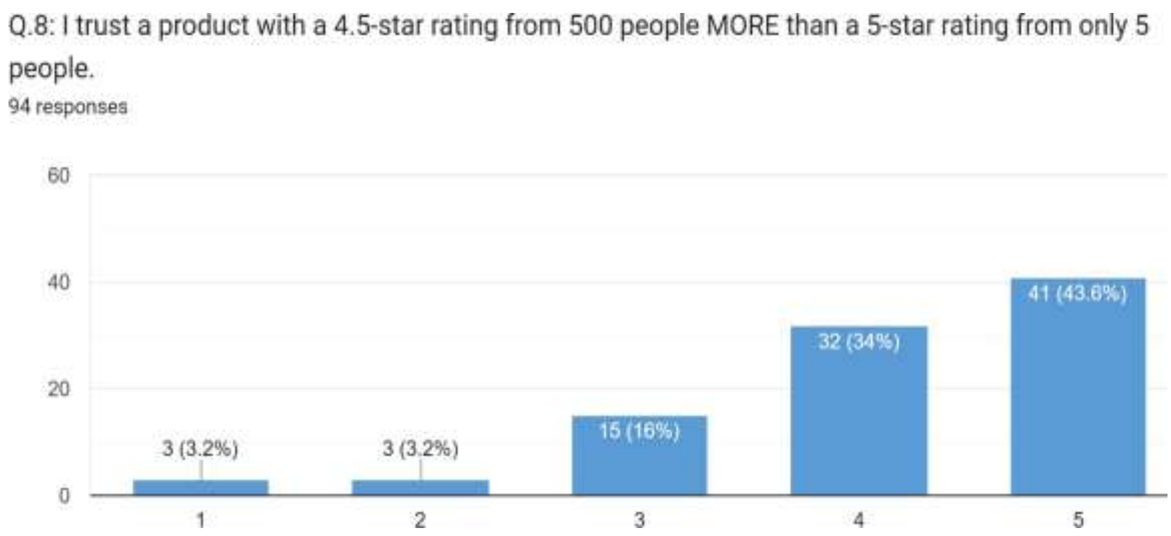

Chart 4.8: Response Over Trust Comparison: Review Volume vs. Review Rating

Table 4.8		
Response Over Trust Comparison: Review Volume vs. Review Rating		
Parameter	**Frequency (N=94)**	**Percentage**
Strongly Disagree	**3**	**3.2%**
Disagree	**3**	**3.2%**
Neutral	**15**	**16%**
Agree	**32**	**34%**
Strongly Agree	**41**	**43.6%**
Total	**94**	**100%**

Analysis and Interpretation: From the above Table 4.8 and Chart 4.8, the data and graphics show that a dominant 77.6% of respondents (combined Agree and Strongly Agree) prefer a slightly lower rating of 4.5 stars from a large sample size of 500 people over a perfect 5-star rating from only 5 people. Only a minor 6.4% of participants disagreed with this preference. This shows that "Review Volume" acts as a major driver of social proof and credibility in the skincare sector. Consumers perceive a larger number of reviews as more "authentic" and less likely to be manipulated or biased. This indicates that for skincare shoppers, the quantity of feedback (Stimulus) significantly enhances their internal trust.

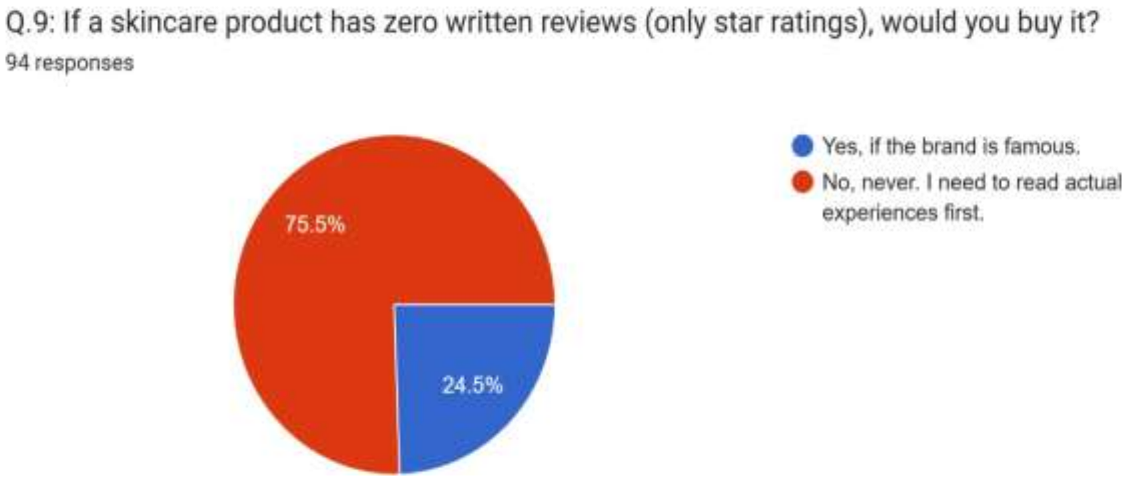

Chart 4.9: Response Over Willingness to Purchase Based on Star Ratings without Written Reviews

Table 4.9		
Response Over Willingness to Purchase Based on Star Ratings without Written Reviews		
Parameter	**Frequency (N=94)**	**Percentage**
No, never. I need to read actual experiences first.	71	75.5%
Yes, if the brand is famous.	23	24.5%
Total	**94**	**100%**

Analysis and Interpretation: From the above Table 4.9 and Chart 4.9, the data and graphics show that **75.5%** of respondents would refuse to buy a skincare product that lacks written reviews, even if it has star ratings, stating a specific need to read about actual user experiences. Only **24.5%** of participants would consider the purchase, and only if the brand was already famous. This shows that numerical ratings alone are insufficient "Stimuli" for the majority of skincare consumers. Because skincare products involve personal health and varying skin types, consumers seek detailed qualitative information to reduce "Perceived Risk." This indicates that written feedback is a mandatory requirement for building "Trust" in the skincare sector, and a famous brand name is only a minor substitute for the social proof provided by peer-generated written content.

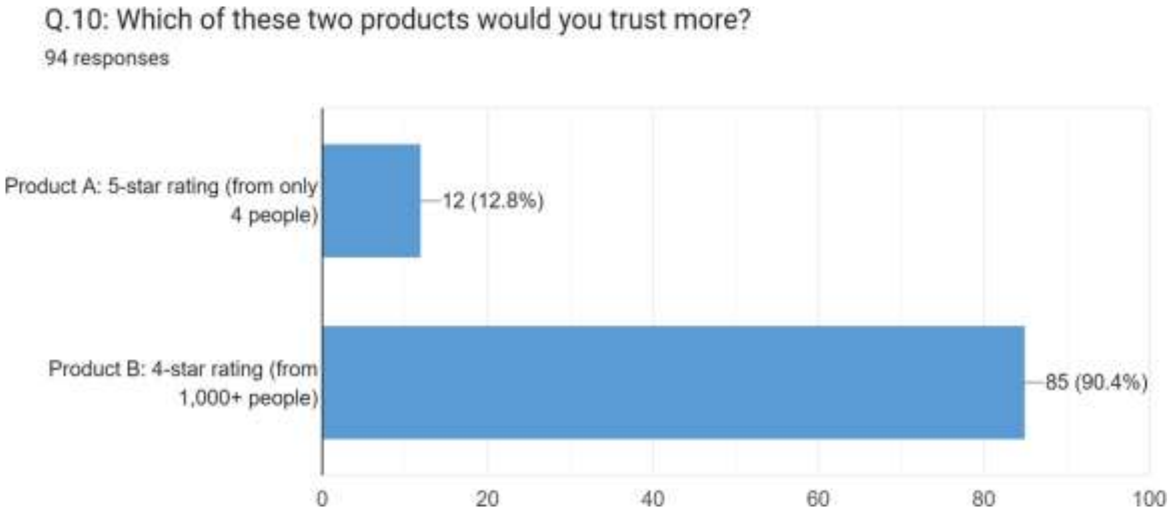

Chart 4.10: Response Over Comparative Trust Analysis: High Rating vs. High Volume

Table 4.10		
Response Over Comparative Trust Analysis: High Rating vs. High Volume		
Parameter	**Frequency (N=94)**	**Percentage**
5-star rating (from only 4 people)	**12**	**12.8%**
4-star rating (from 1,000+ people)	**82**	**90.4%**
Total	**94**	**100%**

Analysis and Interpretation: From the above Table 4.10 and Chart 4.10, the data and graphics show that a massive **87.2%** of respondents would trust a 4-star product with over 1,000 reviews more than a 5-star product with only 4 reviews. Only **12.8%** of participants preferred the perfect rating from the smaller sample. This shows that "social proof" is a far more powerful "Stimulus" than a perfect score in the skincare sector. The overwhelming preference for Product B indicates that consumers perceive high-volume feedback as a shield against bias and manipulation. For skincare brands, this suggests that the "Organism" (internal trust) is more strongly triggered by the consensus of a large crowd than by the flawless rating of a few individuals, proving that quantity often validates quality in the eyes of the consumer.

Section 4: Recency of Reviews

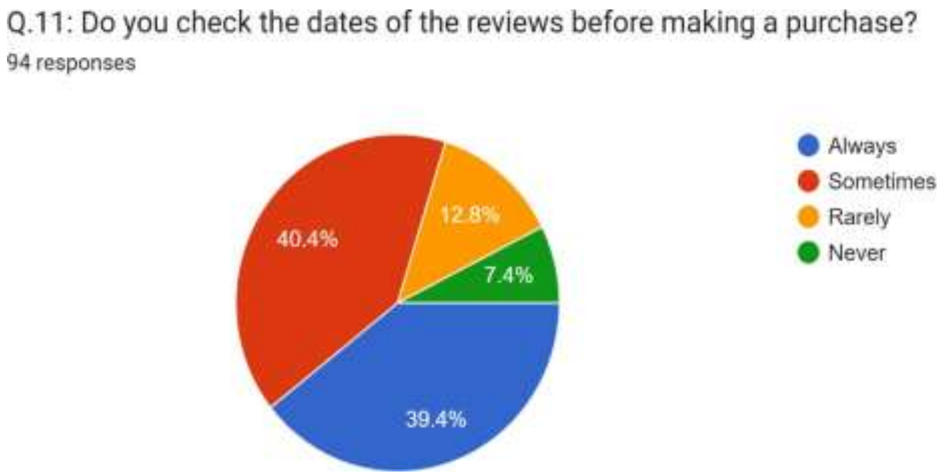

Chart 4.11: Response Over Frequency of Checking Review Recency Before Purchase

Table 4.11		
Response Over Frequency of Checking Review Recency Before Purchase		
Parameter	**Frequency (N=94)**	**Percentage**
Always	**37**	**39.4%**
Sometimes	**38**	**40.4%**
Rarely	**12**	**12.8%**
Never	**7**	**7.4%**
Total	**94**	**100%**

Analysis and Interpretation: From the above Table 4.11 and Chart 4.11, the data and graphics show that a combined 79.8% of respondents (comprising "Always" and "Sometimes") pay attention to the dates of reviews before making a purchase. In contrast, only 7.4% of participants never check the recency of the feedback. This shows that the "Recency" of a review is a significant factor in the consumer's decision-making process. In the skincare sector, where product formulations and brand consistency can change over time, consumers look for recent reviews to ensure the feedback is still relevant. This indicates that older reviews lose their "Stimulus" power over time, and consumers require fresh, updated social proof to maintain "Trust" and reduce the perceived risk of buying an outdated or reformulated product.

Q.12: If a product has a high overall rating (4.5 stars) but the most recent 3 reviews are negative, would you still buy it?

94 responses

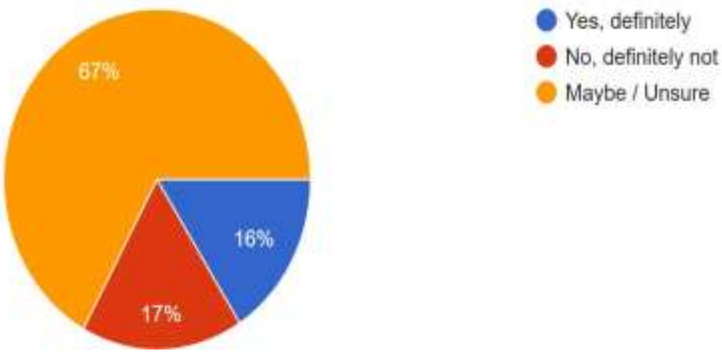

Chart 4.12: Response Over Impact of Recent Negative Reviews on Purchase Intent

Table 4.12		
Response Over Frequency of Checking Review Recency Before Purchase		
Parameter	**Frequency (N=94)**	**Percentage**
Maybe / Unsure	**63**	**67%**
No, definitely not	**16**	**17%**
Yes, definitely	**15**	**16%**
Total	**94**	**100%**

Analysis and Interpretation: From the above Table 4.12 and Chart 4.12, the data and graphics show that **67%** of respondents would be "Unsure" about purchasing a product with a high 4.5-star rating if the three most recent reviews were negative. Furthermore, **17%** would definitively refuse to buy the product, while only **16%** would proceed with the purchase regardless. This shows that the **"Recency Effect"** carries immense weight in the consumer's internal evaluation process. Even when a product has a strong historical reputation (high star rating), recent negative feedback creates immediate "Perceived Risk." This indicates that latest reviews act as a more powerful "Stimulus" than the aggregate average, suggesting that skincare brands must maintain consistent quality to avoid recent negative trends that can paralyze the "Response" (purchase intent) of over **84%** of potential customers.

Section 5: The Final Purchase Decision

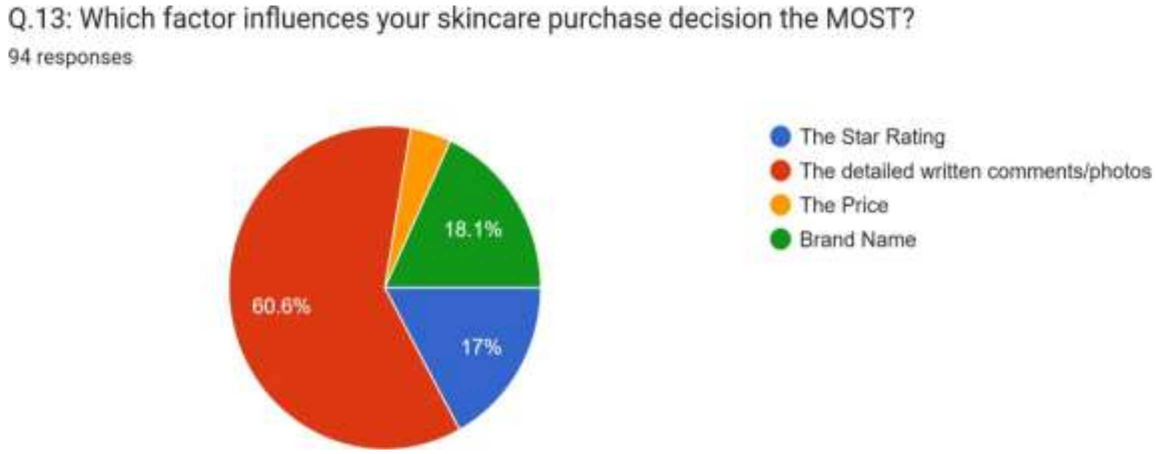

Chart 4.13: Response Over Primary Influencing Factors in Skincare Purchase Decisions

Table 4.13		
Response Over Primary Influencing Factors in Skincare Purchase Decisions		
Parameter	**Frequency (N=94)**	**Percentage**
Detailed written comments/photos	**57**	**60.6%**
Brand Name	**17**	**18.1%**
The Star Rating	**16**	**17%**
The Price	**4**	**4.3%**
Total	**94**	**100%**

Analysis and Interpretation: From the above Table 4.13 and Chart 4.13, the data and graphics show that **60.6%** of respondents are influenced most by **detailed written comments and photos**, followed by Brand Name (**18.1%**) and Star Rating (**17%**). Remarkably, Price is the least influential factor, affecting only **4.3%** of the participants. This shows that for skincare consumers, qualitative "User-Generated Content" is the most powerful "Stimulus" in the S-O-R model. Because skincare is an experience-based product, consumers prioritize the "Media Richness" of actual evidence (photos and descriptions) over numerical scores or brand prestige. This indicates that to drive a positive "Response," brands must focus on encouraging detailed customer feedback, as the internal "Organism" (trust) is more deeply triggered by the shared experiences of others than by financial savings or a high-level star rating.

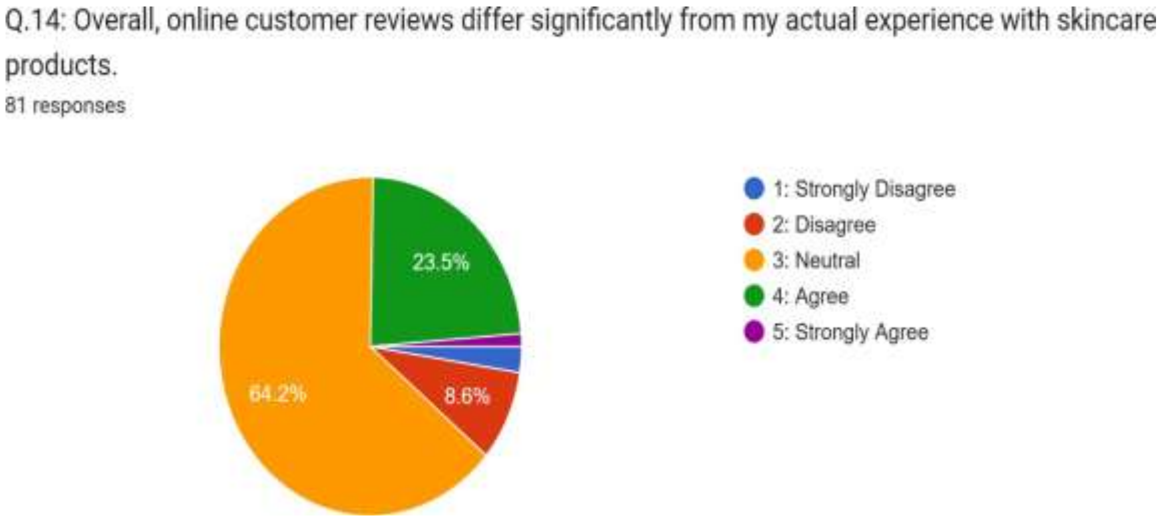

Chart 4.14: Response Over Comparison Between Online Reviews and Actual User Experience

Table 4.14		
Response Over Comparison Between Online Reviews and Actual User Experience		
Parameter	**Frequency (N=81)**	**Percentage**
Strongly Disagree	**2**	**2.5%**
Disagree	**7**	**8.6%**
Neutral	**52**	**64.2%**
Agree	**19**	**23.5%**
Strongly Agree	**1**	**1.2%**
Total	**81**	**100%**

Analysis and Interpretation: From the above Table 4.14 and Chart 4.14, the data and graphics show that a significant majority of **64.2%** of respondents remain "Neutral" regarding whether online reviews differ from their actual experience. Meanwhile, **23.5%** of participants "Agree" that there is a discrepancy between digital feedback and their real- world results. Only a small combined total of **11.1%** disagreed with the statement. This shows that while many consumers rely on reviews as a "Stimulus," a notable portion of the skincare market maintains a level of skepticism about the total accuracy of online claims. This suggests that the internal "Organism" (trust) is fragile; when actual product performance does not perfectly align with the high expectations set by reviews, it can lead to a sense of disconnect.

Q.15: Apart from ratings and reviews, is there any other specific detail on the product page that convinces you to buy a skincare product? (Open Ended)

Response Summary:

- **Ingredients and Product Composition:** The most convincing detail apart from ratings and reviews is the product's composition, including the ingredient list, transparency of contents (especially active ingredients and their percentages), and technical specifications.
- **Brand Reputation and Trust:** Respondents are influenced by brand trust, whether they have used the brand before, the reputation of the brand, and who is promoting or running the company.
- **Suitability and Certification:** Key details include the product's suitability for specific skin types, being dermatologist-tested or certified, and clear information on product usage.
- **Visuals and Results:** Real before-and-after photos, images of the product, and visible results are strong factors; product packaging can also be a deciding factor. Value and Availability: Details like price, quantity, and return guarantees influence purchase decisions, as does the reach of the e-commerce page.

5. Discussion & Conclusion

This final chapter synthesizes the analysed data to discuss the practical and theoretical implications of the research findings in relation to the study's objectives. It provides a definitive conclusion on the role of online reviews as a safety guarantee in skincare e-commerce and offers actionable recommendations for brands to optimize their digital reputation.

5.1 Discussion

- **Star Ratings as Gatekeepers:** Results from Questions 5 and 6 confirm that star ratings are a non-negotiable "Stimulus." With **74.4%** of respondents viewing them as highly important and **66%** requiring at least 4 stars, these ratings act as a primary filter. In the skincare industry, where safety is a major concern, high ratings serve as an initial trust-builder (**Organism**) that reduces perceived risk.

- **Quality and Volume over Perfection:** While ratings are important, Question 13 shows that **60.6%** of consumers are most influenced by detailed comments and photos. Furthermore, **87.2%** prefer a high volume of reviews (1,000+) over a perfect 5-star rating from a small group. This proves that "Social Proof" is driven by the "wisdom of the crowd" and "Media Richness" rather than a singular perfect score.

- **The Recency Effect:** Data from Questions 11 and 12 highlight that timing is everything. Nearly **80%** of shoppers check review dates, and **67%** would avoid a product if the most recent feedback was negative. This indicates that old trust is fragile; consumers require current validation to maintain purchase intent.

- **Value of Trust over Price:** A significant finding is that **Price (4.3%)** is the least influential factor. As seen in Question 7, consumers refuse to compromise on a low- rated product just because it is cheap. This validates that skincare is a "high- involvement" category where safety and trust consistently outweigh financial savings.

5.2 Conclusion

This study shows that online customer reviews are the important thing when people are buying skincare products online. We used the S-O-R framework to see how reviews affect people. What we found is that detailed reviews, a lot of reviews and recent reviews help build trust and make people more likely to buy something. A product is successful on websites like Amazon or Nykaa because of what people say about it not just because it's cheap. For people a review is, like a guarantee that the product's safe. Without reviews people are not likely to buy something.

5.3 Limitations of the Study

This study mainly focuses on people aged 14–34 who grew up using digital technology. Because they tend to rely on online feedback, the results might not represent how older generations behave. Also, since skincare involves personal health and safety, our findings may not apply to everyday products like office supplies, which carry less risk. Finally, since we used a convenient sample of 100 people, the results might not reflect the experiences of those in rural areas or people less comfortable with technology.

5.4 Future Research Directions

In the future, it would be helpful to look at how Artificial Intelligence affects online reviews—especially to see how fake or AI-generated reviews might change the way people trust brands and how platforms keep things honest. It's also important to study how companies handle negative feedback, and whether a thoughtful reply can turn a critic into a loyal customer. Finally, following people's experiences over time or comparing different types of products could give us a clearer picture of how a brand's reputation online shapes the choices of different groups of shoppers.

Annexure - I: References

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