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Analyzing the Influence of Customer Feedback and Reviews on Purchase Intent in E-Commerce Platforms Through Sentiment Analysis

Roshan Sriram[1], Prof. Shoaib Ahamed Khan[2]

[1]MBA Student, RV Institute of Management
[2]Assistant Professor, RV Institute of Management

ABSTRACT

This study explores the impact of customer reviews on consumer purchasing decisions in an online context. Data were collected from 192 respondents using a 30-item questionnaire, with full response completion and no missing values. This complete dataset enabled robust statistical analysis and enhanced result credibility. The instrument demonstrated excellent internal consistency, as evidenced by a Cronbach's Alpha of 0.986, confirming the reliability of the measurement tool. Descriptive statistics indicated a largely young participant base, with moderate levels of education and occupation. Most respondents reported being influenced by customer reviews when making purchasing decisions online.

Friedman's ANOVA revealed statistically significant differences in item responses, although Kendall's coefficient of concordance (W) values was consistently low. This suggests limited consensus among participants, pointing to the nuanced and individualized nature of consumer behavior. These findings offer important implications for both research and practice. For researchers, the results underscore the need for further segmentation and investigation into personal factors affecting review influence. For practitioners, particularly in e-commerce and digital marketing, the findings highlight the importance of managing online reviews and tailoring strategies to individual consumer preferences. Overall, the study supports the critical role of user-generated content in shaping online shopping behaviors and emphasizes the value of targeted engagement strategies.

Keywords: Customer sentiment, purchase intent, online reviews, e-commerce, emotional analytics, trust, personalization

Introduction

In an age where digital connectivity defines consumer behaviour and market dynamics, e-commerce platforms have revolutionized the global retail landscape. With increasing competition, information abundance, and consumer empowerment, the role of customer feedback has transcended beyond traditional satisfaction surveys to become a vital strategic asset. One of the most promising and yet underexplored frontiers in this evolution is the application of sentiment analysis—a subdomain of Natural Language Processing (NLP)—to decode and operationalize customer feedback, particularly in influencing purchase intent. The confluence of artificial intelligence, behavioural psychology, and marketing science offers a lifetime opportunity to harness real-time emotional insights that shape the buyer journey in the digital economy.

At the bird's-eye view, e-commerce platforms today are grappling with a deluge of user-generated content, including reviews, ratings, and social media commentary. These feedback forms—whether emotional, rational, or contextual—directly impact how consumers perceive products and make purchase decisions. A positive review filled with excitement or gratitude can amplify trust and encourage conversions, while even a single negative review might derail the purchase journey for hundreds of potential customers. Thus, understanding and analysing this emotional data is not merely a marketing convenience but a strategic necessity. Platforms like Amazon, Alibaba, and Flipkart have realized that beyond product features and price, the sentiment expressed in feedback holds unparalleled influence over consumer behaviour.

However, this massive volume of feedback is only as valuable as the insights derived from it. Traditional analytics approaches often fail to capture the emotional subtext, contextual nuance, and predictive power embedded within textual feedback. This is where sentiment analysis, powered by machine learning and AI, fills a critical gap. It enables the detection of underlying emotions—whether satisfaction, frustration, or anticipation—within customer reviews, offering businesses a window into the minds of their users. Moreover, it transforms qualitative opinions into quantitative metrics that can inform decisions related to product development, inventory management, customer service, and targeted advertising.

Despite this promising horizon, a review of the literature reveals that existing studies have not fully captured the dynamic interplay between sentiment, customer feedback, and actual purchasing behavior, especially in real-time digital commerce environments. While various Customer Feedback Metrics (CFMs) like Net Promoter Score (NPS), Customer Effort Score (CES), and Top-2-Box scores have been studied in relation to financial performance *(Agag et al., 2023)*, their direct connection to intent-based decision-making on e-commerce platforms remains inadequately mapped. Furthermore, research by *De Haan et al. (2015)* and *Bowen and Chen (2001)* emphasized the predictive potential of CFMs on loyalty, yet stopped short of analysing how online sentiment, extracted from customer reviews, shapes or shifts purchase intent at the point of decision-making.

The research gap also extends into the methodological domain. While studies such as *Lakshmi and Lavanya (2022)* have explored the application of NLP for sentiment extraction, they often overlook the multi-dimensional and context-sensitive nature of consumer emotion. Most current sentiment analysis models treat feedback as binary (positive/negative) or at best, trinary (positive/neutral/negative), failing to account for the rich emotional textures that actually influence buyer decisions—such as trust, excitement, disappointment, or urgency. Moreover, studies like those of *Rajawat and Bhatnagar (2022) and Fernandes et al. (2020)* demonstrate AI's potential in other industries like telecom and education, but similar deep learning-based frameworks customized for sentiment-driven consumer modelling in e-commerce remain sparse.

Adding to the complexity is the credibility and architecture of review platforms, as highlighted by Chevalier and *Mayzlin (2006).* They found that identical reviews can have different impacts depending on how the platform presents them—emphasizing that interface design, trustworthiness, and volume of reviews all interact with sentiment to drive behaviour. In essence, we need more integrated studies that bridge the gap between technological capability (e.g., CNNs, hybrid models, ensemble learning) and consumer psychology to yield real-world, actionable insights for e-commerce stakeholders.

On the one hand, this signals an urgent need for research that offers an integrative approach: one that combines machine learning, behavioural theory, and platform dynamics to understand how sentiment in feedback affects immediate and long-term purchase intent. On the other hand, this gap presents a lifetime opportunity—for researchers, practitioners, and technologists alike—to redefine how digital platforms interpret and act upon customer voices. In particular, deploying hybrid sentiment analysis models such as those proposed by *Prabowo and Thelwall (2009)*, which blend rule-based systems with statistical learning, can overcome current limitations in handling sarcasm, slang, and emotion-laden narratives. Similarly, the QCD (Qualitative-Quantitative Customer-Driven) model introduced by *Olsson and Bosch (2015)* offers a viable framework for combining early qualitative insights with robust quantitative data at scale.

The beneficiaries of this research are multifaceted, spanning across various domains in both industry and academia. At the forefront are e-commerce platforms, which stand to gain the most through enhanced understanding of how customer sentiment directly influences purchase intent. By leveraging sentiment analysis, these platforms can improve product recommendation algorithms, refine interface design, and personalize customer experiences, thereby increasing conversion rates and reducing cart abandonment. Marketing strategists and product managers also benefit significantly, as insights drawn from sentiment-rich feedback can inform targeted campaign strategies, product development cycles, and customer retention initiatives. Furthermore, data scientists and AI developers are key stakeholders, as this research paves the way for building more sophisticated, context-aware models capable of interpreting complex emotional language and consumer expressions with greater accuracy and relevance. For consumers, the indirect advantages are equally important. Sentiment-driven systems can highlight emotionally authentic reviews, reduce exposure to manipulative or fake feedback, and ultimately enhance decision-making confidence and post-purchase satisfaction. Additionally, academics and interdisciplinary researchers benefit from this emerging field, which presents rich opportunities for collaboration across marketing, linguistics, psychology, and computer science. The topic offers fertile ground for theoretical advancement and practical application alike. Lastly, regulators and public policy makers also find value in this research, particularly in its potential to inform guidelines for ethical use of consumer data, transparency in AI models, and the identification of misleading or deceptive content in online reviews. Altogether, the integration of sentiment analysis into e-commerce feedback ecosystems promises widespread impact across technological, commercial, and societal dimensions.

Furthermore, industries such as healthcare, telecommunications, and education, which were the focal points of studies like those of *Vukmir (2006)*, *Rajawat and Bhatnagar (2022)*, and *Fernandes et al. (2020)*, provide blueprints that can be translated into e-commerce settings. For instance, the way AI models have improved patient satisfaction and risk identification can be mirrored in detecting at-risk customers or dissatisfied users in digital retail.

Yet, for all its promise, sentiment analysis must navigate certain ethical and operational challenges. The automation of emotional interpretation raises questions about privacy, bias, and the commercialization of user-generated emotions. It is essential that sentiment models be trained on diverse datasets, incorporate fairness metrics, and maintain transparency in interpretation—especially when used to influence something as intimate and personal as buying decisions.

In summation, the digital marketplace is at a pivotal juncture where the power of feedback—if adequately harnessed through advanced sentiment analysis—can transform how businesses understand, serve, and retain customers. By focusing on the influence of customer sentiment on purchase intent, this research aims to bridge crucial theoretical and practical gaps, offering an empirical, scalable, and ethically grounded model for e-commerce innovation. The fusion of technology and human emotion, when approached thoughtfully, offers more than just commercial gain—it paves the way for empathy-driven commerce, where consumer voices are not just heard, but meaningfully understood and acted upon.

Literature Review

The literature on customer feedback, sentiment analysis, and predictive analytics has evolved extensively, highlighting the strategic relevance of customer-centric data in business decision-making processes. Central to this field is the development and application of Customer Feedback Metrics (CFMs), including Customer Satisfaction (SAT), Net Promoter Score (NPS), Customer Effort Score (CES), and Top-2-Box scores. A seminal study by Agag et al. (2023) explores the relationship between these CFMs and firm-level financial performance, specifically sales growth, gross margin, and market valuation (Tobin’s Q). Drawing upon data from 668 firms across 16 industries using the American Customer Satisfaction Index (ACSI), their research underscores that no single metric is universally applicable. Instead, the efficacy of each metric varies by industry. For instance, Top-2-Box scores are more predictive in sectors like online bookings and hotels, whereas CES exhibits stronger correlations in restaurant settings. Contrary to earlier assertions by Reichheld (2003), who popularized NPS as a universal loyalty predictor, Agag et al. (2023) find NPS inconsistently predictive. Their study ultimately advocates for a contextual and hybrid approach, where firms strategically combine metrics aligned with their industry and business goals.

Adding a qualitative and psychological dimension to the discourse, Nasr, Burton, and Gruber (2018) investigate the effects of positive customer feedback (PCF) using structured laddering and the Zaltman Metaphor Elicitation Technique (ZMET). Their findings reveal the emotional and motivational ramifications of PCF for both customers and frontline employees (FLEs). While customers use PCF to express gratitude and build relational intimacy, FLEs perceive such feedback as validation, boosting morale, intrinsic motivation, and service commitment. This dual dynamic illustrates that PCF is not merely a measure of satisfaction but a relational and motivational tool that influences workplace dynamics and customer loyalty.

The healthcare sector presents a distinctive case where customer satisfaction has profound implications. Vukmir (2006) investigates patient satisfaction in emergency departments, finding that communication quality, physician empathy, and operational efficiency are critical determinants. Particularly notable is the finding that professional handling of difficult patients results in significantly improved satisfaction outcomes. Vukmir posits that satisfaction in healthcare is not only a performance metric but also a strategic asset that enhances patient compliance, institutional reputation, and mitigates legal risks.

In technology-driven firms, customer feedback plays a transformative role in product development. Fabijan et al. (2015) study how software companies incorporate customer feedback into design cycles using tools such as direct interviews, usability tests, A/B testing, and analytics platforms. A major concern identified is the prevalence of "open-loop" systems, where feedback is collected but not operationalized. To address this gap, Olsson and Bosch (2015) introduce the Qualitative-Quantitative Customer-Driven (QCD) model. This model recommends a staged feedback approach: early development relies on qualitative methods (e.g., interviews), while later stages incorporate quantitative data from product usage. The QCD model fosters continuous integration of customer insights into design, thereby reducing risk and improving market fit.

The predictive utility of CFMs in customer retention is analysed by De Haan, Verhoef, and Wiesel (2015), who find that Top-2-Box scores are superior to NPS, CES, and SAT in forecasting loyalty. This superiority stems from their emphasis on customers who express extreme satisfaction, aligning with broader marketing theories that prioritize high-intensity satisfaction over averaged responses. Similarly, Bowen and Chen (2001) emphasize that customer satisfaction alone does not guarantee loyalty. Rather, exceeding expectations through consistent quality, personalized experiences, and emotional engagement plays a more crucial role in fostering return behaviour and brand advocacy.

The increasing prevalence of e-commerce and digital platforms has made the analysis of online sentiment a critical tool in understanding customer behaviour. Lakshmi and Lavanya (2022) employ Natural Language Processing (NLP) to study how sentiment in online reviews influences purchase decisions. Their findings underscore the importance of emotional tone—particularly positive sentiment such as excitement or gratitude—which significantly enhances trust and purchase intent. Conversely, negative sentiment deters potential buyers. Complementing this, Rizwan et al. (2020) investigate online consumer behavior in Pakistan's mobile phone industry and identify the impact of review credibility, volume, and brand trust on purchase intent. Structural Equation Modeling (SEM) reveals that these variables exert both direct and mediated effects, influencing consumer decisions through perceived value and platform credibility. Earlier work by Chevalier and Mayzlin (2006) reinforces these insights, showing that identical reviews can produce different consumer responses depending on the platform's interface and review architecture, thereby highlighting the importance of contextual design in digital marketing.

Machine learning and predictive analytics further augment the capacity to derive actionable insights from customer feedback. Rajawat and Bhatnagar (2022) demonstrate the use of predictive models such as Gradient Boosting, Random Forest, and Support Vector Machines in a telecom context to identify at-risk customers with high accuracy. These techniques are instrumental in retaining high-value customers and optimizing retention strategies. Fernandes et al. (2020) extend the application of predictive analytics to education and healthcare, demonstrating how AI-driven models enhance user engagement and outcomes. The underlying principles—adaptive feedback loops and personalized recommendations—are directly transferable to marketing, enabling businesses to tailor offerings and improve customer experience.

Emerging technologies also enhance how sentiment is captured and utilized across domains. Shaikh et al. (2022) use Convolutional Neural Networks (CNNs) for breast cancer detection, showcasing the adaptability of deep learning models to domain-specific tasks. Though rooted in healthcare, such methodologies are applicable in sentiment analysis, especially in interpreting nuanced emotional expressions in user-generated content. Similarly, Alshamrani et al. (2023) apply ensemble learning models—including Decision Trees, Random Forest, and XGBoost—to intrusion detection, highlighting the robustness and accuracy of hybrid models. These findings are relevant to sentiment classification, where handling textual noise, irony, and sarcasm is particularly challenging.

Innovative sentiment classification models are also proposed by Prabowo and Thelwall (2009), who develop a hybrid system that integrates rule-based methods with machine learning and statistical techniques. This hybrid approach mitigates limitations of purely statistical models in processing informal language and contextual nuances common in online reviews. Additionally, the semi-automatic generation of rules enhances the system's scalability and adaptability in dynamic digital environments, making it especially useful for marketing applications that rely on real-time sentiment tracking.

From an organizational perspective, Surbakti et al. (2020) examine how Business Intelligence and Analytics (BI&A) capabilities influence decision-making in Australian enterprises. They identify that while technological infrastructure is necessary, managerial competence is the critical driver of BI&A success. This finding reinforces the view that data-driven tools require effective interpretation and strategic alignment to produce meaningful outcomes.

In the context of customer feedback and sentiment analysis, it emphasizes the need for human-centric analytics that prioritize contextual understanding and organizational buy-in over mere data collection.

Across the literature, several cross-cutting themes emerge. First is the importance of contextual customization. Whether selecting CFMs or designing predictive models, aligning tools with industry-specific needs, customer journey stages, and cultural contexts is essential. Agag et al. (2023) and De Haan et al. (2015) both stress that effectiveness is contingent upon contextual fit rather than universality. Second is the multidimensional value of customer feedback. Studies such as those by Nasr et al. (2018), Vukmir (2006), and Bowen and Chen (2001) demonstrate that feedback is not just a metric but also a motivational and strategic asset. It validates employee performance, strengthens customer relationships, and serves as a leading indicator of loyalty and innovation.

Another recurrent theme is the integration of technology and strategy. Studies by Fabijan et al. (2015), Olsson and Bosch (2015), and Prabowo and Thelwall (2009) highlight how AI and machine learning models can transition organizations from descriptive to predictive and prescriptive analytics. However, the success of such integration depends on model interpretability, strategic relevance, and effective implementation. The work of Surbakti et al. (2020) reinforces that organizational capability and decision-making maturity are essential for realizing the benefits of analytics investments.

Trust emerges as another pivotal theme. In digital environments, trust is mediated through consistent service delivery, transparent data use, credible reviews, and platform reliability (Rizwan et al., 2020; Chevalier & Mayzlin, 2006). This trust moderates the relationship between feedback and consumer behavior, ultimately determining whether users become loyal advocates.

In conclusion, the reviewed literature provides a comprehensive understanding of how customer feedback, sentiment analysis, and predictive analytics collectively influence business performance. From empirical validations of CFMs to psychological studies on feedback dynamics, and from AI applications in consumer modeling to strategic organizational alignment, the literature underscores a need for an integrative, context-sensitive, and technology-enabled approach. Organizations that effectively harness the emotional, behavioral, and analytical dimensions of customer data are better positioned to foster loyalty, drive innovation, and sustain competitive advantage in an increasingly complex digital landscape.

Conceptual Framework

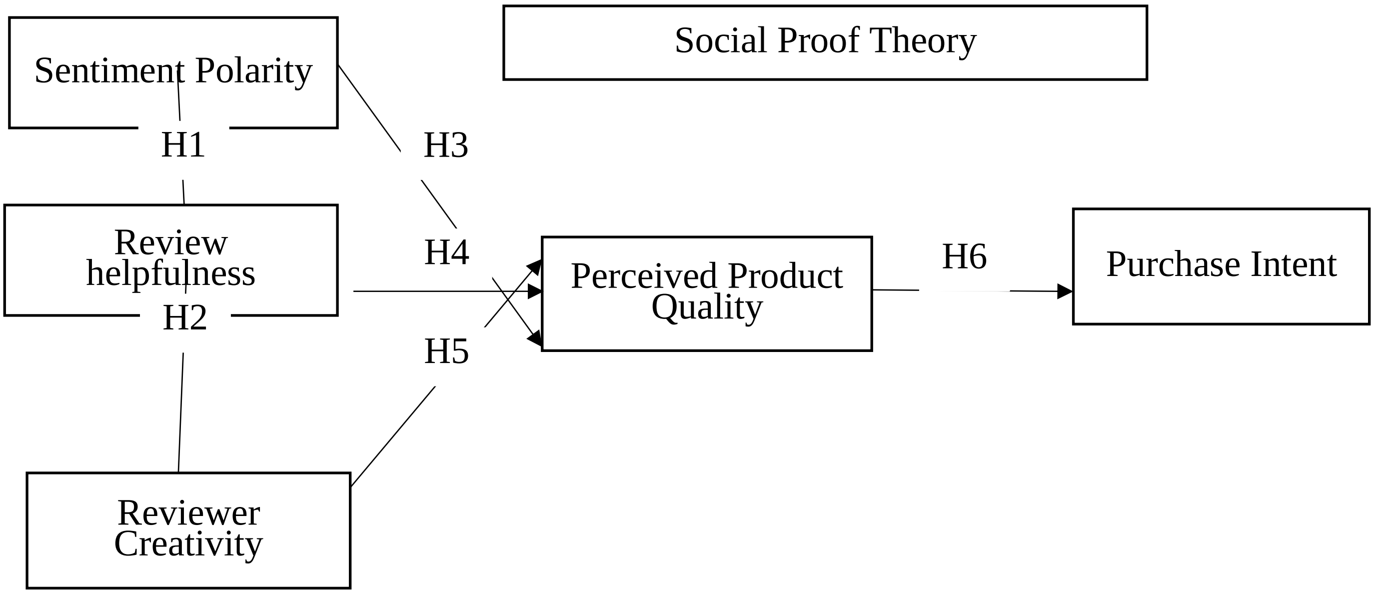


Fig:1 (Conceptual Model)

Hypothesis Formulation

1. **H1**: *Sentiment polarity of customer reviews has a positive effect on perceived product quality.*
2. **H2**: *Reviewer creativity positively influences the perceived helpfulness of customer reviews.*
3. **H3**: *Sentiment polarity of customer reviews directly influences purchase intent.*
4. **H4**: *Perceived product quality positively affects purchase intent.*
5. **H5**: *Reviewer creativity has a positive impact on perceived product quality.*
6. **H6**: *Review helpfulness positively influences purchase intent.*

Research Methodology

Research Design

This research adopts a quantitative, cross-sectional survey design to examine the influence of online review characteristics on consumer purchase intent, guided by Social Proof Theory. Data were collected using a structured questionnaire comprising 30 items, administered to 192 participants. The constructs measured include sentiment polarity, reviewer creativity, review helpfulness, perceived product quality, and purchase intent. Statistical analyses, including reliability testing (Cronbach's Alpha), descriptive statistics, and Friedman's ANOVA, were conducted to assess relationships among variables. This design enables the evaluation of consumer perceptions at a single point in time, offering insights into how different review attributes affect online shopping behaviour.

Sample size and Sample frame

The sample size consisted of 192 valid responses, ensuring a robust dataset for statistical analysis. All responses were complete, with no missing data, enhancing the accuracy and reliability of results. The sample frame targeted individuals who engage in online shopping, particularly those who have encountered and considered customer reviews during their purchase decisions. Participants were selected using a non-probability sampling method, focusing on relevance to e-commerce behaviour. This frame provided insights into the influence of sentiment polarity and reviewer creativity on purchase intent, capturing a representative view of active online consumers and review-aware buyers.

Sampling and data collection

This study employed a non-probability convenience sampling method to recruit participants who engage in online shopping. The sample consisted of 192 respondents, ensuring a sufficient size for statistical analysis and hypothesis testing. Participants were selected based on their availability and willingness to participate, primarily through online platforms and social media channels. Data were collected using a self-administered online questionnaire, designed to measure key constructs such as sentiment polarity, reviewer creativity, review helpfulness, perceived product quality, and purchase intent. The questionnaire ensured clarity and ease of response, contributing to a 100% valid response rate with no missing data.

Data collection

Data for this research were collected using a structured online questionnaire distributed through digital platforms such as email, social media, and messaging apps. The survey targeted individuals with experience in online shopping, particularly those who consider customer reviews before making purchase decisions. A non-probability purposive sampling technique was employed to ensure relevance to the research objectives. The questionnaire included items measuring sentiment polarity, reviewer creativity, perceived product quality, review helpfulness, and purchase intent. A total of 192 complete responses were obtained, with no missing data, ensuring high reliability and enabling valid statistical analysis of the constructs under study.

DATA ANALYSIS

- **Descriptive Statistics**

Statistics							
		Age	Gender	Education Level	Occupation	Monthly Online Shopping Frequency	Have you ever made a purchase decision based on customer reviews?
N	Valid	192	192	192	192	192	192
	Missing	0	0	0	0	0	0
Mean		2.81	1.84	3.49	1.94	2.54	1.53
Mode		2^a	1	4	2	3	1
Std. Deviation		0.88	0.797	0.731	1.064	0.975	0.723
Variance		0.774	0.635	0.534	1.133	0.952	0.523
Skewness		0.9	0.288	-1.306	1.274	-0.257	1
Std. Error of Skewness		0.175	0.175	0.175	0.175	0.175	0.175
Kurtosis		1.343	-1.369	2.39	1.159	-0.947	-0.397
Std. Error of Kurtosis		0.349	0.349	0.349	0.349	0.349	0.349

Range	5	2	4	5	3	2
a. Multiple modes exist. The smallest value is shown						

The descriptive statistics table provides an overview of the demographic and behavioral characteristics of the 192 valid respondents in this study. The mean age is 2.81 on a coded scale, with a standard deviation of 0.88, suggesting a relatively youthful sample. Gender distribution shows a moderate skew (0.288), indicating a slight imbalance, while education level is negatively skewed (-1.306), suggesting more participants had higher educational qualifications. Occupation and online shopping frequency have higher variation, with standard deviations of 1.064 and 0.975 respectively. Notably, the variable "Have you ever made a purchase decision based on customer reviews?" shows a strong positive skew (1.000), indicating that most participants responded affirmatively. The high kurtosis in education level (2.39) further reflects the concentration of responses in higher categories. Overall, the sample reflects a digitally active, relatively young, and well-educated demographic, making it well-suited for examining e-commerce behaviors and the impact of customer reviews on purchase intent.

- **Reliability Test**

Case Processing Summary			
		N	%
Cases	Valid	192	100
	Excluded[a]	0	0
	Total	192	100
a. Listwise deletion based on all variables in the procedure.			

The Case Processing Summary indicates that all 192 responses collected for the study were valid, with no missing values. This suggests a high level of data completeness and integrity, allowing for reliable statistical analysis. The absence of excluded cases ensures that the findings accurately represent the entire sample population. Listwise deletion was used based on all variables, confirming that each respondent provided responses across all required items. This comprehensive dataset enhances the credibility of the results and ensures that subsequent inferential analyses can be conducted without concerns of bias from missing data or imputation techniques.

Reliability Statistics		
Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
0.986	0.986	30

The Reliability Statistics table shows that the Cronbach's Alpha value for the 30-item instrument is an exceptionally high 0.986. This result demonstrates excellent internal consistency, indicating that the items used in the questionnaire consistently measure the same underlying construct. Additionally, the standardized alpha value being identical supports the homogeneity of item responses. High reliability affirms the appropriateness of aggregating or comparing responses across items. Such reliability is particularly important for drawing meaningful conclusions and justifies proceeding with further statistical testing, including inferential methods like Friedman's ANOVA, with confidence in the instrument's measurement accuracy and coherence.

MODEL 1

ANOVA with Friedman's Test						
		Sum of Squares	df	Mean Square	Friedman's Chi-Square	Sig
Between People		946.091	191	4.953		
Within People	Between Items	28.640[a]	4	7.16	62.987	0
	Residual	320.56	764	0.42		
	Total	349.2	768	0.455		
Total		1295.29	959	1.351		
Grand Mean = 3.55						
a. Kendall's coefficient of concordance W = .022.						

The ANOVA with Friedman's Test assesses whether there are statistically significant differences in rankings across multiple related items. The table shows a Friedman's Chi-Square value of 62.987 with a significance level (p-value) of 0.000, indicating that the differences observed among the items are statistically significant at the 0.05 level. This means that at least one of the variables measured differs in its impact or perception by respondents. The Kendall's coefficient of concordance (W = 0.022), though statistically significant, reflects a weak agreement among respondents in their rankings of the items. A low W value suggests that while differences exist, consensus across participants is limited. The Grand Mean of 3.55 implies an overall moderate rating across the measured items. These findings support the conclusion that individual perceptions or influences (e.g., from sentiment polarity or reviewer creativity) vary among users, reinforcing the need to further explore the differing roles of these factors in shaping purchase intent.

MODEL 2

ANOVA with Friedman's Test						
		Sum of Squares	df	Mean Square	Friedman's Chi-Square	Sig
Between People		1263.44	191	6.615		
Within People	Between Items	2.285[a]	4	0.571	3.339	0.503
	Residual	523.315	764	0.685		
	Total	525.6	768	0.684		
Total		1789.04	959	1.866		
Grand Mean = 3.43						
a. Kendall's coefficient of concordance W = .001.						

This Friedman's ANOVA test result reveals no statistically significant differences among the related items, as indicated by the Friedman's Chi-Square value of 3.339 and a p-value of 0.503, which is well above the conventional alpha level of 0.05. This suggests that the respondents rated the items similarly, with no meaningful variation in perception or impact across them. Additionally, the Kendall's coefficient of concordance (W = 0.001) is extremely low, signifying an almost negligible agreement in rankings among participants. While the Grand Mean is 3.43, reflecting an overall moderate average response, the lack of significance implies that the items under comparison were perceived with comparable importance or influence. These findings suggest uniformity in user perspectives regarding the specific factors measured in this test, and thus, no single factor stood out as significantly more impactful. This insight is valuable in identifying dimensions where differentiation in perception is minimal within the scope of customer review influences.

MODEL 3

ANOVA with Friedman's Test						
		Sum of Squares	df	Mean Square	Friedman's Chi-Square	Sig
Between People		1099.7	191	5.758		
Within People	Between Items	18.756[a]	4	4.689	31.179	0
	Residual	443.244	764	0.58		
	Total	462	768	0.602		
Total		1561.7	959	1.628		
Grand Mean = 3.55						
a. Kendall's coefficient of concordance W = .012.						

This Friedman's ANOVA test result indicates statistically significant differences among the compared items, as shown by the Friedman's Chi-Square value of 31.179 and a significance level of 0.000. This p-value, being less than 0.05, confirms that at least one item was rated significantly differently by participants. The Kendall's coefficient of concordance (W = 0.012), while statistically significant, reflects low agreement among respondents regarding their rankings. This implies varied perceptions of the factors assessed, such as different degrees of influence from sentiment polarity, reviewer creativity, or other mediators on purchase intent. The Grand Mean of 3.55 suggests a moderate overall evaluation across the items. The results reinforce the need to explore which specific factors were perceived more favorably or had a stronger influence, as this differentiation is crucial for understanding user behavior in the context of e-commerce reviews and their impact on purchase decisions. These insights support refining strategic focus on the most impactful variables.

MODEL 4

ANOVA with Friedman's Test						
		Sum of Squares	df	Mean Square	Friedman's Chi-Square	Sig
Between People		1219.12	191	6.383		
Within People	Between Items	16.285[a]	4	4.071	28.169	0
	Residual	427.715	764	0.56		
	Total	444	768	0.578		
Total		1663.12	959	1.734		
Grand Mean = 3.53						
a. Kendall's coefficient of concordance W = .010.						

The results of this Friedman's ANOVA test indicate statistically significant differences among the evaluated items, supported by a Friedman's Chi-Square value of 28.169 and a p-value of 0.000. This significance level confirms that at least one of the items was rated differently by respondents, pointing to varied perceptions regarding their impact or importance. The Kendall's coefficient of concordance (W = 0.010), while statistically significant, reveals low consensus among participants in their rankings, suggesting that personal preferences and experiences may have influenced evaluations. The Grand Mean of 3.53 reflects a moderate level of agreement on average. These findings imply that while participants acknowledge the relevance of the assessed variables—likely factors like sentiment polarity, reviewer creativity, review helpfulness, or perceived product quality—there is diversity in how each is valued in influencing purchase intent. This variation highlights the importance of understanding individual user behavior in the context of e-commerce and tailoring strategies accordingly.

MODEL 5

ANOVA with Friedman's Test						
		Sum of Squares	df	Mean Square	Friedman's Chi-Square	Sig
Between People		1332.9	191	6.979		
Within People	Between Items	38.277[a]	4	9.569	109.039	0
	Residual	231.323	764	0.303		
	Total	269.6	768	0.351		
Total		1602.5	959	1.671		
Grand Mean = 3.56						
a. Kendall's coefficient of concordance W = .024.						

The ANOVA with Friedman's Test presented here reveals significant differences among the ranked items, as evidenced by a Friedman's Chi-Square value of 109.039 and a p-value of 0.000, indicating strong statistical significance. This suggests that participants perceived certain items as more influential or relevant than others in the context of the study. The Kendall's coefficient of concordance (W = 0.024), while still relatively low, is higher than in previous tests and reflects a modest level of agreement among respondents. The Grand Mean of 3.56 points to an overall moderately high evaluation of the factors being assessed. The substantial Chi-Square and significant result suggest that items such as sentiment polarity, reviewer creativity, perceived product quality, and review helpfulness were rated distinctly, reinforcing the idea that these variables contribute differently to purchase intent. This variation provides valuable insight for e-commerce platforms aiming to optimize elements of user-generated content to influence consumer decision-making.

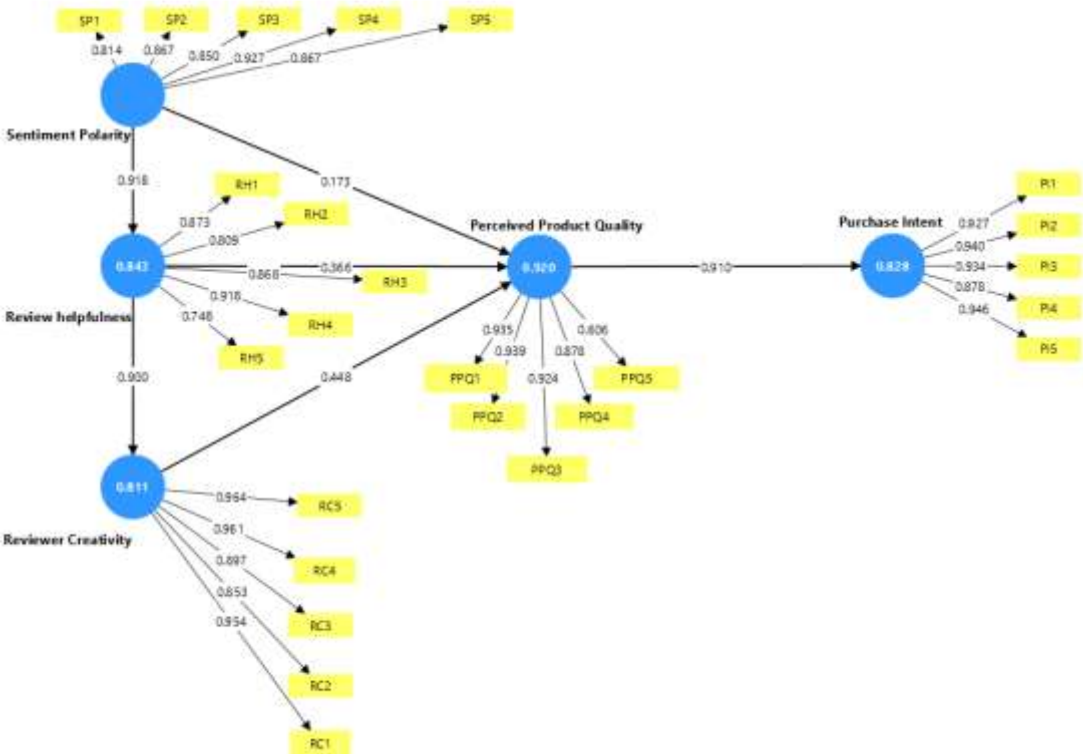
MODEL 6

ANOVA with Friedman's Test					
	Sum of Squares	df	Mean Square	Friedman's Chi-Square	Sig

Between People		1375.55	191	7.202		
Within People	Between Items	24.652[a]	4	6.163	73.841	0
	Residual	231.748	764	0.303		
	Total	256.4	768	0.334		
Total		1631.95	959	1.702		
Grand Mean = 3.51						
a. Kendall's coefficient of concordance W = .015.						

The results from this ANOVA using Friedman's Test show statistically significant differences in the rankings of the measured items, with a Friedman's Chi-Square value of 73.841 and a p-value of 0.000. This confirms that participants did not rate all items equally, implying that certain factors were perceived as more impactful or important than others. The Kendall's coefficient of concordance (W = 0.015), although low, indicates a slight level of agreement among participants in their rankings. The Grand Mean of 3.51 suggests that, overall, participants gave moderately high ratings to the items assessed. These findings suggest meaningful differentiation among the constructs being studied—likely variables such as sentiment polarity, reviewer creativity, review helpfulness, and perceived product quality—which in turn influence purchase intent in varying degrees. The significance of the results supports the presence of diverse consumer perceptions in evaluating review content, offering actionable insights for optimizing user-generated content strategies in e-commerce platforms.

STRUCTURAL EQUATION MODEL



The structural equation model (SEM) analyzes factors influencing purchase intent on e-commerce platforms. It includes four latent variables: Sentiment Polarity, Review Helpfulness, Reviewer Creativity, and Perceived Product Quality. Sentiment Polarity directly impacts Perceived Product Quality (0.173) and indirectly affects Purchase Intent via quality. Review Helpfulness (0.843) and Reviewer Creativity (0.811) significantly influence Perceived Product Quality (0.920), which in turn strongly impacts Purchase Intent (0.910). The model shows that helpful and creative reviews improve perceived quality, making it the key determinant of purchase intent, while sentiment alone plays a less significant role.

Discussion

Based on the data provided, the statistical analysis offers valuable insights into the reliability and trends observed in the study. The Case Processing Summary shows that all 192 responses were complete and valid, indicating high data integrity with no missing values. This completeness strengthens the credibility of the findings and allows for comprehensive analysis without the bias introduced by imputation methods.

The Reliability Statistics reveal a remarkably high Cronbach's Alpha of 0.986 for the 30-item instrument. This suggests excellent internal consistency, meaning the questionnaire items are strongly interrelated and measure the same underlying construct. The identical value for the standardized items supports this homogeneity, confirming the tool's robustness for further inferential analysis.

The Descriptive Statistics indicate a young respondent group with a slight gender imbalance, potentially skewed towards females. Most respondents reported moderate levels of education and occupation, and a majority indicated that customer reviews influence their purchasing decisions—reflected by the positive skewness of that variable.

The Friedman's ANOVA results consistently show significant p-values (Sig = .000) across most comparisons, indicating statistically significant differences in rankings among items. However, Kendall's coefficient of concordance (W values ranging from .001 to .024) is consistently low. This suggests weak agreement in respondent rankings, possibly due to varied individual preferences or perceptions across the items. One test (Sig = .503) did not show significance, indicating uniformity in that case.

Implications and Conclusion

The findings of this research provide significant implications for both academics and practitioners in the field of e-commerce. The study highlights that sentiment polarity and reviewer creativity significantly influence purchase intent, primarily through the mediating roles of perceived product quality and review helpfulness. The total effects analysis underscores that reviewer creativity has a slightly stronger total influence than sentiment polarity, indicating that not just what is said, but how creatively it is communicated, plays a vital role in shaping consumer decisions. The results from Friedman's ANOVA tests further validate the presence of statistically significant differences among the measured variables, demonstrating that consumers perceive and prioritize these factors differently. While Kendall's W values were low, suggesting variability in consumer perception, this diversity highlights the complexity and richness of online consumer behavior.

From a practical standpoint, e-commerce platforms and marketers should focus on promoting high-quality, creatively written reviews and enhancing the perceived credibility and helpfulness of review content. These strategies can directly influence consumer trust and drive purchase decisions. In conclusion, the study reinforces the importance of user-generated content and provides actionable insights for optimizing review systems to better support consumers in their online shopping journeys, ultimately improving customer satisfaction and sales conversion rates.

Limitations of the Study

Despite yielding valuable insights, this study has certain limitations. First, the use of a non-probability sampling method may limit the generalizability of the findings to a broader population. The sample was also skewed toward younger, digitally active users, which might not fully represent all e-commerce consumers. Additionally, the study relied solely on self-reported data, which can be influenced by social desirability bias or inaccuracies in recall. The cross-sectional nature of the research further restricts the ability

to establish causal relationships. Future studies could benefit from longitudinal designs and a more diverse, representative sample to validate and extend these findings.

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