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# An Empirical Analysis of Customer Churn Drivers in Online Retail Businesses: Evidence from E-Commerce Customer Behaviour Data

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## ABSTRACT

Customer churn is a significant problem for online retailers because it has a negative impact on customer retention, profitability, and sustainability. The objective of this study was to find out the most important factors that drive customer churn by using behavioural, demographic and service characteristics from the E-Commerce Customer Churn Dataset. A quantitative cross sectional study design was used in this research, which was based on the data obtained from 5630 customers. The impact of the customer characteristics on churn has been analysed using binary logistic regression. The results indicated that complaint status, customer tenure, warehouse-to-home distance, city tier, number of registered devices, satisfaction score, number of addresses, order count, days since the last order, cashback amount, and preferred login device had significant impact on customer churn. Complaint status proved to be the strongest predictor and having been in the company for longer time decreased the chances of churn. The findings show that there are multiple interrelated factors required to ensure customer retention and emphasize the significance of integration of the customer analytics and customer relationship management strategies. The study offers empirical evidence that can help online retailers create the targeted retention efforts, enhance service quality, build better customer relationships, and help them with the data-driven managerial decision making for sustainable performance.

**KEYWORDS**: Customer churn, E-commerce, Customer retention, Logistic regression, Customer analytics

## Introduction

Digital technologies' swift evolution has transformed the retail sector, resulting in the most rapid growth of e-commerce globally ever recorded. The penetration of internet, the availability of smartphone and secure payment systems, progress in logistics etc. have altered consumer buying behavior and created an environment of convenient, efficient and personalized shopping experience. Nowadays, consumers are able to do a quick comparison of multiple retailers' products, prices and services in the digital marketplace, making it a much competitive space. As a result, ecommerce is one of the fastest growing areas of the global economy, providing business with a great deal of opportunity for growth, as well as bringing a significant competitive challenge. In this dynamic environment it is not only necessary for organisations to gain new customers, but also to keep existing customers for sustainable business growth and competitive advantage [1,2].

Retaining customers is much more cost-effective than continually trying to attract new ones, which is why customer retention has become a pivotal strategic goal. The previous research has shown that acquiring a customer is much more expensive than retaining one whereas loyal customers increase the customer lifetime value, customer profitability, and word-of-mouth promotion [1,3]. But with the proliferation of other online retailers, customers' switching costs have become much lower, allowing them to seamlessly switch from one competitor to the next if they are not happy with the service, price, range of products or delivery times. Consequently, customer churn is one of the toughest problems that e-commerce companies face. Waste in the form of high churn rates hurt the bottom line of an organization, lead to higher customer acquisition expenses, lower customer loyalty, and ultimately put the organization's sustainability at risk. So, research and practitioners in business are given strategic importance to understand what factors contribute to customer churn to enhance the customer relationship management and organisational performance.

Churn is the loss of a customer from a company or the failure to buy something from a company in a defined time period. For online retail businesses, factors such as demographics, buying habits, service experiences, promotions, and customer engagement all play a role in influencing customer churn. Customer behavioural data has evolved at a fast pace with the surge of digital commerce, allowing organizations to use customer analytics and customer business intelligence methods to gain insight into customer preferences and the likelihood of future purchases. The development of predictive analytics and machine learning has enabled organizations to gain a tool and report that can be used to identify customers who are more likely to abandon the product before that point, which allows them to take proactive measures to retain customers before it is too late [2,4,5]. In this context, predictive modelling has emerged as a crucial element in CRM, helping businesses minimize churn, enhance customer satisfaction, and foster customer loyalty.

With recent advancements in the field of business analytics, the importance of data-driven decision making has grown even more in the e-commerce industry. Customer data, including demographic data, transaction history, complaint history, browsing history, response history to promotions, and interactions with service is increasingly being analysed using predictive models to look for patterns related to customers' likelihood to churn off. By applying these analytical methods, companies can make informed decisions about their marketing strategies and allocate their resources more effectively, leading to better customer service and more targeted promotions. Empirical studies have shown that the behavioural parameters like purchase frequency, customer satisfaction, complaint history, cash back incentives, application usage, payment preferences, order recency have significant impact on customer retention in online retail companies [2,4,6]. Crm systems that incorporate predictive analytics can, therefore, help organizations design data-informed retention strategies to enhance customer satisfaction and organizational performance [6,7].

Artificial Intelligence and Machine Learning technologies have also seen significant advancements, contributing to more accurate and efficient customer churn prediction models. Organizations can use predictive methods to handle vast amounts of structured data from their customers and reveal complex patterns and correlations between customer behaviors, demographics, and transactions that traditional statistical analysis struggles to uncover. The emergence of these new technologies has inspired companies to incorporate predictive analysis in their decision-making processes, showing its potential to strengthen customer relationship management, be more personalized in services, and improve the competitive positioning [8–11]. Customer analytics can also aid digital transformation efforts, allowing businesses to predict customer needs, maximise marketing spending and personalize shopping experiences to foster customer loyalty.

While there have been significant advances in the field of customer churn prediction research, there are still several areas that have not been developed. Most of the previous research has been on the predictive power of the machine learning algorithms compared to each other, not on the business factors that drive customer attrition. Furthermore, numerous empirical studies have focused on industries like telecom, banking, insurance and subscription services, while less focus has been paid to customer attrition within online retail. Machine learning models are frequently highly effective in predicting customer attrition, but managers need to better understand the customer behavioural, demographic and service attributes that affect customer retention to be able to make better business decisions. Therefore, there is a gap in the literature for empirical research that not only pinpoints the main reasons behind customer attrition, but also offers practical managerial suggestions for customer relationship management in the context of e-commerce [1,3,7,12].

Another constraint of previous work is that customer behavioural variables were not combined with operational service characteristics. These factors, including warehouse-to-home distance, complaint management, customer satisfaction, cashback incentives, application engagement, and purchase frequency, are important in influencing the purchasing decisions customers make and may act together in this regard; however, these are some factors that have been studied separately rather than in a comprehensive empirical framework [2,4,6]. Considering these factors collectively can give a more comprehensive picture of customer churn behaviour and help organizations prioritize their customer retention efforts. The online retailer in the ever-evolving digital marketplace is especially lucky to have this kind of evidence, especially since expectations are growing faster than ever.

To tackle these research gaps, the present study explores the factors that cause customers to churn from an E-Commerce business through the use of a publicly-available Customer Churn dataset for an E-Commerce business that includes customer demographic, behavioural, transactional and service-related data. A quantitative research design with binary logistic regression analysis is used to study the effect of customer characteristics on customer churn behaviour [1,5,7,9]. The binary logistic regression is more suitable since the dependent variable is binary and reflects whether or not a customer has churned or has not churned from the online retail platform. Analysis can help determine which variables are statistically significant predictors and the percentage contribution of each predictor to customer attrition.

The results from this research will have theoretical and practical implications. Theoretically, the study builds upon the existing literature by providing empirical evidence on the factors that influence customer churn in online retail companies based on the customer behaviour data. As a rule, the findings give a practical direction to managers when formulating an effective customer relationship management strategy, strengthening the quality of service, smoothing the complaint handling process, improving customer satisfaction, creating promotional programmes and applying predictive analytics to detect customers who are likely to turn over [1,3,7,12]. The study helps in making evidence-based managerial decisions and aids sustainable growth of business in the competitive e-commerce industry by identifying the most influential factors determining customer retention. This study aims to:

1.To identify the significant behavioural, demographic, and service-related factors influencing customer churn in online retail businesses

2.To examine the relationship between customer characteristics and the likelihood of customer churn using binary logistic regression analysis

3.To provide empirical evidence supporting customer retention strategies through the analysis of e-commerce customer behavioural data

## 2. Methodology

### 2.1 Research Design

The present research work has applied quantitative cross-sectional empirical research design to understand the factors that affect the customer churn in the online retailing companies. The reason for selecting the quantitative research design is because of the fact that quantitative research makes it possible to statistically analyze the relationship between the behavioral attributes of customers and the status of churn through numerical information.

### 2.2 Data Source and Dataset Description

The data used for the experiment was collected from an E-Commerce Customer Churn Dataset publicly available online [13]. There are 5,630 observations in the dataset, which includes 20 variables, where one variable is the dependent variable (Customer Churn) while the other 19 are the independent variables, which describe the customers' demographics, purchase behavior, service experience, and interaction with the online shopping website. The dependent variable is 'Customer Churn,' where it determines whether the customer has stopped making purchases at the online retailer. Some of the independent variables are tenure, satisfaction score, complaints, number of orders, cash back value, etc.

### 2.3 Variable Description

Customer Churn will be the dependent variable in this case. It indicates whether or not the customer has stopped using the online retail platform and will take the form of a binary variable

(1 = Churned, 0 = Retained). To investigate the factors that influence customer churn, various independent variables have been considered in the study. These include Tenure, Satisfaction Score, Complaint Status, Order Count, Cashback, Coupon Utilization, Preferred Payment Method, Preferred Order Category, Time Spent on App, Days since Last Order, Distance from Warehouse to Home, Number of Devices Registered by the User, Gender, Marital Status, and City Tier. Together, all these independent variables reflect customer behavior patterns, demographics, purchase behavior, customer experience, and their engagement with the online retail platform. This is because past literature and business experience suggests that these factors have a great significance in determining the decision-making behavior of customers regarding churn and retention.

**2.4 Data pre-processing**

Prior to performing any analysis on the data set, the following cleaning activities were done: identification of missing values, detection of duplicate entries, and consistency checks on the data. Where necessary, categorical variables were encoded into numerical variables. The data was also checked for outliers.

**2.5 Data Analysis Techniques**

The results were analyzed using both descriptive and inferential statistics. Descriptive statistics, which include frequency distribution, percentages, mean, and standard deviation, were applied in describing the features of the customers. Correlation analysis was performed in order to find out the relationship between the different variables used in the study. Binary logistic regression analysis was carried out to determine the predictors of customer churn because the dependent variable is dichotomous in nature.

**2.6 Software Used**

Analyses were conducted in Python through the use of packages like Pandas to handle data, NumPy to conduct numerical computations, Matplotlib to visualize the data, Statsmodels to conduct logistic regression analysis, and Scikit-learn to conduct preprocessing and model validation. The initial data preparation was done in Microsoft Excel.

**3. Results**

**3.1 Descriptive Statistics**

The analysis was carried out using data from 5,630 customers from the E-Commerce Customer Churn Dataset. There were 20 variables within the dataset, which included the dependent variable, which was Customer Churn, and nineteen independent variables which included the characteristics of the customers, their behavior in terms of purchasing, experience with the services provided, and involvement with the online shopping portal. The descriptive statistics were used to describe the dataset prior to the inferential analysis, whereby continuous variables like tenure, satisfaction score, number of orders, cashback value, and hours on the application were analyzed in terms of central tendency and dispersion (Figure 1) (Table 1).

**Table 1: Descriptive Statistics of Continuous Variables**

| Variable | Mean | Std. Deviation | Minimum | Maximum |
|---|---|---|---|---|
| **Tenure** | 10.19 | 8.56 | 0 | 61 |
| **Satisfaction Score** | 3.07 | 1.38 | 1 | 5 |
| **Hour Spend on App** | 2.93 | 0.72 | 0 | 5 |
| **Warehouse to Home** | 15.64 | 8.53 | 5 | 127 |
| **Number of Registered Devices** | 3.69 | 1.02 | 1 | 6 |
| **Number of Address** | 4.21 | 2.58 | 1 | 22 |
| **Order Count** | 3.01 | 2.94 | 1 | 16 |
| **Coupon Used** | 1.75 | 1.89 | 0 | 16 |
| **Cashback Amount** | 177.22 | 49.21 | 0.00 | 324.99 |
| **Days Since Last Order** | 4.54 | 3.65 | 0 | 46 |

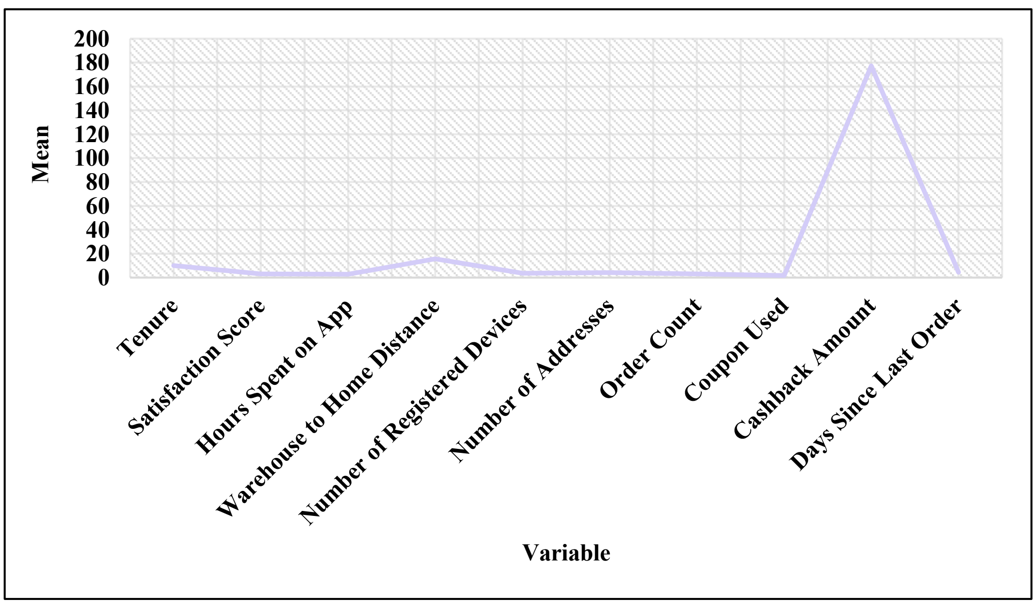


*Figure 1. Mean Values of Continuous Variables*

## 3.2 Customer Demographic Profile

The demographic composition shows that 3,384 customers (60.11%) were male and 2,246 customers (39.89%) were female. For the marital status, 2,986 customers (53.04%) were married, 1,796 (31.90%) were single and 848 (15.06%) were divorced. According to the classification of the cities, 3,666 customers (65.12%) were in City Tier 1, 242 customers (4.30%) in City Tier 2 and 1,722 customers (30.59%) in City Tier 3. The above demographic information gives an overview of the customer base included in the empirical analysis (Figure 2) (Table 2).

**Table 2. Customer Demographic Profile (N = 5,630)**

| Demographic Variable | Category | Frequency (n) | Percentage (%) |
|---|---|---|---|
| Gender | Male | 3,384 | 60.11 |
| | Female | 2,246 | 39.89 |
| | Total | 5,630 | 100.00 |
| Marital Status | Married | 2,986 | 53.04 |
| | Single | 1,796 | 31.90 |
| | Divorced | 848 | 15.06 |
| | Total | 5,630 | 100.00 |
| City Tier | Tier 1 | 3,666 | 65.12 |
| | Tier 2 | 242 | 4.30 |
| | Tier 3 | 1,722 | 30.59 |
| | Total | 5,630 | 100.00 |

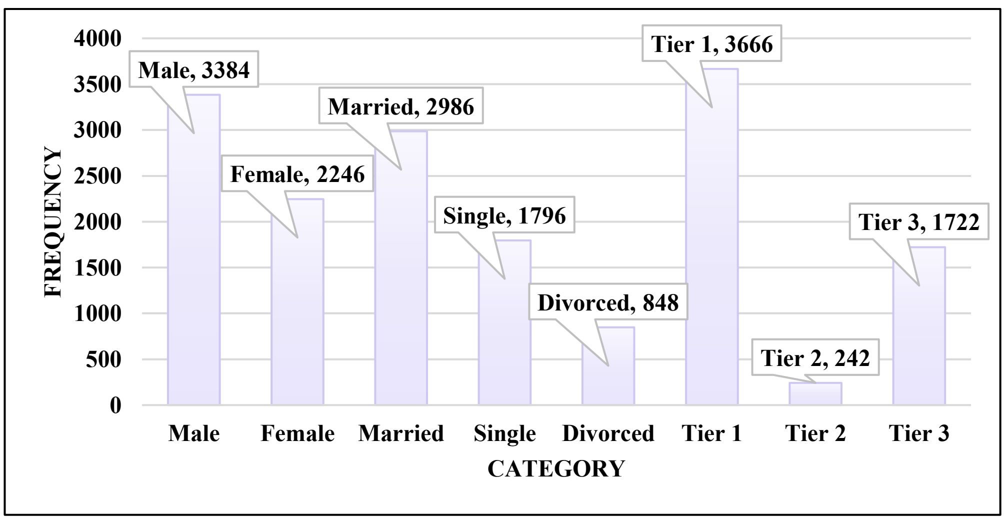


*Figure 2: Customer Demographic Profile*

### 3.3 Churn Distribution Analysis

Dependent Variable Distribution shows that 4,682 customers (83.16%) have been retained by the online retail portal, while 948 customers (16.84%) have churned. The data shows that retention is way higher than customer attrition in this dataset. This data shows the normal customer behavior pattern that takes place in the business of online retailing, in which more customers retain their association with the portal and a few terminate their purchases (Figure 3) (Table 3).

**Table 3. Customer Churn Distribution**

| Customer Status | Frequency | Percentage (%) |
|---|---|---|
| Retained | 4,682 | 83.16 |
| Churned | 948 | 16.84 |
| Total | 5,630 | 100.00 |

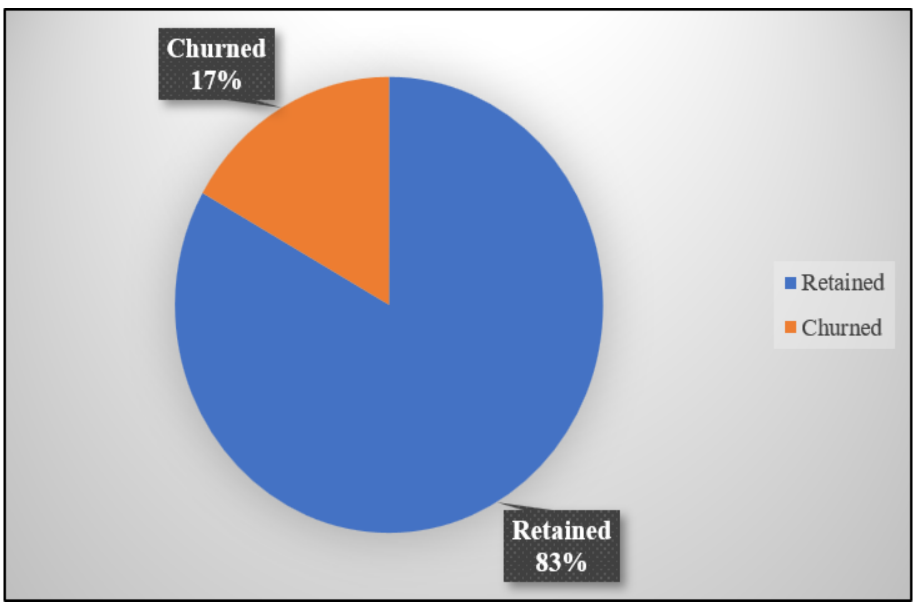


*Figure 3: Customer Churn Distribution*

### 3.4 Correlation Analysis

Pearson correlation coefficient analysis was used to test the relationships between the study variables and detect any multicollinearity issues. Correlation analysis was conducted to assess the relationships between customer churn and explanatory variables such as customer tenure, satisfaction score, complaint, order, cashback, coupons, application, and days since last order. Correlation matrix helped to find the nature of relationships between the variables under consideration, and it acted as an initial step before building the logistic regression model (see Figure 4).

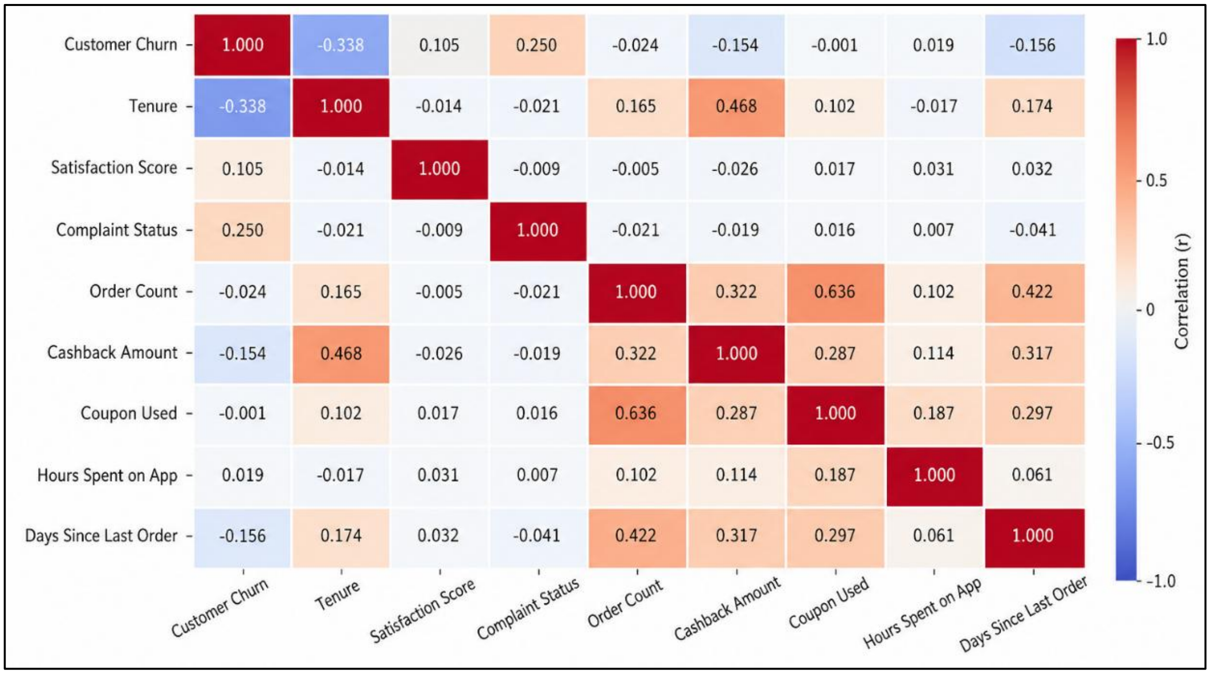

*Figure 4: Pearson Correlation heatmap of the study variables*

### 3.5 Logistic Regression Results

Binary logistic regression model was used in order to determine the most important factors of customer churn. Customer churn was used as the dependent variable and demographic, behavioristic, and service-based variables were used as independent variables. The binary logistic regression output gives the values of coefficients, odds ratio, standard error, Wald statistic, and significance value for every predictor. The predictors having p-value less than 0.05 are considered as the significant factors for customer churn (Figure 5) (Table 4)

**Table 4. Binary Logistic Regression Results for Customer Churn**

| Predictor Variable | Coefficient (β) | Std. Error | Wald (z) | Odds Ratio (Exp(B)) | p-value |
|---|---|---|---|---|---|
| Constant | -1.793 | 0.661 | -2.712 | 0.167 | 0.007 |
| Tenure | -0.209 | 0.010 | -20.963 | 0.811 | <0.001 |
| City Tier | 0.357 | 0.060 | 5.966 | 1.429 | <0.001 |
| Warehouse to Home | 0.040 | 0.006 | 7.192 | 1.041 | <0.001 |
| Hours Spent on App | -0.082 | 0.078 | -1.052 | 0.293 | Not Significant |
| Number of Registered Devices | 0.419 | 0.053 | 7.908 | 1.520 | <0.001 |
| Satisfaction Score | 0.294 | 0.035 | 8.392 | 1.341 | <0.001 |

| | | | | | |
|---|---|---|---|---|---|
| Number of Address | 0.241 | 0.019 | 13.014 | 1.273 | <0.001 |
| Complaint Status | 1.787 | 0.097 | 18.351 | 5.972 | <0.001 |
| Order Amount Hike from Last Year | -0.020 | 0.013 | -1.513 | 0.981 | 0.130 |
| Coupon Used | 0.042 | 0.035 | 1.184 | 1.043 | 0.236 |
| Order Count | 0.129 | 0.026 | 5.013 | 1.138 | <0.001 |
| Days Since Last Order | -0.103 | 0.018 | -5.749 | 0.902 | <0.001 |
| Cashback Amount | -0.018 | 0.003 | -6.326 | 0.982 | <0.001 |
| Preferred Login Device (Mobile Phone) | -0.378 | 0.115 | -3.294 | 0.685 | 0.001 |

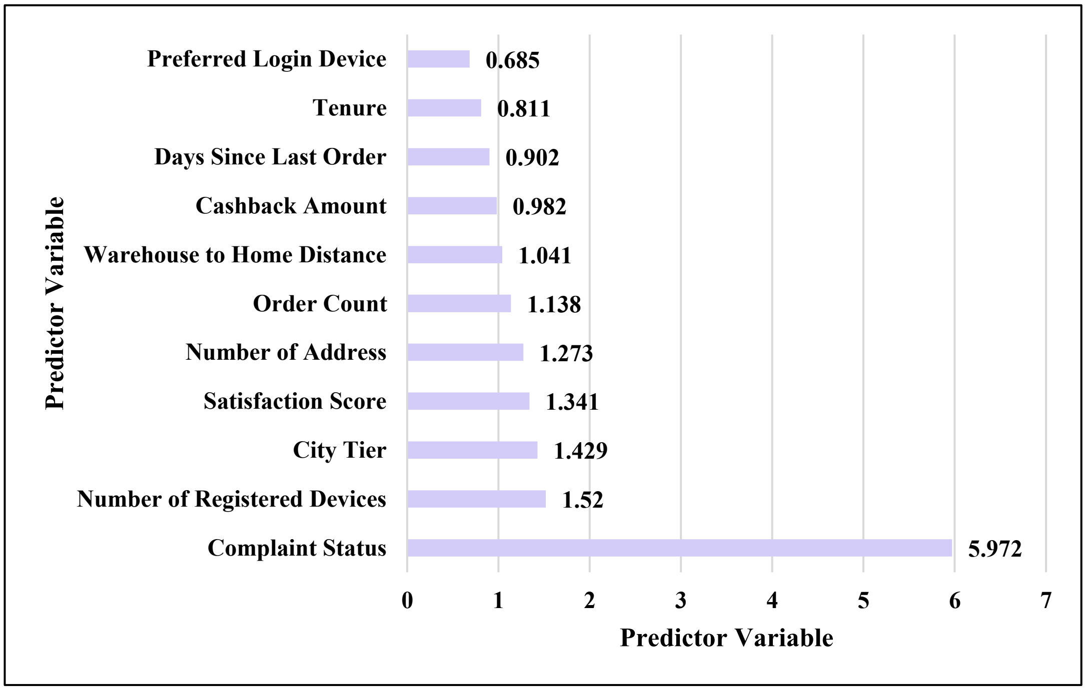


*Figure 5: Odds Ratios of Significant Predictors of Customer Churn*

## 4. Discussion

The results of the current study indicate that customer churn in the e-commerce industry is affected by various behavioral, demographic, service-based and operational factors. The variables such as Complaint Status, Customer Tenure, Warehouse to Home Distance, City Tier, Number of Registered Devices, Satisfaction Score, Number of Addresses, Order Count, Days since Last Purchase, Cashback Amount, and Preferred Login Device indicated significant correlation with customer churn. This indicates that customer retention is not affected by any one variable but by an aggregation of customer experience, purchasing behavior and service quality. If a complaint from the customer is unresolved, he/she may not have any faith in the organization and would result in dissatisfied customers. On the other hand, a customer with higher tenure is likely to have higher trust and loyalty to the retailer making him/her less susceptible to switch to competitors. Behavioral indicators such as order count, days since last purchase and cashback usage indicate greater customer engagement and hence low customer churn probability. The operational factors such as warehouse to home distance and city tier indicate the impact on delivery service and convenience of service on customer satisfaction. With continued observation of such key influencers, it will be possible for organizations to spot potential customer churners and adopt personalization tactics. In general, the research shows that using customer analytics alongside proper service management can lead to increased customer loyalty and better organizational performance within the tough competition that prevails in eCommerce.

Results of this study are also similar to earlier research indicating that customer attrition is a multi-dimensional concept affected by behavioral, demographic and service related attributes. Similar to the earlier studies [14], the results suggest that customer retention is based on the interaction of customer experience, purchasing behavior and performance, rather than being dependent on one factor. The significant effect of customer complaint status indicates support for the earlier research suggesting that proper handling of complaints enhances customer trust, improves their satisfaction and reduces customer attrition [15]. Similarly, significance of customer tenure is in accordance with the relationship marketing literature suggesting that customers who have been associated with an organization for a longer period of time, develop stronger emotional attachments towards organizations and thus become more loyal [16,17]. Significant link between customer satisfaction and retention further supports earlier research indicating that customer satisfaction is the reason behind repeat purchase and referral behavior of customers. In addition to that, behavioral measures such as order frequency, recency, and cashback redemption corroborate prior evidence suggesting customer engagement as an effective churn predictor [19]. Furthermore, the impact of the distance between the warehouse and the home, as well as the city tier, conforms to the literature on the significance of logistics performance and delivery efficiency in increasing customer satisfaction [20–22]. All in all, the current study provides empirical support for existing literature and underlines the growing importance of customer analytics [23–25].

The results of this research bring forth many practical implications for the managers and decision makers within the eCommerce domain. To begin with, there is a need for companies to have effective complaint management strategies by ensuring that customer complaints are resolved in a timely manner. Effective complaint management leads to increased customer satisfaction and decreased customer attrition rates. Secondly, companies should ensure that customer relationship management is strengthened through effective means of communication, loyalty programs, cashbacks and promotional campaigns. Long-term customers and those who purchase more frequently should be provided with customized incentive schemes. Finally, predictive analytics must be applied to CRM systems in order to spot customers at risk of attrition.

It becomes possible for organizations to develop retention strategies proactively and cut down the cost of customer acquisition, at the same time enhancing the lifetime value of the customer. Fourthly, organizations need to conduct regular surveys of the customers to gauge their satisfaction and make necessary improvements in their services. Lastly, organizations need to enhance their efficiency through better management of warehouses, optimizing delivery routes, and cutting down on delivery times, especially when it comes to customers who are farther away from the distribution centers. The consideration of regional variations through city tiers is an added advantage for providing better service and customer experience.

Despite the useful findings obtained from this research regarding the determinants of customer churn in eCommerce, there are some limitations which should be taken into consideration when discussing the results of the analysis. First of all, the analysis was conducted using only one publicly available customer churn data set, which may not reflect the behavior of customers in other eCommerce environments, in other industries, or in different geographic locations, thus restricting the applicability of the results. In addition, only quantitative characteristics have been used for this analysis, whereas qualitative characteristics such as customer's attitude, motivation, and perception have not been included. It is possible to say that the relationships found between the chosen variables and customer churn show their significant interconnection, however, no causality can be established due to other factors that might affect customer churn. Moreover, such external factors as market competition, economic situation, seasonality of the product, pricing, and social network usage have not been taken into account.

These gaps could be resolved through future research, which needs to use bigger and more heterogeneous data sets collected from several eCommerce websites across various locations. The inclusion of behavioral data like click stream data, customer sentiment, browsing history, and even social media interactions along with machine learning algorithms like XGBoost, LightGBM, CatBoost, LSTM and Explainable Artificial Intelligence (XAI) can contribute to an increase in churn prediction accuracy and the interpretation of models used for it. The longitudinal analysis of AI-powered customer relationship management systems and their effect on customer behavior can also help in developing better data-driven retention policies for the changing eCommerce industry.

## 5. Conclusion

This study examined the causes that influence online retail businesses customer churn using E-Commerce Customer Churn Dataset and Binary Logistic Regression Analysis. Implementing the following factors has been seen as having a significant impact on customer churn: Behavioural factors such as: complaint status, customer tenure, distance from warehouse to home, city tier, number of registered devices, satisfaction score, number of addresses, order count, days since order, cashback amount, preferred login device, and demographic factors such as: Age, gender, ethnicity, nationality, marital status, employment status, and education level. Of these, complaint status was the top factor affecting customer churn, while length of time on the platform decreased the risk of customers churning. The results show how studying customer behaviour via the empirical approach can help online retailers to create more successful customer retention strategy. The research found that the focus on customer satisfaction and service quality will hold an important role in preventing churn and building customer loyalty in the long-term. Managing effectively, online retailers need to create efficient complaints resolution systems, offer personalized service to boost customer satisfaction, expand loyalty and cashback schemes to boost repeat business, use predictive analytics to better understand customers who are likely to churn, and improve customer engagement by using digital marketing more effectively and offering customers better customization. Adopting these tactics can help build customer loyalty, boost retention and contribute to the long-term success of your company in the fiercely competitive eCommerce landscape.

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