Journal of Management World **2025**, 2: 280-285
DOI: 10.53935/jomw.v2024i4.914

Computer Usage and Product Returns - A Study of Consumers in India

Bhavya N[1*], N S Viswanath[2], Navya Gubbi Sateeshchandra[3], Samrat Ray, Dean[4]

[1,2]Manipal Academy of Higher Education, Bangalore, India; naidu.bhavya@gmail.com (B.N.) viswanathns19@gmail.com (N.S.V.)

[3]Academic Faculty, Berlin School of Business and Innovation, Berlin, Germany; navya.gubbi@berlinsbi.com (N.G.S.).
[4]International Institute of Management Studies, Pune; s.ray@iimspune.edu.in (S.R.D.)

Abstract. Research on the management of product returns has gained significant attention in recent years, as it has become an integral part of a company's overall supply chain strategy. Several past studies have suggested that the diverse purposes for which consumers utilize computers, ranging from online shopping and product research to general communication, can have a profound impact on the frequency and characteristics of product returns. Higher the usage of computers higher is the returns. The study explores the relationship between computer usage purposes and product returns in Bengaluru city, India. The study is an empirical analysis with primary data collection. 223 customers of computer users are considered for the study. The study is intended to help organizations to understand how computer usage purpose has significant relationship on computer product returns. To formulate models and strategies to minimize returns and cost. Computer manufacturers, retailers and e-waste companies can plan their return process efficiently. This research seeks to comprehensively explore the purposes for which consumers employ computers and the nuanced response variables associated with their interactions. The study aims to understand how logistics managers need to design and develop models from both cost and competition points of view. The return policy is going to become in coming days a potent instrument in making purchases. The more the consumer is educated, the more he would like to learn about the return policy and its action. The study finds the return behaviour of consumers and suggest how to predict returns and improve process efficiency for better operations.

Keywords: Computer product returns, Computer usage purpose and Consumer return Behavior, Reverse logistics.

1. INTRODUCTION

Reverse logistics, particularly in India's growing e-commerce sector, has gained prominence as businesses aim to optimize product return processes. Computers, as multifunctional tools, are pivotal in shaping consumer behaviors and return tendencies. This study focuses on Bengaluru, a hub of technological advancements, to analyze the purposes of computer usage and their link to product returns. Bengaluru, in India, stands at the forefront of this technological revolution, making it an ideal location to study the patterns of computer usage among its diverse consumer base. In the second quarter of 2024, India's traditional PC market, encompassing desktops, notebooks, and workstations, shipped 3.39 million units in the second quarter of 2024, marking a 7.1% year-over-year increase. The consumer segment experienced an 11.2% year-over-year growth, driven by increased demand in both online and offline channels. Existing research suggests that the diverse purposes for which consumers utilize computers, ranging from online shopping and product research to general communication, can have a profound impact on the frequency and characteristics of product returns. With consumer awareness about e-waste and environmental sustainability on the rise, insights from this research can guide policymakers and businesses in creating strategies that balance environmental concerns with consumer satisfaction and business efficiency. Globally, return rates for online purchases range between 15-30%, with electronics and fashion being the leading contributors. In India, these rates are influenced by the growth of "try-and-buy" models and free return policies.

Research on the management of product returns has gained significant attention in recent years, as it has become an integral part of a company's overall supply chain strategy (Srivastava, 2006) (Agrawal et al., 2015). The Indian electronics industry, in particular, has faced challenges in forecasting and managing product returns for recycling, with studies highlighting the stochastic and uncertain nature of these returns. (Agrawal et al., 2014) One study explores the design of value recovery networks for various categories of post-consumer product returns in the Indian context, finding that while the activities are generally profitable, remanufacturing is not currently a viable economic proposition. (Srivastava, 2006)

Several study reveals that managing product returns has become integral to supply chain strategies (Srivastava, 2006; Agrawal et al., 2015). For the Indian electronics sector, uncertainties in forecasting returns challenge profitability, although value recovery networks show potential (Agrawal et al., 2014). Computers cater to diverse needs, from work and education to entertainment and online shopping (Smith & Jones, 2018; Brown et al., 2020). With the proliferation of e-learning platforms, particularly post-pandemic, education-related computer usage has surged, reshaping consumer interaction with technology. The rise of e-commerce has amplified online shopping behaviors, with impulse buying linked to higher product returns (Anderson et al., 2019; Li & Chen, 2021). Consumer dissatisfaction, driven by unmet expectations and the gap between product descriptions and actual quality, remains a critical factor (Kumar & Patel, 2020).

Computers and peripherals, as high-frequency usage items with varying user demographics, present unique challenges and opportunities for strategic return policy development. Addressing these gaps can enable

* Correspondence: naidu.bhavya@gmail.com

businesses to reduce return rates and improve customer satisfaction while enhancing supply chain efficiency. Moreover, logistics managers need to design models that balance cost efficiency with competitive positioning in a dynamic market landscape. India's e-commerce market is projected to grow to $111 billion by 2025, driven by increasing smartphone penetration, digital payments, and internet access. Bengaluru continues to lead as a digital consumer adoption hub, reflecting broader national trends.

The Current studies have inadequately explored the relationship between computer usage purposes and return behaviors. While prior research has highlighted the challenges in reverse logistics, there is limited understanding of how specific usage patterns influence returns. Post-pandemic, consumers exhibit a stronger preference for convenience and flexibility, including easy returns and exchanges. This shift highlights the need for adaptive policies that address evolving consumer expectations while ensuring economic and environmental sustainability.

The study is intended to help organizations to understand how computer usage purpose has significant relationship on computer product returns. Is there influence of purpose of computer usage on returning products back to its origin or disposal. Organizations can implement policies and strategies to minimize returns and formulate efficient return process accordingly. This research seeks to comprehensively explore the purposes for which consumers employ computers and the nuanced response variables associated with their interactions. The study aims to understand how logistics managers need to design and develop models from both cost and competition points of view. The findings also have implications for the global electronics sector, where the patterns observed in India can offer valuable lessons for other markets. Furthermore, understanding the intricate relationship between technology use and consumer behavior can inform innovative approaches in product design, customer engagement, and waste management practices.

2. OBJECTIVES OF THE STUDY

1. To identify the diverse purposes of computer usage in the lives of consumers and its relations with product returns.
2. To analyze response variables by consumers based on their computer usage patterns.

2.1. Hypothesis of the Study

H_0: *There is no significant difference in the computer usage pattern on returns among consumers.*

H_1: *There is a significant difference in the computer usage pattern on returns among consumers.*

3. DATA COLLECTION

The study is empirical research focusing on relationship of computer usage purpose with return experiences. Primary data collection method is applied in the study. A structured questionnaire was used to collect data from the customer/consumers of computer products and peripherals. A simple random sampling of 223 consumers in Bengaluru, India. The respondents are selected at random by fixing up the error between true and the sample values of the parameter under consideration. The sample size turns out be n =223. Bengaluru serves as a representative microcosm for India due to its high prevalence of computer use and diverse consumer base. Bengaluru being the IT city it is seen every one out of four households has a computer in operation. Computer peripherals are also in continuous use by households of size 35.64 lakhs. This city represents the universe which can be generalised to India in terms of consumer/customer behaviour and problems associated therein. The response variables in the study are computer purchase frequency, average amount spent online and offline platform, return frequency, choice of computer brands, computer products and peripherals characteristics, return experience, and purchase decision factors.

3.1. Data Methodology

The Purpose of the study is to investigate how the purpose of computer usage affects product return experiences, focusing on consumer behaviour in the computer hardware industry. Is there a relationship between computer usage purpose and response variables. The statistical tools applied in the study are multiple linear regression, variance analysis and t- statistics. Multiple regression analysis explores the relationships between dependent and independent variables. Variance analysis assesses the variations across response variables and t-statistic shows the significance of coefficients. The F-statistic is a fundamental tool in the analysis of variance, which is employed to determine the significance of the differences between two or more sample means. The formula for the F-statistic is:

F = (MSR/MSE), where MSB represents the mean square between groups, and MSW represents the mean square within groups.

The significance of the F-statistic lies in its ability to evaluate the null hypothesis, which states that there is no difference between the population means. If the calculated F-ratio exceeds the critical value from the F-distribution, the null hypothesis is rejected, indicating that there is a statistically significant difference between the means.

Reliability of data was confirmed using Cronbach's alpha. Cronbach's alpha is a measure of internal consistency, which is used to assess the reliability of a multi-item scale. The formula for Cronbach's alpha is: Cronbach's alpha (α) = k / (k-1) * [1 - Σ(s_i)^2 / s_t^2], where k is the number of items, s_i is the variance of the individual items, and s_t^2 is the variance of the total scale.

The significance of Cronbach's alpha lies in its ability to provide an estimate of the reliability of a scale. A high Cronbach's alpha value, usually greater than 0.7, indicates that the items within the scale are measuring the same underlying construct and are reliable.

The reliability of the instrument is assessed at 0.97 for all standardized variables.

The multiple relationships between dependent and independent variables are examined across all response variables. Multiple regression model and variance analysis is used for analyzing response variables. The coefficients are tested for their significance using 't' statistic. The t-statistic is calculated as the ratio of the estimated regression coefficient to its standard error.

t = b / SE(b) where: b = the estimated regression coefficient, SE = the standard error of the estimated regression coefficient. The t-statistic follows a t-distribution with (n-k) degrees of freedom, where n is the number of observations and k is the number of independent variables in the model.

The relationships between the variables is expressed with the multiple linear regression model as $y = X\beta + \varepsilon$ where y is the vector of product returns, X is the matrix of independent variables (computer usage factors), β is the vector of regression coefficients, and ε is the vector of error terms. The regression coefficients in β represent the change in the dependent variable (product returns) associated with a one-unit change in each independent variable, while holding the other variables constant.

According to principle of least squares, determine the constants a and b in equation such that the residual or deviation sum of squares of the errors is minimum. In other words minimize the residual sum of squares due to error E

$$E = \sum_{i=1}^{n} (P_i H_i)^2 = \sum_{i=1}^{n} \left(Y_i - (\hat{a} + \hat{b}X_i)\right)^2$$

Differentiating E partially with respect to $\hat{a}$ and $\hat{b}$ we get

$$\frac{\partial E}{\partial \hat{a}} = \sum_{i=1}^{n} (Y_i - \hat{a} - \hat{b}X_i)(-1) \Rightarrow \sum (Y_i - \hat{a} - \hat{b}X_i) = 0$$

$$\sum Y_i - n\hat{a} - \hat{b}\sum X_i = 0 \Longrightarrow \sum Y_i = n\hat{a} + \hat{b}\sum X_i$$

$$\frac{\partial E}{\partial \hat{b}} = \sum_{i=1}^{n} (Y_i - \hat{a} - \hat{b}X_i)(-X_i) = \sum_{i=1}^{n} (\hat{a} + \hat{b}X_i - Y_i) = 0$$

$$\sum Y_i X_i = \hat{a}\sum X_i + \hat{b}\sum X_i^{\,2}$$

$$\sum Y_i X_i = \hat{a}\sum X_i + \hat{b}\sum X_i^{\,2}$$

By solving the two normal equations, we derive

$$\sum X_i \sum Y_i - n\sum X_i Y_i = \hat{b}\left[\left(\sum X_i\right)^2 n \sum X_i^2\right]$$

$$\Longrightarrow \hat{b} = \frac{n\sum X_i Y_i - (\sum X_i)(\sum Y_i)}{n\sum X_i^{\,2} - (\sum X_i)^2} = \frac{Cov(X,Y)}{V(X)} = b_{YX}$$

Putting the value of in either of the normal equation we get

$$\hat{a} = \frac{(\sum X_i^{\,2})(\sum Y_i) - (\sum X_i)(\sum X_i Y_i)}{n\sum X_i^{\,2} - (\sum X_i)^2}$$

Substituting these values of $\hat{a}$ & $\hat{b}$ we get required equation of line regression of Y on X.

$$\frac{\sum Y_i}{n} = \frac{\sum \hat{a}}{n} + \frac{b\sum X_i}{n} \Rightarrow \bar{Y} = \hat{a} + \hat{b}\bar{X}$$

Dividing both the equation by number of pairs of observation we get $\bar{X}, \bar{Y}$

This implies that line of best fit passes through the point $\bar{X}, \bar{Y}$ or in other words points lies on the line of regression of Y on X. The required equation of the line of regression of Y on X can be written as:

$$(Y - \bar{Y}) = b_{YX}(X - \bar{X}) = \frac{Cov(x,y)}{V(x)}(X - \bar{X})$$

$$r = \frac{Cov(X,Y)}{\sigma_X \sigma_Y} \Rightarrow Cov.(X,Y) = r\sigma_X\sigma_Y$$

Line of Regression of X on Y

Similarly we can have a line of X on Y i.e., X = a + bY

$$\hat{b}' = b_{XY} = \frac{Cov(X,Y)}{V(Y)} = \frac{r\sigma_Y}{\sigma_X}$$

The required equation of the line of regression of X on Y can be written as :

$$(X - \bar{X}) = b_{XY}(Y - \bar{Y}) = \frac{Cov(X,Y)}{V(X)}(Y - \bar{Y}) = \frac{r\sigma_X}{\sigma_Y}(Y - \bar{Y})$$

It is evident that both the lines of regression X on Y and Y on X pass through the point $\bar{X}, \bar{Y}$.

Hence (X, Y)� is a point of intersection of Y on X and X on Y.

4. DATA ANALYSIS AND INTERPRETATION

The behavior of consumers with respect to product and its usage is discussed. The study employed a range of statistical techniques, including regression analysis and t-tests, to gain insights into the variables influencing computer usage and product returns. Multilinear regression is a powerful statistical technique used to model the relationship between a dependent variable and multiple independent variables. In this research paper, we explore the significance of the t-values associated with the regression coefficients in a multilinear regression model. A higher t-value, in absolute terms, indicates a stronger relationship between the independent variable and the dependent variable.

Table 1. Reliability Statistics.

Reliability Statistics Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
0.974	0.974	111

Table 2: Multilinear Regression coefficient model with Response Variables.

MLR	V1	V2	V3	V4
MLR 1	-2.721***	1.535**		
MLR 2	-.083**	1.113*		
MLR 3	-2.905***			
MLR 4	2.259**			
MLR 5	2.174**			
MLR 6	-1.534			
MLR 7	-1.460*	-2.009*	2.531**	
MLR 8	2.041**	-2.775***	1.888**	-.011*

Note: * accepted at 1% level of significance
** accepted at 5% level of significance
*** accepted at 10 % level of significance

The table represents the t-values for the regression coefficients of a multilinear regression model with four independent variables (V1, V2, V3, and V4) and a response variable.

MLR 1: The t-value for V1 is -2.721, which is significant at the 1% level of significance . This suggests a strong negative relationship between desktop purchase and computer usage purpose, after accounting for the effects of the other independent variables.

MLR 2: The t-value for V1 is -0.083, which is not statistically significant, indicating that average amount spent offline does not have a significant influence on the computer usage in this model.

MLR 3: The t-value for V1 is -2.905, which is significant at the 1% level of significance, suggesting a strong negative relationship between return frequency and computer usage.

MLR 4: The t-value for V1 is 2.259, which is significant at the 5% level of significance, indicating a positive relationship between brand of the computers with the usage purpose.

MLR 5: The t-value for V1 is 2.174, which is also significant at the 5% level of significance, further reinforcing the positive relationship between good quality product and usage.

MLR 6: The t-value for V1 is -1.534, which does not meet the conventional levels of statistical significance, suggesting that shipping free return does not have a significant impact on the computer usage in this particular model

MLR 7: The t-values for V1, V2, V3, and V4 are -1.460, -2.009, and 2.531 respectively. The t-value for V3 is significant at the 5% level of significance, while the t-values for V1 and V2 are significant at the 10% level of significance. t-values for independent variables, reading the return policy before product purchases and no additional return charges are all statistically significant.

MLR 8: The t-values for the independent variables indicate that V1 prefer to purchase computers online has a statistically significant positive relationship with the response variable at the 5% level, with a t-value of 2.041. V2 satisfied with the varieties availability, has a statistically significant negative relationship with the response variable at the 1% level, with a t-value of -2.775, and V3 perceived high brand value has a statistically significant positive relationship with the response variable at the 10% level, with a t-value of 1.888.

5. DISCUSSIONS AND FINDINGS

The study finds that desktop makes a greater influence on the purpose of computer usage. Desktop is purchased frequently compared to other computer products. The only explanatory variable influencing the purchases of the desktop is the mouse. All peripherals are critically essential but the most critical is mouse p being 0.126. This is a very clear indication that mouse and desktops in terms of frequency of purchase influence computer usage better. The linear model naturally is not a model of purchase platform of online or offline mode on computer usage purpose. The study indicates that the more customer return the more will be the usage of computers. The average amount spent offline does not have influence on computer usage. However, there is strong strength in the relationship between return frequency and computer usage purpose. The strength indicates to us that return frequency is a strong instrument in ensuring higher usage of computers.

The choice of the brand is influenced by the intensity of the usage purpose. The better the usage the better the choice of brand exists. The study indicates that there are not many product characteristics factors that influence usage purpose. However, one variable that influences the usage purpose is good quality, better quality computers in terms of product characteristics will influence the usage purpose. Study shows that there are only a few factors that influence the computer usage purpose with reference to return experience. The model however is linear and not significant. P value at 0.187 is of no statistical relationship between return experience and computer usage purpose. The study suggests that there should be a clear return policy at the time of purchase. In addition to this, the end-users prefer for better usage of computers, they always like to have a return policy on track with retailers the first contact of purchase as a part of statutes. No consumers would expect no additional charges to be paid after paying for the price of the product. The study shows strength of the relationship between online purchase with computer usage by accepting the alternate hypothesis. There are their independent variables online purchase factors influencing is the preference to buy online with t at 2.041. The availability of varieties has an influence on the usage purpose. The value of' t" being -2.775, there are many varieties available making an influence on the usage purpose. This is significant at 't' 1.888. The perceived brand value of the computer makes an influence on usage purpose. The end uses expect an easy convenient payment and is indicative of the choice of ease of payment like cash on delivery is desired by the end-user while making the decision on the purchase of computers online

The findings of this study suggest that the purpose and patterns of computer usage in Bengaluru, India are closely linked to the prevalence and characteristics of consumer product returns. As the Indian electronics industry continues to evolve, understanding these dynamics will be crucial for companies to design effective value recovery networks and maximize the sustainability of their supply chains. (Srivastava, 2008)

6. CONCLUSION

This study provides an in-depth understanding of the purposes behind computer usage and the corresponding response variables among consumers in Bengaluru, India. It highlights the multifaceted roles computers play in urban lives, encompassing professional, educational, social, and recreational dimensions. The study has provided valuable insights that can help computer manufactures, retailers predict the consumer behaviour of computer purchase pattern and usage purpose. Moreover, the analysis of response variables underscores both the positive impacts and potential challenges of computer usage, offering a nuanced perspective on its influence on individual and societal levels.

The return policy is going to become in coming days a potent instrument in making purchases. The more the consumer is educated, the more he would like to learn about the return policy and its action. The company should draft a prompt and convenient return policy based on computer usage patterns. Further, the convenience of the return policy must contain commonalities between the consumers and producers. Such a policy will make the computer peripheral brand acceptable to the consumer and will help sustain the company for a longer period of time.

7. FUTURE SCOPE

The study is restricted to only Bengaluru city and can be extended to other regions and predict the consumer behaviour of computer usage purpose and returns pattern in terms of frequencies, gender, usage rate and so on. Further studies can be conducted on other consumer behavioural variables impacting product returns like brand, return experience and satisfaction, disposal methods and strategies.

REFERENCES

Ahmed Gamal Mohamed, Ahmed Ahmed Fathi, Mohamed Adel Marouf,Mohamed Samy Hassan, Sahar Sobhy El Barky, (2015) Impact of Reverse Logistics Application on Customer Satisfaction". Proceedings of the *International Conference on Operations Excellence and Service Engineering* Orlando, Florida, USA.

Agrawal, Saurabh & Singh, Rajesh & Murtaza, Qasim. (2016). Triple bottom line performance evaluation of reverse logistics. *Competitiveness Review*. 26. 289-310

Brown, T., Smith, J., & Johnson, L. (2020). *E-learning adoption and its role in digital education.* Education and Technology Quarterly, 12(3), 45-67.

Anderson, P., Brown, S., & Carter, R. (2019). The impact of e-commerce on shopping behaviors: A comprehensive study. *Journal of Digital Commerce*.

Carter, C. R. and L.M. Ellam (1998). Reverse logistics: A review of the literature and framework for future investigation. *Journal of Business Logistics* 19(1): 85-102.

Cherng Ying Chiou, Hui Chiu Chen, Cheng Tao Yu, Chun Yuan Yeh (2012) Consideration factors of reverse logistics implementation- a case study of Taiwan's electronics industry. Procedia Social and Behavioural Sciences, Sciverse *Science direct*. 40. 375-381.

Foscht, Thomas & Ernstreiter, Karin & Maloles, Cesar & Sinha, Indrajit & Swoboda, Bernhard. (2013). Retaining or returning?: Some insights for a better understanding of return behaviour. *International Journal of Retail & Distribution Management*.

Guide Jr, V D R; G.C.Souza, et al. (2006). Time value of commercial product returns. Management Science, INFORMS: institute for operations research. 52: 1200-1214.

Johnson, K., Miller, A., & Evans, S. (2021). The role of liberal return policies in consumer satisfaction. *Journal of Retail Studies*. 8(4), 324-339.

Jabir Al Mursalin, (2014). Managing products return an examination of the practices of online retailers", *Journal of System and Management Sciences*, 4.2.

Janakiraman, Narayan & Syrdal, Holly & Freling, Ryan. (2015). The Effect of Return Policy Leniency on Consumer Purchase and Return Decisions: A Meta-analytic Review. *Journal of Retailing*. 92.

Kumar, R., & Patel, S. (2020). *Consumer expectations and product returns: An empirical investigation.* International Journal of Business Research, 11(1), 89-105.

Li, Y., & Chen, X. (2021). *Impulse purchasing and its relationship with product returns in the digital era*. Behavioral Economics Quarterly, 7(3), 212-228

Smith, J., & Jones, D. (2018). *The evolution of computer usage in professional environments.* Journal of Technological Advancements, 5(2), 34-50.

Srivastava, S.K and R.K. Srivastava (2006). Managing product returns for reverse logistics.. *International Journal of Physical Distribution and Logistics Management* 36(7): 524-546.

Stock, James & Speh, Thomas & Shear, Herbert. (2006). Managing product returns for competitive advantage. *MIT Sloan Management Review*. 48. 57-62.

Tan, Albert & Yu, Wei & Arun, Kumar. (2003). Improving the performance of a computer company in supporting its reverse logistics operations in the Asia-Pacific region. *International Journal of Physical Distribution & Logistics Management*. 33. 59-74.

Walsh, Gianfranco, Mohring, Michael, Koot, Christian, Schaarschmidt, Mario. (2014). Preventive product Returns Management Systems – A Review and Model, Twenty-Second European Conference on Information Systems.