Executive Report

Customer Purchase Behavior Analysis in E-Commerce

1. Background

In the competitive landscape of e-commerce, understanding customer behavior is crucial for optimizing marketing, personalizing services, and reducing churn. This analysis investigates the purchasing behavior of over 49,000 unique customers based on 250,000 transactions. The dataset includes key attributes such as transaction dates, purchase amounts, product categories, returns, payment methods, age, gender, and churn status.
The central goal of this analysis was to uncover patterns in purchasing behavior, payment preferences, and churn trends segmented by gender and age. These insights aim to support targeted strategies for customer retention and revenue growth.

2. Key Insights

A. Gender-Based Analysis

- **Customer Distribution**: Nearly equal number of male and female customers (≈50% each).
- **Churn Rate**: Similar churn rates across genders (~20% within each gender group).
- **Order & Revenue Behavior**: Male and female customers have nearly identical average order counts (≈5) and mean order values (~13,700 units).

Insight: Gender does not significantly influence churn or purchase volume; both segments behave uniformly in terms of engagement and value.

B. Age-Based Analysis

- **Age Distribution**: Fairly even distribution from age 21 to 70; fewer customers aged 18–20.
- **Purchasing Power**:
    - **Highest Average Purchase**: Age group 61–70 (~14,248 units average purchase).
    - **Lowest Churn**: Slight variations, but no major difference across age groups.
    - **Returns**: Fairly consistent return behavior across age groups.

Insight: Older customers (51–70) tend to spend slightly more per order. No age group shows a significant anomaly in churn, indicating consistent retention challenges across all segments.

C. Payment Method Preferences

- **Distribution**: Cash, Credit Card, and PayPal are equally preferred (≈33% each).
- **By Gender**:
    - Female and male customers show no major deviation in payment method preferences.
- **By Age Group**: Uniform distribution of payment methods across age groups.
- **Revenue by Payment Method**:
    - **Highest Revenue**: Credit Card (33.58%)

- **Followed By**: PayPal (33.33%) and Cash (33.09%)

Insight: All payment methods contribute nearly equally to revenue. No demographic-based preference emerged strongly enough to warrant dedicated optimization.

D. Churn Analysis

- **Overall Churn Rate**: ~20% of customers are churned.
- **Churn Distribution**:
  - Equally distributed across genders and age groups.
  - No specific demographic segment is disproportionately churn-prone.

Insight: Churn is not driven by demographic variables. Behavioral data (e.g., order frequency, recency, returns) may better predict churn.

3. Results Summary

Metric	Observation
Total Customers	49,661
Average Orders per Customer	~5
Churn Rate	~20%
Gender Split	≈50/50
Age Range	18–70 (mostly 21–70)
Revenue by Payment	≈33% split across methods
Highest Spending Age Group	61–70
Most Popular Product Category	Not specified in current analysis
Returns	Present in all groups without strong trends

4. Recommendations

Customer Retention Strategy

- **Introduce Loyalty Programs** targeting all demographics equally, as churn is not demographic-specific.
- **Implement RFM (Recency-Frequency-Monetary) Segmentation** to identify at-risk customers for targeted engagement.
- **Monitor Return Behavior**: Customers with higher return rates could signal dissatisfaction. Offer feedback incentives post-return.

Payment Optimization

- Since no payment method dominates, ensure frictionless checkout for all methods.

- Promote loyalty cards or discounts for digital payments to streamline repeat purchases.

Age-Specific Marketing

- **Older Age Groups (51–70)** spend more per order—target them with premium product promotions and exclusive discounts.
- **Younger Segments (21–30)** represent large volumes—engage them via social campaigns or bundles that encourage higher cart value.

Data Expansion Opportunities

- Consider incorporating product category analysis to link churn with specific types of purchases.
- Use machine learning on behavioral features (purchase frequency, recency, returns) to build predictive churn models.