

Predictive Modeling and Customer Segmentation for Quick Commerce User Behaviour Analysis

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Abstract—On-demand shopping sites have seen a lot of growth lately because more consumers are wanting their items delivered to them very quickly. Despite the high demand for fast delivery, there are still a lot of problems facing on-demand shopping platforms such as: high user churn (loss of customers), dependence on discounts, and high operational costs. For this paper, I analyzed consumer behaviours, identified which consumers are likely to churn, created meaningful user segments and estimated average order values (AOV) through various machine learning techniques using survey data from 603 consumers. Data used to create and train the machine learning models consisted of different variables such as: how often the consumer uses a delivery service; how urgently they are ordering; if delivery and order services are important to a customer; customer satisfaction; and AOV. Logistic regression and decision trees were used to identify consumers that will likely churn, while K-Means clustering provided meaningful segments of consumers within the data set. Linear regression was used to estimate AOV for targeted promotions. Findings from the above analysis showed that delivery delays had a negative effect on customer satisfaction, a majority of consumers were influenced by discounts, and weekly consumers had the highest AOV on average. The above findings have led to some recommendations that would improve on-demand delivery service providers such as: optimising delivery services, ensuring product availability during peak hours, and targeting consumers that generate AOVs for premium pricing. This research contributes to a better understanding of consumer behaviour in the field for academics and can provide practical solutions for the business side of the on-demand marketplace.

Index Terms—Quick Commerce, Customer Behavior, Churn Prediction, Customer Segmentation, Machine Learning, K-Means Clustering, Average Order Value (AOV)

I. INTRODUCTION

Quick commerce has become very popular in urban areas with platforms providing delivery within an hour experiencing more than 35 percent year-on-year growth in India; nonetheless, there are still numerous platforms that continue to experience substantial amounts of customer churn. The causes behind customer churn typically include: the inability to fulfill delivery promises, customers' continuous use of pricing promotions and their switching from one application to another

for product availability and speed. To reduce churn rates, it is important for a quick commerce platform to understand why customers discontinue business with them, in order to implement operational and marketing strategies to retain those customers and see overall greater revenue generation. Despite the increasing need for businesses to understand how customers are responding to quick commerce, most research on this topic addresses customer churn individually or customer segmentation individually or average order values (AOVs) individually; therefore, the large amount of prior research does not provide practical guidance through churn prediction, customer segmentation, or estimating average order values (AOVs). This research utilizes machine learning techniques to a data set collected via an online survey methodology, in order to provide insights into customer churn, segmentation, and average order value (AOVs), which may assist in developing strategies to increase revenues generated through the resale of products on quick commerce platforms.

II. LITERATURE REVIEW

This article presents an overview of the impact that Quick Commerce (Q-commerce) is having on retailing today, from providing instant gratification rather than scheduled delivery service. This literature review develops an understanding of all four areas of research- Q-commerce's market development, infrastructure, consumer psychology and socio-economic implications to date, as required by this literature review.

- Theme: Market Drivers and Their Evolution The catalysts for transitioning to Q-commerce include widespread internet coverage and COVID-19, which helped to normalize the use of online grocery shopping. Ranjekar and Roy (2023) discuss the steps involved in going from traditional kirana stores to the "third generation" of instant delivery, with a multibillion-dollar valuation achieved in less than three years. Goyal (2024) discusses the adoption of smartphones (with a global user base exceeding one billion) and government programs (such as UPI) as foundational factors.
- Theme: Operational Infrastructure and Technology An effective operational infrastructure and

technology is at the heart of Q-commerce. The authors Ranjekar and Roy (2023) identified the need for an Order Management System (OMS) that processes an incoming order within five minutes in order to provide sufficient time to complete the last mile delivery. The authors also provide information on the shift toward the use of Robotics as a Service (RaaS) and automated storage within "dark stores" in order to address surges in demand. Siddiqui (2025) states that while automation can lead to increased efficiencies, it brings about risks associated with high initial capital investments and issues relating to sustainability (in relation to packaging waste).

- Theme: Consumer Behavior and Psychology The main motivation for use and time is self-explanatory; however, psychologists are now finding a range of ways to understand consumer behavior and how they work together. In his research, Sheikh (2025) found that almost all (i.e., 98 percent) participants identified time savings as one of their greatest motivators; however, delivery charges are one of the most significant deterrents to the actual use of online retailers. Goswami and Kumari (2024) state that ultra-rapid delivery creates a desire to purchase on impulse, and therefore decreases the amount of time available to make a decision on the purchase. Ambaliya et al. (2025) also point out that customer service and order accuracy (i.e., satisfaction is almost 72 percent for these aspects) are now as critical as delivery speed.
- Theme: Socio-Economic Impact and Sustainability Q-commerce creates a substantial number of jobs through its high-volume/gross merchandise business model (Kearney 2024), producing 62-64 jobs for INR 1 crore of gross merchandise value (GMV) generated – on par with traditional retail and very much higher than traditional e-commerce. Although they did not provide acceptable and comparable estimates to Kearney (2024), Singh (2024) and Goyal (2024) provided some estimates of the safety of gig workers versus speed in delivering (creating) environmentally friendly, small-volume, frequently-delivered products.

III. GAPS ADDRESSED

- A.Geographical Limitations: The majority of studies focus on metropolitan and Tier 1 cities while very little published research surrounding less major cities such as Tier 2 or Tier 3 cities exists.
- B.Methodological Limitations: The majority of studies have relied on using descriptive statistics for their data rather than using inferential statistics.
- C.Financial Reporting Gaps: Most of the largest startups in the sector are private companies and hence do not disclose unit economics or profitability measures other than on a very broad basis.
- D.Customer Retention Measurement Gaps: Most of the existing research has focused only on customer acquisition metrics and not on longitudinal consumer research to determine whether or not a company can remove dis-

counting programs from the marketplace without losing customers.

IV. OBJECTIVES

- General Objective - This study will examine consumer behaviors on quick commerce platforms and develop predictive models that better identify how to retain consumers, properly segment users, and optimize average order values (AOV) to implement business strategies accordingly.
- A.Predicting Customer Churn: Use a variety of machine-learning techniques to develop models predicting which users are likely to churn based on their level of satisfaction with your service, the extent to which they rely on discounts and their tendency to switch between brands.
- B.Segment Customers: Classify customers by utilizing clustering methods based on frequency of use, urgency of need, discount sensitivity, average order value (AOV), and overall satisfaction.
- C.Estimate Average Order Value (AOV): Create regression analysis to associate AOVs with customer profiles to add growth potential through targeted promotions to customers with high-value AOVs
- D.Extract Actionable Insights: Review survey responses to identify what factors affect customer behaviors such as the impact of delayed orders, their importance of receiving discounts and products, and when they are most likely to order.

V. SCOPE

- Customer Behavior Analysis: This is discussed in terms of what can be learned from survey responses regarding frequency of use, urgency of order, importance of discounts, product preferences and satisfaction ratings.
- Predictive Modeling: Machine learning models are used for predictive modeling/cart analysis and segmentation/average order value (AOV). These models include: Logistic Regression, Decision Trees, KMeans Clustering and Linear Regression.
- Actionable Insights: Research results offer insight into how companies should operate. Companies should therefore use these findings to develop their operating plan (e.g. delivery optimized, high-value user targeted, discount campaign design).
- Geographic Focus: In total, the study sampled users living in Metro, Tier-2, Tier-3 and Village Geographies across India and allows comparisons with Users in Urban Geographies and Semi-Urban Geographies.
- Academic and Practical Relevance: The methodology and findings are pertinent for research and the practical application in the quick commerce industry.

A. Limitations

- I.Survey-Based Data: The analysis primarily relies upon self-reported survey responses that can be distorted either

by the individual providing inaccurate responses or the individual being provided with inaccurate data.

- II. Proxy Churn Definition: Churn is measured using behavioral proxies instead of actual transactional data that could ultimately lead to biased definitions of the measure of churn that may produce variance in its' true meaning as defined by user behavior.
- III.Limited Feature Set: Only selected survey features were included in the analysis; other behavioral or demographic features may affect the results and issue a timeframe effect on the final result.
- IV.Sample Size: A data set of 603 users may limit the generalizability of the findings to all users within the quick commerce market in India.
- V.Model Constraints: Basic machine learning models were employed rather than more advanced models (e.g., ensemble or deep learning), which may provide greater accuracy in creating the analytical model of the dataset.
- VI.Temporal Scope: Data represents user behavior at one time; user behavior may differ throughout the year or over time depending on the seasonality of user behavior trends.

VI. METHODOLOGY

- Research Design: This study employs a survey-based quantitative research design complemented with machine learning analysis. The workflow involves:
- I.Survey Administration: A structured questionnaire was used to collect data from 603 users across Metro, Tier-2, Tier-3, and rural areas in India. The survey covered demographics, usage patterns, purchase preferences, discount importance, satisfaction ratings, and switching behavior.
- II.Data Analysis: Collected responses were processed and analyzed using Python-based tools to build predictive and segmentation models. •
- III.Experimental Modeling: Machine learning techniques were applied to classify churn risk, segment customers, and calculate Average Order Value (AOV). The design allows for understanding predicting key business metrics,behavioural patterns, and generating actionable insights for quick commerce platforms.

VII. EXPERIMENTS

A. Tools and Technologies

- The following tools and technologies were employed:
- Python version 3.13: Primary programming language for data processing, feature engineering, and model development
- Jupyter Notebook: Interactive environment for coding, visualizations, and model evaluation.
- Pandas and NumPy : Libraries for data manipulation, cleaning, and numerical operations.
- Matplotlib and Seaborn: Visualization libraries for exploratory data analysis (EDA) and reporting.

- Scikit-learn: Machine learning library for implementing logistic regression, decision trees, linear regression, and KMeans clustering.
- Column Transformer and Pipeline: For preprocessing, encoding, and scaling features efficiently.

B. Data Collection

Data were collected via an online survey designed for academic purposes. Key survey components included:

I.Demographics: Age, gender, occupation, and city type. II.Behavioral Patterns: Usage frequency, preferred order time, average order value, order urgency. III.Preferences and Satisfaction: Product categories, motivation for using quick commerce, discount importance, satisfaction with delivery, delay experience, app used, and switching behavior. IV.Sample Size: 603 respondents, providing a balanced representation of Metro, Tier-2, Tier-3, and rural users.

C. Data Preprocessing

Before analysis, the dataset underwent the following preprocessing steps: I.Missing Value Handling: Forward-fill method was applied for incomplete responses. II.Feature Engineering: [a]Average order value(AOV)Conversion:Categorical ranges converted into numeric values: LESS THAN RS.300 → 250, RS.300–600 → 450,GREATER THAN RS.600 → 700. [B]Proxy Churn Variable: Defined using dissatisfaction with delivery, reliance on discounts, and app-switching behavior. [C]Encoding: One-hot encoding applied to categorical features such as usage frequency, discount importance, city type, and app usage. [D]Scaling: Standard Scaler applied to numeric features (AOV,satisfaction rating) to normalize values for model training.

D. Analysis Methods

- Approaches for Analyzing were Conducted utilizing the following methodologies:
- I.Churn Prediction: Through the application of Logistic Regression and Decision Tree Classifier; this provides a method for classifying customers into those that are high risk of churn and low risk, evaluation metrics include: accuracy, precision, recall, F1-score and confusion matrix.
- II.Customer Segmentation: K-Means Clustering was applied to behaviour features (frequency of usage, urgency to order, discount sensitivity, average order value, satisfaction) to create 3 segments of customers. The Elbow Method was utilized to determine if 3 customers were optimal.
- III.AOV Prediction: Linear Regression was utilized for predicting the numerical average order value based on customers' usage behaviours, urgency levels and discount sensitivities, and this sample of predictions were used to determine which customers may be high value in order to target them as a strategy to increase sales.

VIII. RESULT

A. Key Results Anticipated:

The study is expected to offer valuable customer behavioral insights about the quick commerce industry that will be actionable across a variety of use-cases. Key Results Anticipated:

- **Churn Prediction:** Predicting which customers are at risk of churning based on logistic regression and decision tree models will allow platforms like yours to proactively retain those customers. As part of the validation process of the two models, we expect to derive accurate measures of the two models through their respective accuracy and F1-scores.
- **Customer Segmentation:** Customer segment clusters will be created based on customer usage frequency, urgency, price sensitivity to discounts, average order value, and overall Customer Satisfaction Rating. This will help identify high-value customers, price-sensitive customers with respect to discounts, and customers with low engagement levels.
- **Average Order Value Estimation:** Predictive insights on Average Order Value will come from linear regression models, allowing platforms to create targeted marketing efforts based on expected average order values and revenue optimization strategies.
- **Behavioral Patterns:** Analysis of customers behaviors will provide a better understanding of traditional buying habits. This includes peak ordering times, product categories and sensitivity to sales. The above insights will also play a significant role in business operational and marketing decision-making..

B. Contributions:

- **Data-Driven Framework:** This is a full-fledged approach which includes raw survey data, pre-processing, and machine-learning models which can be utilized for prototyping proposals of analysis for quick commerce.
- **Publication Potential:** Research study results may lead to publications at conferences, or in journals dedicated to data analytics, eCommerce, or consumer behaviour.
- **Decision-Support Tool:** The predictive models and segmentation method can be embraced by companies to assist in building personal marketing, retention strategies, and improved business operations.

C. Broader Impact

- **Business Optimization Using Customer Segmentation and Churn Analysis to Improve Retention, Target High Value Customers and Create Effective Promotions.**
- **Customer Satisfaction: Operational Suggestions** (e.g., improve delivery times during busy times) and guarantee that well-known products are available.
- **Industry Insights:** This report identifies a systematic way to evaluate the behaviour of consumers. This framework will allow for easy implementation across the entire Indian quick commerce sector and will help to enhance quality of service and profitability.

D. Age Distribution

- **Summary of Demographic and Behavioral Trends :** The most recent dataset indicates that the customer base is predominantly comprised of young to middle-aged adults (typically between the ages of 18 and 40 years), showing large amounts of engagement in both the 18-22 and 30-40 age ranges. The demographic split represents an opportunity for dual market appeal, focusing on both the student market and more established households. The ratio of males to females using the platform is relatively balanced, although there is a substantial portion of the population that does not disclose their gender in order to maintain their privacy. In general terms, the majority of customers use the platform "Occasionally", but that segment who use the site "Weekly" generates the greatest Average Order Value (AOV); therefore, even though the platform has done a good job acquiring customers in terms of reach, there is a clear business opportunity to increase the frequency of purchases among occasional shoppers through targeted retention strategies.
- **Operational Performance and Delivery Satisfaction** Data relating to operational performance reveals a prominent "Golden Window" for service delivery. The majority of orders occur in the morning. As such, the majority of inventory and logistics resources need to be concentrated at this time to provide appropriate service levels during the first part of the day. In addition, delivery timing is the most conclusive indication of delivery satisfaction. Those customers that never experience a delivery delay rate their satisfaction at 4.05/5, while customers that frequently experience delays rate their satisfaction at 1.82/5. Consistency in delivery is the most important factor in maintaining high levels of customer satisfaction and preventing churn.
- **Product Category and Economic Drivers** According to the business view of a platform, a primary offering as a product is Grocery and Pantry Stocking. The Grocery Category represents a more substantial percentage of users' overall orders than Electronics and Essentials Categories, indicating that the grocery category will play the most prominent role in establishing future inventory and partnership decisions. A majority of the user base is economically sensitive (over 53 percent say discounts are "Very Important"). Based on the analysis of Average Order Value (AOV), there is a clear distinction in the return from the two different types of users; users who access the platform more frequently ("Weekly") are more likely to purchase larger quantities of grocery items (AOV of approximately Rs.458), while users who access the platform less frequently ("Daily") are more likely to purchase smaller quantities of grocery items for immediate consumption (AOV of approximately Rs.421). Aligning promotional strategies with distinct shopper tendencies (i.e., volume-based discounts for weekly shoppers) may increase overall profitability of the business.

- Evaluation of Predictive Modeling and Model Accuracy** The results of the technical outcomes of the predictive modeling displayed an intricate landscape. The results of Logistic Regression and Decision Tree show the total model accuracy to be 84.5 percent and 82.3 percent, respectively – impressive on the surface, yet, upon deeper inspection, both models have an enormous ‘Accuracy Trap’. The churn class (Class 0) is a small portion of the dataset and the number of users that have not churned constitute the majority of the users measured. Consequently, both Logistic Regression and Decision Tree prediction recall is 0.00 for the churn class (Class 0). In other words, both models achieved high accuracy through the default prediction of “No Churn”, therefore not providing any use to proactively retaining customers (i.e., predicting the likelihood of a user to churn). To improve these results, advanced sampling techniques such as SMOTE or undersampling must be employed to enable the models to correctly identify users at risk of churning.

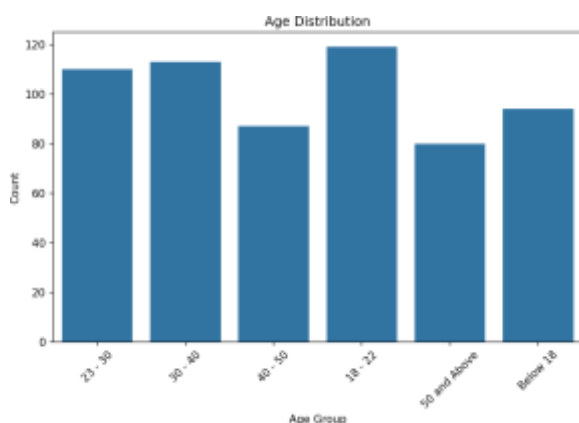


Fig. 1. Customer Age Groups

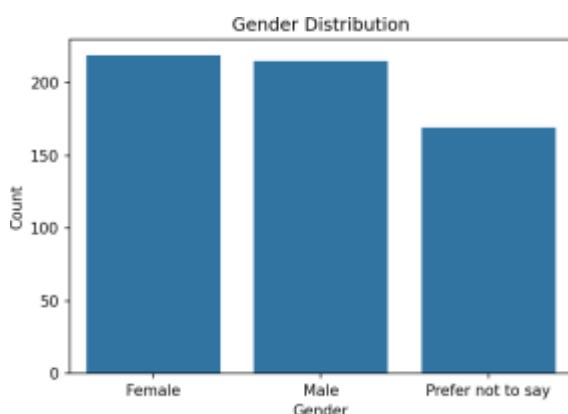


Fig. 2. Customer Gender Distribution

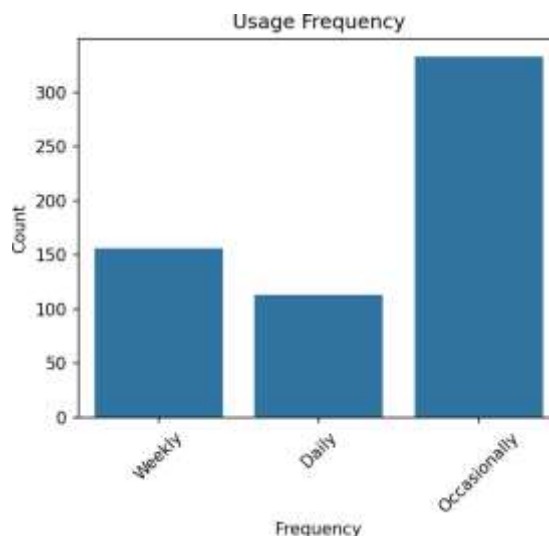


Fig. 3. Customer Usage Frequency

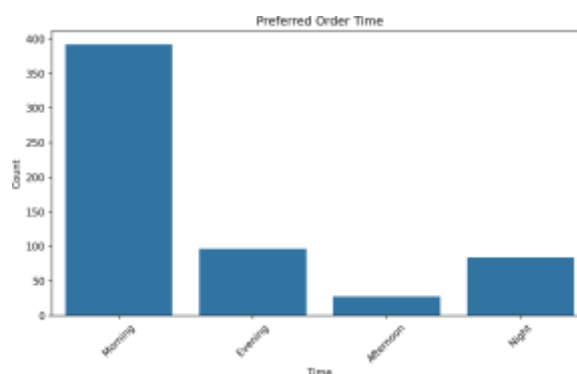


Fig. 4. Customer Preferred Order Time

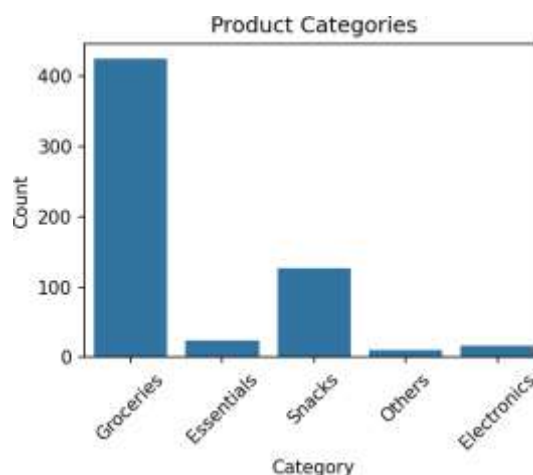


Fig. 5. Order Product Categories

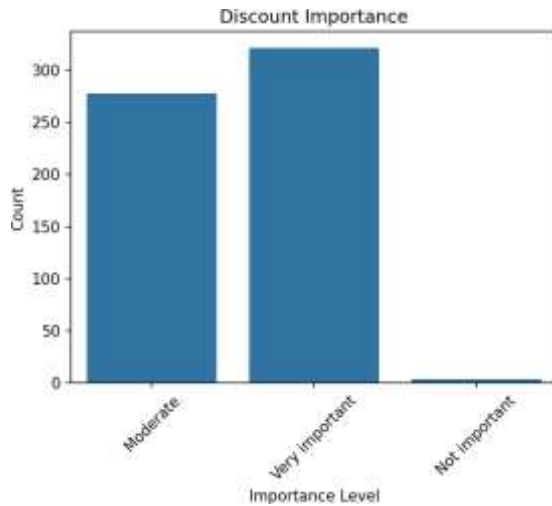


Fig. 6. Discount Importance

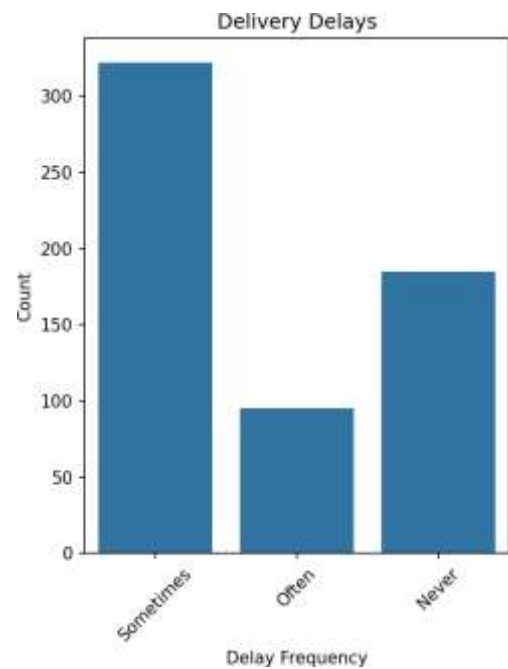


Fig. 8. Distribution of delivery delay frequency among customers

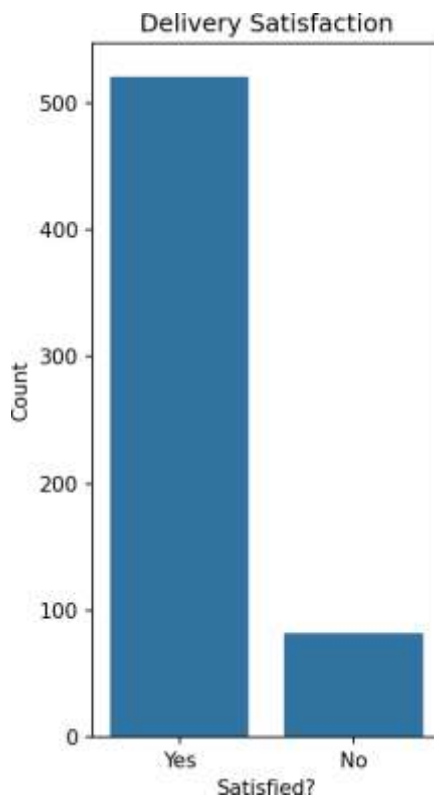


Fig. 7. Customer Delivery Satisfaction

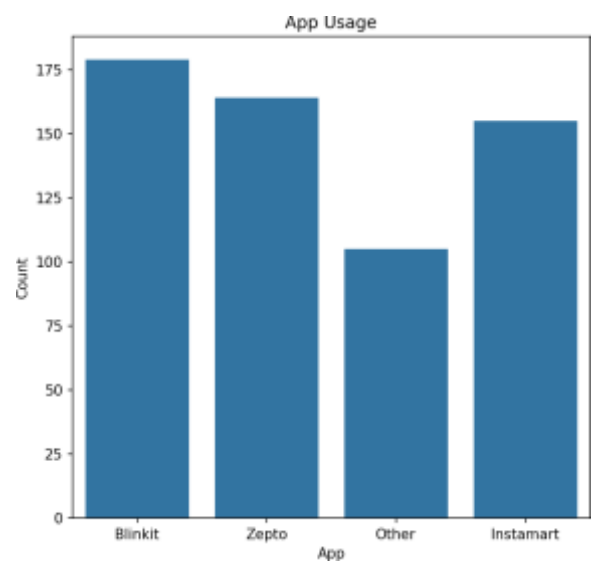


Fig. 9. Customer app usage distribution across Blinkit, Zepto, Instamart, and Other categories

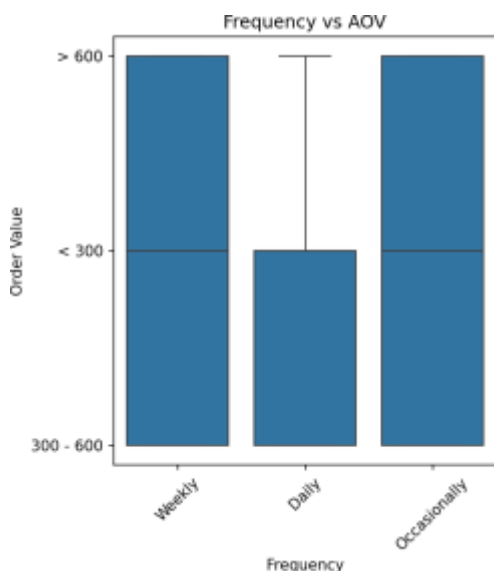


Fig. 10. Average order value (AOV) comparison across different purchase frequencies

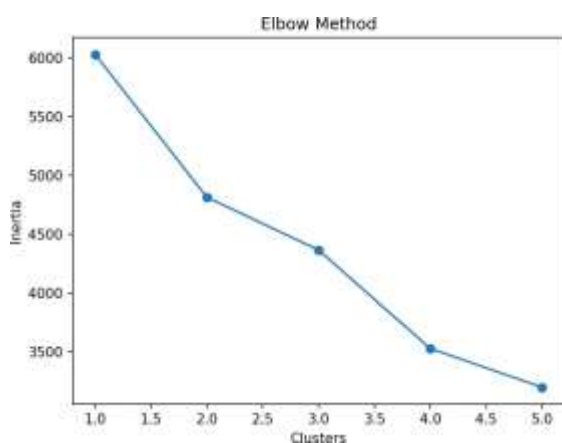


Fig. 11. Elbow method showing optimal number of clusters

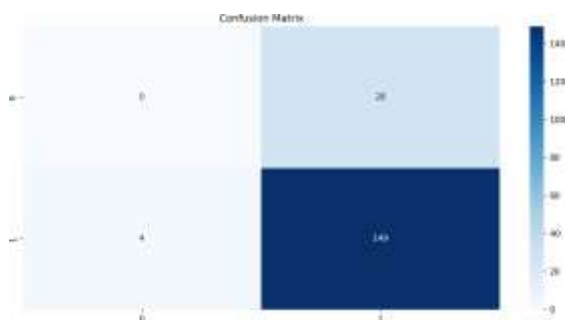


Fig. 12. Confusion matrix for classification results

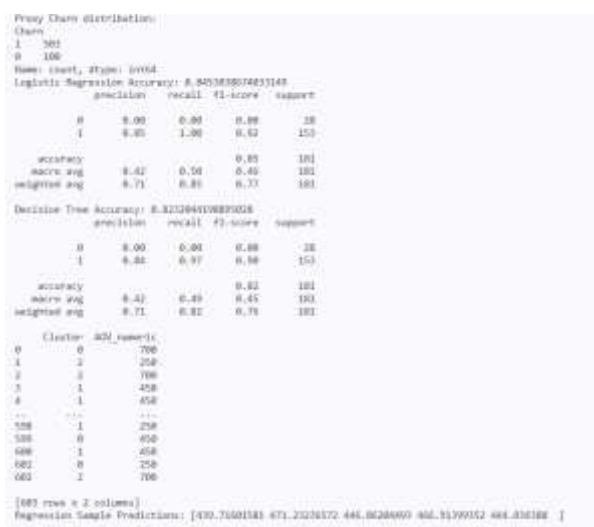


Fig. 13. proxy churn distribution

TABLE I
PROXY CHURN DISTRIBUTION

Churn	Count
1 (Churned)	503
0 (Not Churned)	100

TABLE II
LOGISTIC REGRESSION CLASSIFICATION METRICS (ACCURACY = 0.8453083674033149)

Class	Precision	Recall	F1-score	Support
0 (Not Churned)	0.00	0.00	0.00	28
1 (Churned)	0.85	1.00	0.92	153
Accuracy	0.8453083674033149 (181 samples)			
Macro Avg	0.42	0.50	0.46	181
Weighted Avg	0.71	0.85	0.77	181

TABLE III
DECISION TREE CLASSIFICATION METRICS (ACCURACY = 0.8232044198895028)

Class	Precision	Recall	F1-score	Support
0 (Not Churned)	0.00	0.00	0.00	28
1 (Churned)	0.84	0.97	0.90	153
Accuracy	0.8232044198895028 (181 samples)			
Macro Avg	0.42	0.49	0.45	181
Weighted Avg	0.71	0.82	0.76	181

TABLE IV
CLUSTER-WISE AVERAGE ORDER VALUE (AOV)

Cluster	AOV (Numeric)
1	250
2	450
3	450
4	450
...	...
598	250
599	450
600	250
601	250
602	700

TABLE V
SAMPLE REGRESSION PREDICTIONS

Observation	Predicted Value
1	439.71601581
2	471.23236572
3	446.86204493
4	466.91399352
5	444.03438800

IX. CONCLUSION

The findings from the current study indicate that this company has a solid core demand but also has significant room for improvement on the frequency of use by current users. It is critical for this organization to ensure that morning delivery schedules are stabilized, allowing for good customer satisfaction without the overwhelming negative feelings produced when customers experience delays. In addition, a loyalty

program that targets "Occasional" users in order to turn them into "Weekly" users will be very effective due to the amount of discounting currently required. Finally, technical changes must be made in order to be able to retrain predictive models using balanced data; otherwise, the ability to forecast and minimize customer churn will be nothing more than a theory. Aligning operational capacity with morning volume peaks and improving predictive analytics will allow this platform to move from wide-ranging occasional usage to long-term, high-value customer loyalty.

ACKNOWLEDGMENT

Priyanka Goraksha Bhandare, the creator of this paper, would first like to thank Dr. Faizur Rashid, her Academic Advisor at JSPM university Pune, for providing valuable guidance, constructive criticism, and ongoing support throughout my project. The advice and support have greatly impacted the quality and direction of this work. Priyanka would also like to thank all the participants in her survey including students, teachers, relatives, friends and family for taking the time to respond to her survey. Without their valuable input, there would not be. The author would like to thank the members of the Faculty and students of the Master of Computer Applications (MCA) Program at JSPM University for providing their support, input and encouragement during the development of this document. JSPM University has provided an excellent environment and resources for Priyanka to successfully complete her research paper. The author would like to thank her family and all well wishers for their unwavering support and encouragement throughout this entire research project. Thank you to all who have provided her the strength and inspiration to complete her research project.

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