Predict Customer Personality to Boost Marketing Campaign by using Machine Learning

Supported by:
Rakamin Academy
Career Acceleration School
www.rakamin.com

Created by:
Aziz Prabowo
azizprabowo128@gmail.com
linkedin.com/in/aziz-prabowo

A fresh graduate in Data Science with high interest artificial intelligence, data science, and business analytics. Experienced in data cleaning, exploratory data analysis, visualization, machine learning, and basic deep learning through academic, bootcamps, courses, and personal projects.

Project Overview

Rakamin Academy

Background

A company can grow rapidly when it understands its customers' behavior, enabling it to provide better services and benefits to customers who have the potential to become loyal customers. By processing historical marketing campaign data to improve performance and target the right customers for transactions on the company's platform, we focus on creating a cluster prediction model based on this insight, making it easier for the company to make decisions.

Goal

Understand and analyze customer behavior using historical marketing data to enhance service offerings and deliver targeted benefits that increase customer loyalty and company growth.

Objective

Develop a cluster prediction model that segments customers based on behavioral patterns, enabling the company to make data-driven marketing and service decisions.

Dataset Information

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2240 entries, 0 to 2239
Data columns (total 29 columns):
 #   Column               Non-Null Count  Dtype
---  ------               --------------  -----
 0   ID                   2240 non-null   int64
 1   Year_Birth           2240 non-null   int64
 2   Education            2240 non-null   object
 3   Marital_Status       2240 non-null   object
 4   Income               2216 non-null   float64
 5   Kidhome              2240 non-null   int64
 6   Teenhome             2240 non-null   int64
 7   Dt_Customer          2240 non-null   object
 8   Recency              2240 non-null   int64
 9   MntCoke              2240 non-null   int64
 10  MntFruits            2240 non-null   int64
 11  MntMeatProducts      2240 non-null   int64
 12  MntFishProducts      2240 non-null   int64
 13  MntSweetProducts     2240 non-null   int64
 14  MntGoldProds         2240 non-null   int64
 15  NumDealsPurchases    2240 non-null   int64
 16  NumWebPurchases      2240 non-null   int64
 17  NumCatalogPurchases  2240 non-null   int64
 18  NumStorePurchases    2240 non-null   int64
 19  NumWebVisitsMonth    2240 non-null   int64
 20  AcceptedCmp3         2240 non-null   int64
 21  AcceptedCmp4         2240 non-null   int64
 22  AcceptedCmp5         2240 non-null   int64
 23  AcceptedCmp1         2240 non-null   int64
 24  AcceptedCmp2         2240 non-null   int64
 25  Complain             2240 non-null   int64
 26  Z_CostContact        2240 non-null   int64
 27  Z_Revenue            2240 non-null   int64
 28  Response             2240 non-null   int64
dtypes: float64(1), int64(25), object(3)
memory usage: 507.6+ KB
```

This dataset contains **customer data** from a marketing campaign, with **2,240 total entries** and **29 columns** detailing various customer attributes.

- **Demographics & Household Information:** Includes `ID`, `Year_Birth`, `Education`, `Marital_Status`, and the number of children and teenagers in the household (`Kidhome`, `Teenhome`).
- **Financial & Purchasing Behavior:** Features like `Income` (with 24 missing values), `Mnt...` (monetary spending on different products), and `Num...` (number of purchases across various channels like web, catalog, and store).
- **Marketing Response & Engagement:** Data points such as `Recency` (days since last purchase), `Dt_Customer` (enrollment date), `AcceptedCmp...` (campaign acceptance status), `Complain`, and `Response`.

Link to Google Colab

Data Cleaning

Rakamin Academy

Before Imputation

```
[89]: # Cek null values di dataset
      df.isnull().sum()[df.isnull().sum() > 0]

[89]: Income    24
      dtype: int64
```

Imputation

After Imputation

```
[90]: # impute missing values in 'Income' column with median
      df['Income'].fillna(df['Income'].median(), inplace=True)

[91]: # Cek null values di dataset
      df.isnull().sum()[df.isnull().sum() > 0]

[91]: Series([], dtype: int64)
```

Missing values were imputed in the **Income** column using the **median value**. This was chosen because these three columns have a highly skewed data distribution, making the median a more appropriate imputation value than the mean, which is more sensitive to outliers.

Data Cleaning

Rakamin Academy

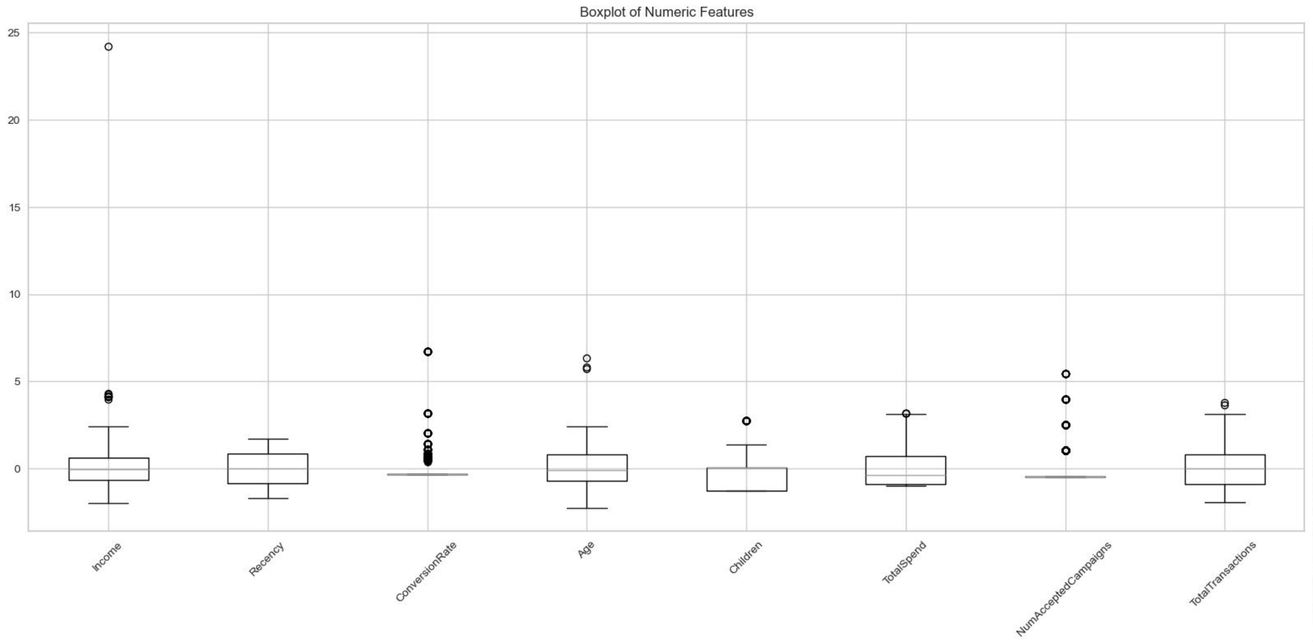
Duplicate Values

```
[212]: # check for duplicates
       df.duplicated().sum()

[212]: np.int64(183)

[213]: # Drop duplicates
       df.drop_duplicates(inplace=True, ignore_index=True)
```

There are **183 duplicate rows** after the **ID** column was removed from the dataset. Therefore, these rows need to be removed from the dataset using the **drop_duplicates** function.

Data Cleaning

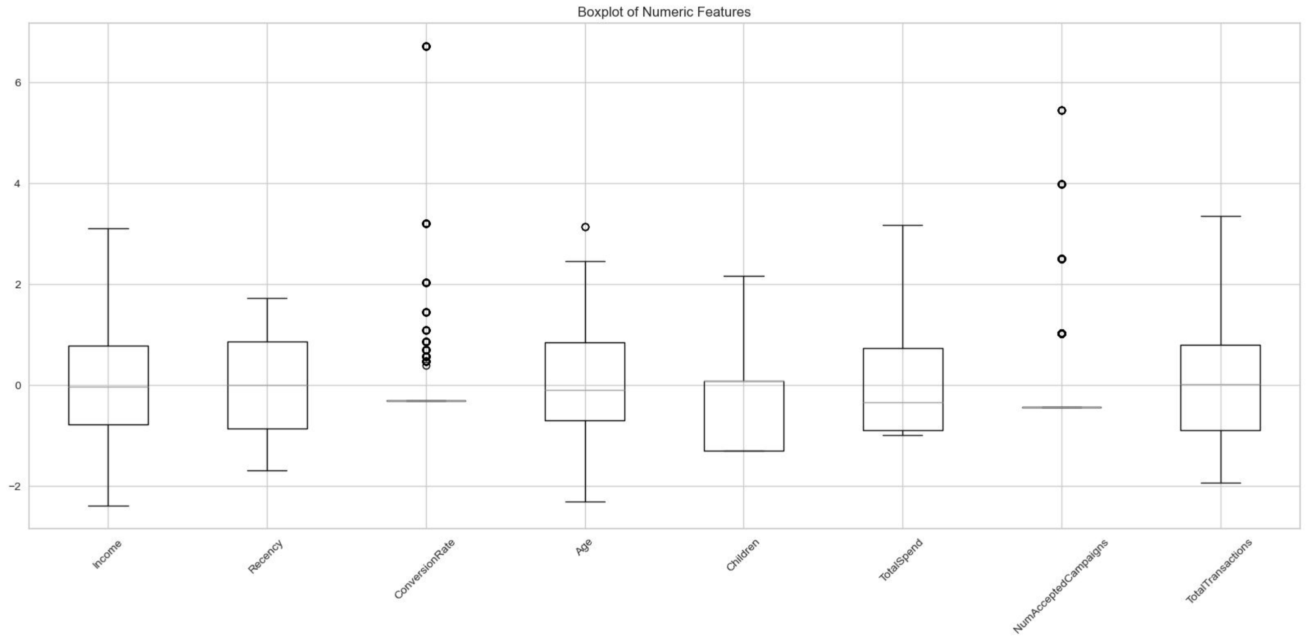
Before Outliers Handling



There are outlier values in almost all numeric columns in the dataset.

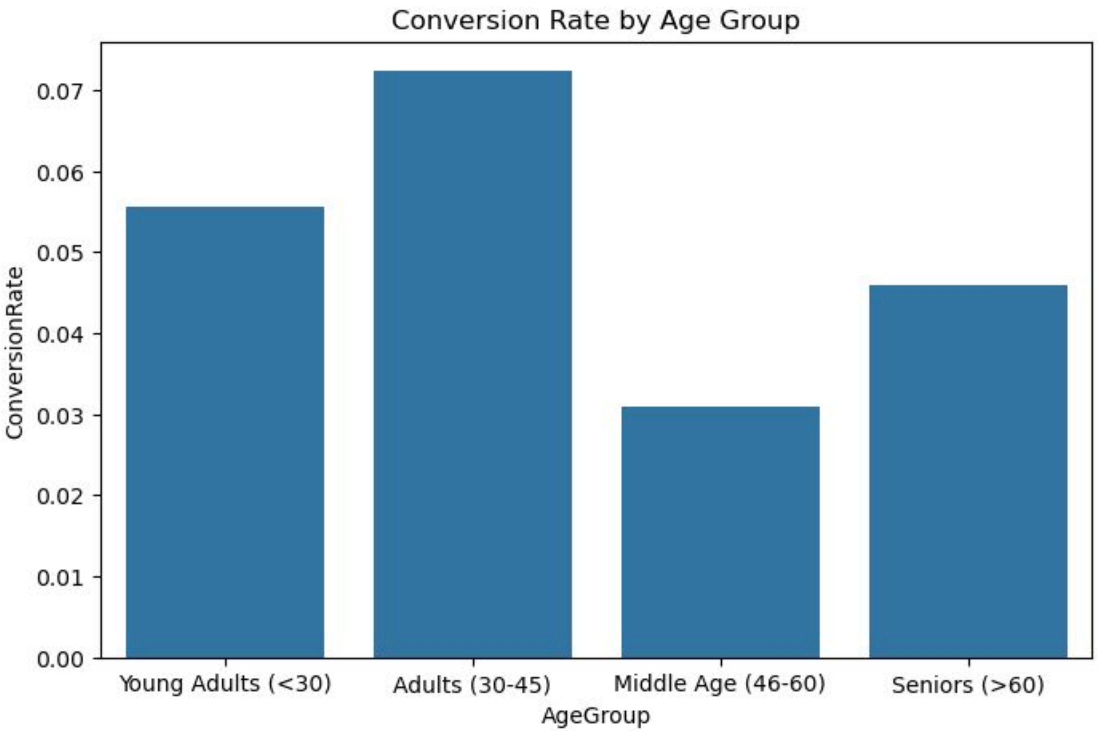
Data Cleaning

After Outliers Handling



Outliers are addressed by capping based on the IQR. This is done to avoid missing the most valuable customer segments, which often fall outside the normal distribution.

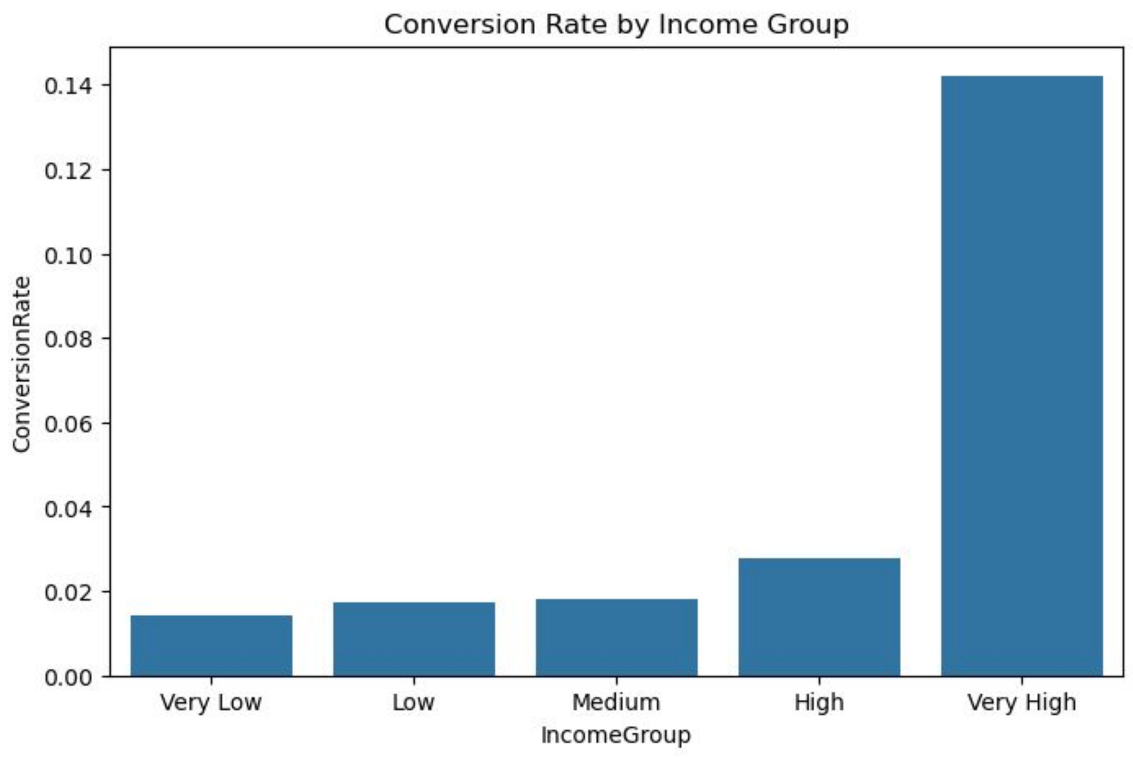
Younger Audiences Are More Likely to Convert



Customers in the **Young Adults (<30) and Adults (30–45) age groups have a conversion rate of more than 5%**, much higher than the Middle Age (46–60) and Seniors (>60) groups.

Exploratory Data Analysis

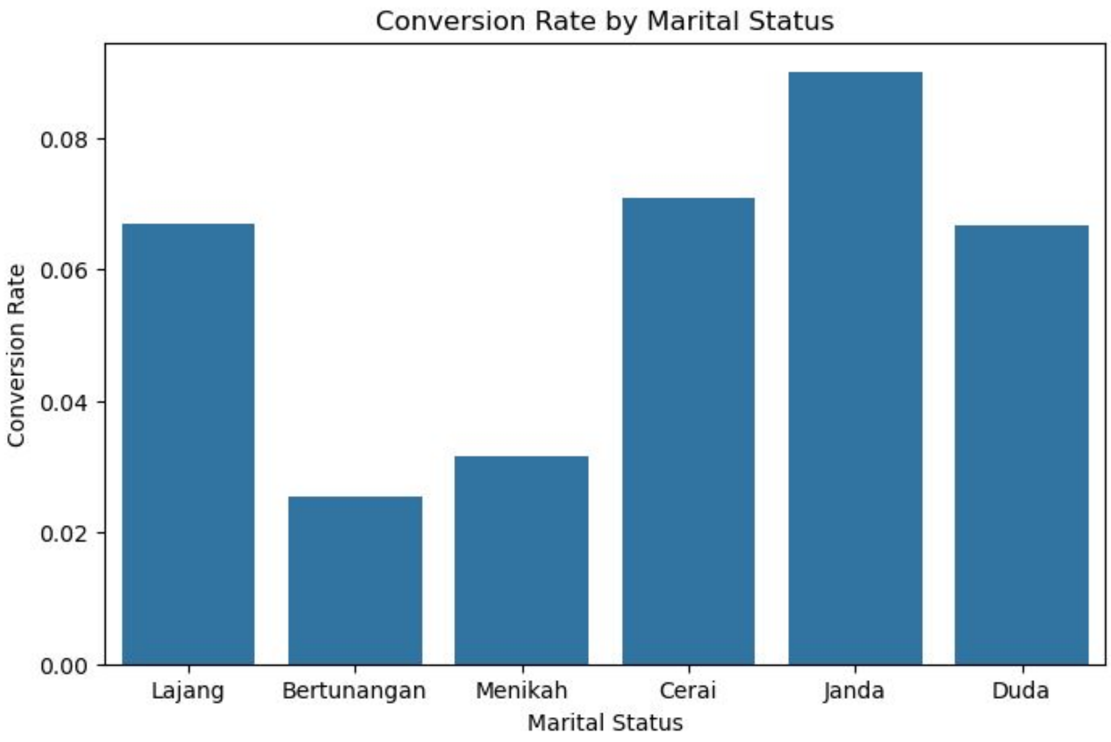
High-Income Customers Drive Conversions



Customers in the **Very High income group (>70 million) showed the highest conversion rate**, **reaching over 14%**. Conversely, customers in the High to Very Low income groups only showed a conversion rate of under 4%.

Exploratory Data Analysis

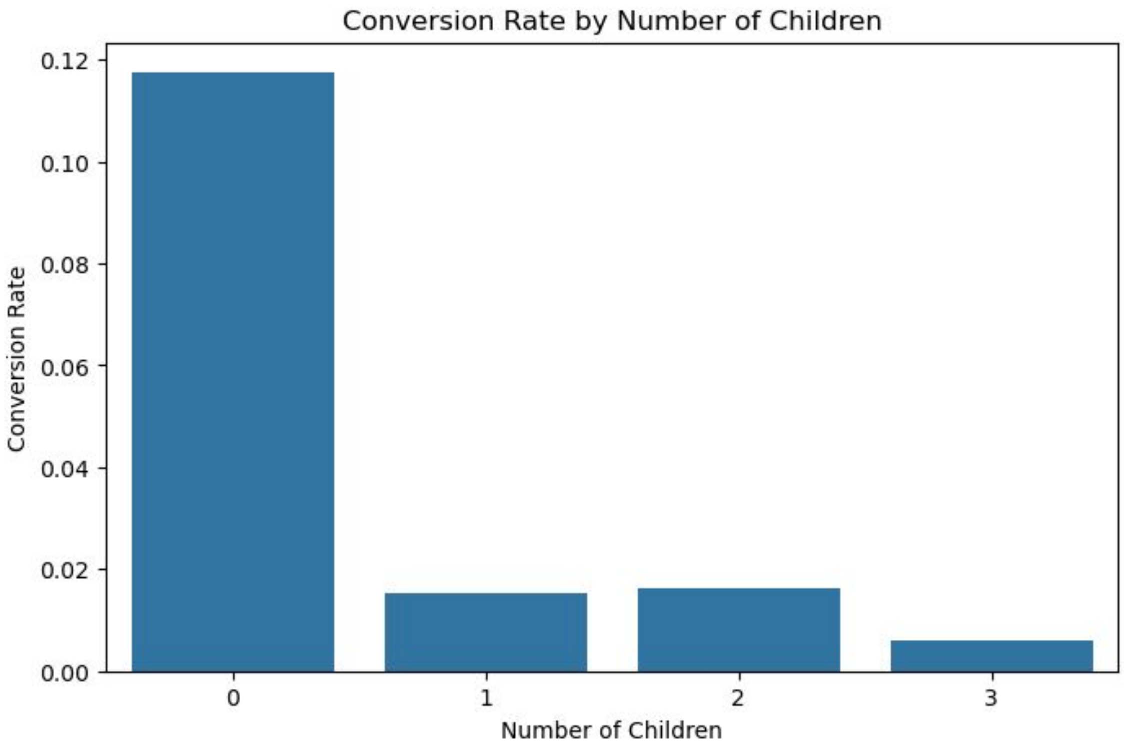
Non-Marital Customers Convert More



Customers who are not currently in a relationship—such as **single, widowed, widowed, or divorced—show higher conversion rates, above 6%**. Meanwhile, customers who are married or engaged have lower conversion rates, below 4%.

Exploratory Data Analysis

Customers Without Children Convert Up to 5x More

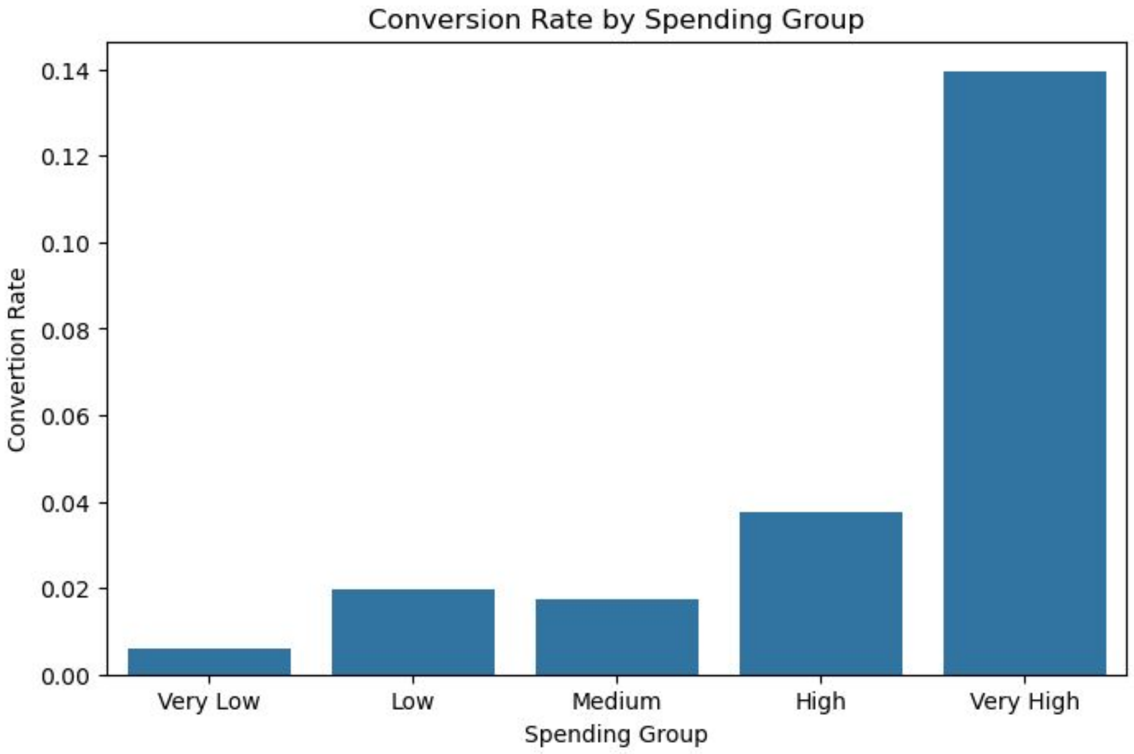


Customers without children showed the highest conversion rates, above 10%. Conversely, customers with one to three children only showed conversion rates below 2%.

Exploratory Data Analysis

Rakamin Academy

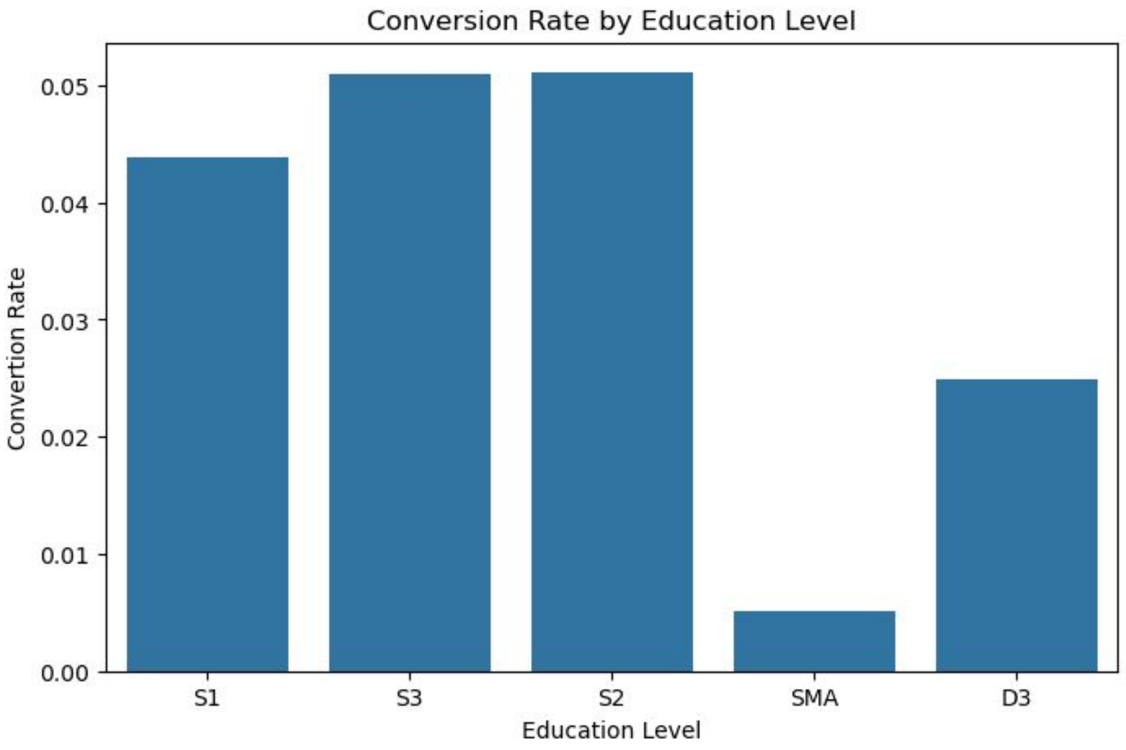
Top Spenders Are 3x More Likely to Convert



Customers **spending over 1 million rupiah showed the highest conversion rate, exceeding 12%**. Conversely, customers with lower spending—from Very Low to High—had a conversion rate of just under 4%.

Exploratory Data Analysis

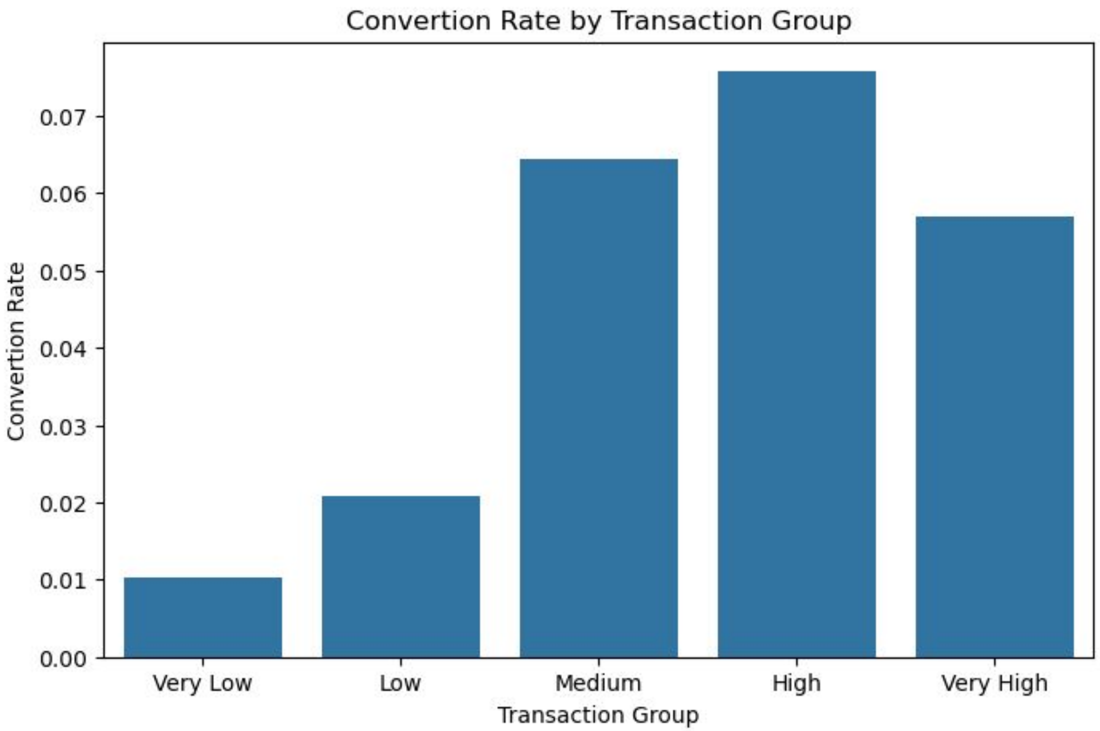
Higher Education, Higher Conversion



Customers with **undergraduate and postgraduate education levels (S1, S2, S3) show a conversion rate above 4%**, higher than customers with lower education levels (D3 and SMA).

Exploratory Data Analysis

Frequent Shoppers Convert More



Customers with **more than 11 transactions—in the Medium to Very High categories—showed conversion rates above 5%**. Meanwhile, customers with fewer transactions (Very Low and Low) recorded significantly lower conversion rates.

Data Preprocessing

Before Encoding

	Education	Marital_Status
251	D3	Bertunangan
1813	S1	Lajang
1827	S1	Menikah
1574	S3	Menikah
1516	S1	Bertunangan

After Encoding

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2057 entries, 0 to 2056
Data columns (total 25 columns):
 #   Column                    Non-Null Count  Dtype
---  ------                    --------------  -----
 0   Income                    2057 non-null   float64
 1   Dt_Customer               2057 non-null   object
 2   Recency                   2057 non-null   int64
 3   NumWebVisitsMonth         2057 non-null   int64
 4   Complain                  2057 non-null   int64
 5   Z_CostContact             2057 non-null   int64
 6   Z_Revenue                 2057 non-null   int64
 7   Response                  2057 non-null   int64
 8   ConversionRate            2057 non-null   float64
 9   Age                       2057 non-null   int64
 10  Children                  2057 non-null   float64
 11  TotalSpend                2057 non-null   int64
 12  SpendingGroup             2057 non-null   category
 13  NumAcceptedCampaigns      2057 non-null   int64
 14  TotalTransactions         2057 non-null   float64
 15  TransactionGroup          2057 non-null   category
 16  AgeGroup                  2057 non-null   category
 17  IncomeGroup               2057 non-null   category
 18  Marital_Status_Bertunangan  2057 non-null   float64
 19  Marital_Status_Cerai      2057 non-null   float64
 20  Marital_Status_Duda       2057 non-null   float64
 21  Marital_Status_Janda      2057 non-null   float64
 22  Marital_Status_Lajang     2057 non-null   float64
 23  Marital_Status_Menikah    2057 non-null   float64
 24  Education                 2057 non-null   float64
dtypes: category(4), float64(11), int64(9), object(1)
memory usage: 346.5+ KB
```

The **Marital_Status** column is encoded using the **One-Hot Encoding** method, while the **Education** column uses the **Ordinal Encoding** method. This selection is based on the characteristics of each column: **Education** has an intrinsic value order (such as SMA < D3 < S1 < S2 < S3), so it is more appropriate to use Ordinal Encoding. Meanwhile, **Marital_Status** does not have a logical order between its categories, so One-Hot Encoding is more appropriate.

Data Preprocessing

Rakamin Academy

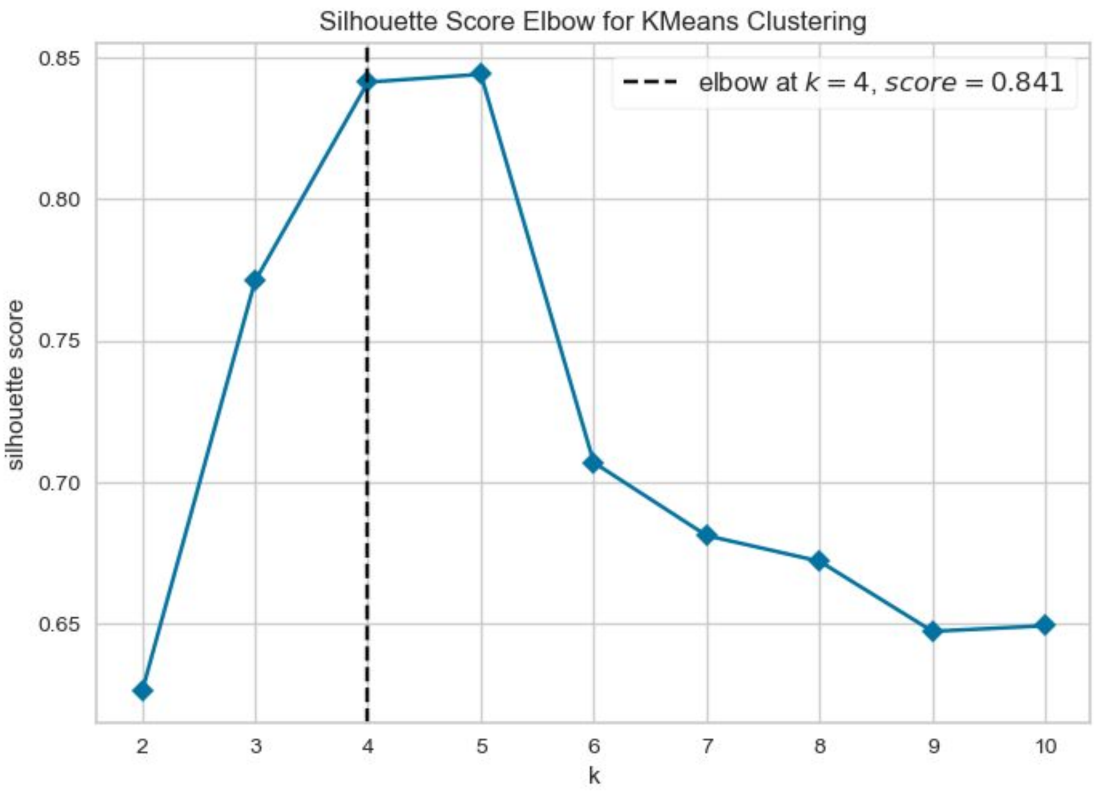
Before Standardization

	Age	Income	Children	Recency	TotalSpend	NumWebVisitsMonth	TotalTransactions	NumAcceptedCampaigns
count	2057.000	2.057000e+03	2057.000	2057.000	2057.000	2057.000	2057.000	2057.000
mean	56.164	5.194200e+07	0.943	48.974	606313.563	5.318	14.864	0.300
std	11.745	2.095013e+07	0.720	28.989	602922.034	2.440	7.654	0.678
min	29.000	1.730000e+06	0.000	0.000	5000.000	0.000	0.000	0.000
25%	48.000	3.570100e+07	0.000	24.000	69000.000	3.000	8.000	0.000
50%	55.000	5.138150e+07	1.000	49.000	396000.000	6.000	15.000	0.000
75%	66.000	6.827400e+07	1.000	74.000	1047000.000	7.000	21.000	0.000
max	93.000	1.171335e+08	2.500	99.000	2514000.000	20.000	40.500	4.000

After Standardization

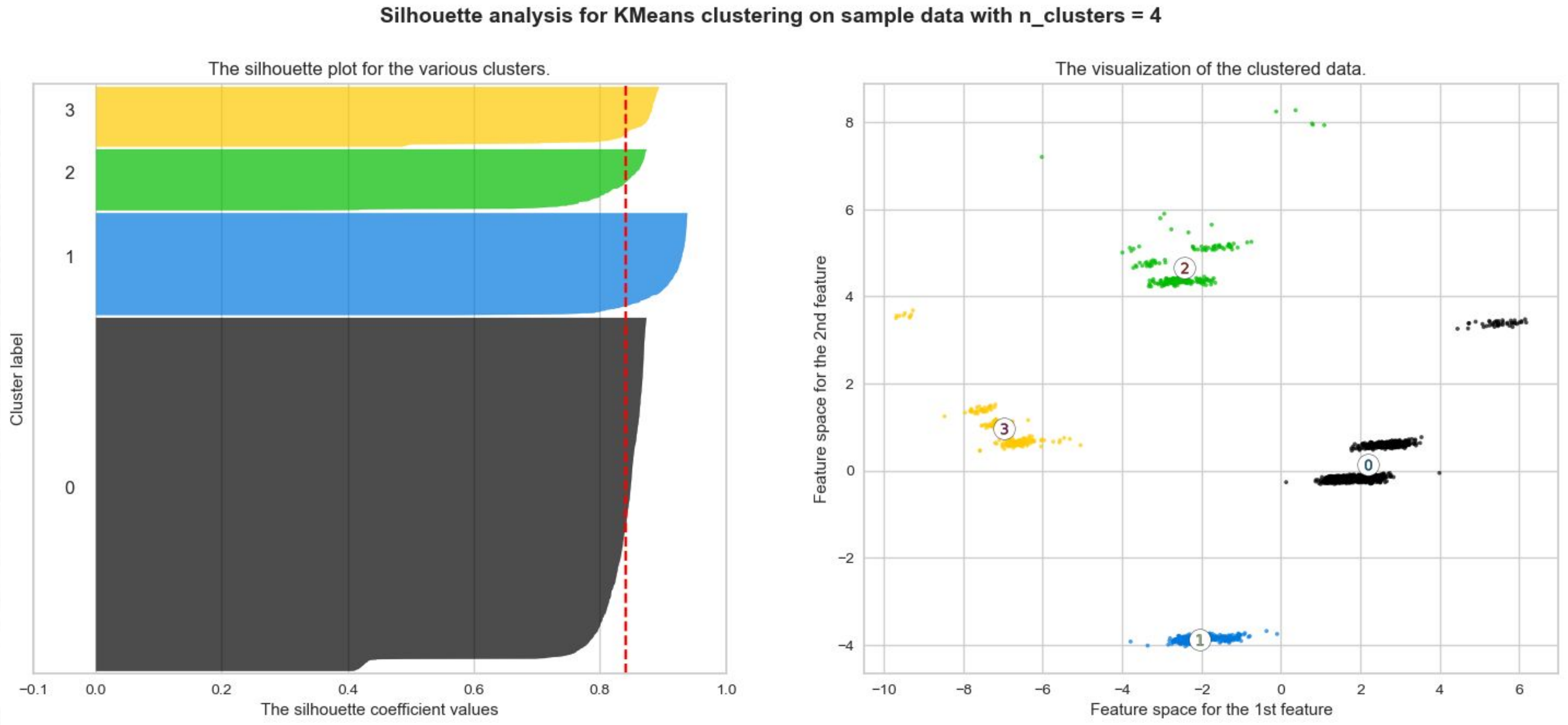
	Age	Income	Children	Recency	TotalSpend	NumWebVisitsMonth	TotalTransactions	NumAcceptedCampaigns
count	2057.000	2057.000	2057.000	2057.000	2057.000	2057.000	2057.000	2057.000
mean	-0.000	-0.000	0.000	-0.000	0.000	-0.000	0.000	-0.000
std	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
min	-2.313	-2.397	-1.310	-1.690	-0.998	-2.251	-1.942	-0.443
25%	-0.695	-0.775	-1.310	-0.862	-0.891	-0.977	-0.897	-0.443
50%	-0.099	-0.027	0.079	0.001	-0.349	0.298	0.018	-0.443
75%	0.838	0.780	0.079	0.864	0.731	0.722	0.802	-0.443
max	3.137	3.113	2.162	1.726	3.165	3.271	3.350	5.454

Elbow Method & Silhouette Score



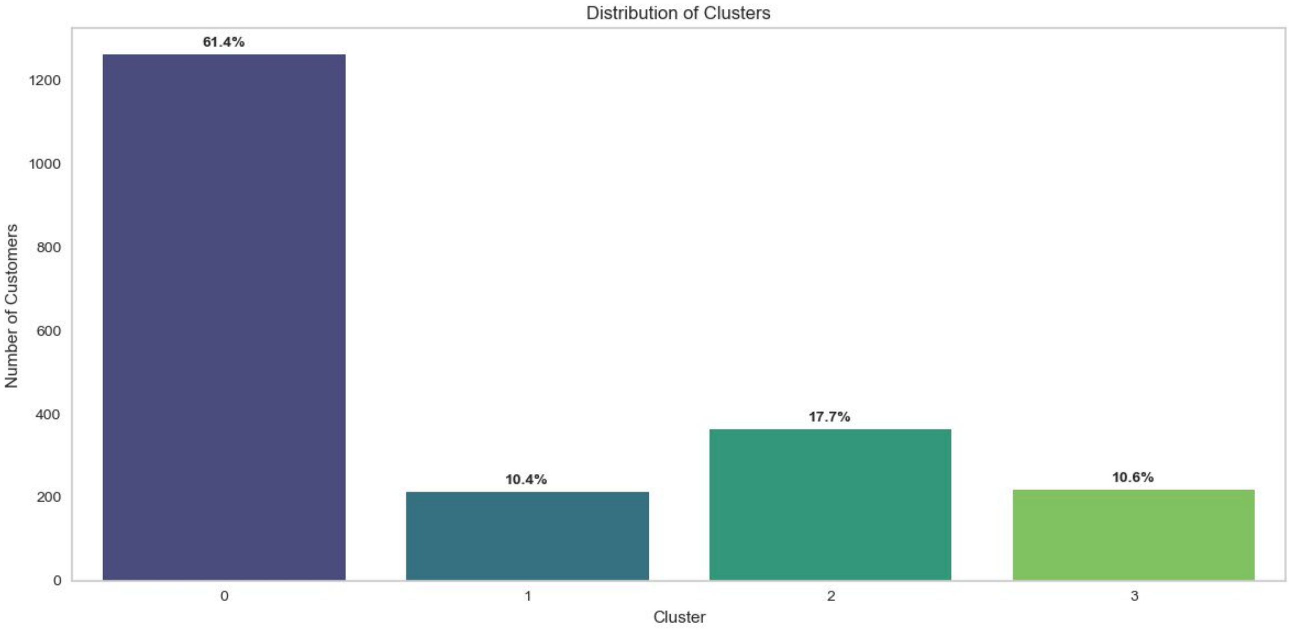
The results of the clustering analysis show that the elbow method with evaluation using the silhouette score produces an **optimal number of clusters of four clusters**, with a fairly high silhouette score value of 0.84.

Silhouette Analysis & Cluster Graph



Data Modeling

Distribution of Clusters

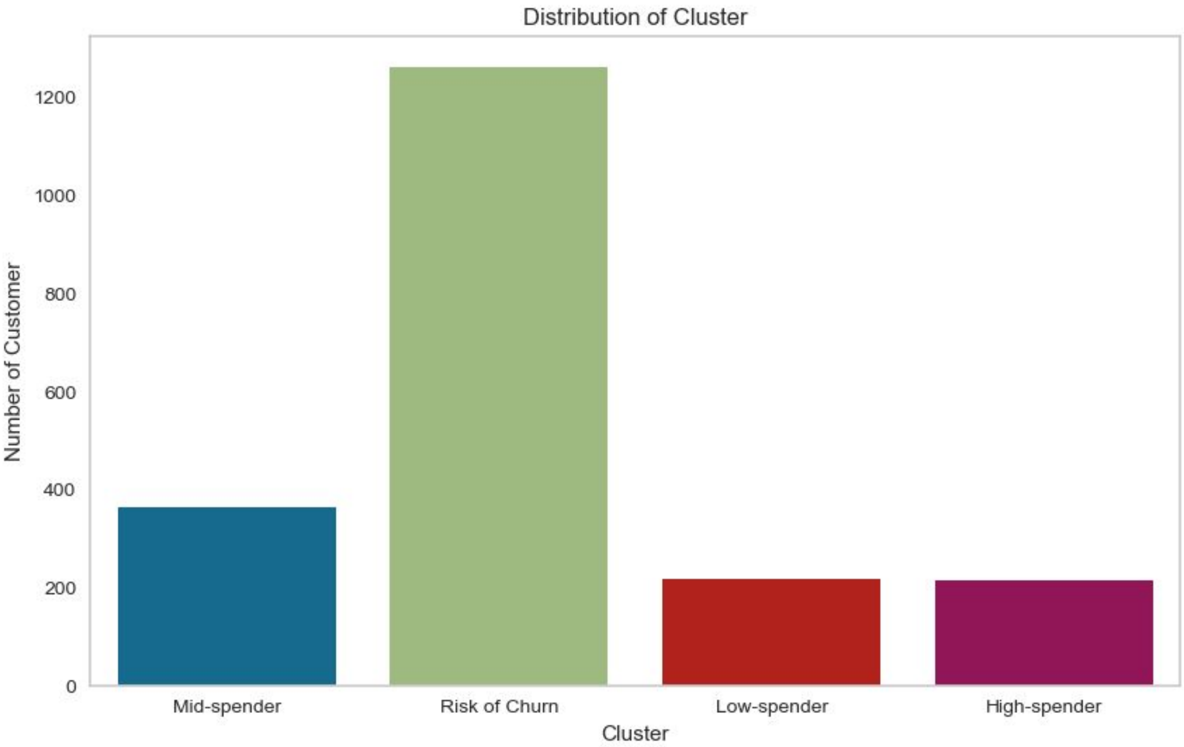


Of these four clusters, **Cluster 0 dominates with the largest proportion, accounting for 61.4% of total customers**. This means that more than half of these customers share similar characteristics and can be considered the company's primary segment.

Meanwhile, **Cluster 1** and **Cluster 3 represent groups with similar and smaller proportions of customers**, and therefore may represent specialized or niche segments with more specific needs.

Model Interpretation

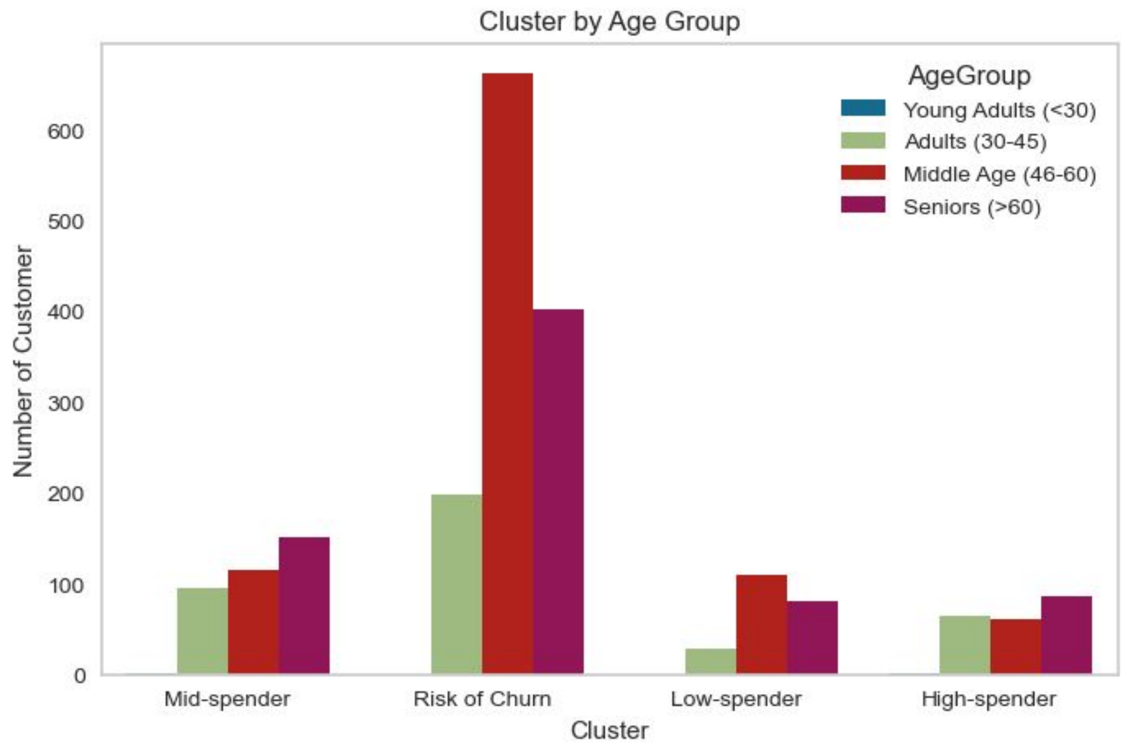
Most Customers Are at Risk of Churning



More than 1,200 customers fall into the Risk of Churn cluster, far more than Mid-Spender (±390), Low-Spender, and High-Spender (±200).

Model Interpretation

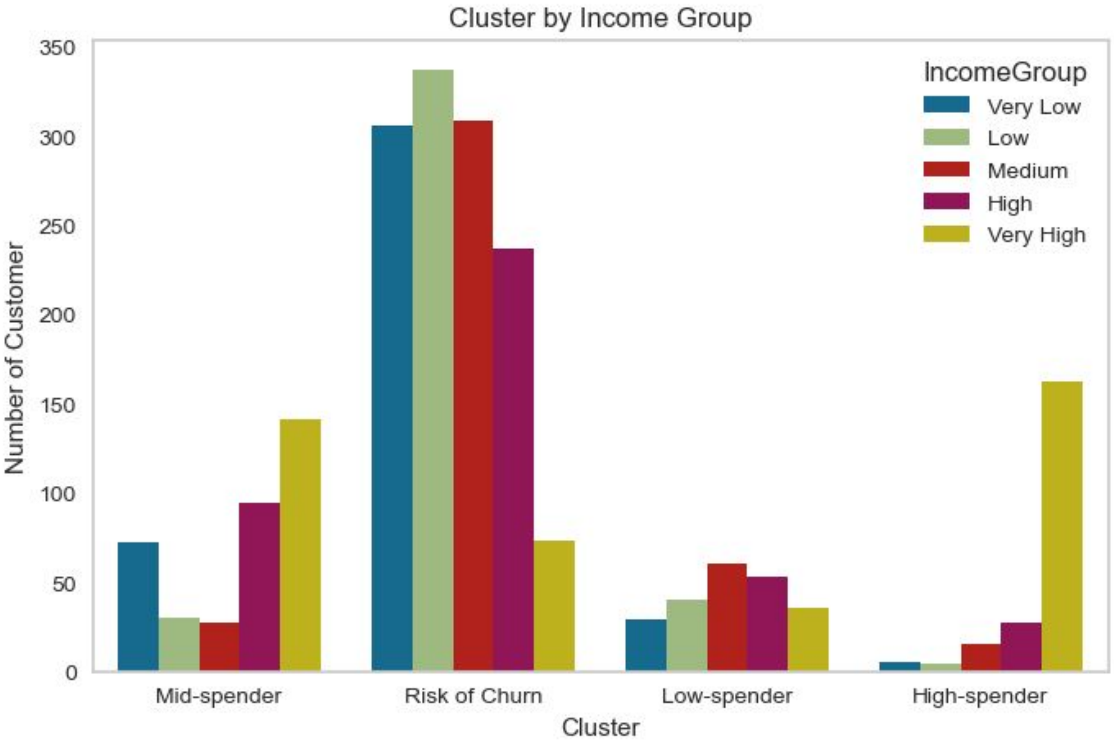
Older Customers Dominate Risk and Low-Spending Clusters



The **risk of churn and low spenders is dominated by middle-aged customers (46–60),** followed by seniors (>60) and adults (30–45). Seniors make up the majority of mid-spenders and high-spenders, followed by middle-aged and adult customers.

Model Interpretation

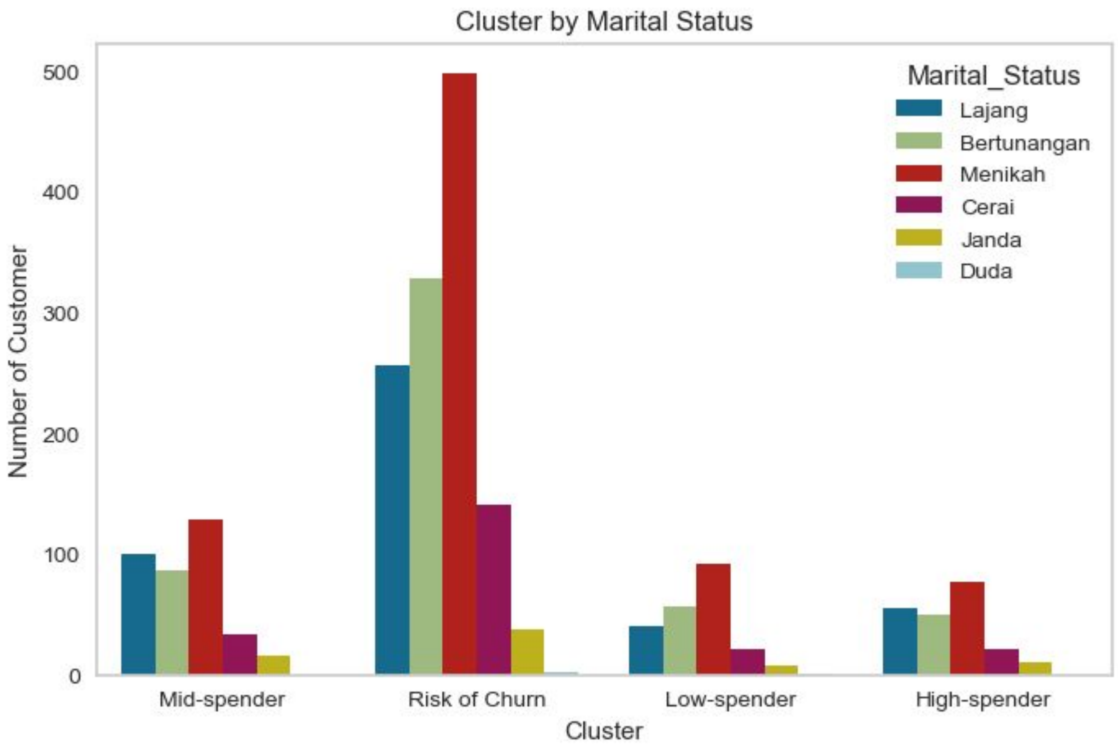
Low-Income Customers Dominate Risk of Churn Cluster



The Risk of Churn cluster is dominated by customers with Very Low (1.73–32.23 million), Low (>32.23–44.94 million), and Medium (>44.94–58.17 million) income levels. In contrast, customers with **High** and **Very High income are more commonly found in the High-Spender and Mid-Spender clusters**.

Model Interpretation

Married Customers Dominate All Clusters

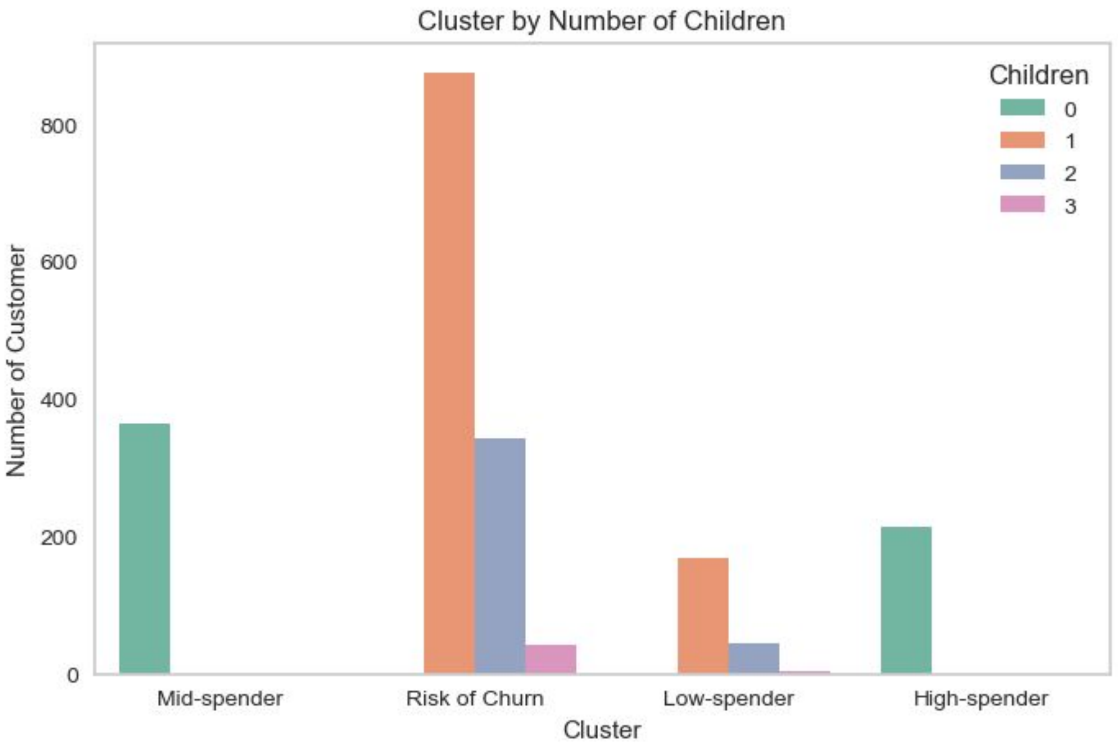


Married customers dominate across all clusters, followed by those who are **Engaged**, **Single**, **Divorced**, **Widowed**, and **Separated**.

Marital status appears to be associated with **stability** and **customer engagement** in transactions.

Model Interpretation

Customers With Children Tend to Spend Less and Churn More

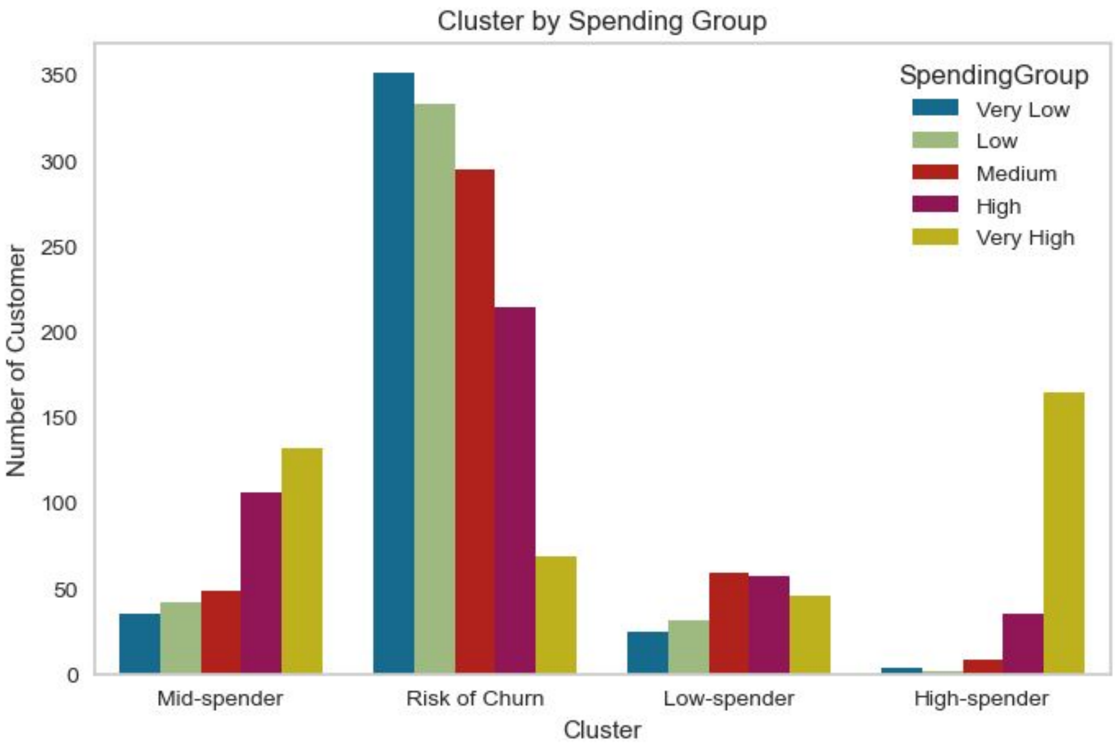


The **Risk of Churn** and **Low-Spender** clusters are dominated by customers **with children**.

In contrast, the **Mid-Spender** and **High-Spender** clusters consist exclusively of customers **without children**.

Model Interpretation

High-Spenders Mostly Come From Very High-Income Group

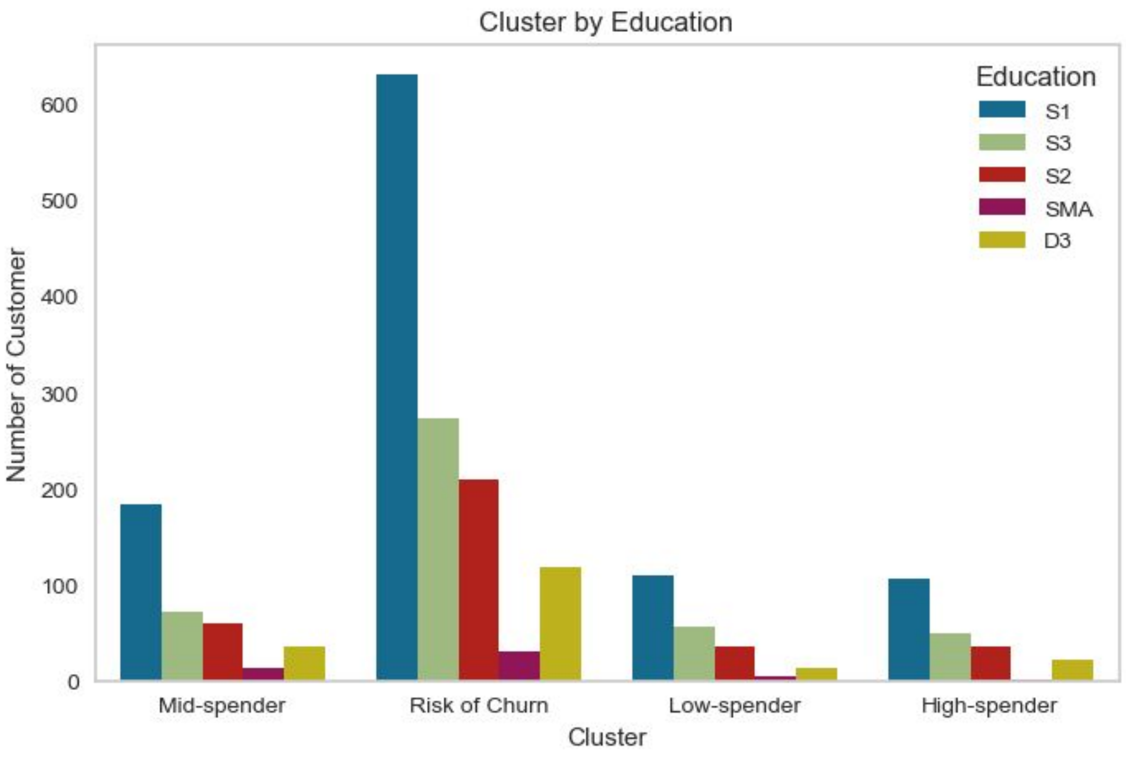


The **Risk of Churn** cluster is dominated by customers with **Very Low to Medium** income levels. **Low-Spender** and **Mid-Spender** clusters have a more **diverse income distribution**.

In contrast, the **High-Spender** cluster is **mostly composed of** customers from the **Very High Income** group.

Model Interpretation

Highly Educated Customers Dominate All Clusters

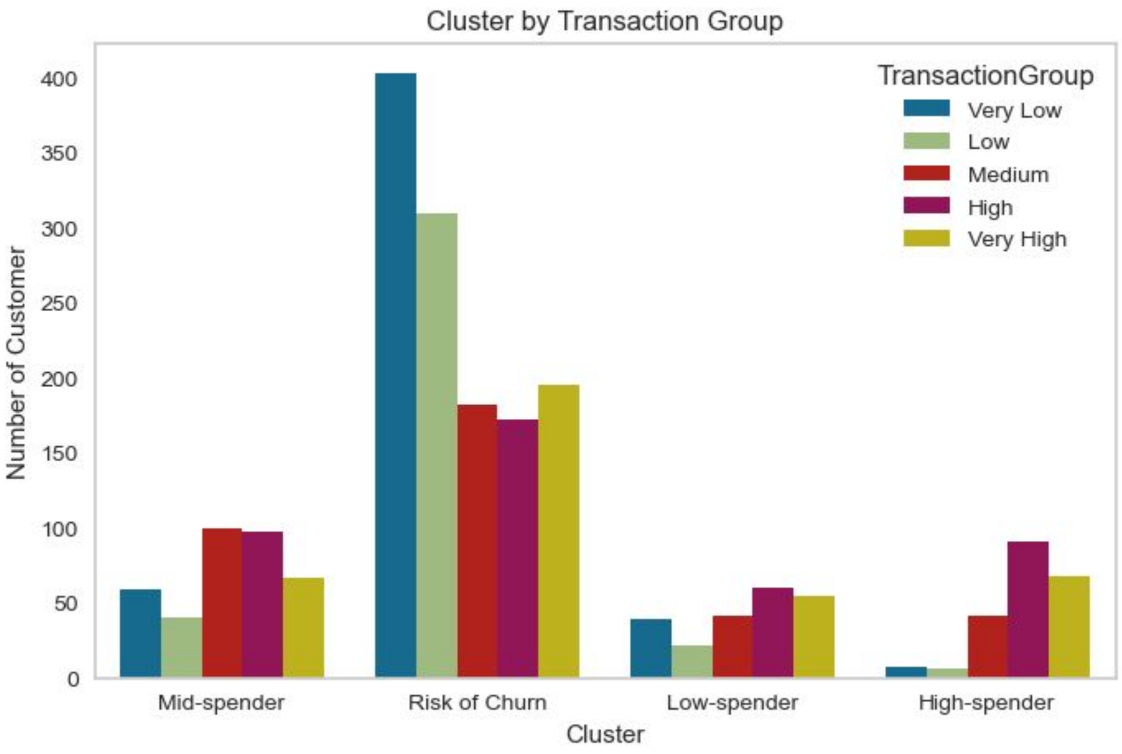


The majority of customers with **Bachelor's (S1)**, **Master's (S2)**, and **Doctoral (S3)** degrees dominate across all clusters.

This indicates that a **higher level of education** is associated with greater **customer engagement**, **purchasing power**, and **loyalty potential**.

Model Interpretation

Very Low Transactions Dominate Risk of Churn Cluster



All clusters include customers with **varying numbers of transactions** (from **Very Low** to **Very High**).

However, the **majority of customers** with **Very Low transaction frequency** are concentrated in the **Risk of Churn** cluster.

Model Interpretation

Risk of Churn Generates the Highest GMV Despite Inactivity

The **Risk of Churn** cluster generated the **highest GMV** (Rp 445.8 million), primarily due to its **very large customer base**.

Although customers in this cluster are currently **inactive**, they were **key contributors** to **historical revenue**.

Recommendations & Potential Impacts

Recommendations

- **Re-engage the Risk of Churn Segment**: Target inactive customers with exclusive offers and personalized messages to encourage them to return and re-engage with the platform.
- **Retain and Upsell Mid & High Spenders:** Provide loyalty programs or exclusive promotions to drive repeat purchases and increase transaction value among high-potential, active customers.
- **Segment Based on Potential Value:** Combine historical data and customer lifetime value (CLV) to identify dormant but high-value customers for targeted reactivation efforts.
- **Optimize Targeting Using Stable Demographics:** Leverage insights from age, marital status, and education level to create more relevant and effective marketing campaigns tailored to each customer segment.

Potential Impacts

- **Increase Customer Retention:** Reactivating just 20% of Risk of Churn customers (~240 customers) has the potential to generate an additional Rp89 million+ in GMV, based on average historical contribution.
- **Drive GMV Growth from Loyal Segments**: Upselling 10% of Mid and High Spender customers could result in an estimated Rp64 million in additional GMV.
- **Reduce Churn Among High-Value Customers:** Early identification of high-value customers at risk could help preserve up to Rp 445.8 million in GMV currently at risk of being lost.
- **Unlock Dormant GMV Potential:** If all Risk of Churn customers were successfully reactivated, the GMV potential could reach Rp445.8 million — equivalent to 31% of current total GMV.

THANK YOU