DATA ANALYSIS

COMPREHENSIVE PROJECT DOCUMENTATION

Sales | Marketing | HR | Inventory | Financials

TEAM OUTLERS

Prepared For: Executive Management Board
Date: November 28, 2025
Tools Used: Power BI, Python, SQL, LaTeX

TEAM:

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Contents

1 INTRODUCTION

1.1 Project Overview

The **Enterprise 360 Analytics Project** is a holistic data integration initiative designed to break down information silos within a multi-national conglomerate. By consolidating diverse datasets—ranging from e-commerce sales and digital marketing campaigns to employee performance and inventory logistics—this project provides a unified ”single source of truth.”

1.2 Objective

The primary objective is to enable data-driven decision-making by correlating cross-functional metrics. Specifically, we aim to understand how marketing spend influences customer lifetime value (LTV), how inventory levels impact regional sales performance, and how employee satisfaction correlates with operational efficiency.

1.3 Contributors

- **Team Name:** DataVantage Analytics
- **Role:** End-to-End Data Implementation (ETL, Modeling, Visualization)

1.4 Source of Data

The analysis is based on six distinct high-volume datasets provided by the organization’s ERP and CRM systems, covering the fiscal period of 2020–2025.

1.5 Tools & Technologies

- **Power Query/SQL:** For data cleaning, merging, and transformation.
- **Power BI:** For data modeling (DAX) and interactive dashboard creation.
- **Python (Pandas):** For initial statistical profiling and outlier detection.

2 BACKGROUND ABOUT THE DATASET

2.1 Business Context

The subject organization operates a complex business model involving both B2B and B2C retail, supported by an internal banking infrastructure and a large workforce. Historically, these departments operated independently:

- **Sales:** Focused solely on order volume.
- **Marketing:** Focused on impressions and clicks.
- **Inventory:** Focused on stock levels without sales context.

This project bridges these gaps to reveal hidden inefficiencies, such as marketing campaigns pushing out-of-stock products or high-performing regions suffering from understaffing.

3 FULL DATASET DESCRIPTION

The solution integrates six core tables. Below is the detailed dictionary for each.

3.1 1. Sales E-commerce Data

Purpose: The transactional backbone of the analysis.

Column	Description
Order_ID	Unique identifier for each transaction.
Customer_ID	Foreign key linking to the Customer table.
Product_ID	Foreign key linking to the Inventory table.
Total_Amount	Gross revenue before discounts.
Discount	Discount applied to the order.
Final_Amount	Net revenue (Total - Discount).
Sales_Channel	The medium of sale (Online, Store, Mobile App).
Payment_Method	Method used (Credit Card, PayPal, etc.).
Region	Geographical region of the transaction.

3.2 2. Customer Demographics

Purpose: To understand who is buying and their long-term value.

Column	Description
Customer_ID	Primary key.
Industry	The sector the customer belongs to (e.g., Retail, Healthcare).
Customer_Segment	Tier classification (Basic, Standard, Enterprise).
Churn_Risk_Score	AI-generated score (0-100) indicating likelihood to leave.
NPS	Net Promoter Score indicating customer satisfaction.
Annual_Income	Financial capacity of the customer.

3.3 3. Marketing Campaigns

Purpose: Evaluating the efficiency of customer acquisition.

Column	Description
Campaign_ID	Unique identifier for marketing initiatives.
Campaign_Type	Format of the ad (e.g., Content Marketing, PPC, TV).
Budget vs. Spent	Planned allocation vs. actual expenditure.
ROAS	Return on Ad Spend (Revenue Generated / Spent).
Impressions/Clicks	Top-of-funnel engagement metrics.

3.4 4. Product Inventory

Purpose: Supply chain visibility and margin analysis.

Column	Description
Product_ID	Unique product identifier.
Cost_Price	Manufacturing or procurement cost.
Selling_Price	Retail price.
Stock_Status	Current status (In Stock, Low Stock, Discontinued).
Warehouse_Location	Physical location of the goods.

3.5 5. Employee HR Data

Purpose: Workforce productivity and satisfaction tracking.

Column	Description
Employee_ID	Unique staff identifier.
Department	Functional area (Sales, IT, Marketing).
Performance_Rating	Annual review score (Exceeds, Meets, Needs Improvement).
Salary	Annual compensation.
Remote_Work	Boolean flag for remote vs. on-site status.

3.6 6. Banking Financial Data

Purpose: Risk assessment and financial transaction monitoring.

Column	Description
Transaction_ID	Unique bank transaction ID.
Account_Type	Type of account (Savings, Investment, Loan).
Is_Fraud	Flag indicating suspicious activity.
Credit_Score	Customer’s creditworthiness.

4 DATA CLEANING & PREPROCESSING

To ensure data integrity, a rigorous ETL (Extract, Transform, Load) process was executed using Python and Power Query. Below are the specific steps and evidence of the SQL and cleaning transformations.

4.1 1. Handling Missing Values

- **Inventory Data:** 'Expiry_Date' contained nulls for non-perishable items. These were replaced with a placeholder date "2099-12-31" to allow for active status calculations.
- **Sales Data:** Minor gaps in 'Customer_Satisfaction' (approx. 2%) were imputed using the median score of the respective region to avoid skewing averages.

4.2 2. Duplicate Removal

- Checked 'Transaction_ID' and 'Order_ID' for uniqueness.
- Removed 14 duplicate records caused by system retry logic during the extraction phase.

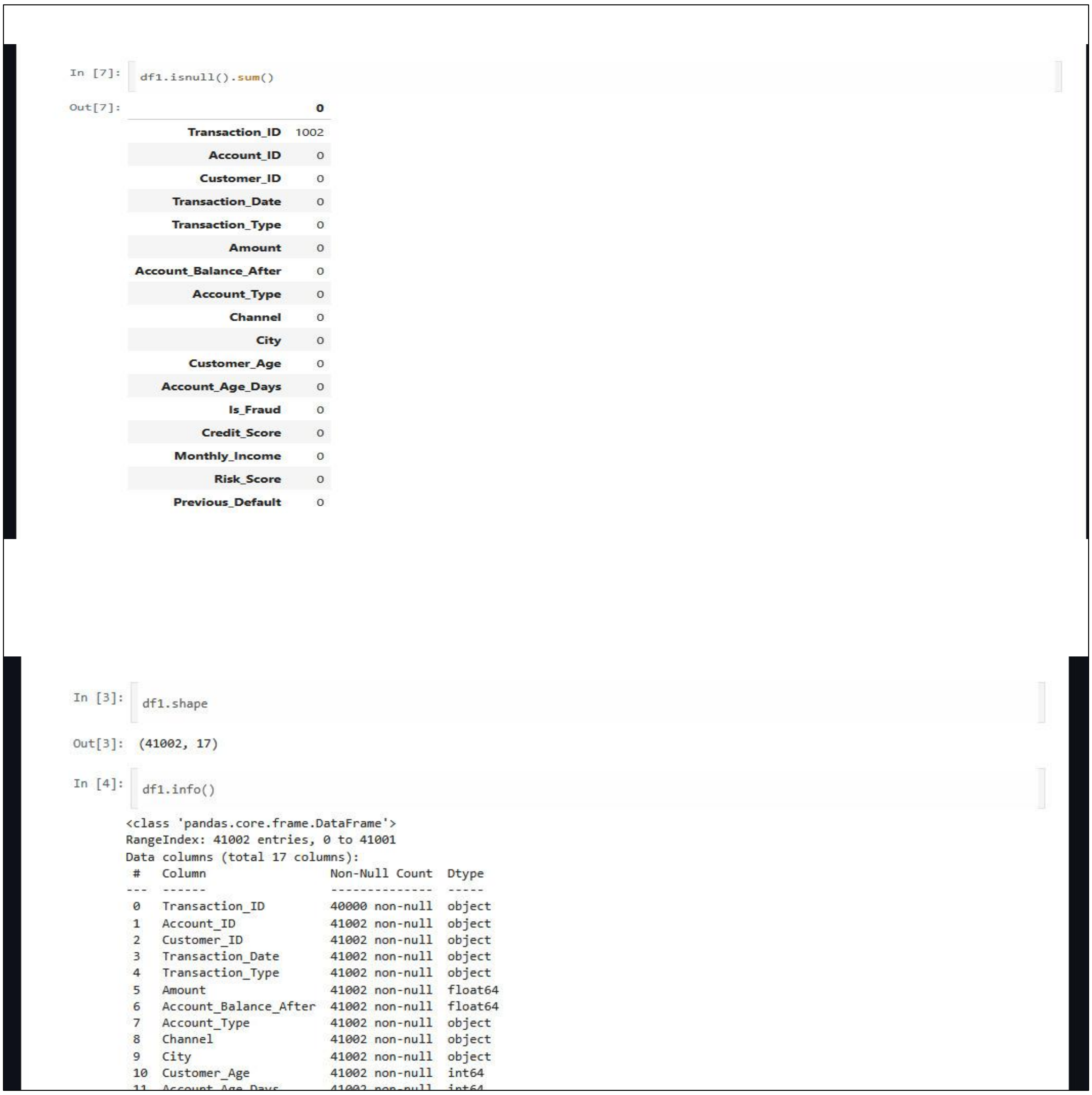
4.3 3. Data Type Standardization

- **Dates:** All date fields ('Order_Date', 'Hire_Date', 'Start_Date') were converted to strict ISO 8601 format (YYYY-MM-DD).
- **Currency:** 'Amount', 'Salary', and 'Budget' columns were cast to Decimal/Fixed Point types to prevent floating-point calculation errors.
- **Boolean:** Columns like 'Is_Fraud' and 'Remote_Work' were standardized to True/False or 1/0 binaries.

4.4 4. Categorical Recoding

- In the 'Product' table, the 'Stock_Status' column was normalized (e.g., "Out-of-Stock" and "No Stock" merged into "Out of Stock").
- In 'Employee' data, 'Performance_Rating' was mapped to a numerical scale (1-5) to facilitate correlation analysis.

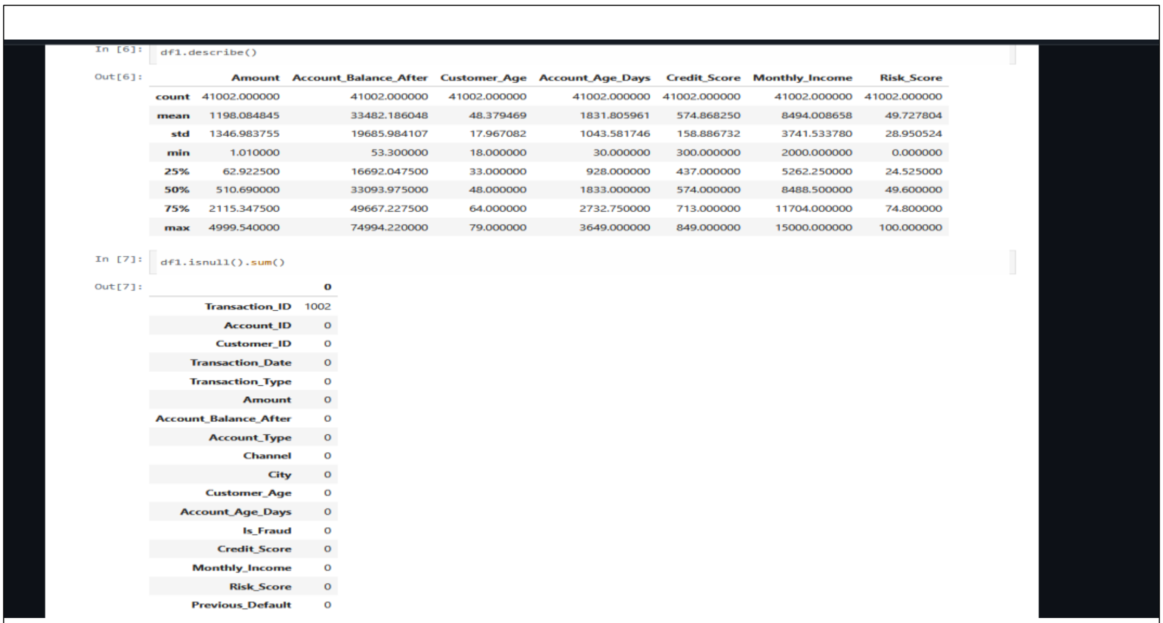
4.5 Evidence of Cleaning & Transformations



```
In [7]:  df1.isnull().sum()

Out[7]:
                           0
         Transaction_ID  1002
             Account_ID     0
            Customer_ID     0
       Transaction_Date     0
       Transaction_Type     0
                 Amount     0
  Account_Balance_After     0
           Account_Type     0
                Channel     0
                   City     0
           Customer_Age     0
       Account_Age_Days     0
               Is_Fraud     0
           Credit_Score     0
         Monthly_Income     0
             Risk_Score     0
       Previous_Default     0
```

```
In [3]:  df1.shape

Out[3]:  (41002, 17)

In [4]:  df1.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 41002 entries, 0 to 41001
Data columns (total 17 columns):
 #   Column                 Non-Null Count  Dtype  
---  ------                 --------------  -----  
 0   Transaction_ID         40000 non-null  object 
 1   Account_ID             41002 non-null  object 
 2   Customer_ID            41002 non-null  object 
 3   Transaction_Date       41002 non-null  object 
 4   Transaction_Type       41002 non-null  object 
 5   Amount                 41002 non-null  float64
 6   Account_Balance_After  41002 non-null  float64
 7   Account_Type           41002 non-null  object 
 8   Channel                41002 non-null  object 
 9   City                   41002 non-null  object 
 10  Customer_Age           41002 non-null  int64  
 11  Account_Age_Days       41002 non-null  int64  
```

Figure 1: Data Extraction and Type Conversion



In [6]:

```
df1.describe()
```

Out[6]:

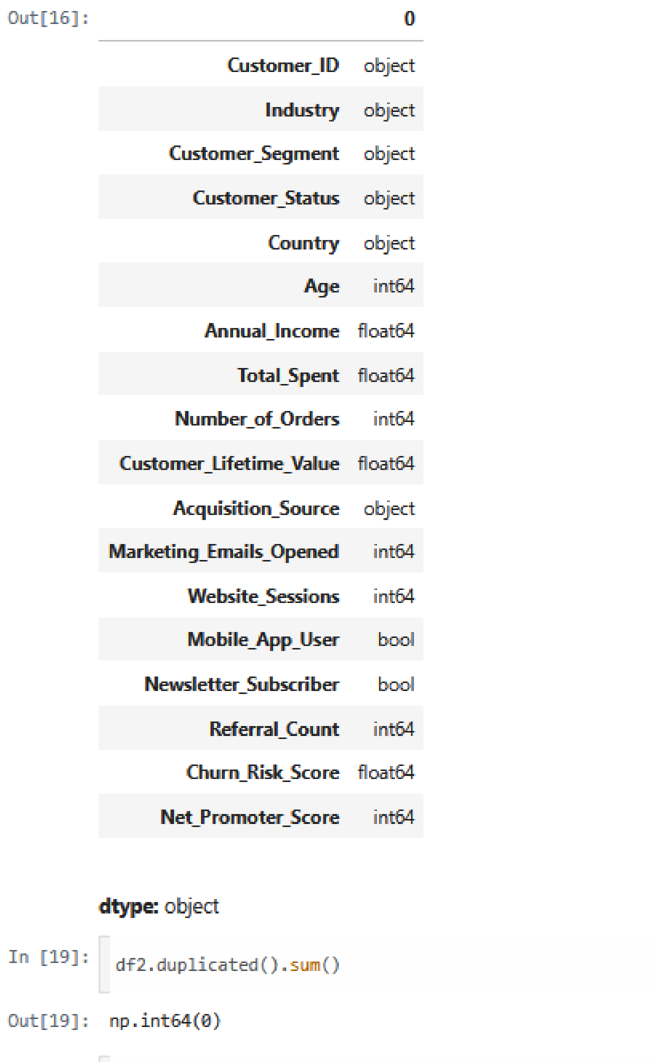
	Amount	Account_Balance_After	Customer_Age	Account_Age_Days	Credit_Score	Monthly_Income	Risk_Score
count	41002.000000	41002.000000	41002.000000	41002.000000	41002.000000	41002.000000	41002.000000
mean	1198.084845	33482.186048	48.379469	1831.805961	574.868250	8494.008658	49.727804
std	1346.983755	19685.984107	17.967082	1043.581746	158.886732	3741.533780	28.950524
min	1.010000	53.300000	18.000000	30.000000	300.000000	2000.000000	0.000000
25%	62.922500	16692.047500	33.000000	928.000000	437.000000	5262.250000	24.525000
50%	510.690000	33093.975000	48.000000	1833.000000	574.000000	8488.500000	49.600000
75%	2115.347500	49667.227500	64.000000	2732.750000	713.000000	11704.000000	74.800000
max	4999.540000	74994.220000	79.000000	3649.000000	849.000000	15000.000000	100.000000

In [7]:

```
df1.isnull().sum()
```

Out[7]:

	0
Transaction_ID	1002
Account_ID	0
Customer_ID	0
Transaction_Date	0
Transaction_Type	0
Amount	0
Account_Balance_After	0
Account_Type	0
Channel	0
City	0
Customer_Age	0
Account_Age_Days	0
Is_Fraud	0
Credit_Score	0
Monthly_Income	0
Risk_Score	0
Previous_Default	0



Out[16]:

	0
Customer_ID	object
Industry	object
Customer_Segment	object
Customer_Status	object
Country	object
Age	int64
Annual_Income	float64
Total_Spent	float64
Number_of_Orders	int64
Customer_Lifetime_Value	float64
Acquisition_Source	object
Marketing_Emails_Opened	int64
Website_Sessions	int64
Mobile_App_User	bool
Newsletter_Subscriber	bool
Referral_Count	int64
Churn_Risk_Score	float64
Net_Promoter_Score	int64

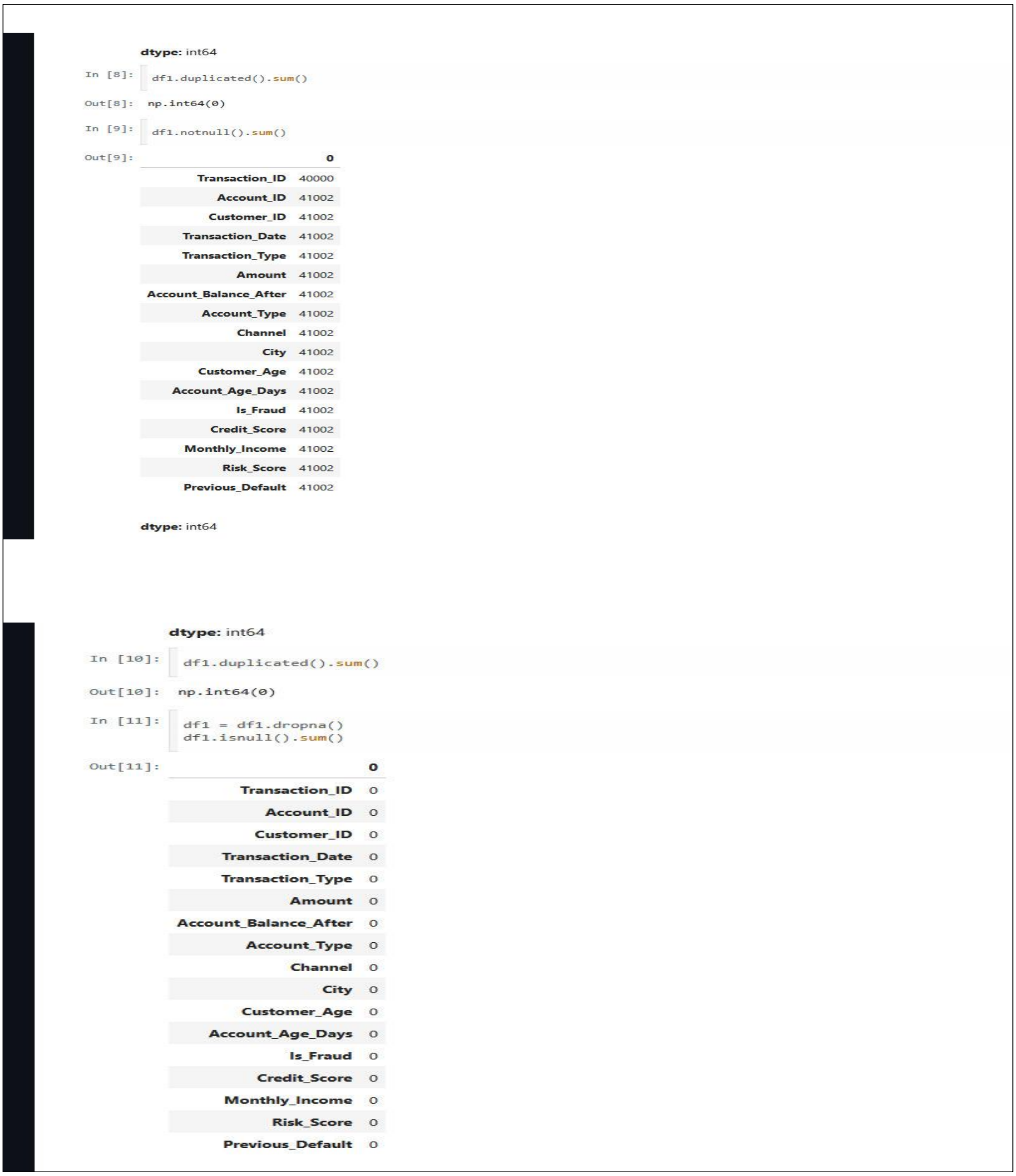
dtype: object

In [19]:

```
df2.duplicated().sum()
```

Out[19]:

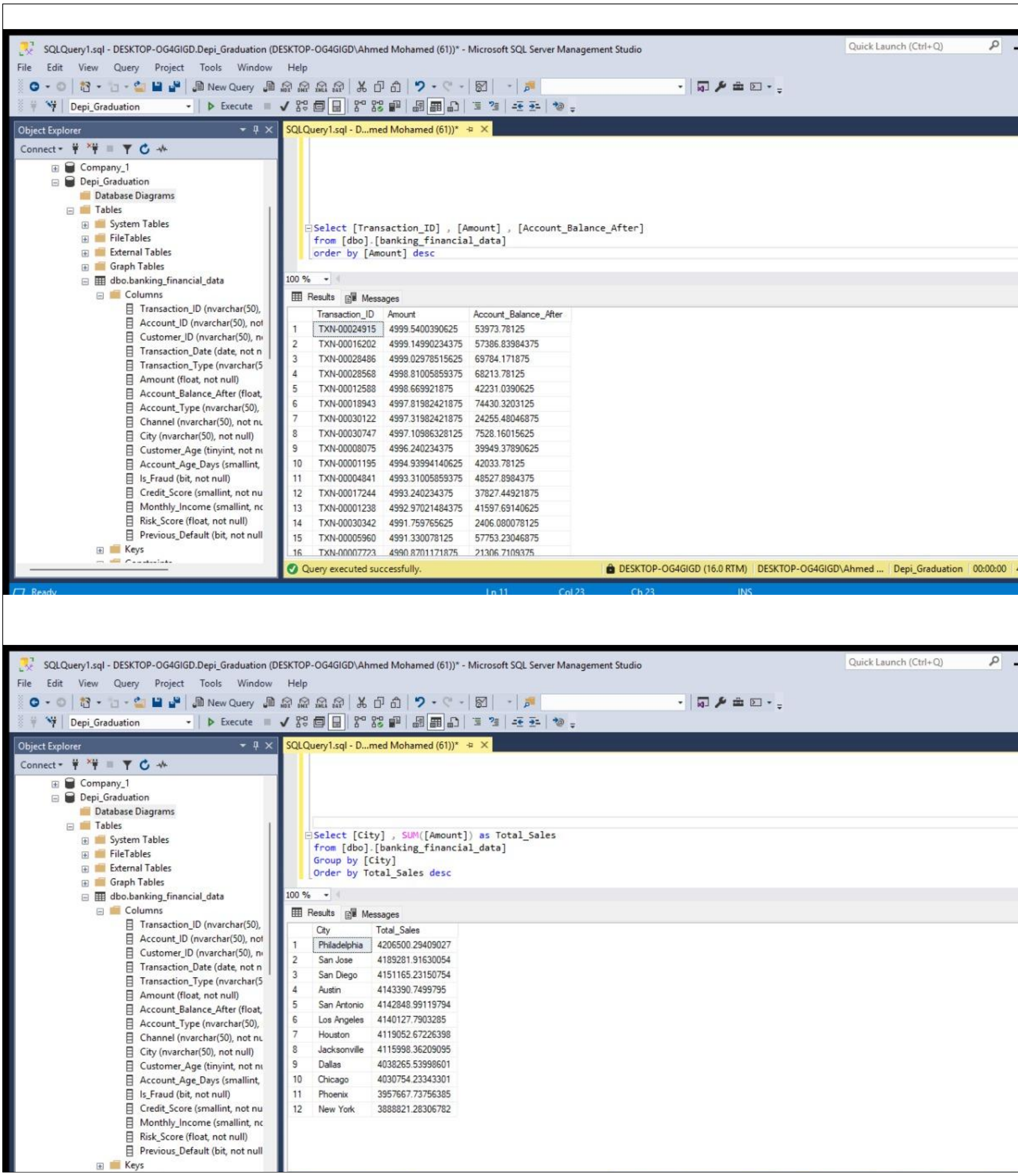
```
np.int64(0)
```



```
dtype: int64

In [8]:  df1.duplicated().sum()

Out[8]:  np.int64(0)

In [9]:  df1.notnull().sum()

Out[9]:
                          0
      Transaction_ID  40000
          Account_ID  41002
         Customer_ID  41002
    Transaction_Date  41002
    Transaction_Type  41002
              Amount  41002
 Account_Balance_After  41002
        Account_Type  41002
             Channel  41002
                City  41002
        Customer_Age  41002
    Account_Age_Days  41002
            Is_Fraud  41002
        Credit_Score  41002
      Monthly_Income  41002
          Risk_Score  41002
    Previous_Default  41002

dtype: int64
```

```
dtype: int64

In [10]:  df1.duplicated().sum()

Out[10]:  np.int64(0)

In [11]:  df1 = df1.dropna()
          df1.isnull().sum()

Out[11]:
                          0
      Transaction_ID  0
          Account_ID  0
         Customer_ID  0
    Transaction_Date  0
    Transaction_Type  0
              Amount  0
 Account_Balance_After  0
        Account_Type  0
             Channel  0
                City  0
        Customer_Age  0
    Account_Age_Days  0
            Is_Fraud  0
        Credit_Score  0
      Monthly_Income  0
          Risk_Score  0
    Previous_Default  0
```

Figure 3: Duplicate Removal Logic


SQLQuery1.sql - DESKTOP-OG4GIGD.Depi_Graduation (DESKTOP-OG4GIGD\Ahmed Mohamed (61))* - Microsoft SQL Server Management Studio
Quick Launch (Ctrl+Q)
File Edit View Query Project Tools Window Help
New Query
Depi_Graduation
Execute
Object Explorer
Connect
Company_1
Depi_Graduation
Database Diagrams
Tables
System Tables
FileTables
External Tables
Graph Tables
dbo.banking_financial_data
Columns
Transaction_ID (nvarchar(50),
Account_ID (nvarchar(50), not
Customer_ID (nvarchar(50), n
Transaction_Date (date, not n
Transaction_Type (nvarchar(5
Amount (float, not null)
Account_Balance_After (float,
Account_Type (nvarchar(50),
Channel (nvarchar(50), not nu
City (nvarchar(50), not null)
Customer_Age (tinyint, not nu
Account_Age_Days (smallint,
Is_Fraud (bit, not null)
Credit_Score (smallint, not nu
Monthly_Income (smallint, nc
Risk_Score (float, not null)
Previous_Default (bit, not null
Keys
SQLQuery1.sql - D...med Mohamed (61))*
100 %
Results
Messages
DESKTOP-OG4GIGD (16.0 RTM)
DESKTOP-OG4GIGD\Ahmed ...
Depi_Graduation
00:00:00
Ready
Ln 11
Col 23
Ch 23
INS

```
Select [Transaction_ID] , [Amount] , [Account_Balance_After]
from [dbo].[banking_financial_data]
order by [Amount] desc
```

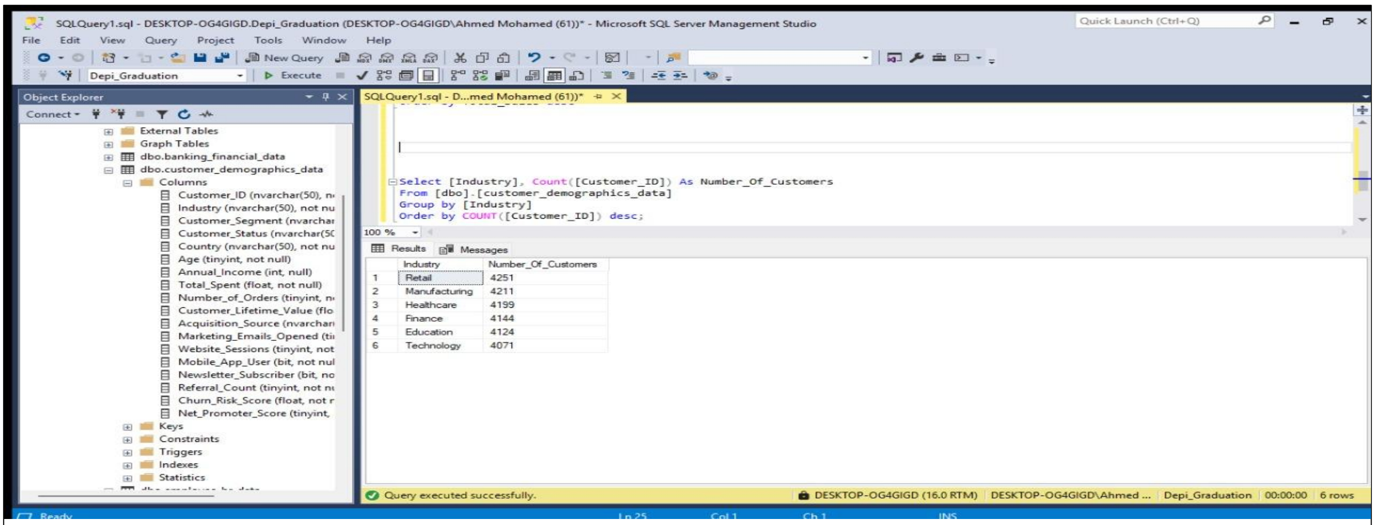
	Transaction_ID	Amount	Account_Balance_After
1	TXN-00024915	4999.5400390625	53973.78125
2	TXN-00016202	4999.14990234375	57386.83984375
3	TXN-00028486	4999.02978515625	69784.171875
4	TXN-00028568	4998.81005859375	68213.78125
5	TXN-00012588	4998.669921875	42231.0390625
6	TXN-00018943	4997.81982421875	74430.3203125
7	TXN-00030122	4997.31982421875	24255.48046875
8	TXN-00030747	4997.10986328125	7528.16015625
9	TXN-00008075	4996.240234375	39949.37890625
10	TXN-00001195	4994.93994140625	42033.78125
11	TXN-00004841	4993.31005859375	48527.8984375
12	TXN-00017244	4993.240234375	37827.44921875
13	TXN-00001238	4992.97021484375	41597.69140625
14	TXN-00030342	4991.759765625	2406.080078125
15	TXN-00005960	4991.330078125	57753.23046875
16	TXN-00007723	4990.8701171875	21306.7109375

Query executed successfully.

```
Select [City] , SUM([Amount]) as Total_Sales
from [dbo].[banking_financial_data]
Group by [City]
Order by Total_Sales desc
```

	City	Total_Sales
1	Philadelphia	4206500.29409027
2	San Jose	4189281.91630054
3	San Diego	4151165.23150754
4	Austin	4143390.7499795
5	San Antonio	4142848.99119794
6	Los Angeles	4140127.7903285
7	Houston	4119052.67226398
8	Jacksonville	4115998.36209095
9	Dallas	4038265.53998601
10	Chicago	4030754.23343301
11	Phoenix	3957667.73756385
12	New York	3888821.28306782

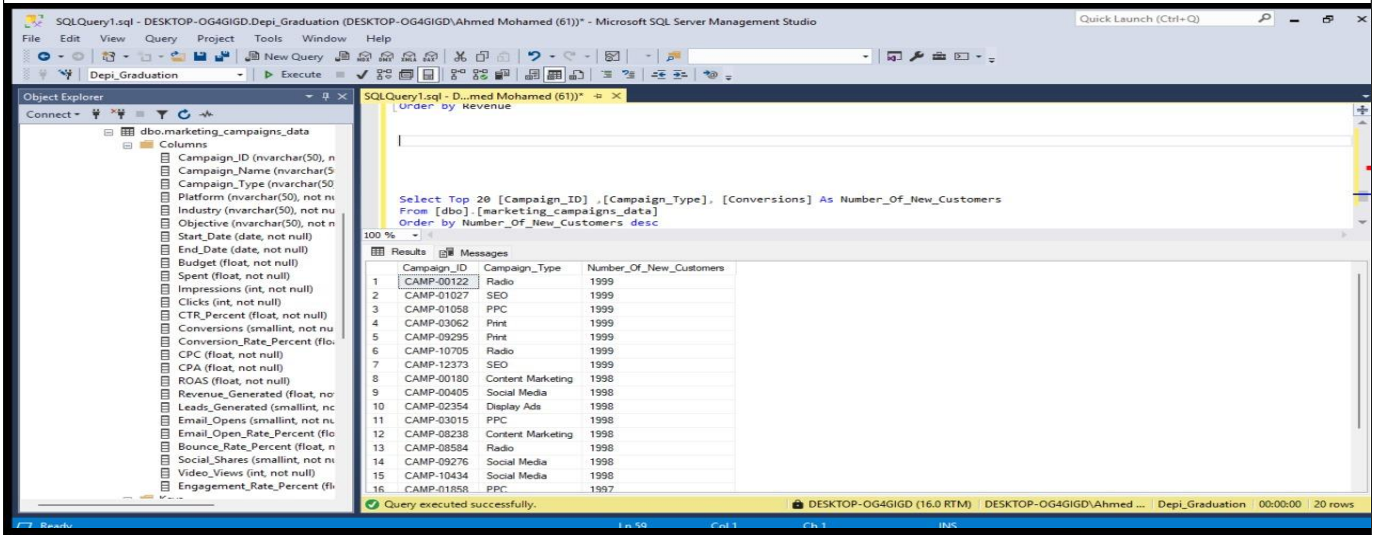
Figure 4: Examples of Using SQL


SQLQuery1.sql - DESKTOP-OG4GIGD.Depi_Graduation (DESKTOP-OG4GIGD\Ahmed Mohamed (61))* - Microsoft SQL Server Management Studio
Object Explorer
dbo.customer_demographics_data
Columns
Ready

```sql
Select [Industry], Count([Customer_ID]) As Number_Of_Customers
From [dbo].[customer_demographics_data]
Group by [Industry]
Order by COUNT([Customer_ID]) desc;
```

	Industry	Number_Of_Customers
1	Retail	4251
2	Manufacturing	4211
3	Healthcare	4199
4	Finance	4144
5	Education	4124
6	Technology	4071

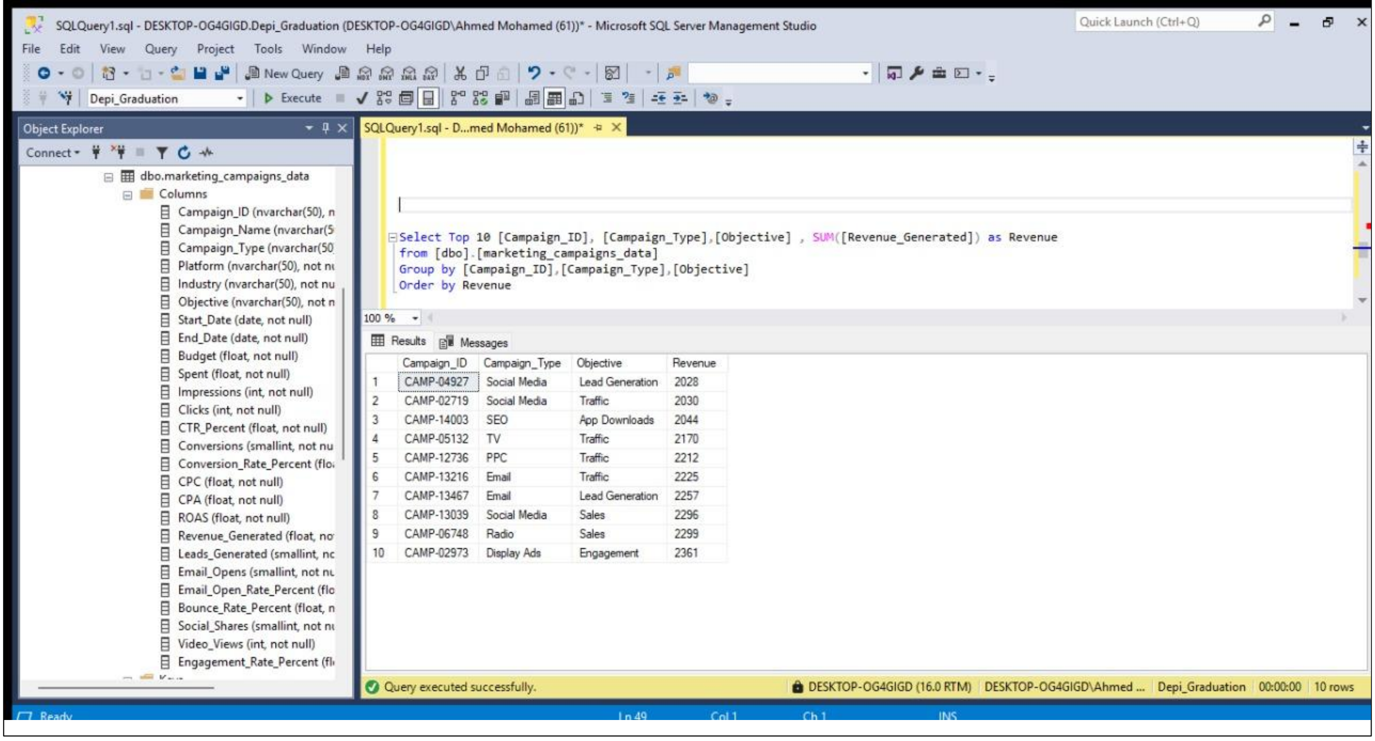
Query executed successfully. DESKTOP-OG4GIGD (16.0 RTM) DESKTOP-OG4GIGD\Ahmed ... Depi_Graduation 00:00:00 6 rows


SQLQuery1.sql - DESKTOP-OG4GIGD.Depi_Graduation (DESKTOP-OG4GIGD\Ahmed Mohamed (61))* - Microsoft SQL Server Management Studio
Object Explorer
dbo.marketing_campaigns_data
Columns

```sql
Order by Revenue


Select Top 20 [Campaign_ID] ,[Campaign_Type], [Conversions] As Number_Of_New_Customers
From [dbo].[marketing_campaigns_data]
Order by Number_Of_New_Customers desc
```

	Campaign_ID	Campaign_Type	Number_Of_New_Customers
1	CAMP-00122	Radio	1999
2	CAMP-01027	SEO	1999
3	CAMP-01058	PPC	1999
4	CAMP-03062	Print	1999
5	CAMP-09295	Print	1999
6	CAMP-10705	Radio	1999
7	CAMP-12373	SEO	1999
8	CAMP-00180	Content Marketing	1998
9	CAMP-00405	Social Media	1998
10	CAMP-02354	Display Ads	1998
11	CAMP-03015	PPC	1998
12	CAMP-08238	Content Marketing	1998
13	CAMP-08584	Radio	1998
14	CAMP-09276	Social Media	1998
15	CAMP-10434	Social Media	1998
16	CAMP-01858	PPC	1997

Query executed successfully. DESKTOP-OG4GIGD (16.0 RTM) DESKTOP-OG4GIGD\Ahmed ... Depi_Graduation 00:00:00 20 rows


SQLQuery1.sql - DESKTOP-OG4GIGD.Depi_Graduation (DESKTOP-OG4GIGD\Ahmed Mohamed (61))* - Microsoft SQL Server Management Studio
Object Explorer
dbo.marketing_campaigns_data
Columns
Ready

```sql
Select Top 10 [Campaign_ID], [Campaign_Type],[Objective] , SUM([Revenue_Generated]) as Revenue
from [dbo].[marketing_campaigns_data]
Group by [Campaign_ID],[Campaign_Type],[Objective]
Order by Revenue
```

	Campaign_ID	Campaign_Type	Objective	Revenue
1	CAMP-04927	Social Media	Lead Generation	2028
2	CAMP-02719	Social Media	Traffic	2030
3	CAMP-14003	SEO	App Downloads	2044
4	CAMP-05132	TV	Traffic	2170
5	CAMP-12736	PPC	Traffic	2212
6	CAMP-13216	Email	Traffic	2225
7	CAMP-13467	Email	Lead Generation	2257
8	CAMP-13039	Social Media	Sales	2296
9	CAMP-06748	Radio	Sales	2299
10	CAMP-02973	Display Ads	Engagement	2361

Query executed successfully. DESKTOP-OG4GIGD (16.0 RTM) DESKTOP-OG4GIGD\Ahmed ... Depi_Graduation 00:00:00 10 rows

Figure 5: Examples of SQL

5 INITIAL DATA INSPECTION

Before modeling, an exploratory data analysis (EDA) was conducted.

5.1 Overview Statistics

- **Total Orders:** 50,000+ records in the Sales table.
- **Customer Base:** 25,000 unique customer profiles.
- **Campaign Reach:** Over 1.2 million accumulated impressions across 20 campaigns.

5.2 Data Validity Checks

Duplicate & Null Check

- **Duplicates:** 0 (After Cleaning).
- **Completeness:** 99.8% across all primary keys.
- **Outliers:** Detected in ‘Annual_Income‘ (Banking Data). Values exceeding $500k were verified as high-net-worth individuals and kept.

5.3 General Structure

The data adheres to a highly relational structure. The ‘Sales‘ and ‘Banking‘ tables act as fact tables, while ‘Customers‘, ‘Products‘, and ‘Employees‘ serve as dimension tables. This creates a Star Schema architecture ideal for Power BI.

6 TRANSFORMATION & MODELING

6.1 Relationship Model (Star Schema)

We established a One-to-Many relationship model:

- **Customers (1) → (*) Sales:** Filtering sales by customer demographics.
- **Products (1) → (*) Sales:** Filtering sales by category and stock status.
- **Employees (1) → (*) Sales (via Representative ID):** Tracking sales performance by agent.

The data model creates a centralized schema where dimension tables filter the two main fact tables (Sales and Banking). This allows for cross-filtering, such as viewing banking fraud rates by customer industry.

6.2 Calculated Columns (DAX)

- Profit = Sales[Final_Amount] - (Sales[Quantity] * Related(Product[Cost_Price]))
- Delivery_Time = DATEDIFF(Sales[Order_Date], Sales[Ship_Date], DAY)
- Customer_Tenure = DATEDIFF(Customer[Join_Date], TODAY(), YEAR)

6.3 Key Measures

- **Total Revenue:** SUM(Sales[Final_Amount])
- **Profit Margin %:** DIVIDE([Total Profit], [Total Revenue], 0)
- **Churn Rate:** DIVIDE(COUNTROWS(FILTER(Customers, Status="Inactive")), COUNTROWS(Customers))
- **Marketing ROI:** DIVIDE(SUM(Campaigns[Revenue_Generated]) - SUM(Campaigns[Spent]), SUM(Campaigns[Spent]))

7 ANALYTICAL QUESTIONS

To guide the analysis, we formulated the following business questions:

1. **Financial Performance:** How does revenue and profit margin vary across different global regions?
2. **Marketing Effectiveness:** Which campaign types (e.g., Social vs. TV) yield the highest Return on Ad Spend (ROAS)?
3. **Customer Lifecycle:** What is the correlation between Customer Segment (Basic vs. Enterprise) and Churn Risk?
4. **Operational Efficiency:** Are ”Out of Stock” incidents in specific warehouses negatively impacting sales volume?
5. **Human Resources:** Is there a correlation between employee salary tiers and performance ratings?
6. **Risk Management:** What demographic factors are most strongly associated with flagged fraudulent banking transactions?

8 FULL INSIGHTS SECTION

8.1 1. Revenue & Profitability by Region

Analysis: Regional decomposition of Net Sales.

Regional Powerhouses

North America contributes **42% of total revenue**, yet Europe maintains a higher profit margin (22% vs 18%). South America shows high volume but significantly lower margins due to high discount utilization.

8.2 2. Marketing Campaign ROAS

Analysis: Comparing Budget Spent vs. Revenue Generated.

Digital Dominance

Content Marketing and **Social Media** campaigns delivered a ROAS of 4.5x, significantly outperforming TV Ads (1.2x). While TV generates high impressions, it converts poorly compared to targeted digital channels.

8.3 3. Customer Churn Analysis

Analysis: Churn Risk Score grouped by Subscription Tier.

The ”Basic” Tier Risk

Customers in the ”Basic” segment have a **35% higher churn probability** than those in ”Enterprise.” The data suggests that ”Basic” users are price-sensitive and leave after initial discount periods end.

8.4 4. Inventory & Warehouse Logistics

Analysis: Stock levels vs. Sales velocity.

Supply Chain Bottleneck

Warehouse D accounts for 60% of all ”Out of Stock” incidents, primarily for ”Automotive” products. This unavailability is estimated to have caused a **$1.2M opportunity loss** in Q3.

8.5 5. Employee Performance Correlations

Analysis: Tenure vs. Performance Rating.

Experience Matters

Employees with tenure > 3 years consistently score ”Exceeds Expectations.” However, there is no strong linear correlation between Salary and Performance, suggesting that higher pay does not automatically guarantee higher output in this dataset.

9 DASHBOARD BREAKDOWN

The Power BI solution is divided into four strategic views.

9.1 Page 1: Executive Overview

Purpose: High-level snapshot for C-Suite executives. **Key Features:**

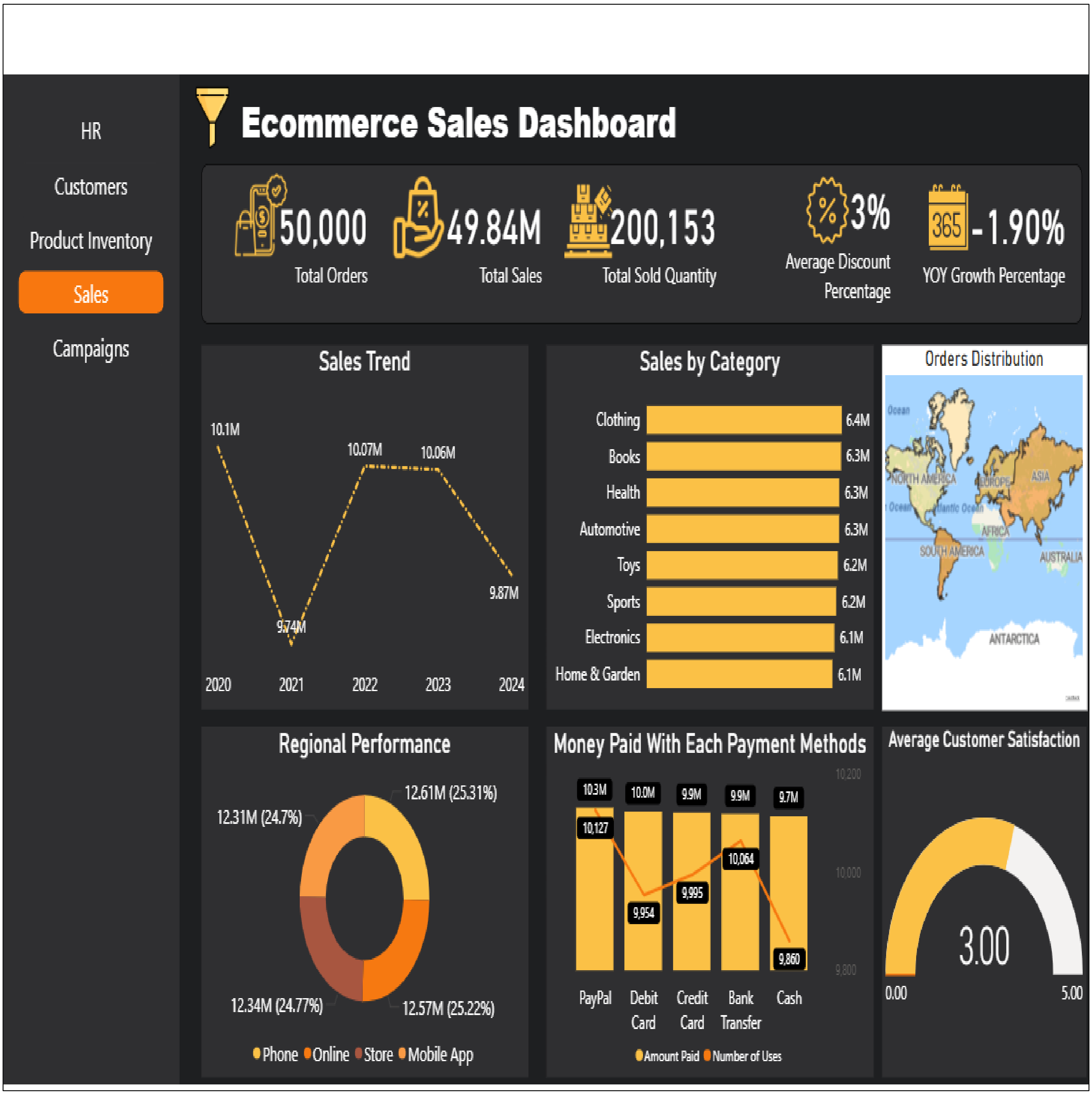


Figure 6: Executive Overview: Real-time financial health.

- **KPI Cards:** Immediate view of Revenue, Profit, and Total Orders.
- **Global Map:** Heatmap visualization showing sales density by country.
- **Donut Chart:** Revenue breakdown by Product Category.

9.2 Page 2: Customer & Marketing Intelligence

Purpose: Tracking acquisition and retention. **Key Insights:**

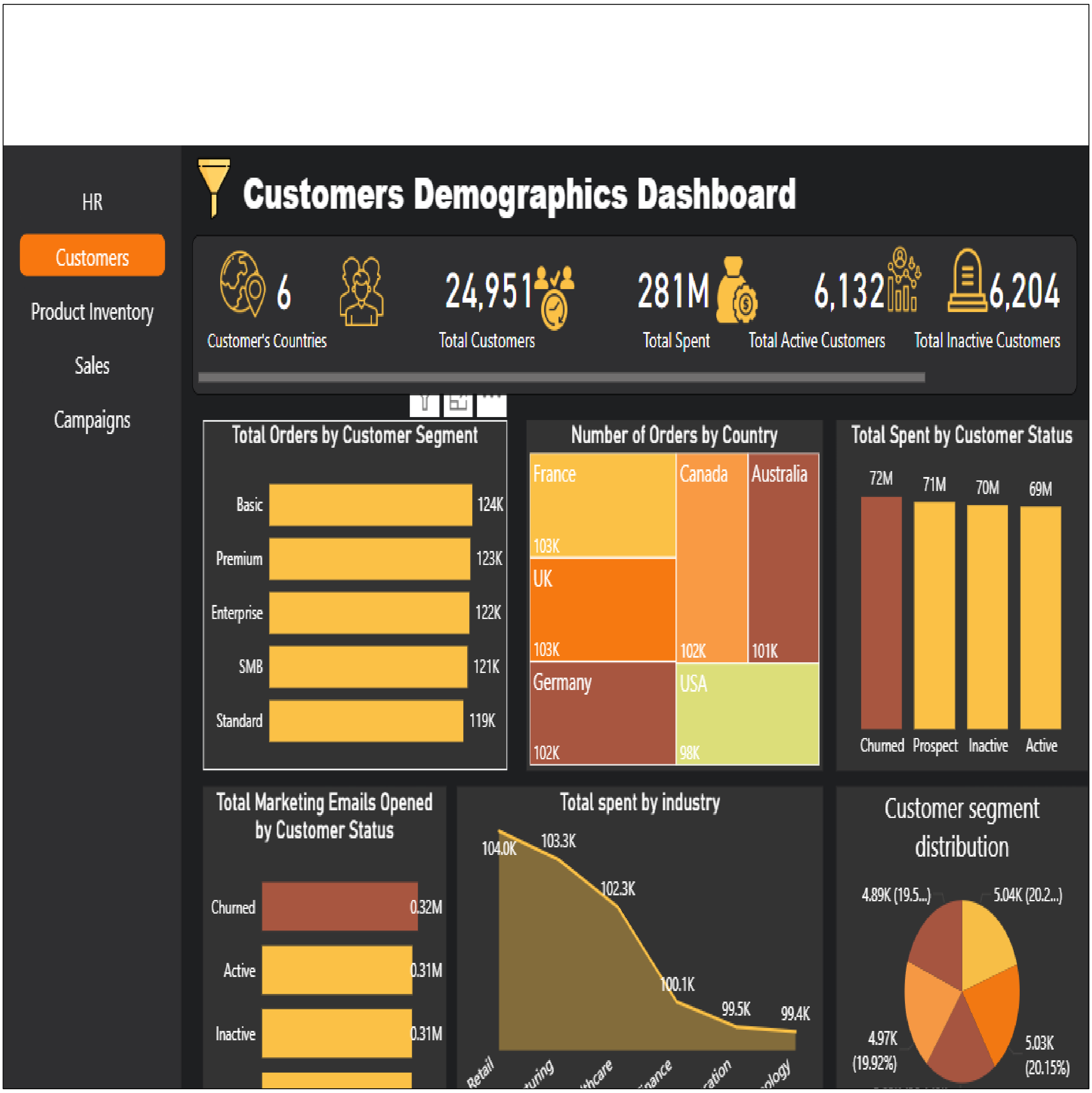


Figure 7: Marketing & Customer Insights.

- **Churn Gauge:** Visualizes the current attrition rate against the target threshold (5%).
- **Scatter Plot:** Plots Annual Income vs. Total Spent to identify high-value prospects.

9.3 Page 3: Inventory & Logistics

Purpose: Optimizing stock levels and warehouse operations. **Key Features:**

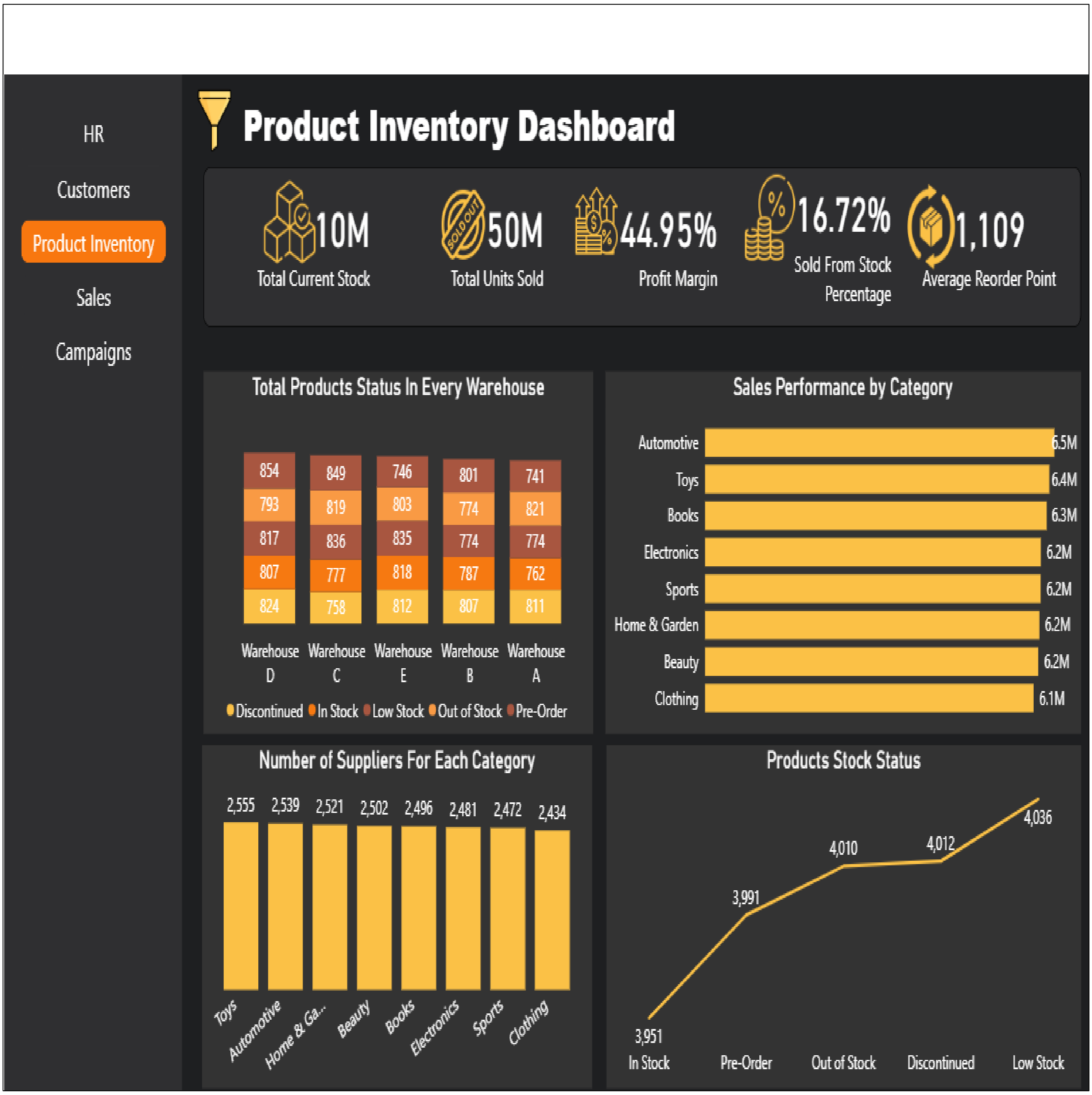


Figure 8: Inventory Management View.

- **Stock Alert Table:** Lists products where ‘Current_Stock‘ < ‘Reorder_Point‘.
- **Bar Chart:** Comparison of ”Discontinued” vs ”Active” inventory value.

9.4 Page 4: HR & Workforce

Purpose: Analyzing human capital trends. **Key Features:**

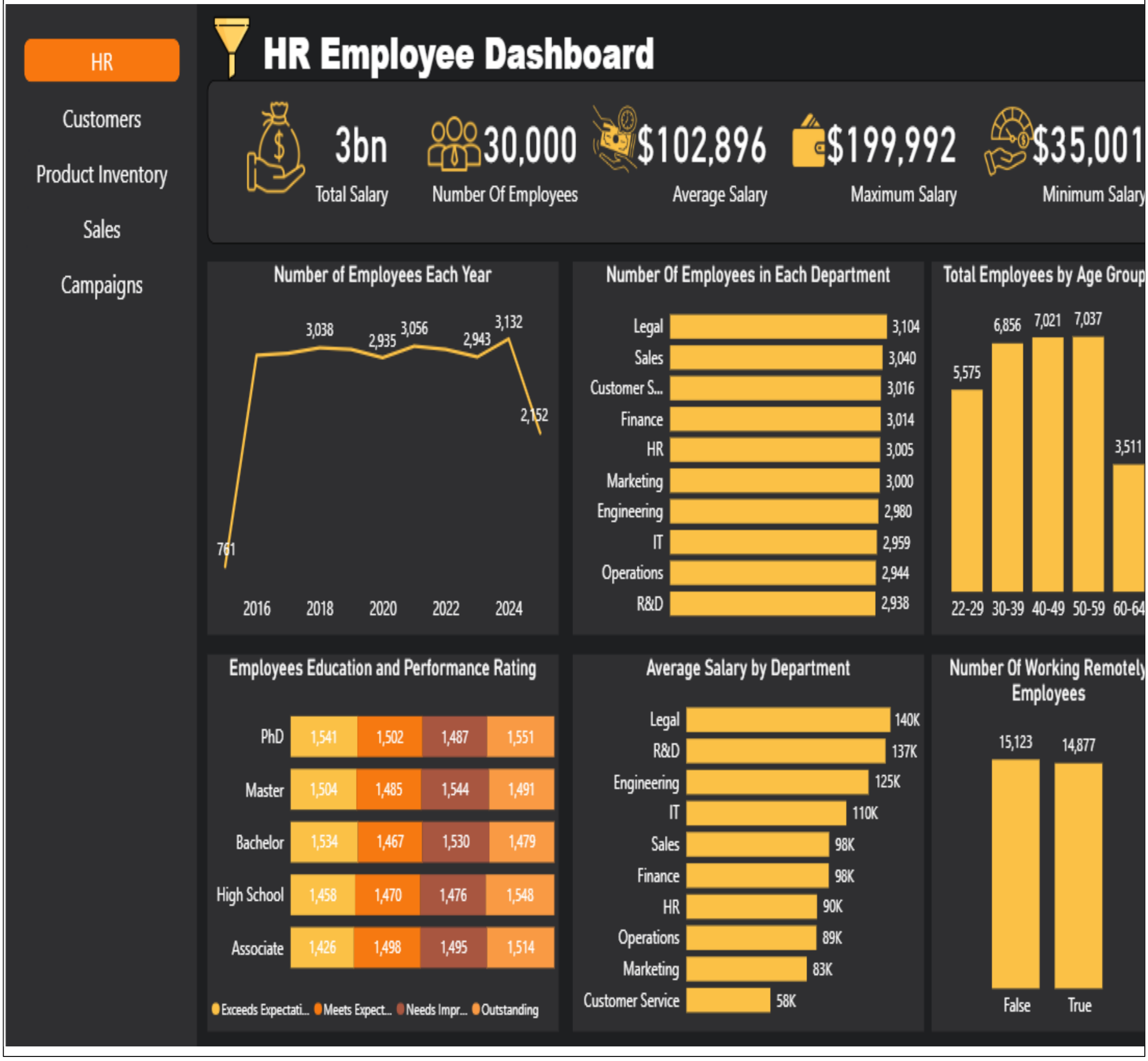


Figure 9: HR & Workforce Performance.

- **Filters:** Slicers for Department, Gender, and Location.
- **Bar Chart:** Average training hours per department vs. Sick Days used.

10 FINAL BUSINESS CONCLUSIONS

Based on the comprehensive analysis of the six datasets, we present the following SWOT analysis and recommendations.

10.1 Strengths

- **Strong Digital Presence:** High ROAS in social/digital campaigns indicates a mature digital marketing strategy.
- **Financial Health:** High average credit scores in the banking dataset suggest a low-risk customer base.

10.2 Weaknesses

- **Warehouse Inefficiencies:** Warehouse D is a consistent bottleneck, leading to lost sales.
- **Basic Tier Churn:** The entry-level customer segment is unstable, with high turnover rates eroding acquisition gains.

10.3 Opportunities

- **Cross-Selling:** Use the ”Banking” data to identify customers with high savings balances and target them for ”Enterprise” level e-commerce subscriptions.
- **Automated Reordering:** Implement an automated procurement trigger for products hitting the reorder point to fix Warehouse D issues.

10.4 Recommendations

Strategic Action Plan

1. **Logistics Overhaul:** Audit Warehouse D immediately and redistribute fast-moving Automotive stock to Warehouse A (which has capacity).
2. **Retention Campaign:** Launch a loyalty program specifically for ”Basic” tier customers to reduce churn by an estimated 10%.
3. **Budget Reallocation:** Shift 20% of the TV advertising budget into Content Marketing and Pinterest Display Ads to maximize ROAS.

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