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# Data Glacier – Final Project

## Week 11: EDA Presentation

### Data Analyst: Cross-Selling Recommendation

-by Asha K C

LISUM43

Date: 20-May-2025

# Agenda

- Team Details
- Problem Statement
- Business Understanding
- GitHub Repo Link
- EDA Summary
- Final Recommendations

# Team Details



**Team Member Details: Individual project (no team)**

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**Country:** India

**Company:** Data Glacier

**Specialization:** Data Analyst

# Problem Statement



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The XYZ bank is having difficulty cross-selling its products to existing customers. Customers are not buying additional products sold by their bank. Hence, data analysts must provide the information required to enhance their cross-selling methods.

## **Dataset provided:**

1. Train.csv (1,36,47,309 entries) – This dataset is 2.13 MB. There are a total of 48 features. Features mainly consist of customer code, age, gender, income, address, products held, seniority, active/passive index,...

# Business Understanding



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The problem statement indicates that XYZ Bank excels at acquiring new customers but struggles with customer retention and service diversification. Cross-selling involves offering complementary or related products to current customers.

For example:

- A customer with a checking account might be offered a credit card or a retirement savings plan.
- A customer with a home loan could benefit from the option to acquire a safe deposit box or an insurance product.

## Cross-sell vs Upsell

	Definition	Use case
Cross-sell	Selling additional products to customers	Someone has a checking account → offers a credit card
Upsell	Selling a higher-ed or upgraded version of a product	Customer has a basic savings account → suggest a premium account with benefits

# GitHub Repository link



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[https://github.com/Asha-KC-07/Data-Glacier-Internship-2025--  
-LISUM43/blob/main/Week%2010%20-  
%20Data%20Analyst Cross-  
selling%20recomendation/EDA\\_v1.ipynb](https://github.com/Asha-KC-07/Data-Glacier-Internship-2025--LISUM43/blob/main/Week%2010%20-%20Data%20Analyst%20Cross-selling%20recomendation/EDA_v1.ipynb)



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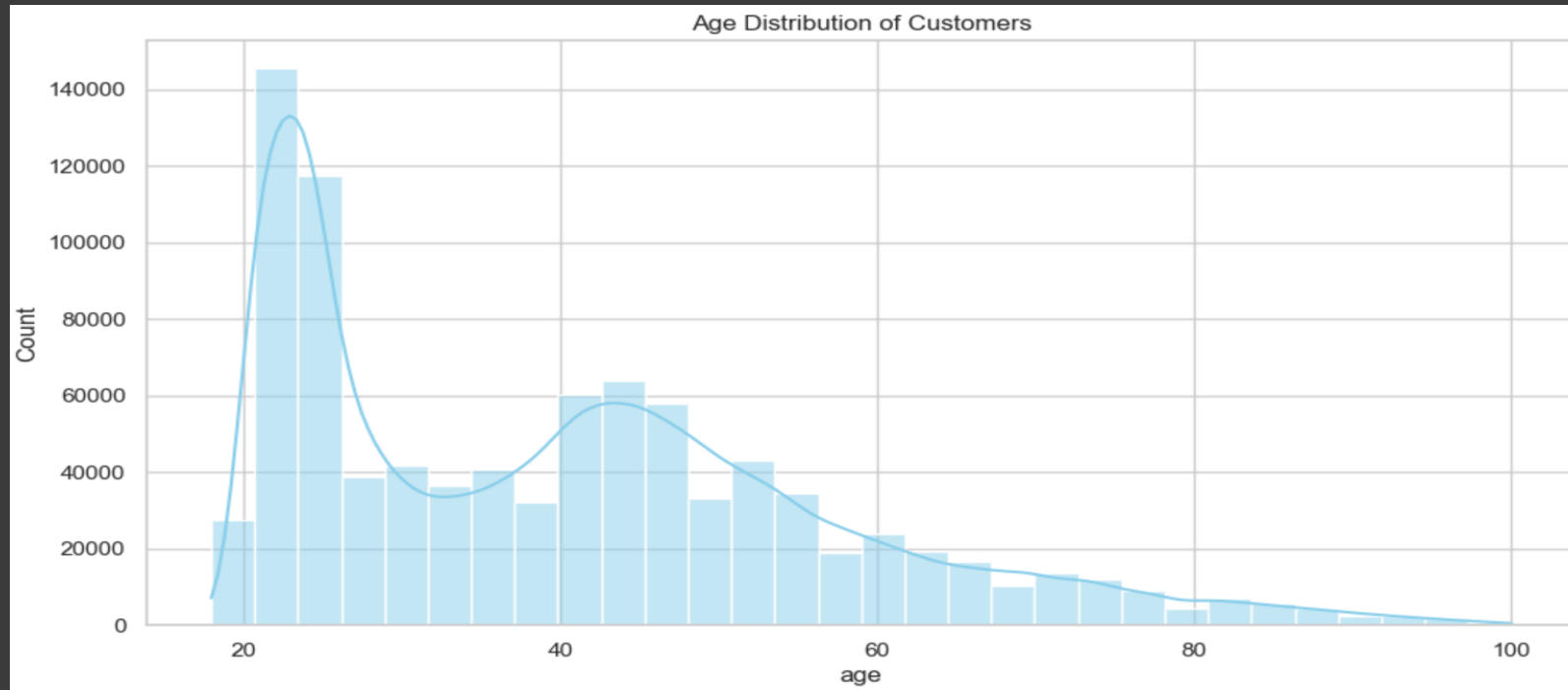
# EDA Summary

# 1. Demographics Analysis



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## 1. Age Distribution Histogram

- Most customers fall between **25 to 60 years**.
- There's a visible right skew due to older age values.
- Minor counts exist for extremely old ages (over 90).

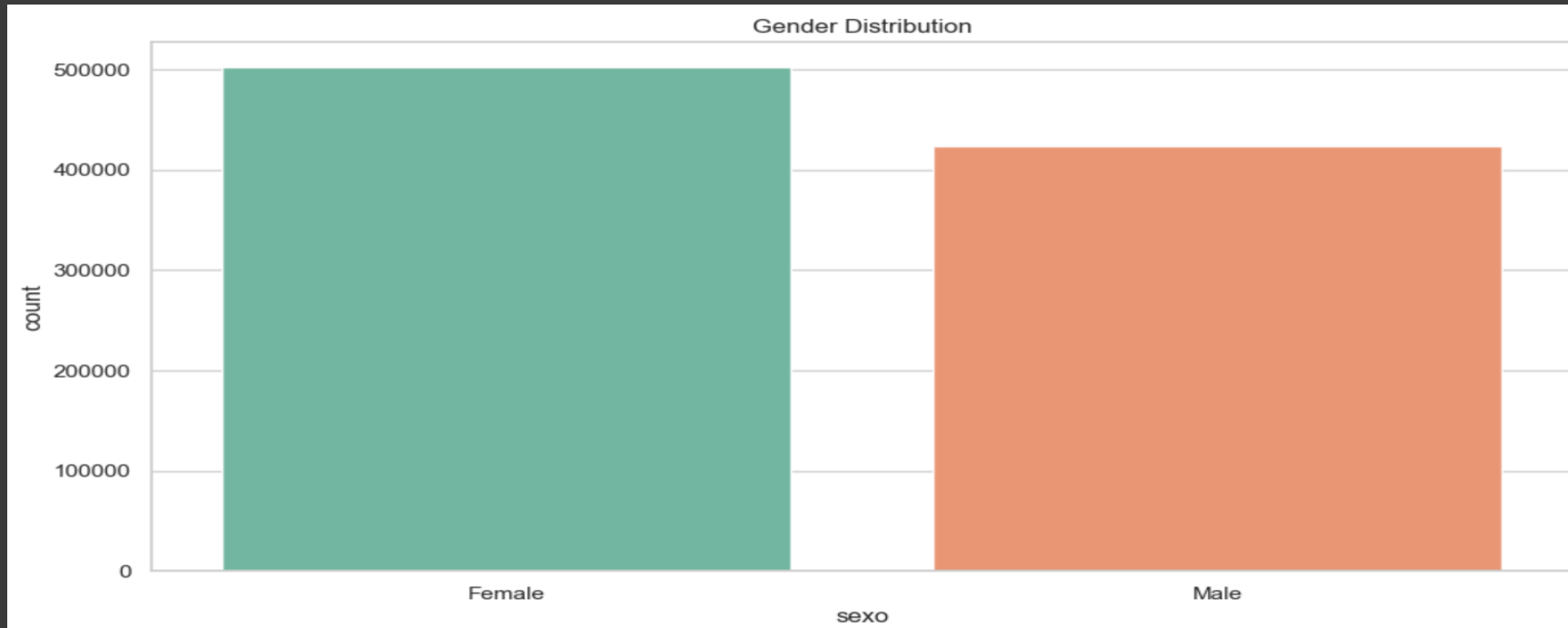


# 1. Demographics Analysis



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## 2. Gender Distribution

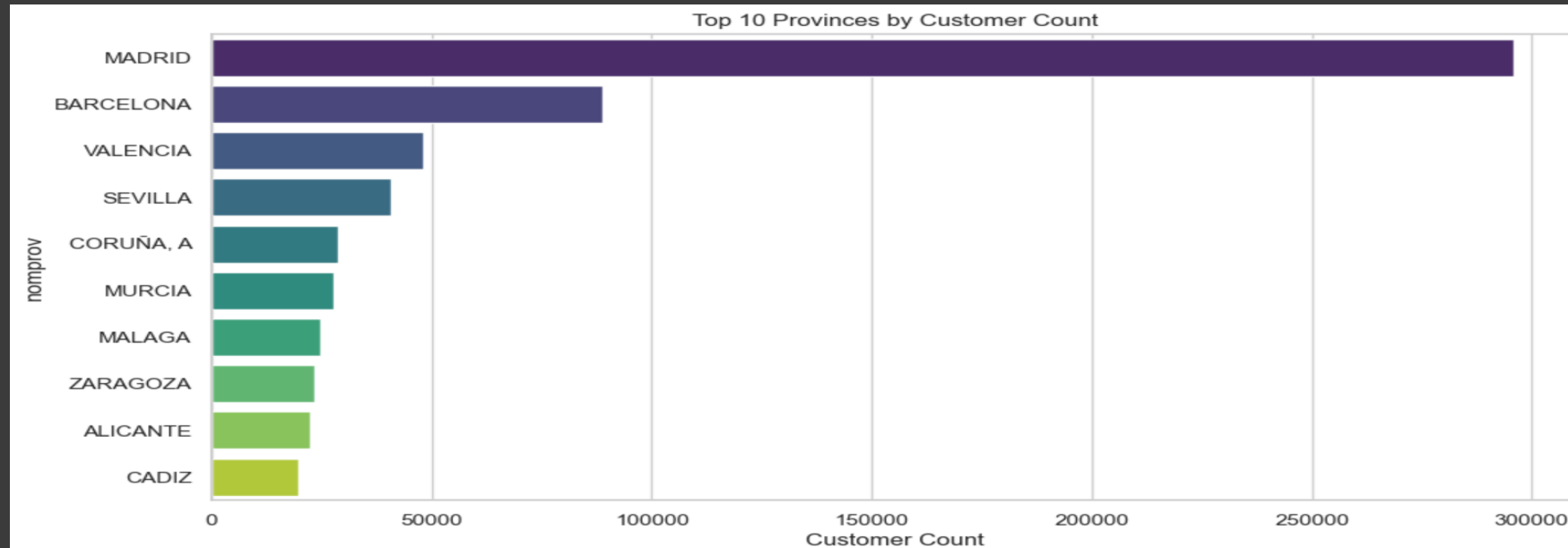
- Slightly more females than males.
- Imbalance isn't significant but could affect segment-specific targeting.

# 1. Demographics Analysis



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## 3. Top 10 Provinces by Customer Count

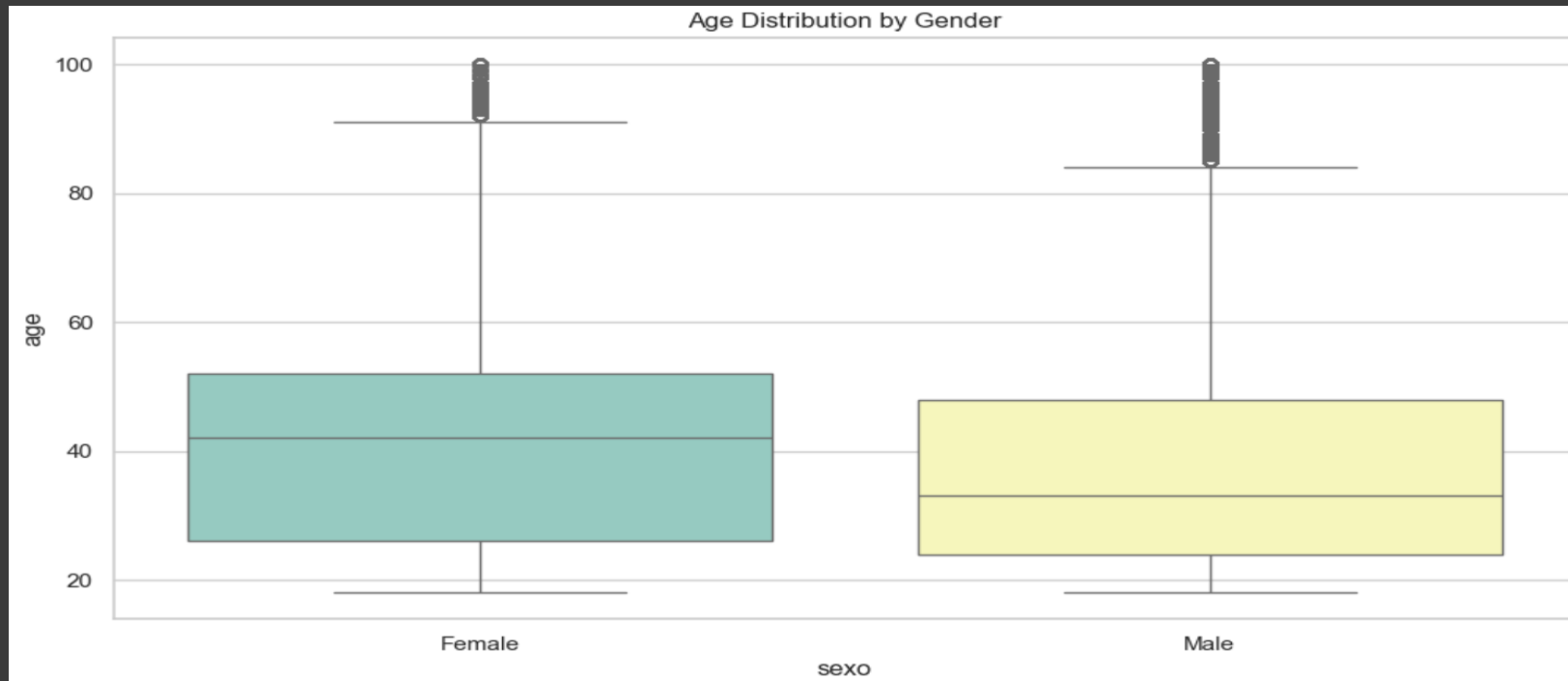
- Certain provinces (like **Madrid**, **Barcelona**, etc.) dominate the customer base.
- Indicates geographic concentration — great for region-specific marketing strategies.

# 1. Demographics Analysis



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## 4. Age by Gender Boxplot

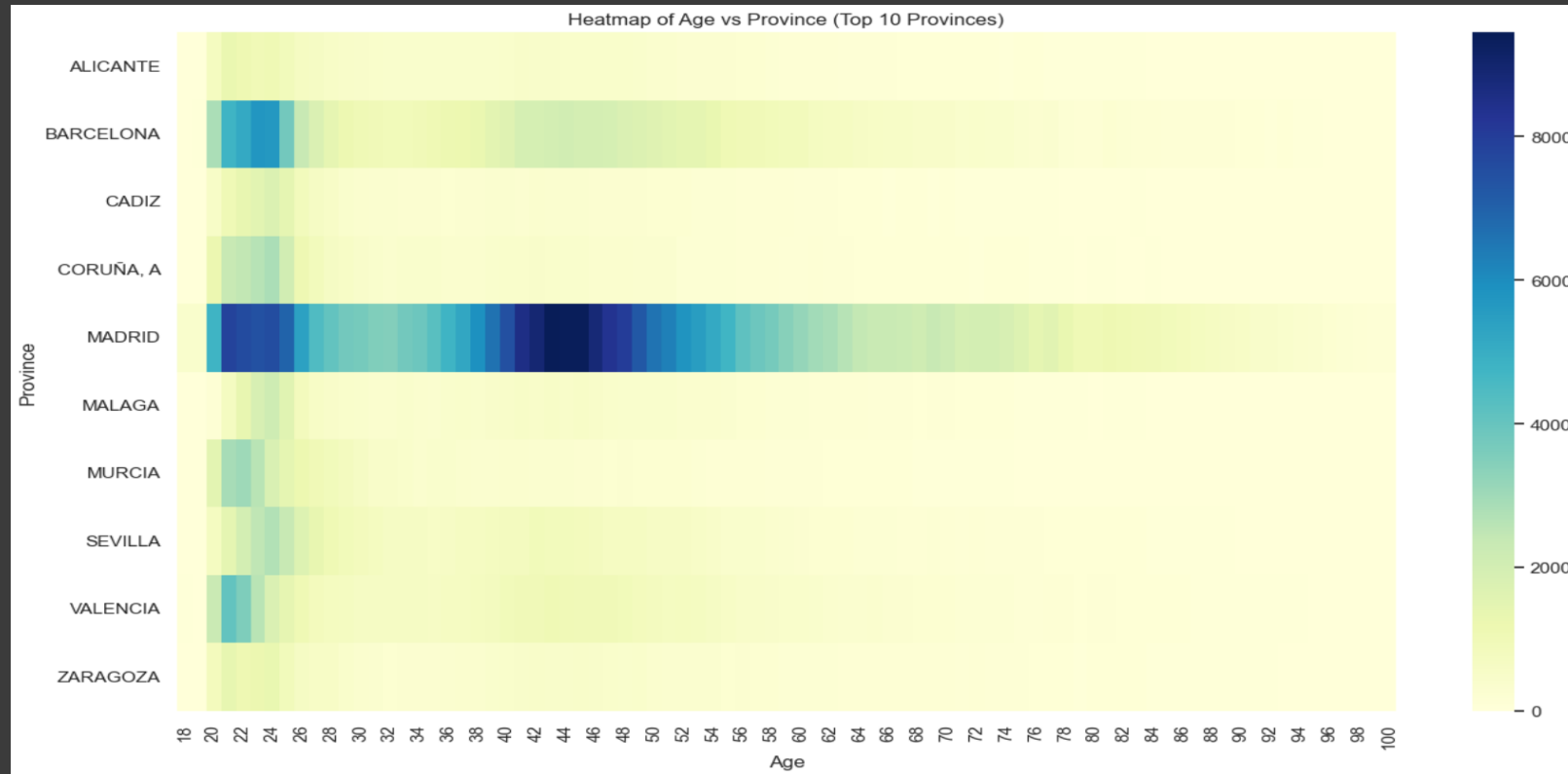
- Female customers tend to be **slightly older** on average.
- The age spread is similar for both genders but has a few more high-age outliers.

# 1. Demographics Analysis



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## 5. Heatmap of Age vs. Province

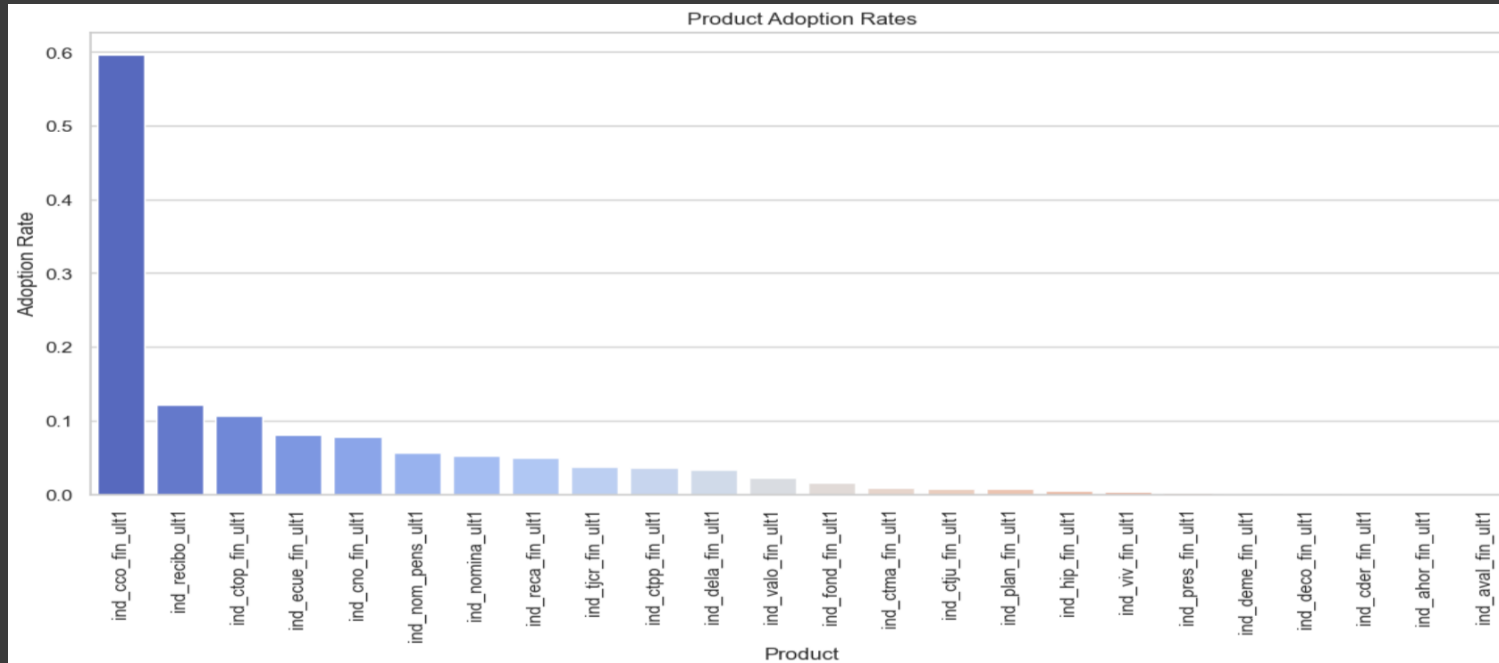
- Each province shows a **strong concentration around ages 40-55**.
- Useful to identify which regions have a younger vs older customer base.

## 2. Product Adoption Rates:



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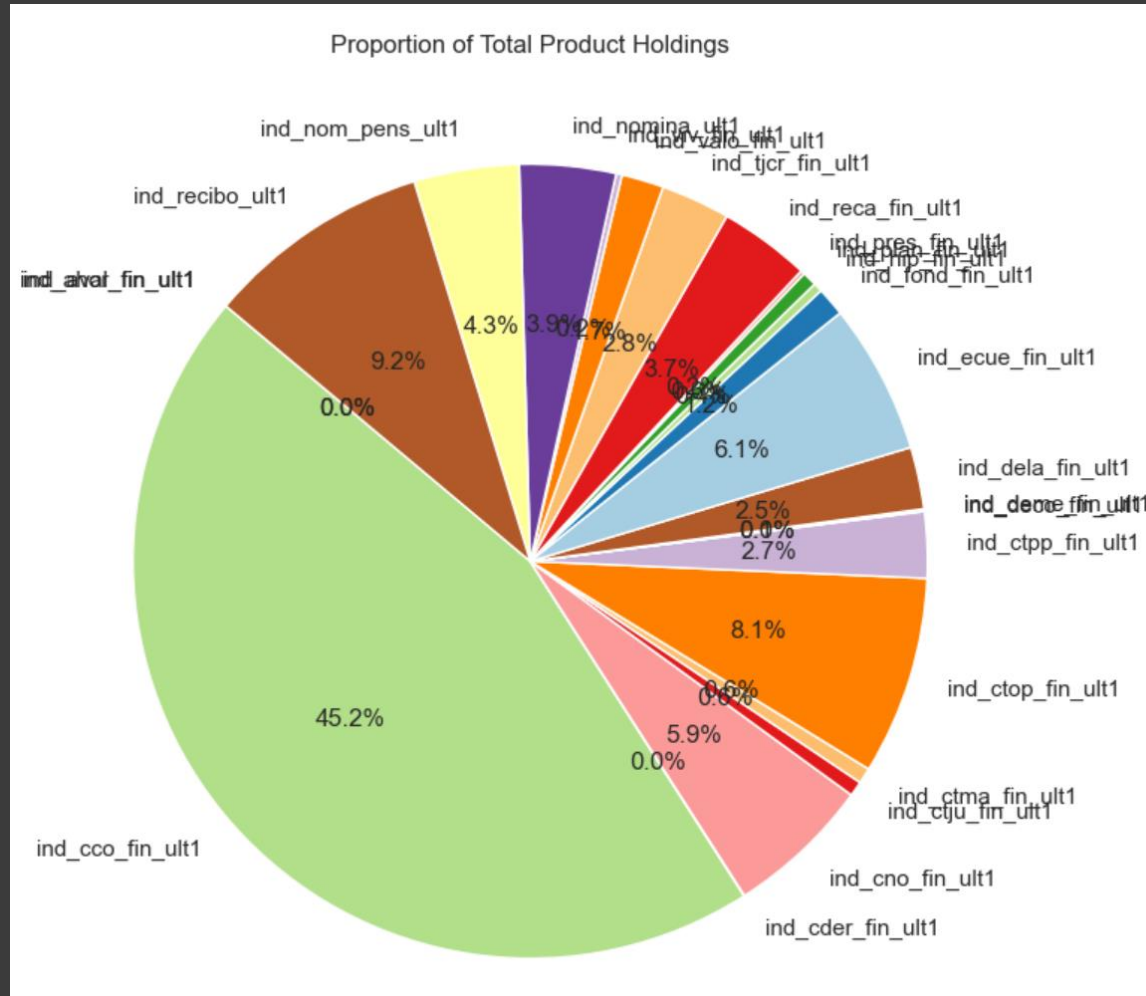
- Most commonly held products:
  - **ind\_recibo\_ult1 (12.1%)**: Utility Bill Payments
  - **ind\_nom\_pens\_ult1 (5.5%)**: Pension Deposits
  - **ind\_nomina\_ult1 (5.1%)**: Salary Deposits
  - **ind\_tjcr\_fin\_ult1 (3.8%)**: Credit Cards
- Least commonly held products:
  - **ind\_plan\_fin\_ult1, ind\_pres\_fin\_ult1, ind\_viv\_fin\_ult1**: All below 1%

## 2. Product Adoption Rates:



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Pie Chart: Total Product Holdings

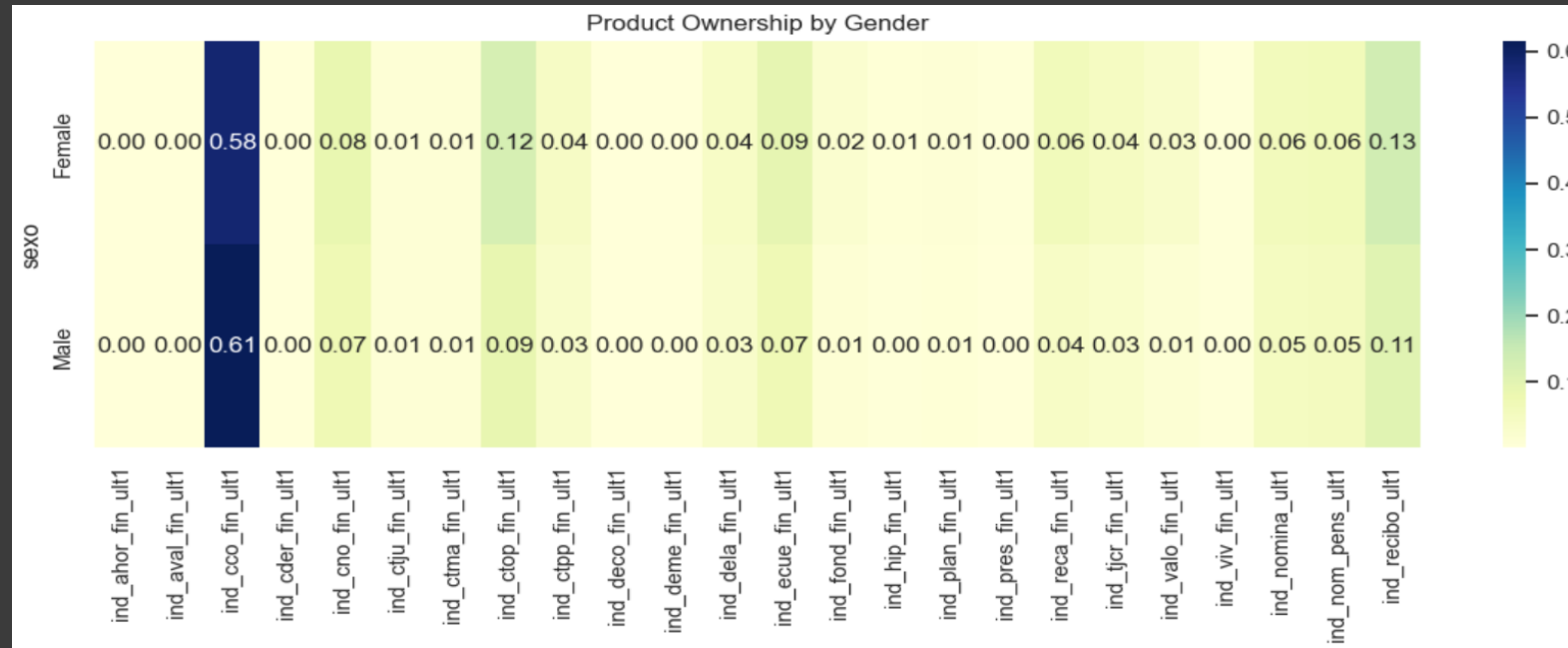
- A few product types dominate the customer portfolio space.
- Products like **salary/pension deposits** and **recurring payments** represent the bulk of ownership.

### 3. Product Ownership by Segment:



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#### 1. Gender-Based Ownership

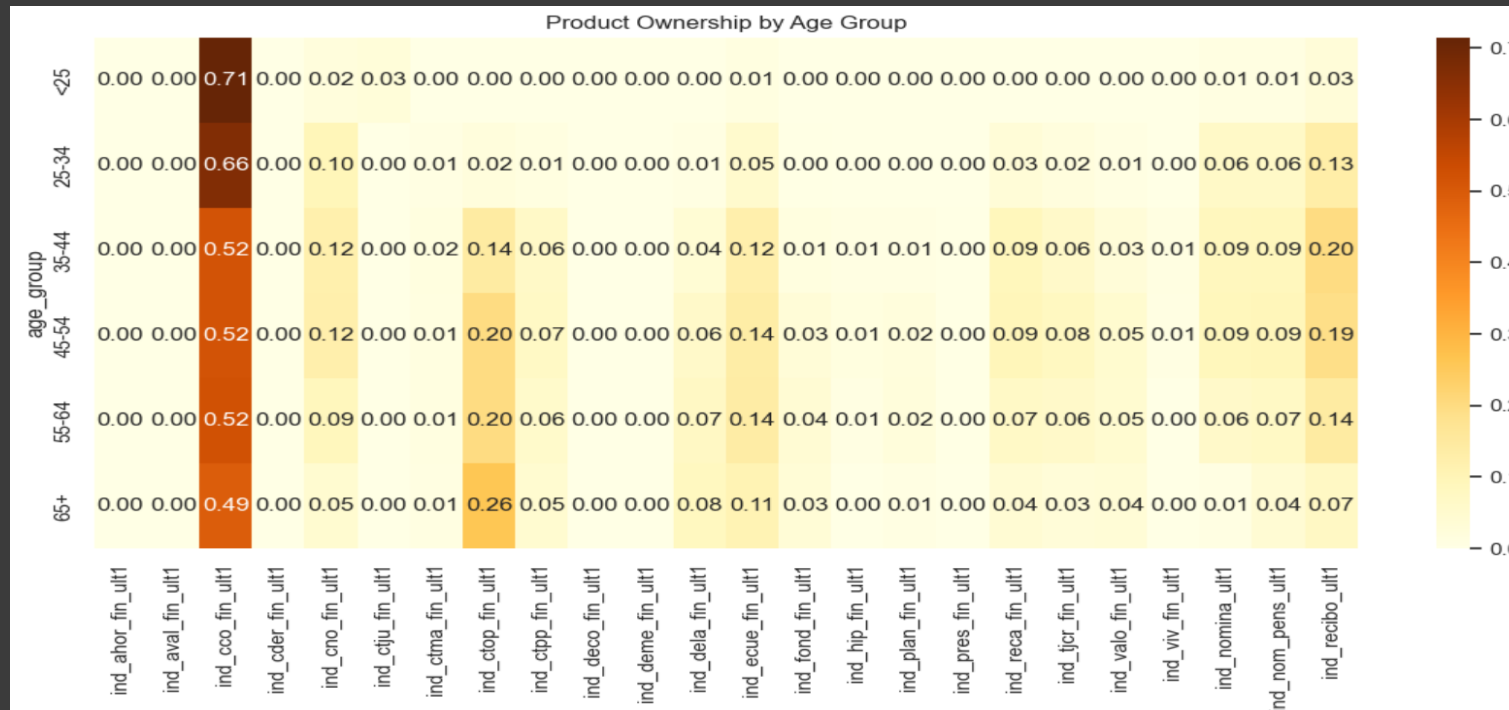
- **Females** slightly lead in products like:
  - **ind\_nomina\_ult1** (salary deposits)
  - **ind\_recibo\_ult1** (recurring bill payments)
- **Males** show marginally higher ownership in:
  - Investment-related products (**ind\_valo\_fin\_ult1**, **ind\_fond\_fin\_ult1**)

### 3. Product Ownership by Segment:



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#### 2. Age Group Trends

- Young adults (<25) rarely hold any product.
- Ages 35-54 dominate across almost every product — especially:
  - Salary deposits ([ind\\_nomina\\_ult1](#))
  - Credit cards ([ind\\_tjcr\\_fin\\_ult1](#))
- Older groups (65+) tend to show less ownership of credit or investment products.

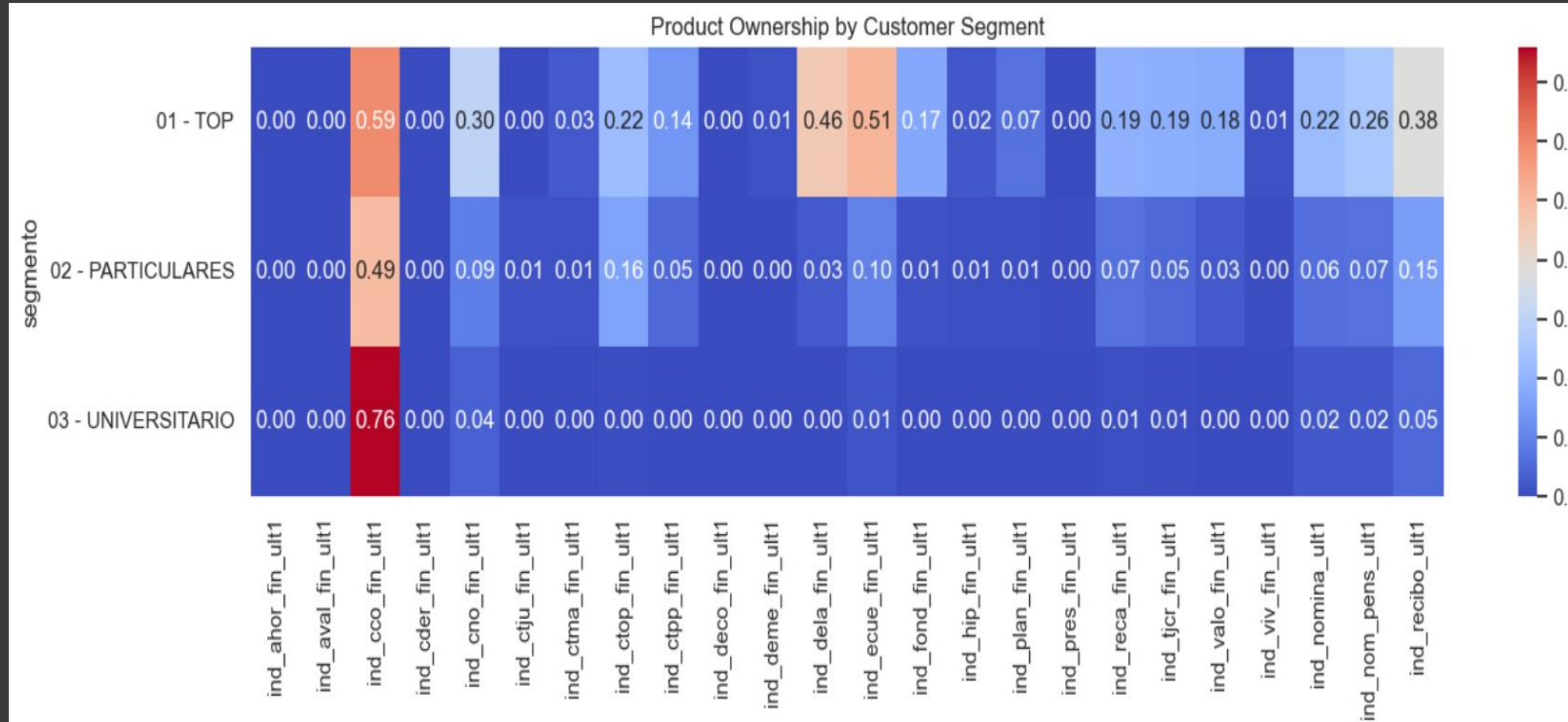


### 3. Product Ownership by Segment:



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#### 3. Segment-Based Trends

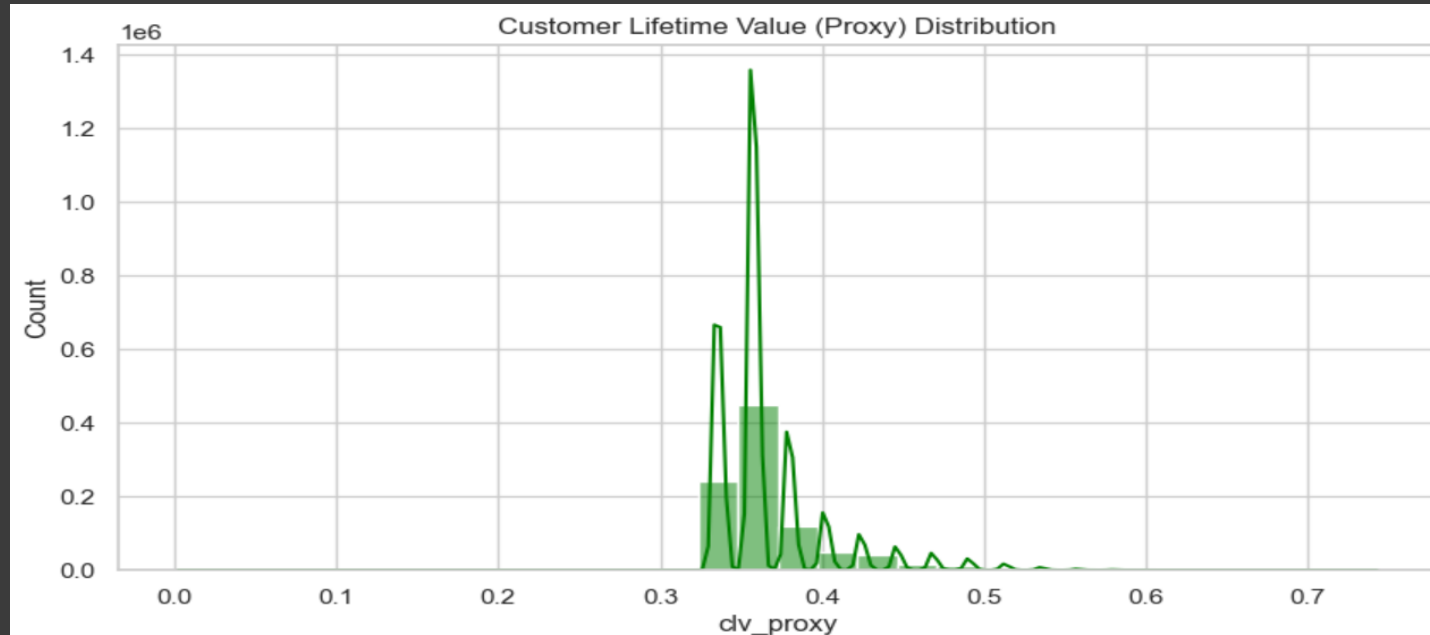
- **segmento** indicates customer types like "01 - VIP", "02 - Individuals", "03 - College students":
  - **VIPs** show highest ownership in multiple financial products, especially credit and investment tools.
  - **College students** exhibit minimal product ownership — mostly basic accounts.

## 4. Customer Lifetime Value Proxies



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### 1. Distribution of CLV Proxy

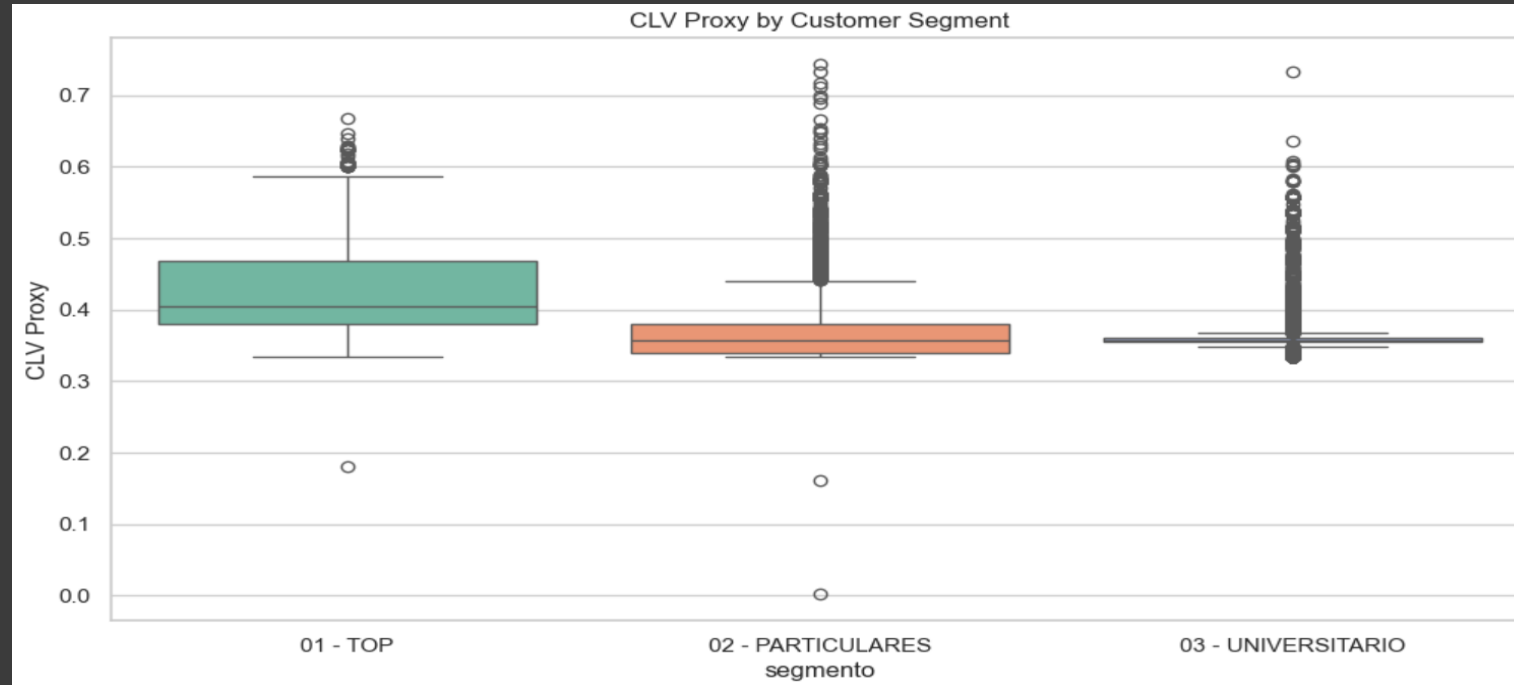
- Most customers fall within **mid** CLV proxy scores.
- Right-skewed: a smaller segment shows high-value potential (top 10–15%).

## 4. Customer Lifetime Value Proxies



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### 2. Boxplot by Segment

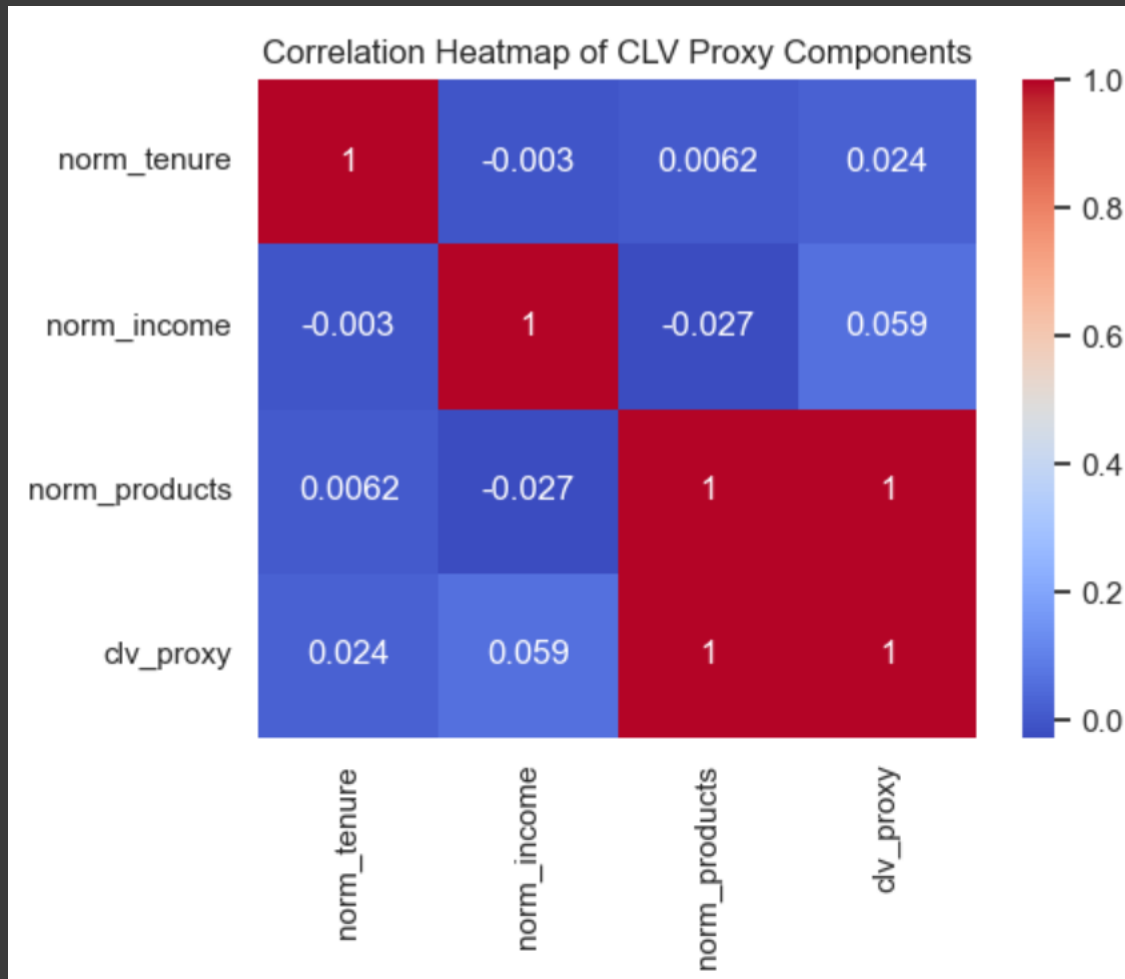
- VIPs (01 - VIP) have the highest median and spread of CLV.
- College students (03 - UNIVERSITARIO) score lowest in CLV — expected due to low tenure, product count, and income.
- Mass Market Individuals (02 - PARTICULARES) span the full spectrum, indicating a diverse customer base.

## 4. Customer Lifetime Value Proxies



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### 3. Correlation Heatmap

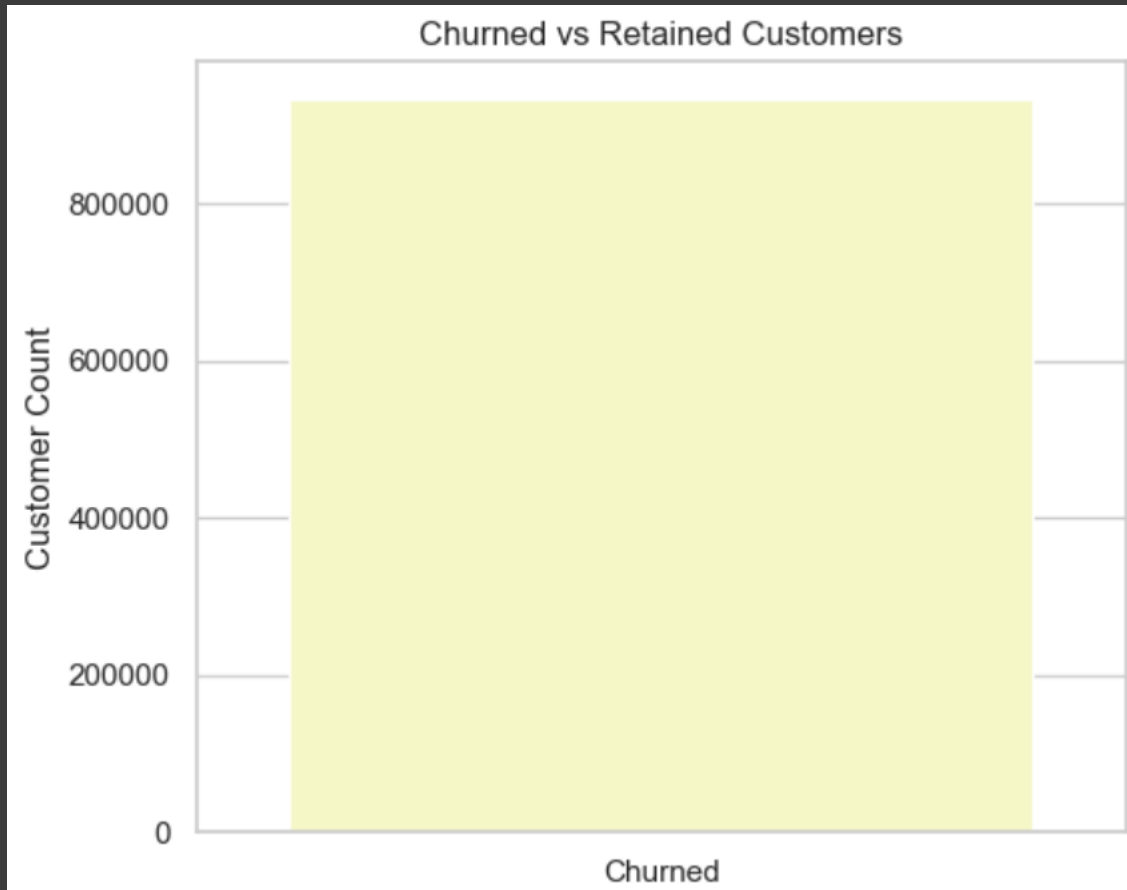
- Product count (**norm\_products**) is most strongly correlated with overall CLV score.
- **Income and tenure** also contribute but less dominantly.

## 5. Churn Indicators



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### 1. Churned vs Retained Customers

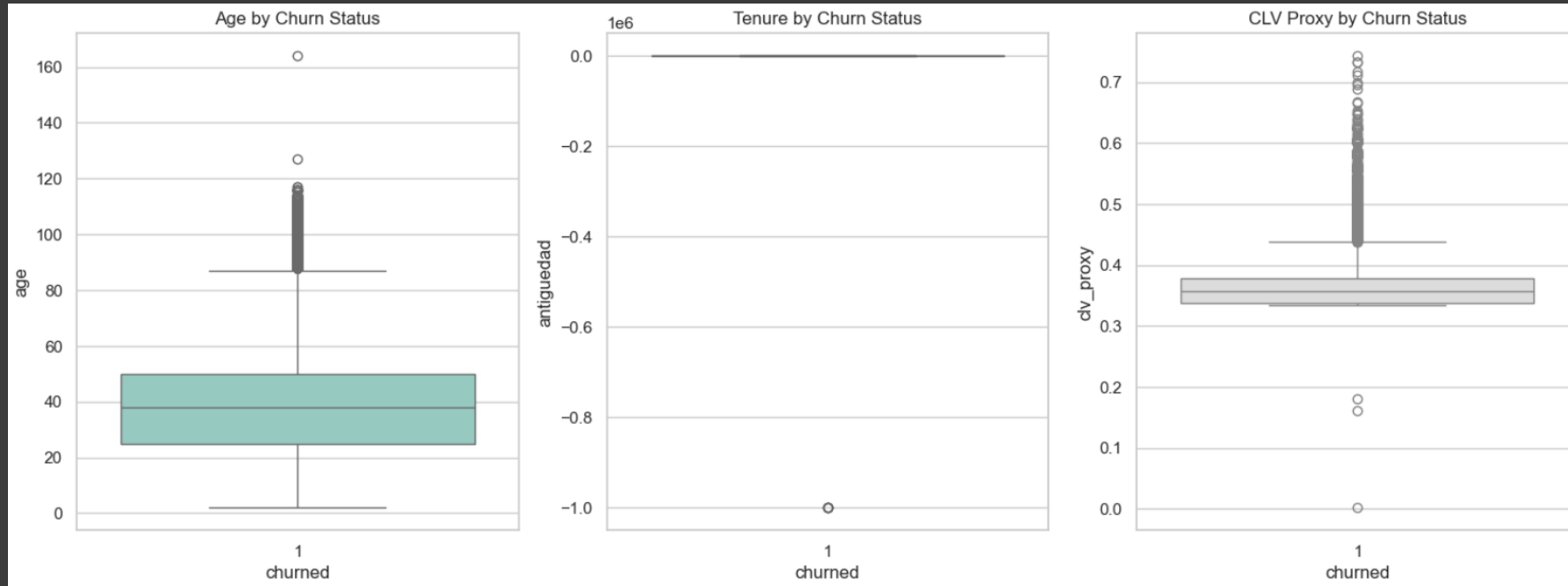
- A **very small fraction** of the customers is marked as "churned".
- Indicates the dataset mostly includes **active customers**.

# 5. Churn Indicators



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## 2. Age, Tenure, and CLV Comparisons

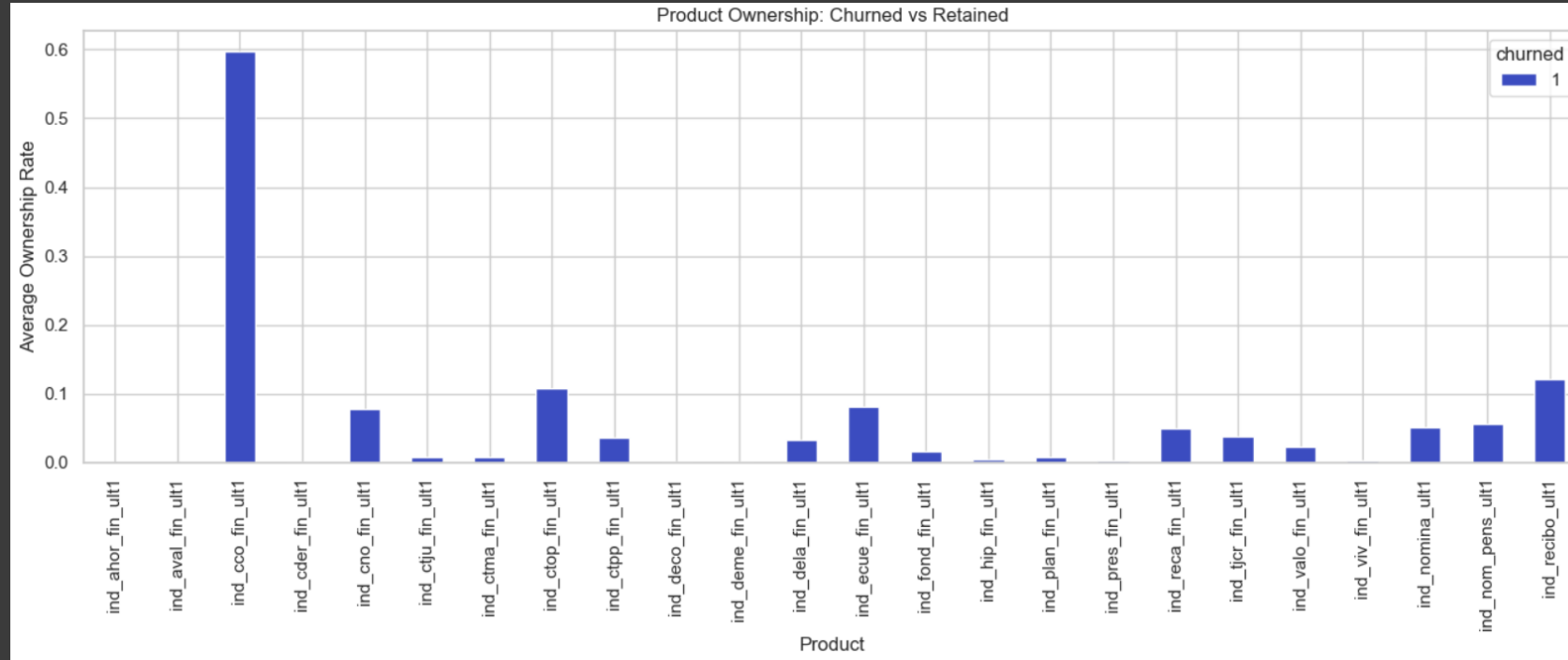
- Churned customers tend to:
  - Be **older on average**
  - Have **shorter tenure** (surprising — might reflect new users abandoning)
  - Have **lower CLV scores** overall
- Retained users dominate in higher tenure and product count distributions.

## 5. Churn Indicators



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### 3. Product Ownership Drop-Off

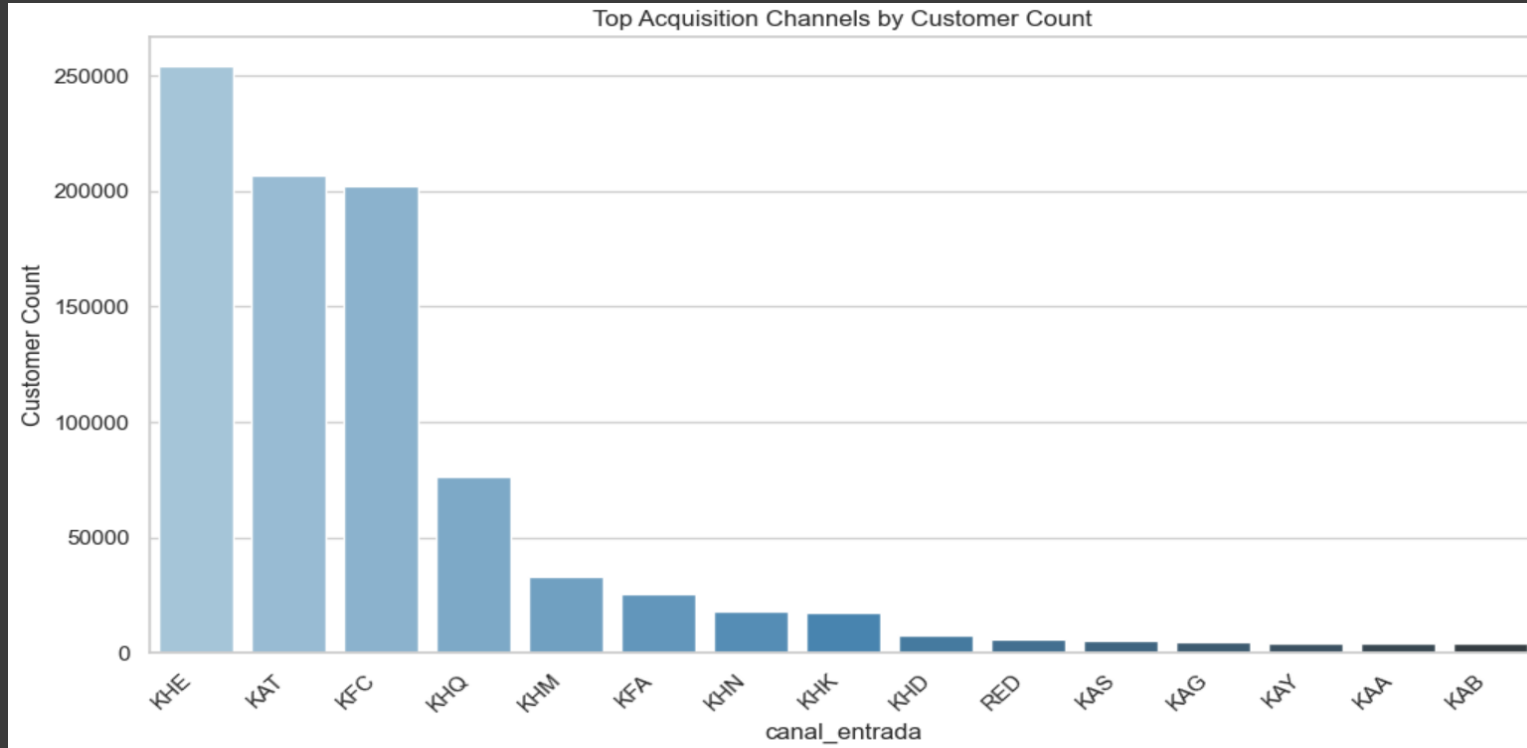
- Churned users have **lower ownership rates across nearly all products**.
- Largest relative drop in products like:
  - Credit Cards (**ind\_tjcr\_fin\_ult1**)
  - Salary/Pension Accounts

## 6. Channel Effectiveness



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### 1. Top Acquisition Channels by Customer Count

- A few channels dominate customer acquisition:
  - KHE, KAT, and KFC are among the most used.
- These likely represent physical or digital acquisition pathways.

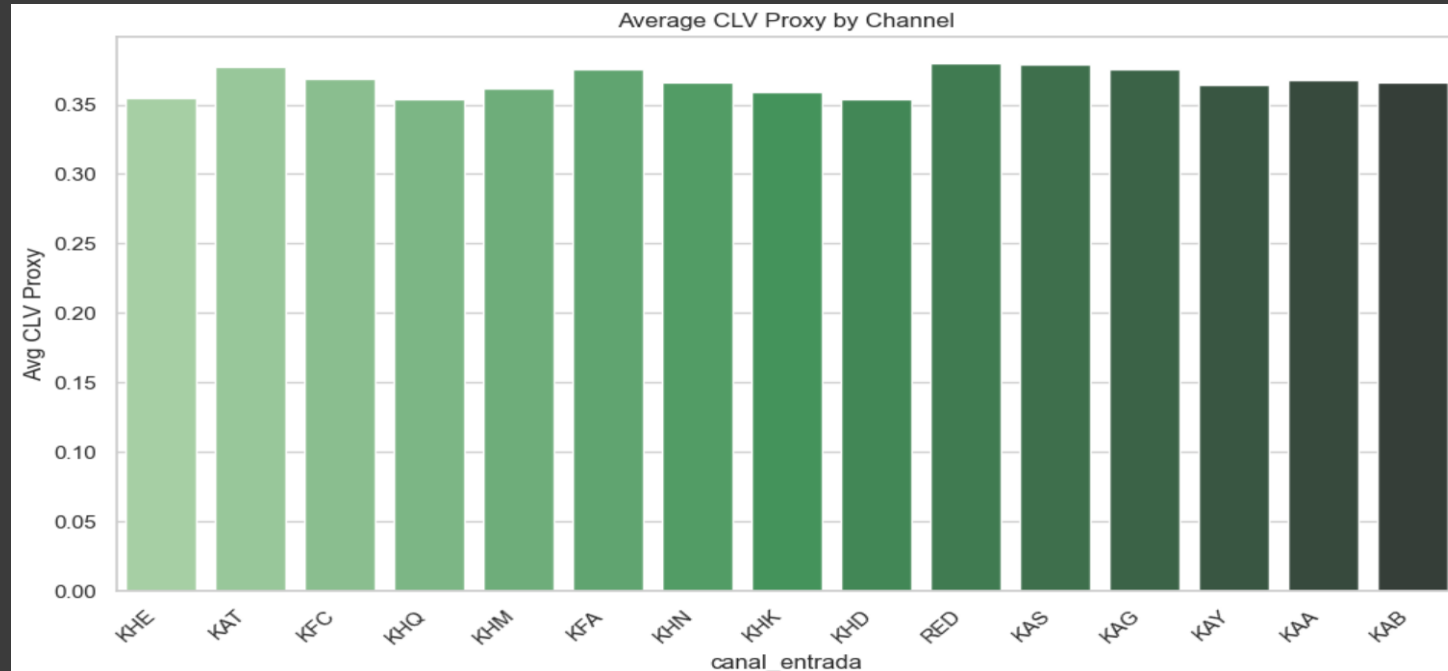


## 6. Channel Effectiveness



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### 2. Average CLV Proxy by Channel

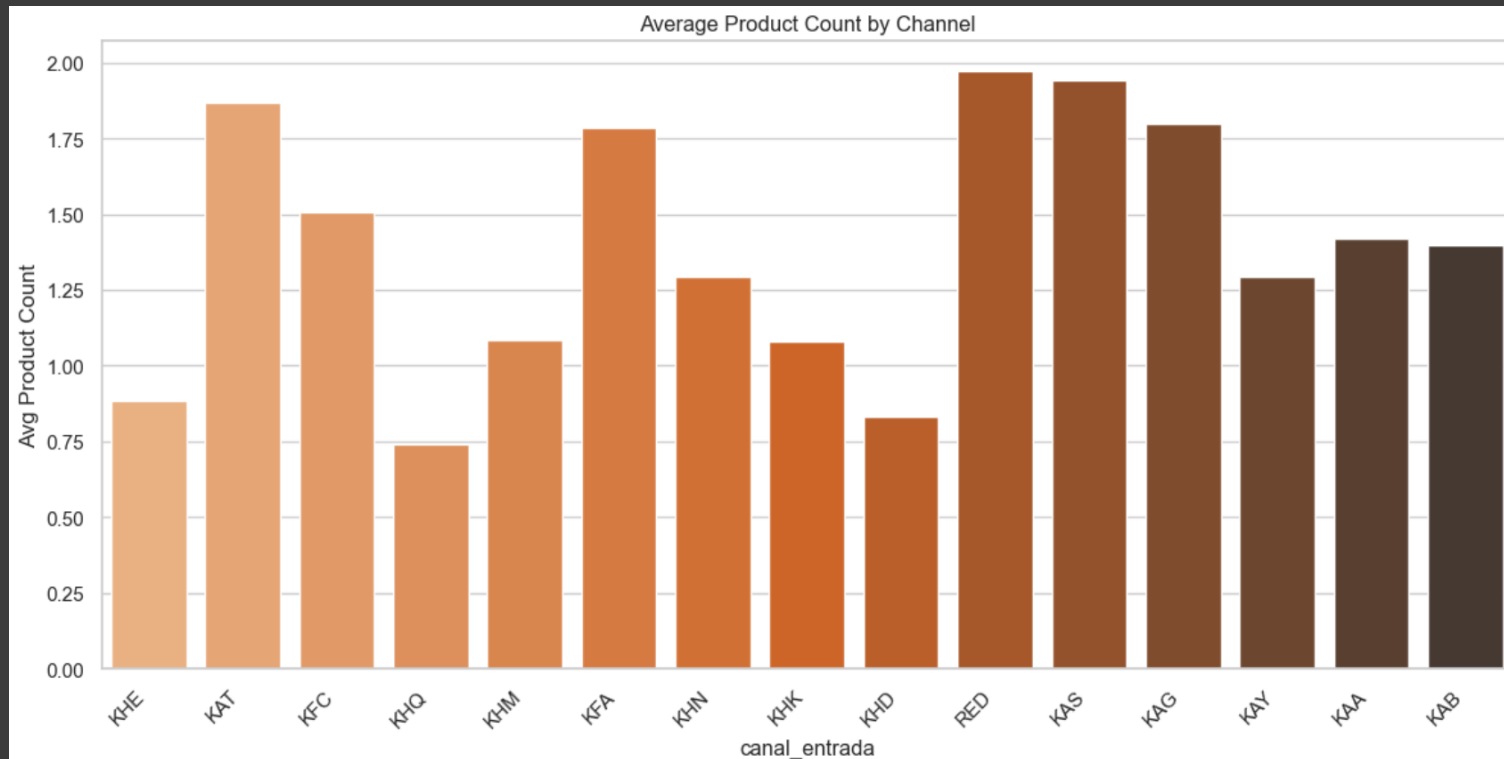
- High customer volume **does not always mean high value:**
  - Channels like **KAT** and **KFA** show **higher CLV**, despite smaller customer bases.
- Mass channels may acquire many users, but **niche or referral-based ones attract higher value clients.**

## 6. Channel Effectiveness



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### 3. Average Product Count by Channel

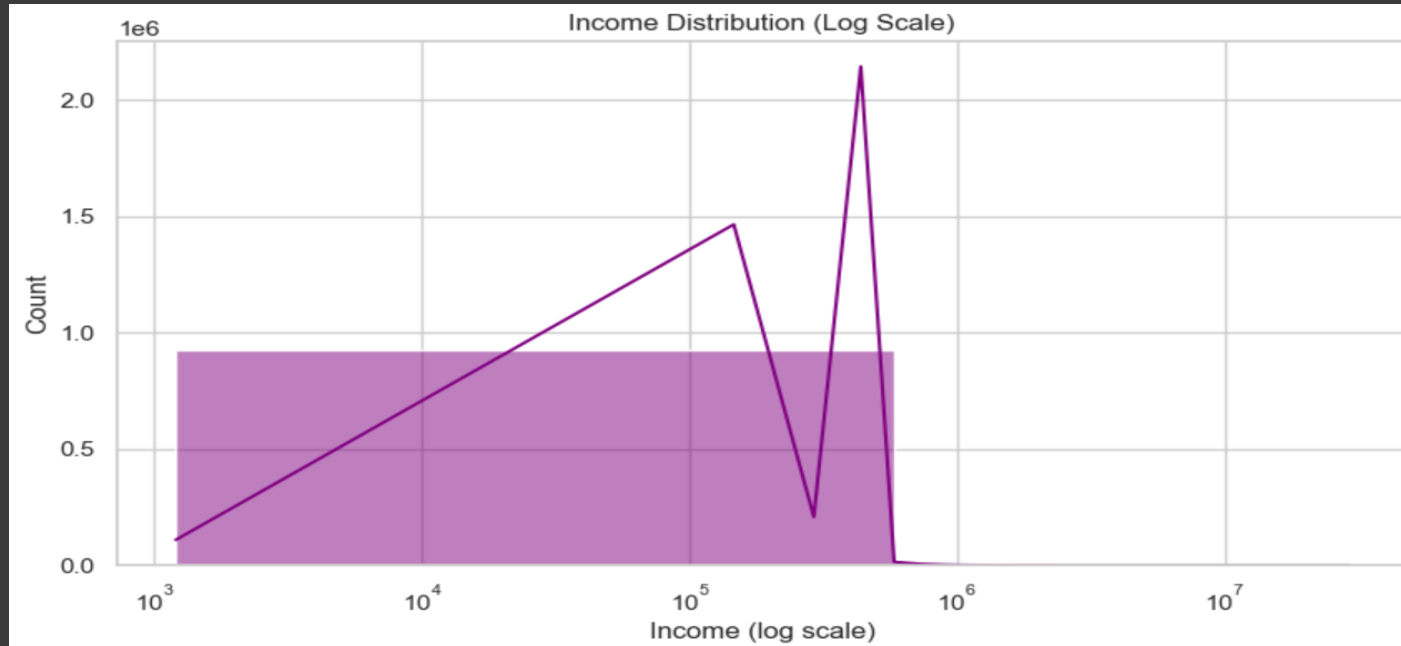
- Channels with higher CLV also typically yield **more product engagement**.
- **KFA** and **KAT** again appear as effective **quality acquisition routes**.

# 7. Income Analysis



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## 1. Income Distribution (Log Scale)

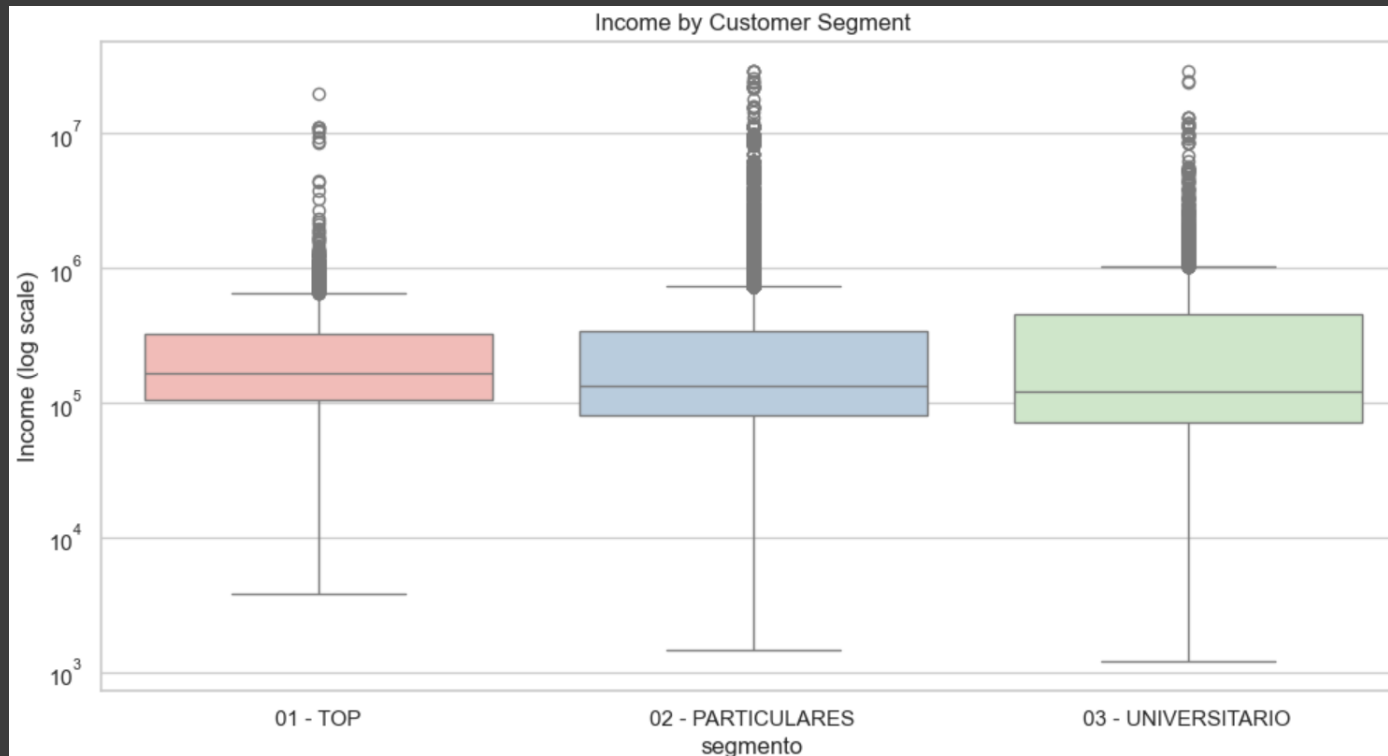
- Highly **right-skewed**: majority of incomes lie below ~60,000.
- A few customers report **extremely high income** ( $>100,000$ ), suggesting income outliers.

# 7. Income Analysis



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## 2. Income by Customer Segment

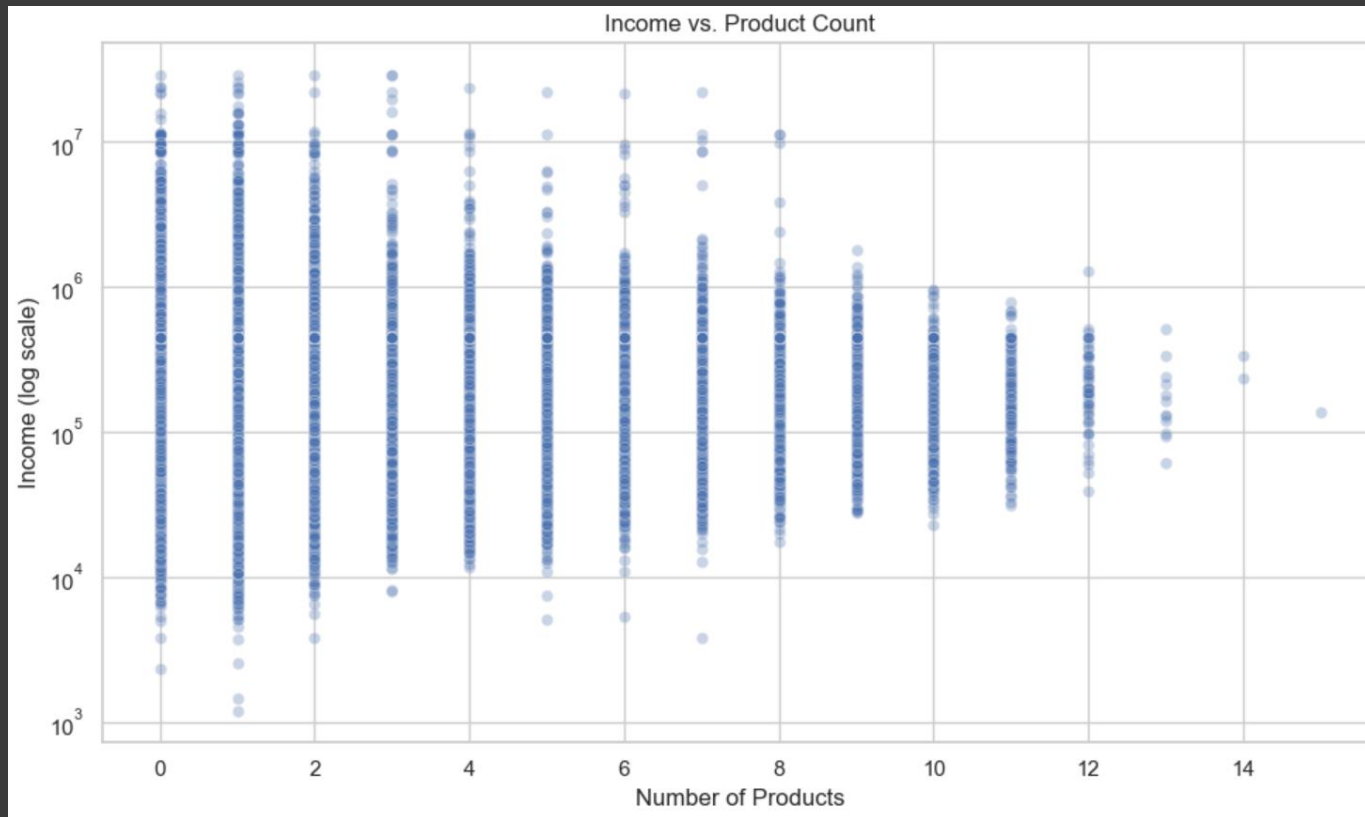
- VIPs (01 - VIP) predictably show the **highest income range**.
- College students (03 - UNIVERSITARIO) have the lowest and most compact income distribution.
- Segments are well-separated, validating the segmentation strategy by income

# 7. Income Analysis



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## 3. Income vs. Product Count

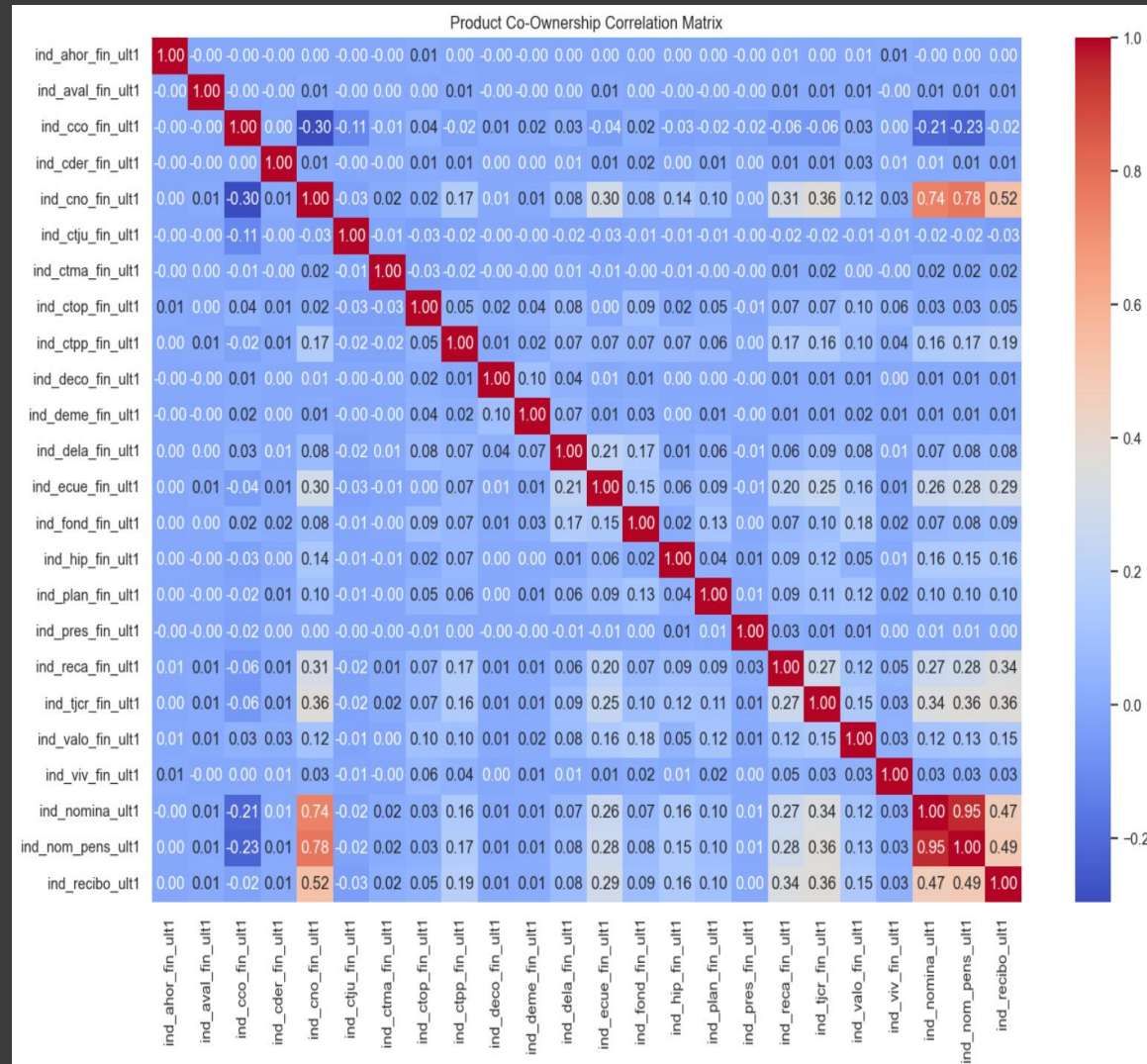
- Positive trend: **higher product count tends to correlate with higher income.**
- However, some **high-income customers own few products**, indicating potential for upselling.

# 8. Product Co-Ownership Patterns



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## Key Product Correlations

- High Positive Correlation Pairs:

- ind\_nomina\_ult1 (salary) ↔ ind\_recibo\_ult1 (bill payments): 0.66
  - Customers receiving salaries tend to set up recurring payments.
- ind\_nom\_pens\_ult1 (pension) ↔ ind\_recibo\_ult1: 0.45
  - Similar trend with pension-based income.

- Investment-related Products like ind\_fond\_fin\_ult1, ind\_valo\_fin\_ult1, ind\_deco\_fin\_ult1 are often held together:

- Moderate correlations (~0.3–0.5), indicating bundled behaviours.

- Minimal or Near-Zero Correlations:

- Savings accounts (ind\_ahor\_fin\_ult1) and insurance (ind\_plan\_fin\_ult1) don't strongly align with others.



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# Final Recommendations

# Final Recommendation:

## Product Adoption Patterns

- High adoption in salary deposits, bill payments, and credit cards.
- Very low adoption of investment and insurance products.
- ***Cross-sell opportunity***: Promote underutilized products like investment funds to salary account holders.

## Demographic & Segment Analysis

- Females slightly lead in essential banking services; males show more interest in investments.
- Ages 35-54 dominate product holdings.
- VIPs hold diverse product portfolios; students are underpenetrated.
- ***Cross-sell opportunity***: Bundle investment and savings products for VIPs and the 35-54 age group.

## CLV-Based Targeting

- Higher CLV is linked with tenure, income, and product count.
- CLV proxy helps identify top-tier clients for premium services.
- ***Cross-sell opportunity***: Upsell additional products to high CLV clients with moderate product usage.



# Final Recommendation:



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## Channel Performance

- Mass acquisition channels deliver volume but not value.
- Channels like KAT and KFA yield higher CLV and product engagement.
- ***Cross-sell opportunity***: Invest in quality acquisition channels for better LTV.

## Product Pairing Insights

- Salary accounts strongly correlate with bill payments.
- Investment products are frequently co-owned.
- ***Cross-sell opportunity***: Automate bundled recommendations (e.g., salary + bills + investment starter).

## Behavioral & Anomaly Insights

- Users with zero product ownership and high income are prime cross-sell targets.
- Anomalous age and income entries should be reviewed.
- ***Cross-sell opportunity***: Trigger onboarding flows for dormant accounts.

# Final Recommendation:

## Strategic Recommendations

- Prioritize high-CLV customers for personalized upselling.
- Develop segment-specific product bundles.
- Promote low-adoption products through targeted campaigns.
- Use acquisition channel metrics to guide marketing investments.
- Launch proactive outreach to zero-product customers with entry-level offers.

# Thank You