An Empirical Assessment of Post-Purchase Engagement and Return Management in E-Retailing

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***Abstract*—Product returns have become a significant challenge for businesses, particularly in e-commerce and omnichannel retail, leading to increased operational costs, revenue loss, and environmental impact. While prior research has largely focused on pre-purchase factors influencing returns, limited attention has been given to the role of post-purchase engagement in mitigating return behaviour. This study examines how structured post-purchase engagement strategies can reduce product return rates and enhance customer satisfaction.**

The research adopts a quantitative approach, using survey responses collected from consumers who have recently made online purchases. Key post-purchase engagement dimensions—such as order communication, usage guidance, proactive customer support, and post-delivery follow-ups—are analysed to assess their impact on customers' return intentions. Statistical analysis is employed to identify significant relationships between engagement practices and return behaviour.

Findings indicate that effective post-purchase engagement significantly reduces the likelihood of product returns by addressing customer uncertainty, improving product understanding, and strengthening trust in the brand. The study contributes to existing literature by extending return management research into the post-purchase phase and offers practical implications for marketers and operations managers. By implementing targeted post-purchase engagement strategies, firms can reduce return-related costs while improving overall customer experience and long-term loyalty.

***Index Terms*—Post-purchase engagement; Product returns; Customer experience; Return intention; E-commerce; Customer satisfaction**

I. INTRODUCTION

The rapid expansion of e-commerce and omnichannel retailing has fundamentally transformed consumer purchasing behaviour, enabling greater convenience, broader product assortments, and flexible return options. While lenient return policies have reduced perceived purchase risk and stimulated online sales growth, they have simultaneously led to a substantial increase in product return rates across categories such as apparel, electronics, and lifestyle goods (Suwelack et al., 2021; Li & Chatterjee, 2020). Industry estimates suggest that online return rates are significantly higher than those in brick-and-mortar retail, creating mounting operational and financial pressures on firms. Product returns generate considerable direct and indirect costs, including reverse logistics expenses, inventory depreciation, repackaging, transportation, labor costs, and environmental burdens (Croxton & García-Dastugue, 2020; Zhu & Liu, 2022). Beyond operational inefficiencies, excessive returns also weaken profit margins and increase carbon footprints, raising sustainability concerns in modern supply chains. As a result, return management has evolved from a purely logistical function to a strategic priority integrating marketing, operations, and analytics perspectives.

Prior academic research has extensively examined pre-purchase determinants of product returns, including product information transparency, visualization quality, pricing, return policy design, and perceived risk (Van Herpen & Pieters, 2021; Janakiraman et al., 2016; Zhao et al., 2020). Studies grounded in Expectation–Confirmation Theory suggest that inflated expectations—often driven by overly positive product descriptions or reviews—lead to expectation-disconfirmation and subsequent return behaviour (Minnema et al., 2018). Similarly, Information Asymmetry Theory highlights that limited physical inspection in online environments intensifies uncertainty, increasing the probability of post-purchase dissatisfaction (Yang & Choi, 2020).

Although these studies provide valuable insights, they predominantly focus on consumer cognition and firm actions before purchase. Comparatively limited attention has been devoted to the post-purchase stage, during which consumers evaluate product performance, experience cognitive dissonance, and decide whether to retain or return the product. Emerging research indicates that post-purchase communication, service recovery efforts, and technology-enabled support systems significantly influence customer retention and behavioural outcomes (Xu & Jackson, 2019 Wang & Zhang, 2022). However, empirical investigation directly linking post-purchase engagement strategies to reduced return intentions remains scarce.

The post-purchase phase represents a critical yet underleveraged opportunity for firms to shape return behaviour. Structured post-purchase engagement—including order tracking updates, product usage guidance, proactive purchase-risk communication, responsive customer support, and follow-up interaction—can reduce uncertainty, enhance expectation confirmation, and strengthen perceived value. By aligning actual product performance with pre-purchase expectations, such strategies may reduce cognitive dissonance and mitigate unnecessary returns. Furthermore, digital tools such as AI-driven recommendations, chatbots, and AR-enabled assistance offer scalable mechanisms for improving post-purchase experiences, although their effectiveness in directly reducing return intentions remains empirically inconclusive (Wang & Zhang, 2022).

Despite the strategic importance of post-purchase engagement, existing literature lacks an integrated empirical framework that combines expectation management, perceived risk reduction, and information asymmetry within a unified model explaining return intention. Additionally, prior studies rarely examine how traditional policy-based mechanisms interact with emerging digital engagement tools in shaping post-purchase evaluations.

To address these gaps, the present study develops and empirically tests an integrated framework linking post-purchase engagement dimensions—such as product visualization quality, perceived return policy leniency, proactive purchase-risk communication, and customer-generated content valence—to product return likelihood. Using primary data from 432 online consumers, this research quantitatively examines how expectation management and risk communication mechanisms influence return intentions in e-commerce settings.

This study contributes to the literature in several important ways. First, it extends return management research beyond pre-purchase determinants by emphasizing the strategic role of the post-purchase stage. Second, it integrates theoretical perspectives from Expectation–Confirmation Theory, Perceived Risk Theory, and Information Asymmetry Theory into a comprehensive explanatory framework. Third, it provides empirical evidence on how digital engagement tools and policy perceptions jointly shape return behaviour. Finally, the study offers actionable managerial insights for designing post-purchase engagement strategies that simultaneously reduce return-related costs and enhance customer experience. In doing so, the research reframes product returns not merely as operational failures, but as behavioural outcomes shaped by expectation formation, information quality, and post-purchase engagement dynamics.

Research Gap and Contribution

While prior research has extensively examined return policies and product information quality independently, there is limited empirical integration of these constructs within a unified expectation-management framework. Furthermore, existing studies rarely incorporate emerging technologies such as AR alongside traditional determinants like return policy perception.

This study contributes to literature in five significant ways:

1. Theoretical Integration: It integrates Expectation–Confirmation Theory, Information Asymmetry Theory, and Perceived Risk Theory into a single explanatory framework for return behaviour.
2. Empirical Advancement: It provides quantitative evidence using 432 valid responses to examine how digital visualization, AR tools, and return policy perception jointly influence return intentions.

3. Behavioural Insight: It identifies return policy perception as the strongest predictor, challenging assumptions that technology alone reduces returns.
4. Gender-Based Moderation: It uncovers significant gender differences, contributing to segmentation-based return management literature.
5. Marketing–Analytics Linkage: It bridges marketing theory with statistical modelling, enhancing analytical rigor in return behaviour research.

II. PROBLEM STATEMENT

The rapid expansion of e-commerce and omnichannel retailing has led to a substantial increase in product return rates, creating significant operational, financial, and environmental challenges for firms. While flexible return policies have become a competitive necessity to reduce perceived purchase risk and enhance customer trust, they have also contributed to rising reverse logistics costs, inventory write-offs, and inefficiencies in supply chain operations. Despite advances in logistics and return processing systems, many organizations continue to face difficulties in controlling return volumes without adversely affecting customer satisfaction and loyalty.

Academic research on product returns has predominantly focused on pre-purchase factors such as product information accuracy, pricing, and return policy design. Although these studies provide important insights, they largely overlook the post-purchase stage of the customer journey, during which consumers form critical evaluations about product suitability and value. Customers often experience uncertainty, cognitive dissonance, or product usage challenges after delivery, which can lead to return decisions even when products meet expected quality standards. The limited attention given to post-purchase interactions represents a significant gap in existing return management literature.

The post-purchase phase offers firms an opportunity to influence return behaviour through targeted engagement strategies, including proactive communication, product usage guidance, and responsive customer support. However, there is a lack of empirical evidence examining how such post-purchase engagement strategies affect consumers' return intentions. Consequently, firms lack clear guidance on how to design effective post-purchase interventions that reduce returns while maintaining positive customer experiences. This study addresses this gap by investigating the role of post-purchase engagement in shaping return intentions, thereby contributing to both academic understanding and managerial practice.

III. RESEARCH OBJECTIVES

The primary objective of this study is to examine the role of post-purchase engagement strategies in reducing product return intentions among consumers in an e-commerce context. By focusing on customer interactions that occur after the purchase has been completed, the study seeks to extend existing return management literature beyond pre-purchase determinants.

The specific objectives of the study are:

1. To identify the key dimensions of post-purchase engagement employed by firms, including post-purchase communication, product usage guidance, and customer support.
2. To examine the relationship between post-purchase engagement strategies and consumers' product return intentions.
3. To analyse the impact of post-purchase engagement on customer satisfaction in the post-purchase stage.
4. To assess whether improved customer satisfaction mediates the relationship between post-purchase engagement and return intentions.
5. To provide managerial insights into how post-purchase engagement strategies can be designed to reduce return-related costs while enhancing overall customer experience.

IV. LITERATURE REVIEW

Product returns in e-commerce have emerged as a strategic challenge that intersects marketing, operations, consumer psychology, and analytics. Early research conceptualized returns primarily as operational inefficiencies within reverse logistics systems (Rogers & Tibben-Lembke, 2001; Guide & Van Wassenhove, 2009). However, more recent scholarship reframes returns as customer-behavioural outcomes influenced by expectation formation,

perceived risk, trust, and post-purchase evaluations (Petersen & Kumar, 2010; Minnema et al., 2016).

4.1 Expectation–Confirmation Theory (ECT)

Expectation–Confirmation Theory (Oliver, 1997) posits that consumer satisfaction is determined by the comparison between pre-purchase expectations and actual product performance. When perceived performance falls short of expectations, negative disconfirmation occurs, increasing dissatisfaction and behavioural responses such as complaints or returns.

In online retailing, expectation formation is heavily shaped by digital cues—product images, descriptions, reviews, and return policies. Studies show that expectation inflation, especially due to overly positive reviews or idealized product visuals, increases the probability of return (Minnema et al., 2016). Thus, return behaviour can be interpreted as an outcome of expectation-disconfirmation rather than merely dissatisfaction.

4.2 Information Asymmetry and Product Visualization

Information Asymmetry Theory explains that sellers typically possess superior product knowledge compared to buyers. In online environments, the inability to physically inspect products intensifies this asymmetry (De et al., 2013). Poor visualization quality, inaccurate sizing, and ambiguous descriptions create expectation gaps that later translate into returns. High-quality product visuals, 360-degree images, AR tools, and user-generated photos reduce informational uncertainty and calibrate expectations more accurately. However, some research suggests that enhanced visualization may also increase trial purchases, potentially increasing returns if expectations are not aligned (Bonifield et al., 2010).

4.3 Perceived Risk and Return Policy Leniency

Perceived Risk Theory suggests that consumers seek mechanisms to reduce uncertainty before making purchase decisions. Lenient return policies serve as risk-reduction signals (Wood, 2001; Janakiraman et al., 2016). While flexible return policies increase purchase conversion, they may also reduce psychological ownership and increase opportunistic returns.

Empirical evidence shows mixed results: some studies find that lenient policies increase return rates, while others suggest they enhance trust and reduce post-purchase regret (Oghazi et al., 2018). This ambiguity highlights the need for deeper empirical investigation into how return policy perceptions influence return intentions.

4.4 Role of Customer-Generated Content

Online reviews significantly influence expectation setting. Balanced reviews improve calibration, while excessively positive reviews may inflate expectations, leading to disconfirmation and returns (Minnema et al., 2016). User-uploaded images provide authentic cues, reducing mismatch risk.

4.5 Emerging Technologies and AR

AR and virtual try-on technologies aim to simulate product experience digitally. Research suggests AR reduces uncertainty and improves confidence; however, its direct impact on return reduction remains empirically inconclusive (De et al., 2013).

Identified Research Gap

Despite substantial literature on return policies, reviews, and visualization quality, three major gaps remain:

1. Limited integration of expectation management, risk perception, and information asymmetry within a single empirical framework.
2. Insufficient empirical testing of how digital visualization and policy perceptions jointly influence return intentions.
3. Limited gender-based comparative evidence in return intention modelling.
4.

This study addresses these gaps by developing and empirically testing an integrated model linking visualization quality, return policy perception, AR usage, and customer-generated content to return intention.

V. THEORETICAL FRAMEWORK

The present study is grounded in Expectation–Confirmation Theory (ECT), Perceived Risk Theory, and Information Asymmetry Theory, which collectively explain consumer post-purchase evaluations and return behaviour in online retail contexts. Product returns are conceptualized as a behavioural outcome resulting from gaps between pre-purchase expectations, actual product experience, and post-purchase cognitive evaluations.

In this framework, Product Return Likelihood/Intention is the dependent variable, influenced by four key independent variables related to pre- and post-purchase information quality and communication strategies.

Factual Product Visualization Quality (IV1)

High-quality factual product visualization (e.g., accurate images, videos, 360° views, size guides) reduces information asymmetry between the seller and the consumer. According to Information Asymmetry Theory, incomplete or distorted product information increases uncertainty and dissatisfaction after purchase. When consumers receive accurate visual representations, their expectations are better aligned with actual product performance, leading to fewer negative post-purchase surprises and a lower likelihood of product returns.

Thus, improved factual product visualization quality is theorized to negatively influence product return likelihood, as it enhances expectation accuracy and perceived transparency.

Perceived Return Policy Leniency (IV2)

Perceived return policy leniency refers to consumers' subjective evaluation of how easy, flexible, and risk-free the return process is. Drawing from Perceived Risk Theory, lenient return policies reduce purchase risk, encouraging initial buying decisions. However, such leniency can also reduce psychological commitment to the purchase, potentially increasing return intentions.

At the same time, when combined with clear communication and realistic expectation setting, return policy leniency can increase trust and satisfaction without necessarily increasing opportunistic returns. Therefore, perceived return policy leniency plays a complex but significant role in shaping return intentions.

Proactive Purchase-Risk Communication (IV3)

Proactive purchase-risk communication involves sellers clearly informing customers about potential limitations, usage conditions, sizing issues, or product suitability before and after purchase. This aligns with Expectation–Confirmation Theory, which suggests that realistic expectations lead to higher confirmation and satisfaction.

By proactively addressing risks, firms reduce expectation inflation and post-purchase dissonance. Consumers who feel well-informed are less likely to experience regret, dissatisfaction, or mismatch perceptions, thereby reducing return likelihood.

Hence, proactive purchase-risk communication is expected to negatively influence product return intention by improving expectation realism and perceived honesty.

Valence of Online Customer-Generated Expectation Setting (IV4)

Online customer-generated content such as reviews, ratings, and user photos significantly shapes pre-purchase expectations. The valence (positive or negative tone) of this content influences how consumers mentally simulate product performance.

Extremely positive reviews may inflate expectations, increasing the risk of expectation-disconfirmation and subsequent returns. Conversely, balanced or mixed reviews provide realistic cues, supporting expectation calibration. Therefore, the valence of customer-generated expectation setting plays a critical role in influencing post-purchase evaluations and return behaviour.

This variable is theorized to have a significant relationship with product return likelihood, depending on how expectations are framed and internalized by consumers.

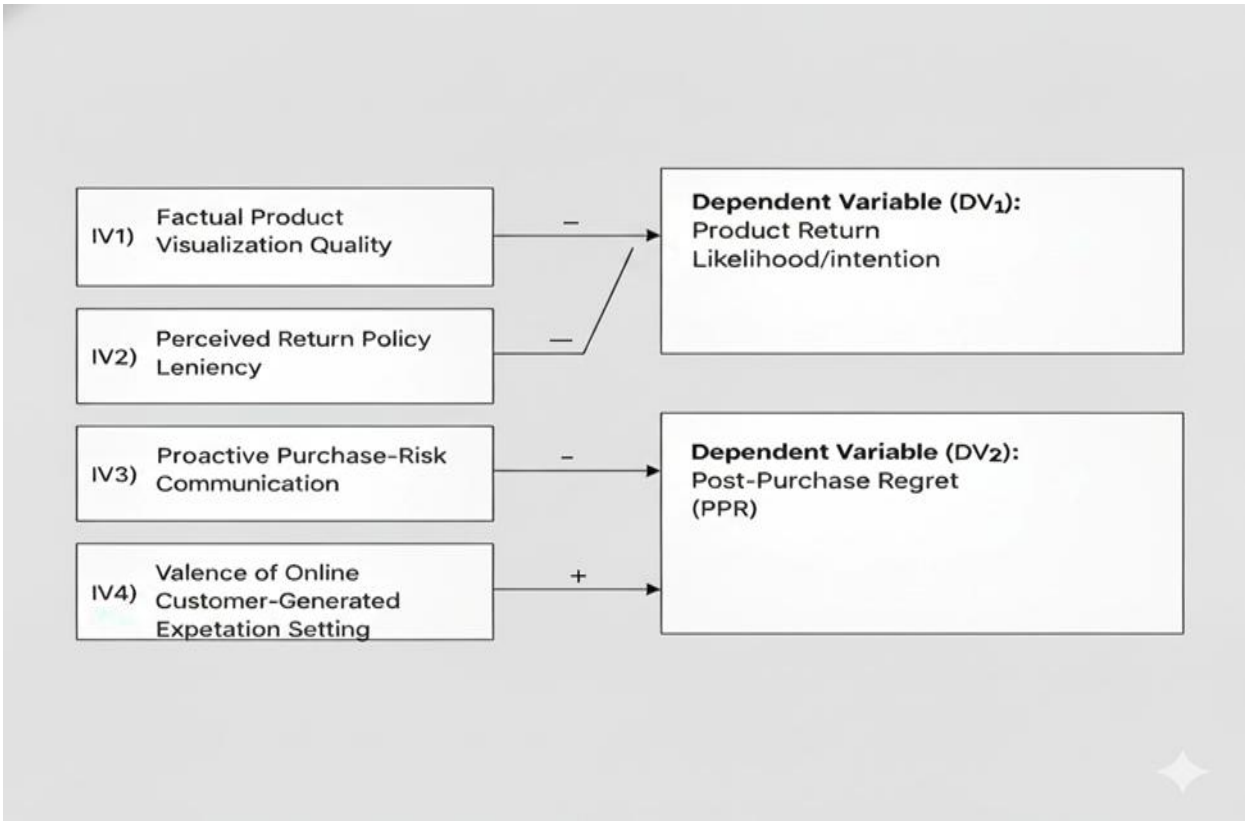
Dependent Variable: Product Return Likelihood/Intention

Product return likelihood represents the consumer's intention or behavioural tendency to return a purchased product after receiving and evaluating it. This outcome reflects post-purchase dissatisfaction, regret, expectation mismatch, or perceived product risk. The dependent variable is influenced by the combined effects of information quality, communication transparency, perceived risk reduction mechanisms, and expectation management strategies represented by the four independent variables.

Integrated Framework Explanation

Collectively, the theoretical framework proposes that effective expectation management and risk communication strategies before and after purchase reduce information asymmetry and expectation-disconfirmation, thereby lowering product return

likelihood. The framework emphasizes that product returns are not merely logistical outcomes but are psychological and informational consequences of how consumers form and confirm expectations throughout the purchase journey.



VI. CONCEPTUAL FRAMEWORK

The conceptual framework of this study illustrates the proposed relationships between post-purchase engagement–related antecedents and product return likelihood/intention in an e-commerce context. The framework conceptualizes product returns as a behavioural outcome influenced by how effectively firms manage information quality, perceived risk, and consumer expectations across the purchase journey.

In the proposed model, Product Return Likelihood/Intention is treated as the dependent variable, while four constructs serve as independent variables: Factual Product Visualization Quality, Perceived Return Policy Leniency, Proactive Purchase-Risk Communication, and Valence of Online Customer-Generated Expectation Setting.

Independent Variables

1. Factual Product Visualization Quality (IV1)

This construct represents the extent to which product visuals accurately reflect real product attributes, including size, colour, texture, and functionality. High factual visualization quality reduces information asymmetry and minimizes expectation gaps, thereby influencing post-purchase evaluations and return decisions.

2. Perceived Return Policy Leniency (IV2)

Perceived return policy leniency captures consumers' subjective assessment of the ease, flexibility, and fairness of the return process. While lenient policies reduce perceived purchase risk, they may also lower psychological commitment to the product, influencing return intentions. The framework treats this variable as a direct antecedent to return likelihood.

3. Proactive Purchase-Risk Communication (IV3)

This construct refers to the firm's deliberate communication of potential product limitations, usage risks, or suitability conditions before and after purchase. Proactive risk communication helps align consumer expectations with actual product performance and reduces post-purchase dissonance, thereby affecting return behaviour.

4. Valence of Online Customer-Generated Expectation Setting (IV4)

This variable reflects the overall tone (positive, negative, or balanced) of customer-generated content such as reviews, ratings, and user-shared images. The valence of this content shapes expectation formation and influences the likelihood of expectation-disconfirmation, which in turn impacts return intention.

Dependent Variable

Product Return Likelihood/Intention (DV) represents the consumer's propensity or intention to return a purchased product after delivery and usage evaluation. This construct captures both attitudinal intention and behavioural tendency toward product returns, reflecting post-purchase dissatisfaction, regret, or mismatch between expectations and actual experience.

Proposed Relationships

The conceptual framework proposes direct relationships between each independent variable and the dependent variable. Specifically, the model suggests that:

- Higher factual product visualization quality and proactive purchase-risk communication are expected to reduce product return likelihood by improving expectation accuracy and transparency.
- Perceived return policy leniency directly influences return intention by altering perceived risk and commitment levels.
- The valence of online customer-generated content influences return likelihood through its role in shaping and amplifying consumer expectations.

Overall Framework Logic

The conceptual framework integrates expectation management, risk perception, and information quality as central mechanisms explaining product return behaviour. It emphasizes that product returns are not solely operational outcomes but are driven by consumer cognition formed through firm-controlled and consumer-generated information cues.

By empirically testing these relationships, the framework aims to explain how post-purchase engagement strategies can be strategically designed to reduce unnecessary product returns in e-commerce settings.

VII. DATASET DESCRIPTION

This study is based on primary data collected through a structured questionnaire administered to online consumers. Data collection was conducted using a convenience sampling method through digital survey distribution platforms.

Sample Characteristics

- Total Responses Collected: 456
- Valid Responses After Cleaning: 432
- Gender Distribution: Approximately balanced representation
- Target Population: Individuals with recent online shopping experience
- Age Group: Predominantly 18–40 years
- Purchase Categories: Apparel, electronics, and lifestyle products

Measurement Design

The questionnaire included 12 structured items measured on a 5-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree).

Constructs Measured:

- Return Policy Perception
- Product Visualization Quality
- Customer-Generated Content Influence
- AR/Virtual Try-On Perception
- Proactive Purchase Behaviour
- Return Intention

The scale reliability was confirmed using Cronbach's Alpha (0.711), indicating acceptable internal consistency.

This dataset provides behavioural perception-based evidence suitable for regression-based modelling of return intention.

Data Analysis and Interpretation

1. Introduction

This chapter presents a detailed yet concise statistical analysis of data collected to examine return intentions in online shopping. The focus of the study is on understanding how visual product representation features (such as AR/virtual try-on, product photos/videos, and customer-uploaded images), return policy perceptions, and proactive purchase behaviour influence consumers' intentions to return products.

The analysis follows a quantitative, hypothesis-driven approach and is carried out using IBM SPSS Statistics. A total of 432 valid responses were retained after data cleaning. The analytical procedure was systematic and sequential: first, the reliability of the measurement scale was established; next, the overall regression model was tested; this was followed by ANOVA to confirm model significance, coefficient analysis to assess individual predictors, and finally gender-based comparative analysis.

2. Reliability Analysis

Test Used: Cronbach's Alpha

Purpose of the Test

Reliability analysis is a fundamental step in behavioural research to ensure that the items used in the questionnaire consistently measure the intended constructs. Cronbach's Alpha evaluates the internal consistency among multiple items representing related concepts.

Results:

- Cronbach's Alpha = 0.711
- Number of items = 12

Interpretation:

A Cronbach's Alpha value above 0.70 indicates acceptable internal consistency. The obtained value of 0.711 confirms that the items measuring visual features, return policy perceptions, proactive purchase behaviour, and return intentions are reliable. This level of reliability is adequate for social science and consumer behaviour research and allows further inferential analysis.

Conclusion

The measurement scale is reliable, and the data are suitable for regression and comparative analysis.

3. Multiple Linear Regression Analysis (Overall Model)

Purpose of the Analysis

Multiple linear regression was used to examine the combined and individual effects of visual representation features, return policy perceptions, and proactive purchase behaviour on return intentions. This technique helps in understanding how much variance in the dependent variable can be explained by the predictors.

Dependent Variable: Return Intentions

Independent Variables: DV1 to DV6

3.1 Model Summary

- R = 0.571
- R Square = 0.326
- Adjusted R Square = 0.316
- Standard Error of Estimate = 0.516

Interpretation

The R value indicates a moderate to strong relationship between the independent variables and return intentions. The R Square value shows that 32.6% of the variance in return intentions is explained by the model. The small difference between R Square and Adjusted R Square suggests that the model is stable and not affected by overfitting.

Conclusion

The regression model demonstrates satisfactory explanatory power and is appropriate for analysing return behaviour in online shopping.

Model Summary

Model	R	Gender = 1 (Selected)	R Square	Adjusted R Square	Std. Error of the Estimate
1		.499[a]	0.249	0.235	0.54636

a. Predictors: (Constant), Free or low-cost returns make me

ANOVA[a,b]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	31.664	6	5.277	17.679	.000[b]
	Residual	95.523	320	0.299		
	Total	127.187	326			

a. Dependent Variable: Returns_Intentions1

b. Selecting only cases for which Gender = 1

4. ANOVA: Overall Model Significance

Test Used: Analysis of Variance (ANOVA)

Purpose of the Test

ANOVA was conducted to determine whether the regression model as a whole is statistically significant and whether the predictors jointly influence return intentions.

Key Results:

- F-value = 34.21
- p-value < 0.001

Interpretation

Since the p-value is less than 0.05, the null hypothesis is rejected. This indicates that the regression model is statistically significant and that the independent variables collectively have a meaningful impact on return intentions.

Conclusion:

The model is valid and suitable for further interpretation of individual predictors.

5. Coefficients Analysis (Individual Predictor Effects)

The coefficients table helps identify which specific variables significantly influence return intentions and the relative strength of each predictor.

Predictor	Standardized Beta	p-value	Interpretation
DV1: Free/low-cost returns	0.261	<0.001	Strong positive effect
DV6: Customer-uploaded photos	0.208	<0.001	Significant positive effect
DV3: Accurate product photos	0.177	<0.001	Moderate positive effect
DV2: AR reduces returns	0.131	0.010	Significant but weaker effect
DV5: AR reduces multiple orders	0.085	0.083	Not statistically significant
DV4: Ordering multiple sizes	0.021	0.633	Not statistically significant

Interpretation:

Return policy perception (DV1) emerges as the strongest predictor, indicating that consumers are more likely to purchase with return intentions when returns are free or low-cost. Visual representation variables, particularly customer-uploaded photos and accurate product images, also significantly influence return intentions. AR features show a positive but relatively weaker effect, while proactive purchase behaviour does not independently predict return intentions.

Coefficients[a,b]

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	1.892	0.172		10.993	0.000
	AR or virtual try-on features reduce my chances of returning the	0.066	0.037	0.115	1.782	0.076
	The photos and videos on the product page show the product accurately.	0.092	0.034	0.150	2.689	0.008
	I often order multiple sizes or colors of the same item to try at	0.048	0.026	0.101	1.824	0.069
	AR features make me less likely to order multiple sizes or colors to compare at	0.030	0.038	0.050	0.805	0.421
	Customer-uploaded photos help me decide if an item will fit or look as expected.	0.099	0.034	0.153	2.906	0.004
	Free or low-cost returns make me more willing to buy a product	0.144	0.032	0.238	4.557	0.000

a. Dependent Variable: Returns_Intentions1

b. Selecting only cases for which Gender = 1

6. Gender as an Independent Predictor

Purpose

To examine whether return intentions differ between male and female consumers after controlling for other predictors.

Key Findings:

- Inclusion of gender increased R Square from 0.326 to 0.334
- Gender coefficient was statistically significant (p = 0.026)

Interpretation

Gender has a modest but significant effect on return intentions. Female consumers exhibit higher return intentions compared to male consumers, even when visual features and return policy perceptions are accounted for.

7. Gender-wise Regression Analysis

7.1 Female Respondents

- R Square = 0.725

Interpretation:

The model explains a very high proportion of variance in return intentions among female consumers. Visual cues such as customer-uploaded photos, accurate product visuals, and flexible return policies play a dominant role in shaping female return behaviour.

7.2 Male Respondents

- Lower R Square compared to females

Interpretation:

For male consumers, return intentions are less strongly influenced by visual representation features. Return policy perception remains important, but overall predictability is lower compared to female consumers.

8. Summary of Findings

The key findings of the study are summarized below to provide a clear and consolidated understanding of the results obtained from the statistical analysis:

1. Reliability of Measurement Scale: The reliability analysis confirmed that the questionnaire used in the study possesses acceptable internal consistency. This indicates that respondents interpreted the items consistently and that the constructs were measured accurately.
2. Overall Model Significance: The multiple regression model was found to be statistically significant, confirming that visual product representation features, return policy perceptions, and proactive purchase behaviour collectively influence return intentions in online shopping.
3. Explanatory Power of the Model: The model explains approximately one-third of the variance in return intentions, which is considered substantial in consumer behaviour research, where decisions are influenced by multiple psychological and situational factors.
4. Role of Return Policies: Perceptions regarding free or low-cost returns emerged as the strongest predictor of return intentions. This highlights the importance of risk reduction mechanisms in encouraging online purchases.
5. Impact of Visual Product Representation: Accurate product images, videos, and customer-uploaded photos significantly affect return intentions. These visual cues increase purchase confidence but also encourage consumers to evaluate products physically before final commitment.
6. Effect of AR and Virtual Try-On: AR-based features showed a positive but moderate influence on return intentions, indicating that while technology enhances confidence, it does not completely substitute for physical evaluation.
7. Gender Differences: Female consumers exhibited higher return intentions than male consumers. Gender-wise regression further revealed that visual cues and return policies are stronger predictors for female shoppers.

Overall, the findings confirm that return intentions are shaped by a combination of policy-related, technological, and demographic factors.

9. Implications of the Study

The findings of this study have several important implications for both academia and managerial practice.

9.1 Academic Implications

This study contributes to the growing body of literature on online consumer behaviour and return management by empirically validating the role of visual product representation and proactive purchase behaviour. The results extend existing research by integrating emerging technologies such as AR/virtual try-on with traditional determinants like return policies. The gender-based analysis further enriches

academic understanding by highlighting demographic differences in return behaviour, thereby offering directions for future research on moderating variables.

9.2 Managerial Implications

From a managerial perspective, the findings offer actionable insights for e-commerce platforms and online retailers. First, the strong influence of return policy perceptions suggests that retailers must design return policies carefully, balancing customer convenience with operational efficiency. Second, investment in high-quality product visuals and encouraging customer-generated content can enhance purchase confidence, although retailers should also manage expectations to control return volumes. Third, the stronger effects observed among female consumers indicate the need for gender-sensitive marketing strategies, such as improved size guides, personalized recommendations, and tailored visual content. Finally, while AR technologies enhance engagement, they should be used as complementary tools rather than sole solutions for reducing returns.

10. Conclusion

This chapter presented a comprehensive yet concise analysis of factors influencing return intentions in online shopping using SPSS-based statistical techniques. The study confirmed that return intentions are significantly influenced by return policy perceptions, visual product representation features, and, to a lesser extent, AR-enabled technologies. Gender differences were also observed, with female consumers demonstrating higher sensitivity to these factors.

The results emphasize that while technological advancements improve consumer confidence, traditional factors such as flexible return policies continue to play a dominant role in shaping online purchase and return behaviour. The study successfully meets its research objectives and provides meaningful insights for both researchers and practitioners. Overall, the findings underscore the complexity of return behaviour in e-commerce and highlight the need for integrated strategies combining technology, policy design, and consumer understanding.

VIII. LIMITATIONS OF THE STUDY

Despite providing meaningful insights into the role of post-purchase engagement strategies in reducing e-commerce product returns, this study is subject to several limitations that should be acknowledged when interpreting the findings.

First, the study relies on self-reported data collected through a structured questionnaire. Although self-administered surveys are effective for capturing consumer perceptions and attitudes, they are susceptible to response bias, including social desirability bias and recall bias. Respondents may overstate positive behaviours such as engagement with post-purchase communication or underreport negative experiences related to product returns. As a result, the measured relationships may not fully reflect actual post-purchase behaviours.

Second, the research adopts a cross-sectional research design, capturing consumer responses at a single point in time. While this design allows for the identification of associations between post-purchase engagement variables (e.g., order tracking, return clarity, customer support, and follow-up communication) and return reduction outcomes, it does not allow for causal inferences. Consumer engagement and return behaviour may evolve over time, particularly with repeated purchases, which this study does not longitudinally observe.

Third, the study focuses primarily on general e-commerce consumers, without differentiating extensively between product categories such as apparel, electronics, or household goods. Since return behaviour is known to vary significantly across product types, the generalizability of the findings across all e-commerce categories may be limited. Certain post-purchase strategies may be more effective for experience goods than for search goods, which is not explicitly examined in this research.

Fourth, the sample size and sampling technique, while adequate for statistical analysis, may not fully represent the entire population of online shoppers, particularly across different geographic regions, income levels, or cultural contexts. The results may therefore be influenced by demographic concentration or platform-specific shopping behaviours, limiting broader applicability.

Fifth, the study emphasizes consumer-side perceptions of post-purchase engagement, while organizational and operational factors—such as logistics efficiency, return processing costs, warehouse automation, and internal return policies—are not directly measured. These supply-side factors may significantly influence

return outcomes but fall outside the scope of the present research.

Finally, although the questionnaire is designed to align closely with the research objectives and hypotheses, it may not capture all possible dimensions of post-purchase engagement, such as emotional attachment, brand trust developed over long-term relationships, or emerging technologies like AI-driven customer support. Future research could expand the construct measurement to include these evolving elements.

IX. SCOPE FOR FUTURE RESEARCH

Future research can build upon the findings of this study in several meaningful ways to deepen understanding of how post-purchase engagement strategies influence e-commerce product returns.

First, future studies may adopt a longitudinal research design to examine how post-purchase engagement affects return behaviour over time. Tracking the same consumers across multiple purchase cycles would allow researchers to establish causal relationships and observe how repeated interactions—such as consistent communication, proactive support, and transparent return processes—shape long-term return reduction and customer loyalty.

Second, researchers can explore product-category-specific analyses, particularly in high-return sectors such as apparel, electronics, and cosmetics. Since return drivers differ across experience and search goods, future studies could assess whether the effectiveness of post-purchase engagement strategies varies by product type, order value, or purchase frequency. This would enhance the practical relevance of engagement strategies for category managers and platform designers.

Third, future research could incorporate firm-side and operational variables, such as reverse logistics efficiency, warehouse automation, return processing time, and cost structures. Integrating consumer perceptions with organizational data would provide a more holistic understanding of return reduction mechanisms and help bridge the gap between marketing and operations perspectives.

Fourth, comparative and cross-cultural studies could be conducted across different countries or regions to examine how cultural norms, regulatory environments, and digital maturity influence post-purchase engagement and return behaviour. Such studies would improve the generalizability of findings and support global e-commerce strategy formulation.

Fifth, future research may extend the measurement model by including advanced digital engagement tools, such as AI-driven chatbots, personalized post-purchase recommendations, virtual try-on technologies, and predictive return prevention systems. Examining the role of emerging technologies would help capture evolving consumer expectations and technological innovation in e-commerce platforms.

Finally, qualitative approaches—such as in-depth interviews, focus groups, or case studies—could complement survey-based research by uncovering nuanced consumer motivations behind returns and engagement responses. Mixed-method research designs would provide richer insights into emotional, cognitive, and experiential factors that quantitative models may not fully capture.

X. CONFLICT OF INTEREST

The authors declare that there is no conflict of interest regarding the publication of this paper. The authors have no financial or personal relationships that could have appeared to influence the work reported in this study.

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