KALBE Nutritionals

Optimization Strategy for Sales and Customer Loyalty at Kalbe Nutritionals: A Data-Driven Approach Using RFM, Cohort Analysis, and CLV

Hijir Della Wirasti

Final Project
Business Intelligence
Batch 13
Saturday, 08 March 2025

ibimbing

GitHub:
https://github.com/hijirdella/Kalbe-Nutritionals-BI-Final-Project-Sales-RFM-Cohort-Churn-CLV-Optimization

Outline

Education

Institut Teknologi Bandung
Bachelor's in Ocean Engineering
GPA: 3.21 (2011-2016)

Relevant coursework: Information of Technology B, Statistic and Probability Analysis, Numerical Analysis, Engineering Economics, Field Data Acquisition and Analysis, and Modelling in Coastal Engineering.

Universitas Pendidikan Indonesia
Bachelor's in Music Education
GPA: 3.57 (2013-2019)

Telkom University
Master's in Information Systems
GPA: 3.71 (2022-Present)

Relevant coursework: Data Governance and Information Technology, Business Analysis and Company Data, Integration and Architecture of Company Applications, and Information Assurance and Security.

Working

PT Dinamaritama Konsultan Rekayasa

Ocean Engineer Consultant
July 2016 – March 2022

Analyzed millions of wave, current, and geotechnical data points for designing docks, coastal protection structures, and other maritime infrastructure across 20 government projects.

Sony Music Entertainment Indonesia

Artist & Repertoire Executive
October 2022 – October 2023

Released 136 songs annually for 29 Sony artists, analyzed music trends via dashboards, and guided curation, collaborations, and artist development.

Believe

Artist & Repertoire Manager
December 2023 – May 2024

Successfully acquired Javanese Pop and hyperlocal artists, utilizing sales and marketing analytics with dashboard data for revenue projections, contract management, and A&R strategies.

A. Introduction

Self-Overview

I am a data-driven professional passionate about leveraging analytics, visualization, and predictive modeling to drive business decisions. With a diverse background in **engineering, music, and information systems**, I bring a unique blend of **technical expertise and creativity** to solve complex problems.

My expertise lies in **Business Intelligence**, with a strong focus on **data analysis, A/B testing, customer segmentation, uplift modeling, and churn prediction** using **SQL, Python, Tableau, and Power BI**. I thrive on transforming raw data into actionable insights that optimize strategies and enhance decision-making.

As I continue to grow in the **data industry**, my goal is to **bridge the gap between data and business impact**, ensuring organizations harness the full power of their data assets. I am eager to collaborate, innovate, and contribute to **data-driven success stories**.

South Jakarta
hijirdw@gmail.com
https://www.linkedin.com/in/hijirdella/
GitHub https://github.com/hijirdella

B. Projects Overview

During this bootcamp, I have worked on various projects focused on data analysis, business modeling, and data visualization.

Data Warehouse Design

Design a Data Warehouse (DWH) for Employee & Sales, including an ERD diagram, Star Schema, Data Mart tables, SQL scripts, and a presentation on schema, relationships, and insights. View Project

PostgreSQL ETL Procedure for Data Warehouse

This project contains dwh.generate_sales(), a stored procedure for ETL in PostgreSQL, moving transaction data to staging and loading it into the data warehouse. Includes documentation and a step-by-step presentation. View Project

House Price Analysis (EDA) and Correlation-Insights

Analyzing housing data using EDA, preprocessing, and statistical techniques like Pearson Correlation, Chi-Square Test, Linear Regression, T-Test, and ANOVA to identify trends and relationships. View Project

Bank Marketing Campaign Impact Analysis on Term Deposits

Analyze marketing campaign impact on term deposits using EDA, correlation, chi-square tests, and linear regression. View Project

Automated ETL Pipeline with Airflow for School Data

Showcasing an Airflow ETL pipeline to extract school data from an API, transform it, and load it into PostgreSQL. Includes Python scripts, documentation, and examples. View Project

Netflix Recommendation System Using Machine Learning

A Netflix Recommendation System using machine learning models (KNN, Decision Tree, Random Forest, Logistic Regression, Naive Bayes, K-Means) evaluated for accuracy and clustering, with insights into content trends and user preferences. View Project

Customer Analysis and RFM Segmentation for Superstore

Analyzing Superstore customer data with RFM segmentation, EDA, and visualizations, identifying key insights, and presenting findings with a report and Tableau dashboard. View Project

Funnel & Cohort Analysis Dashboard

This project features a Business Intelligence case study using Funnel and Cohort Analysis in Tableau, including data preprocessing, visualization, and trend analysis. It provides interactive dashboards and a presentation with key insights and recommendations. View Project

Bank Customer Churn Prediction and CLV Optimization

Analyzing bank customer churn and optimizing Customer Lifetime Value (CLV) using 11 machine learning models (e.g., Logistic Regression, Random Forest, XGBoost). Includes EDA, churn prediction, CLV analysis, and model evaluation with metrics like Precision, Recall, F1-score, and Confusion Matrix. View Project

A/B Testing for Spotify Playlist Recommendation

This project evaluates the impact of a new playlist recommendation algorithm on engagement, retention, and conversion rates using t-tests and chi-square tests. It includes randomized test design, feature engineering, statistical analysis, and visualizations to optimize recommendations. View Project

Uplift Modeling for Marketing Promotions

This project analyzes the impact of Discount vs. BOGO offers compared to No Offer (Control) using S-Learner & Uplift Random Forest. It includes EDA, AUUC, Gain Chart, and model evaluation to optimize marketing conversions. View Project

Olist E-Commerce Executive & Operational Dashboard

An interactive Tableau dashboard providing both executive and operational insights into Olist's sales trends, customer satisfaction, order fulfillment, and strategic performance for data-driven decision-making. View Project

C. Main Project

GitHub

https://github.com/hijirdella/Kalbe-Nutritionals-BI-Final-Project-Sales-RFM-Cohort-Churn-CLV-Optimization

tableau

https://public.tableau.com/app/profile/hijir.della.wirasti5486/viz/KalbeNutritionalsBusinessPerformanceDashboardUnderstandingSalesDynamicsCustomerRetentionRFMCohortandCLVStrategies/Sales-Dashboard

01. Combine Kalbe Data.ipynb
02. Preprocessing - EDA - RFM - Kalbe Farma.ipynb
03. Churn Analysis - Kalbe Farma.ipynb

PostgreSQL

04. Cohort Query.sql

1. Project Background

- **General Description:** This project aims to enhance sales and customer loyalty at Kalbe Nutritionals using a data-driven approach. By implementing RFM analysis, cohort analysis, and CLV estimation, the project seeks to understand customer behavior and identify effective strategies for improving retention and customer value.
- **Primary Objectives:** Improve marketing strategy effectiveness, reduce customer churn, and increase Customer Lifetime Value (CLV).
- **Expected Outcomes:** Increased customer retention, higher sales, and more targeted marketing strategies.
- **Project Importance:** In the competitive nutrition industry, understanding and meeting customer needs is crucial to maintaining market share and increasing profitability.
- **Beneficiaries:** Management teams, marketing departments, and Kalbe Nutritionals customers.

2. Business Problem

- **Business Challenge:** Kalbe Nutritionals faces challenges in retaining customers and increasing sales in a highly competitive market. High churn rates and a lack of deep understanding of customer segmentation hinder marketing effectiveness.
- **Problem Importance:** A high churn rate can reduce revenue and increase customer acquisition costs. Without proper segmentation, marketing campaigns may be ineffective, leading to wasted resources.
- **Impact of Solving the Problem:** By identifying valuable customer segments and understanding their behavior, Kalbe Nutritionals can design effective retention strategies, reduce churn, and increase profitability.

Literature Review

The implementation of data-driven strategies such as **RFM Analysis (Recency, Frequency, Monetary), Cohort Analysis, and Customer Lifetime Value (CLV)** can significantly impact **sales and customer loyalty** at **Kalbe Nutritionals**. Below are some data and figures supporting the effectiveness of this approach:

Increase in Customer Loyalty and Revenue

- **Eastwood**: Achieved a **21% increase in email marketing profits** after implementing RFM analysis.
- **L'Occitane**: Experienced a **25-fold increase in revenue per email** through customer segmentation using the RFM model.
- **Frederick's of Hollywood**: Recorded a **6-9% conversion rate** in their campaigns after adopting RFM analysis. **(Desai et al, 2021)**

Reduction in Churn Rate

- Companies utilizing churn prediction can **reduce churn rates by up to 30%** with more targeted strategies.
- By **identifying at-risk customers early**, businesses can implement retention strategies such as **loyalty programs and exclusive discounts** (Yulianti, 2018).

Marketing Cost Efficiency

- With **better customer segmentation**, businesses can allocate marketing budgets more efficiently, focusing on high-value customers.
- Using **RFM and CLV analysis** can **reduce Customer Acquisition Cost (CAC) by up to 25%**, as companies can concentrate on **more profitable customers** (Feaseo, 2022)

Better Customer Behavior Insights

- Cohort analysis helps businesses track customer behavior over time, improving retention strategies. Companies using this approach saw a 15% retention increase in six months (DQLab, 2023).

Optimized Customer Lifetime Value (CLV)

- RFM-based CLV calculations and clustering techniques like K-Means can improve marketing efficiency by 30% and long-term profitability by 20% (Laksono et al, 2023).

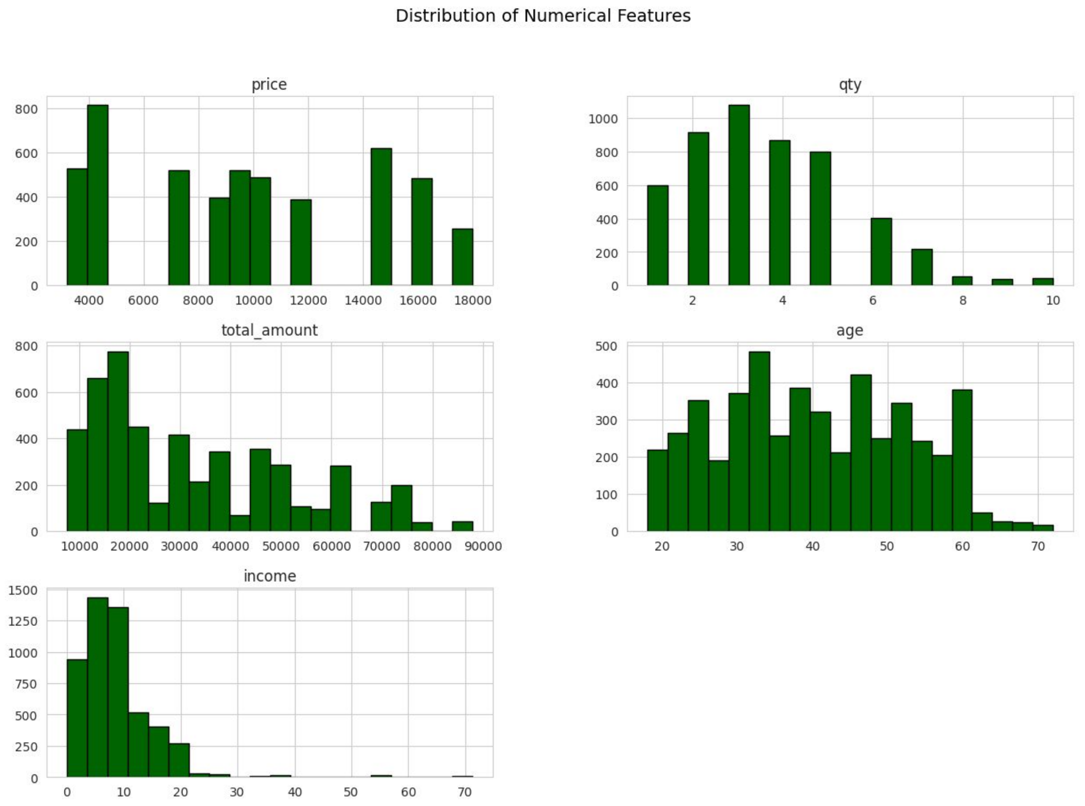
3. Data Analysis and Insights

DATASET OVERVIEW

This **dataset** consists of four CSV files: Customer, Store, Product, and Transaction. It is a dummy dataset created for an FMCG case study covering a one-year period, collected through a membership program.

This case study utilizes four key datasets:

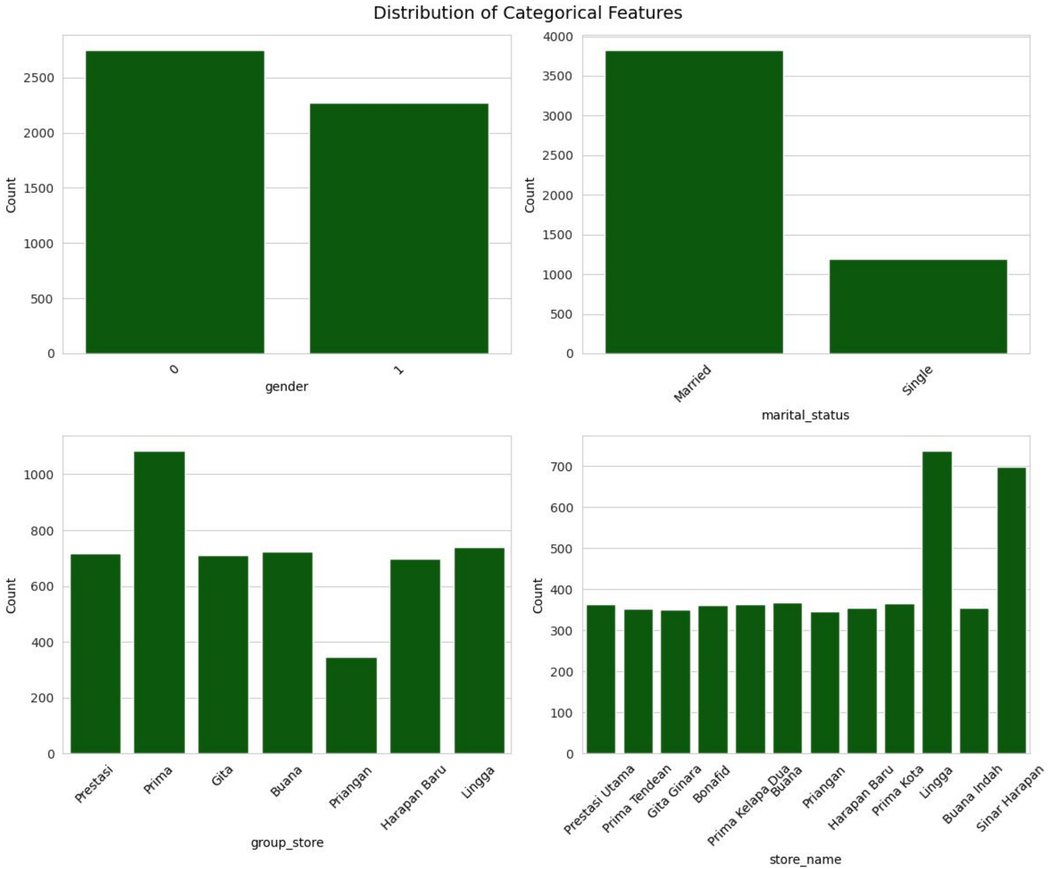
- **Customer Data**: Contains demographic details such as age, gender, marital status, and income levels.
- **Store Data**: Provides store-related information including store name, group affiliation, trade type (Modern or General Trade), and geographical coordinates.
- **Product Data**: Lists product names, unique IDs, and pricing details.
- **Transaction Data**: Includes transactional records such as transaction date, product details, quantity purchased, and total purchase amount.



Uniavariate Analysis

Key Insights & Recommendations:

- **Popular price points:** 4000-5000 & 14000-16000 → **Focus promotions here**
- **Small purchase trend (1-5 items) → Use upselling & bundling**
- **Most transactions: 10,000 - 30,000 IDR → Encourage higher spend with discounts**
- **Main audience: 25-55 years old → Target working professionals**
- **Low to mid-income customers → Offer paylater & budget-friendly deals**
- **High-income segment → Introduce premium products**



Uniavariate Analysis

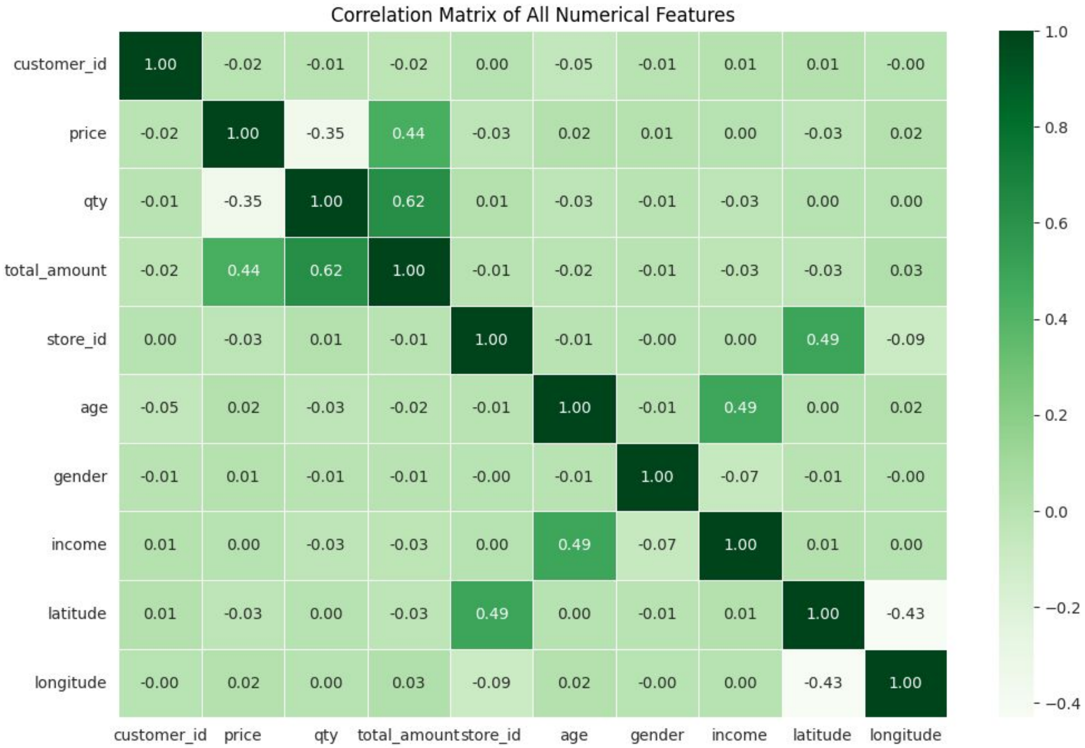
Key Insights & Recommendations:

1. **Gender Distribution:**
   - More female (0) than male (1) customers.
   - **Target female-oriented promotions & product selections.**
2. **Marital Status:**
   - Majority of customers are **married**.
   - **Family/bundle deals & household product promotions** may perform well.
3. **Group Store Distribution:**
   - **Prima dominates sales**, followed by other groups like Gita and Lingga.
   - **Strengthen partnerships with top-performing stores** for better sales.
4. **Store Name Distribution:**
   - **Lingga & Sinar Harapan lead in store transactions.**
   - **Optimize inventory & exclusive promotions in these stores.**

Multivariate Analysis

Key Insights from Pairplot Analysis:

✅ **Price vs. Quantity:** Lower-priced products are bought in higher quantities.
✅ **Total Amount vs. Quantity:** Higher quantity leads to higher spending, but not always linearly.
✅ **Income vs. Total Amount:** Higher-income customers **don't necessarily spend more.**
✅ **Age vs. Income:** Younger customers have more varied income levels.



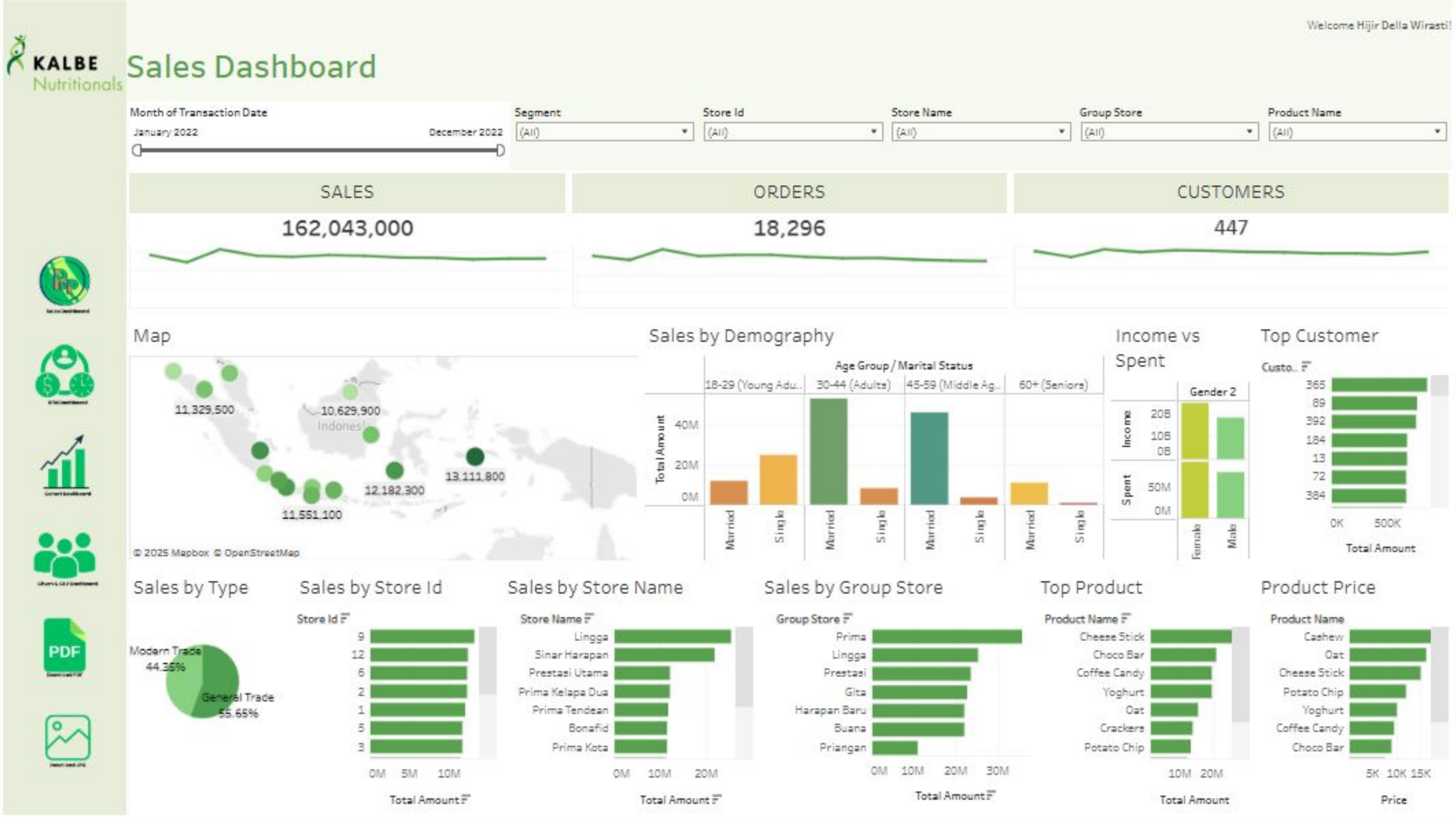
Multivariate Analysis

Key Insights from Correlation Matrix:

✅ **Price & Total Amount (0.44):** Higher-priced items contribute more to total spending.
✅ **Quantity & Total Amount (0.62):** More items purchased = higher total spending.
✅ **Income & Age (0.49):** Older customers tend to have higher income.
✅ **Income & Total Amount (~0):** No strong correlation → **high-income customers don't always spend more.**

4.
DASHBOARD

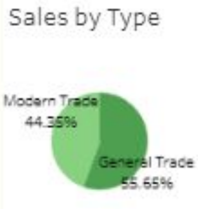
Tableau Link



Welcome Hijir Della Wirasti!
KALBE Nutritionals
Sales Dashboard
Month of Transaction Date
January 2022
December 2022
Segment
Store Id
Store Name
Group Store
Product Name
(All)
SALES
162,043,000
ORDERS
18,296
CUSTOMERS
447
Map
11,329,500
10,629,900
Indonesia
13,111,800
12,182,300
11,551,100
© 2025 Mapbox © OpenStreetMap
Sales by Demography
Age Group / Marital Status
18-29 (Young Adu..
30-44 (Adults)
45-59 (Middle Ag..
60+ (Seniors)
Total Amount
40M
20M
0M
Married
Single
Income vs Spent
Gender 2
Income
20B
10B
0B
Spent
50M
0M
Female
Male
Top Customer
Custo..
365
89
392
184
13
72
384
0K
500K
Total Amount
Sales by Type
Modern Trade
44.35%
General Trade
55.65%
Sales by Store Id
Store Id
9
12
6
2
1
5
3
0M
5M
10M
Total Amount
Sales by Store Name
Store Name
Lingga
Sinar Harapan
Prestasi Utama
Prima Kelapa Dua
Prima Tendean
Bonafid
Prima Kota
0M
10M
20M
Total Amount
Sales by Group Store
Group Store
Prima
Lingga
Prestasi
Gita
Harapan Baru
Buana
Priangan
0M
10M
20M
30M
Total Amount
Top Product
Product Name
Cheese Stick
Choco Bar
Coffee Candy
Yoghurt
Oat
Crackers
Potato Chip
10M
20M
Total Amount
Product Price
Product Name
Cashew
Oat
Cheese Stick
Potato Chip
Yoghurt
Coffee Candy
Choco Bar
5K
10K
15K
Price
PDF

SALES ANALYSIS

Overall Performance: Sales, orders, and customer trends appear stable over time.



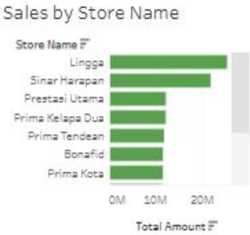
Sales by Type
Indicating traditional retail channels still play a crucial role.

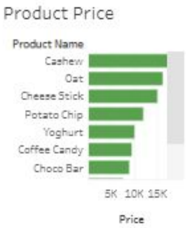
Demographic Analysis

- **Married adults (30-44 years old)** contribute the highest sales.
- **Younger (18-29) and senior (60+) segments** have lower sales, suggesting potential for targeted marketing.

Geographic Insights

- Eastern Indonesia & Sulawesi lead in sales, indicating strong market presence.
- Jakarta & Java contribute significantly but are behind emerging regions.
- Potential for growth in Sumatra and Kalimantan, where sales are slightly lower.
- Expansion opportunities in Bali/Nusa Tenggara, which have strong demand.



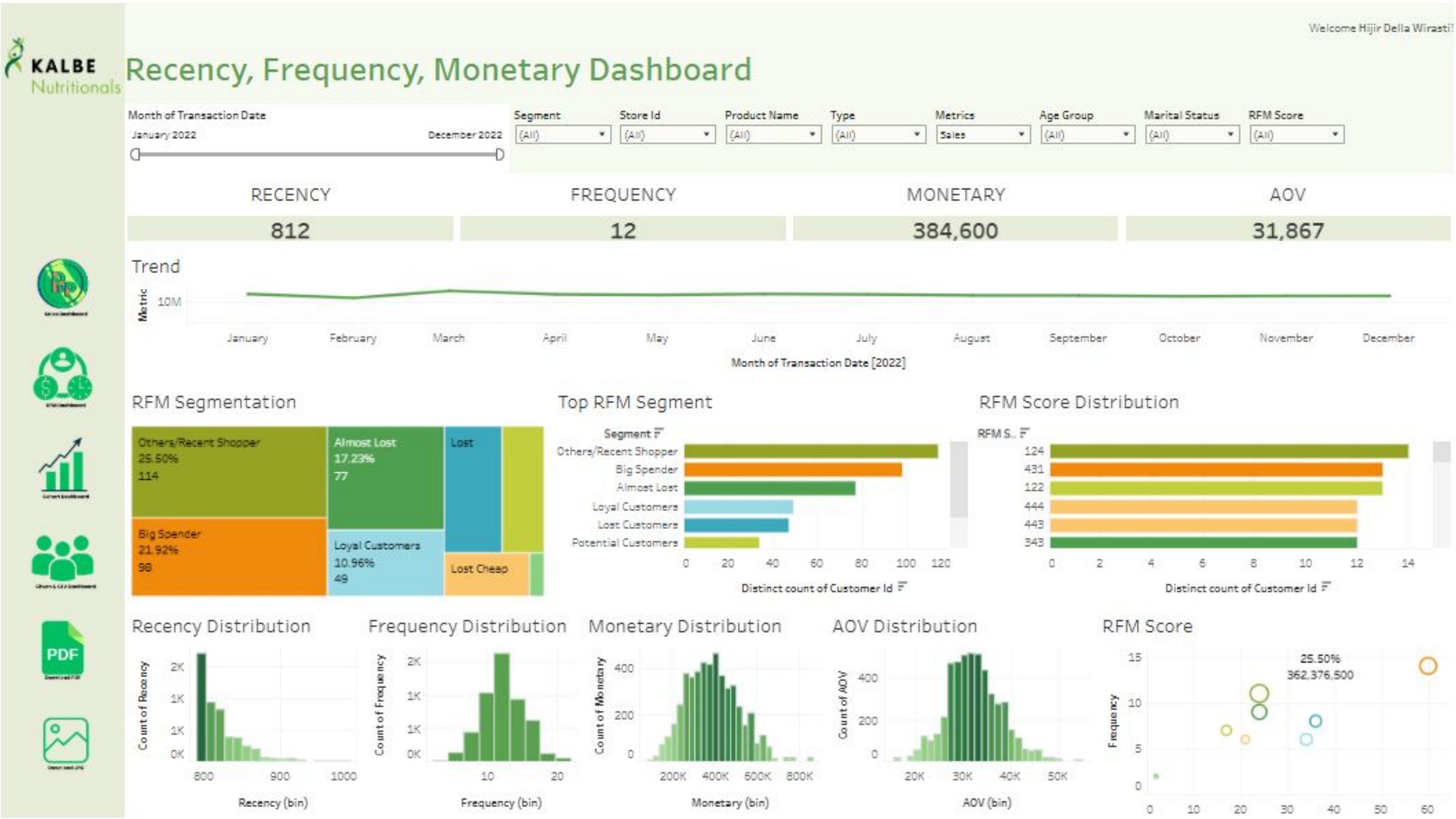


Store & Group Store Performance

- **Top-performing stores**: Lingga, Sinar Harapan, and Prestasi Utama.
- **Best-performing group stores**: Prima and Lingga.

Top Products & Pricing

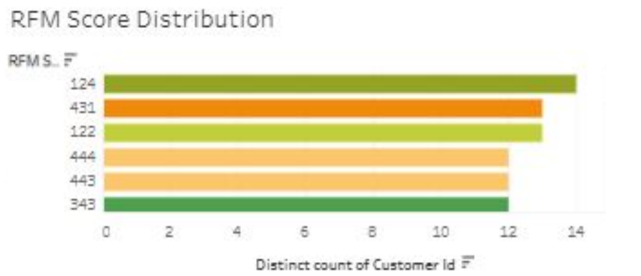
- **Best-selling products**: **Cheese Stick, Choco Bar, and Coffee Candy.**
- **Higher-priced products like Cashew and Oat** might need premium marketing strategies.

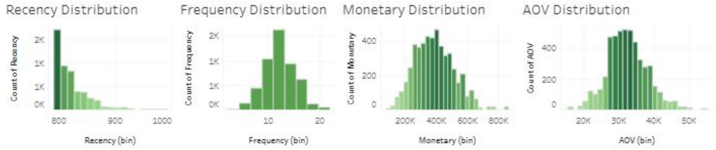

Welcome Hijir Della Wirasti!
KALBE Nutritionals
Recency, Frequency, Monetary Dashboard
Month of Transaction Date
January 2022
December 2022
Segment (All)
Store Id (All)
Product Name (All)
Type (All)
Metrics Sales
Age Group (All)
Marital Status (All)
RFM Score (All)
RECENCY 812
FREQUENCY 12
MONETARY 384,600
AOV 31,867
Trend
Metric
10M
January February March April May June July August September October November December
Month of Transaction Date [2022]
RFM Segmentation
Others/Recent Shopper 25.50% 114
Almost Lost 17.23% 77
Lost
Big Spender 21.92% 98
Loyal Customers 10.96% 49
Lost Cheap
Top RFM Segment
Segment
Others/Recent Shopper
Big Spender
Almost Lost
Loyal Customers
Lost Customers
Potential Customers
0 20 40 60 80 100 120
Distinct count of Customer Id
RFM Score Distribution
RFM S..
124
431
122
444
443
343
0 2 4 6 8 10 12 14
Distinct count of Customer Id
Recency Distribution
Count of Recency
2K 1K 1K 0K
800 900 1000
Recency (bin)
Frequency Distribution
Count of Frequency
2K 1K 1K 0K
10 20
Frequency (bin)
Monetary Distribution
Count of Monetary
400 200 0
200K 400K 600K 800K
Monetary (bin)
AOV Distribution
Count of AOV
400 200 0
20K 30K 40K 50K
AOV (bin)
RFM Score
25.50%
362,376,500
Frequency
15 10 5 0
0 10 20 30 40 50 60

RFM ANALYSIS

RECENCY	FREQUENCY	MONETARY	AOV
812	12	384,600	31,867

Key Metrics: Recency (812) indicates declining engagement, Frequency (12) shows moderate repeat purchases, Monetary (384,600) reflects good spending, and AOV (31,867) highlights high-value transactions per order.





RFM Analysis

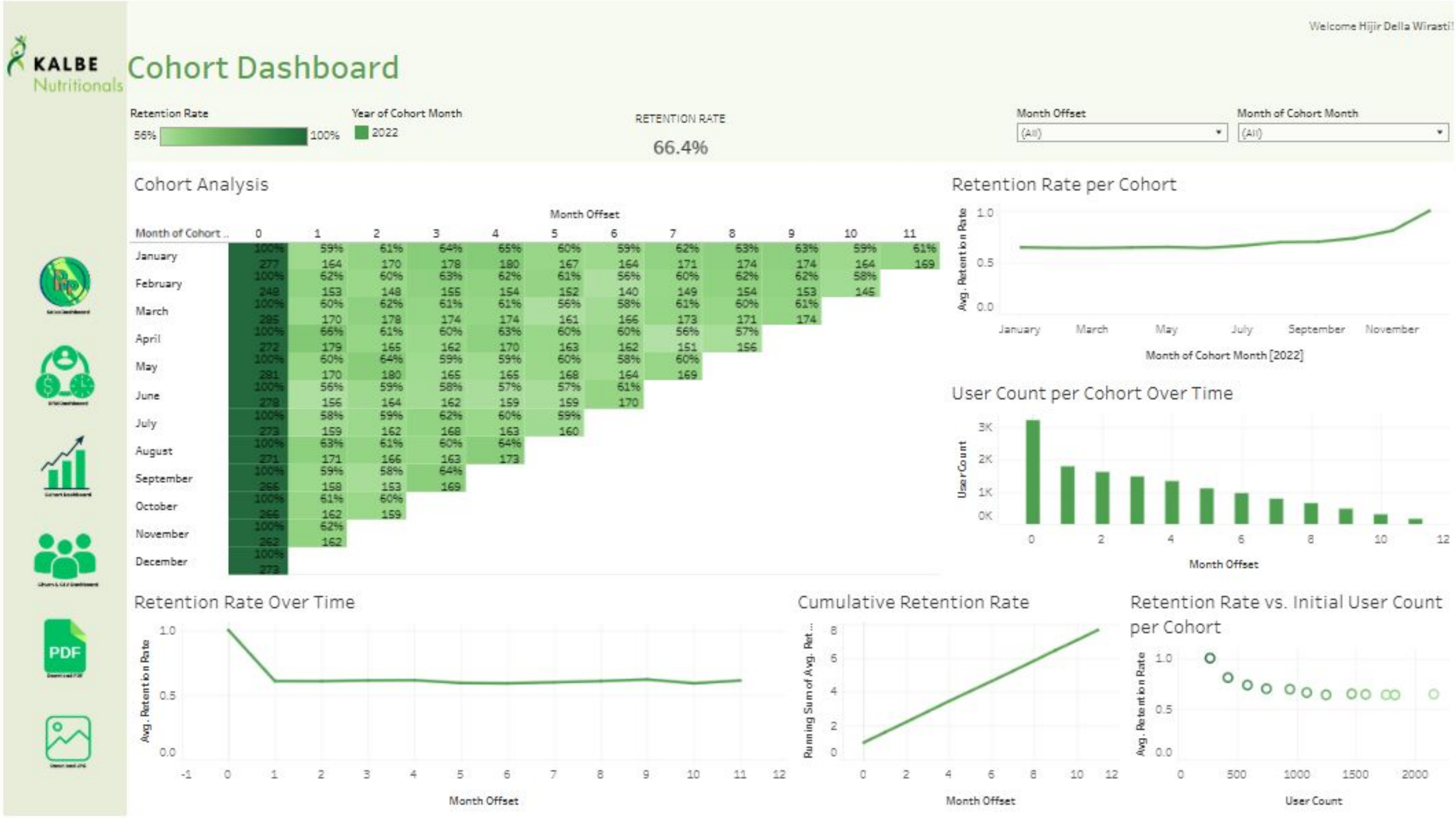
- **Largest Segments**: **Recent Shoppers (25.50%)** and **Big Spenders (21.92%)** – Key focus for retention and upselling.
- **At-Risk**: **Almost Lost (17.23%)** and **Lost Customers (10.51%)** – Need re-engagement strategies.
- **Loyal Customers (10.69%)** – Maintain with personalized offers.
- **Smaller Segments**: **Potential Customers (7.61%)**, **Lost Cheap (5.37%)**, and **Best Customers (0.89%)** – Growth and retention opportunities.

Score Analyis:

Most customers have mid-to-high RFM scores, meaning opportunities exist for upselling and loyalty programs.

RFM Distribution Insights

1. **Recency (Left-Skewed)** – Most customers haven't purchased in a long time. **Reactivation needed.**
2. **Frequency (Normal)** – Majority buy **10-15 times**. **Encourage more repeat purchases.**
3. **Monetary (Normal)** – Most spend **300K-500K**. **Upsell strategies can boost spending.**
4. **AOV (Slight Right-Skewed)** – with most transactions between **25K-40K**, peaking at **30K-35K**, suggesting opportunities for **bundling, volume discounts, and premium upselling.**


Welcome Hijir Della Wirasti!
KALBE Nutritionals
Cohort Dashboard
Retention Rate
56%
100%
Year of Cohort Month
2022
RETENTION RATE
66.4%
Month Offset
(All)
Month of Cohort Month
(All)
Cohort Analysis
Month Offset
Month of Cohort .. 0 1 2 3 4 5 6 7 8 9 10 11
January 100% 277 59% 164 61% 170 64% 178 65% 180 60% 167 59% 164 62% 171 63% 174 63% 174 59% 164 61% 169
February 100% 248 62% 153 60% 148 63% 155 62% 154 61% 152 56% 140 60% 149 62% 154 62% 153 58% 145
March 100% 285 60% 170 62% 178 61% 174 61% 174 56% 161 58% 166 61% 173 60% 171 61% 174
April 100% 272 66% 179 61% 165 60% 162 63% 170 60% 163 60% 162 56% 151 57% 156
May 100% 281 60% 170 64% 180 59% 165 59% 165 60% 168 58% 164 60% 169
June 100% 278 56% 156 59% 164 58% 162 57% 159 57% 159 61% 170
July 100% 273 58% 159 59% 162 62% 168 60% 163 59% 160
August 100% 271 63% 171 61% 166 60% 163 64% 173
September 100% 266 59% 158 58% 153 64% 169
October 100% 266 61% 162 60% 159
November 100% 262 62% 162
December 100% 273
Retention Rate per Cohort
Avg. Retention Rate
Month of Cohort Month [2022]
User Count per Cohort Over Time
User Count
Month Offset
Retention Rate Over Time
Avg. Retention Rate
Month Offset
Cumulative Retention Rate
Running Sum of Avg. Ret...
Month Offset
Retention Rate vs. Initial User Count per Cohort
Avg. Retention Rate
User Count
PDF

COHORT ANALYSIS

Cohort Analysis

Month of Cohort ..	0	1	2	3	4	5	6	7	8	9	10	11
January	100% 277	59% 164	61% 170	64% 178	65% 180	60% 167	59% 164	62% 171	63% 174	63% 174	59% 164	61% 169
February	100% 248	62% 153	60% 148	63% 155	62% 154	61% 152	56% 140	60% 149	62% 154	62% 153	58% 145	
March	100% 285	60% 170	62% 178	61% 174	61% 174	56% 161	58% 166	61% 173	60% 171	61% 174		
April	100% 272	66% 179	61% 165	60% 162	63% 170	60% 163	60% 162	56% 151	57% 156			
May	100% 281	60% 170	64% 180	59% 165	59% 165	60% 168	58% 164	60% 169				
June	100% 278	56% 156	59% 164	58% 162	57% 159	57% 159	61% 170					
July	100% 273	58% 159	59% 162	62% 168	60% 163	59% 160						
August	100% 271	63% 171	61% 166	60% 163	64% 173							
September	100% 266	59% 158	58% 153	64% 169								
October	100% 266	61% 162	60% 159									
November	100% 262	62% 162										
December	100% 273											

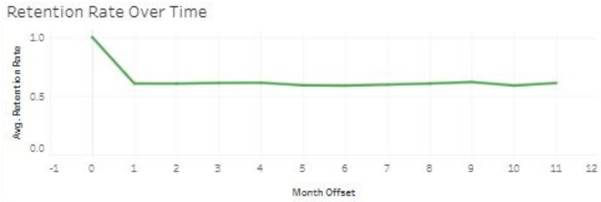
Month Offset

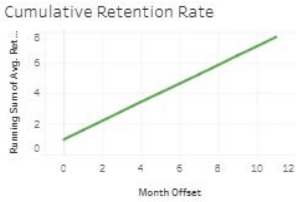
Retention Rate per Cohort

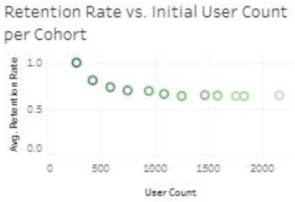
- Retention is **relatively stable but slightly increasing towards the end**.
- **Action:** Identify recent strategies boosting retention and optimize them.

Key Insights:

✔ **Strong Early Retention (~60%+), but declines by month 6** → Enhance post-acquisition engagement.
✔ **Some cohorts (March, May, August) retain better** → Analyze and replicate success factors.
✔ **Later cohorts (Q3 & Q4) show improved retention** → Recent strategies are working; sustain them.
✔ **Long-term retention drops below 20% by month 9-12** → Strengthen loyalty and re-engagement efforts.



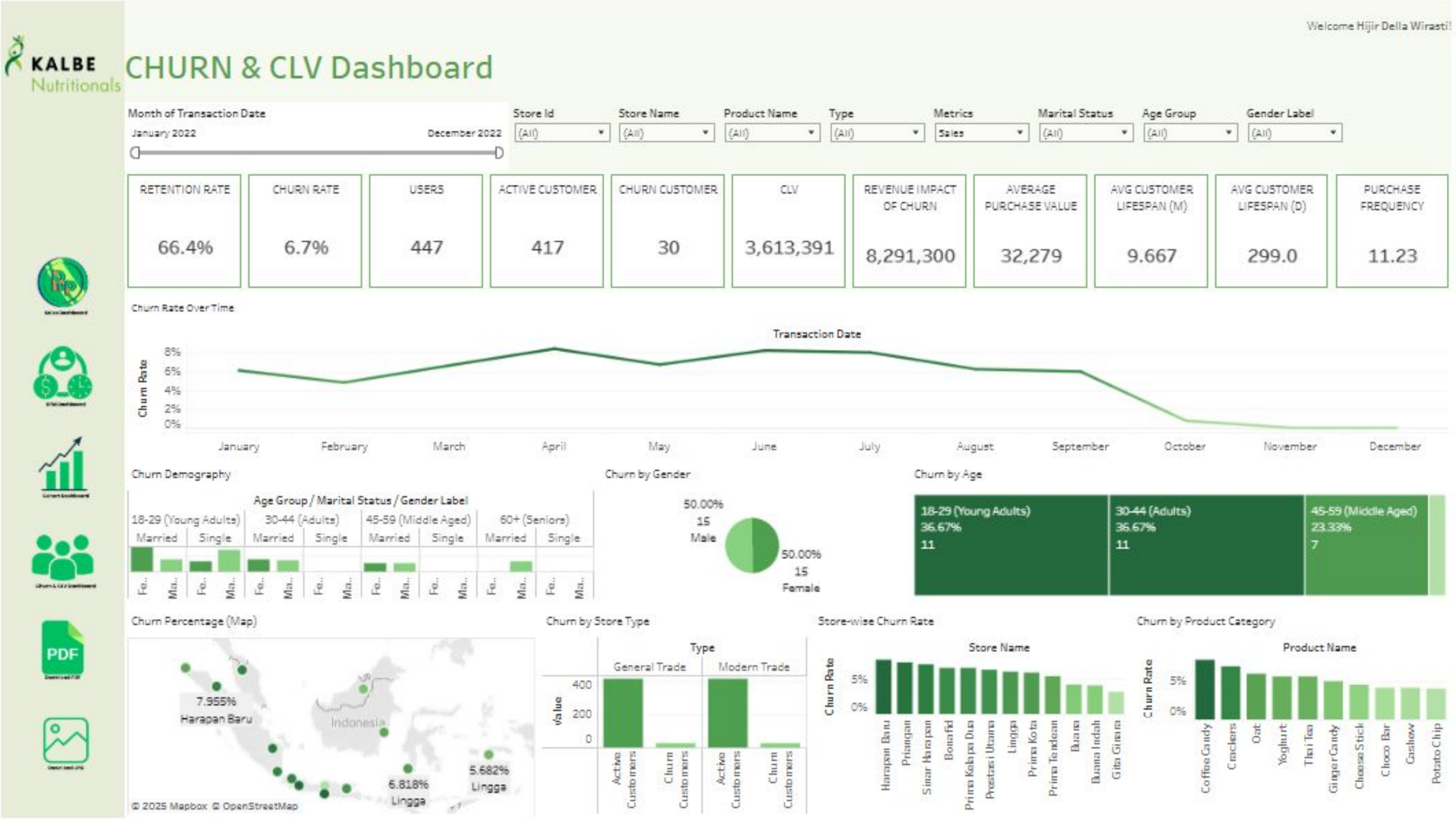




User Count per Cohort Over Time

- **Most users drop off quickly after the first month.**
- **Action:** Improve onboarding and early engagement incentives.

✔ **Early Drop-Off** – Retention falls sharply in the first month; strengthen onboarding and engagement.
✔ **Loyal Core Users** – Cumulative retention grows over time; leverage loyalty programs.
✔ **Acquisition Quality** – Larger cohorts show lower retention; improve targeting strategies.



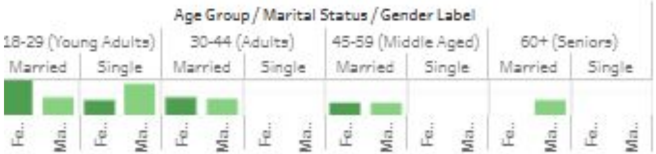
Welcome Hijir Della Wirasti!
KALBE
Nutritionals
CHURN & CLV Dashboard
Month of Transaction Date
January 2022
December 2022
Store Id
(All)
Store Name
(All)
Product Name
(All)
Type
(All)
Metrics
Sales
Marital Status
(All)
Age Group
(All)
Gender Label
(All)
RETENTION RATE
66.4%
CHURN RATE
6.7%
USERS
447
ACTIVE CUSTOMER
417
CHURN CUSTOMER
30
CLV
3,613,391
REVENUE IMPACT OF CHURN
8,291,300
AVERAGE PURCHASE VALUE
32,279
AVG CUSTOMER LIFESPAN (M)
9.667
AVG CUSTOMER LIFESPAN (D)
299.0
PURCHASE FREQUENCY
11.23
Churn Rate Over Time
Transaction Date
Churn Rate
8%
6%
4%
2%
0%
January
February
March
April
May
June
July
August
September
October
November
December
Churn Demography
Age Group / Marital Status / Gender Label
18-29 (Young Adults)
30-44 (Adults)
45-59 (Middle Aged)
60+ (Seniors)
Married
Single
Fe..
Ma..
Churn by Gender
50.00%
15
Male
50.00%
15
Female
Churn by Age
18-29 (Young Adults)
36.67%
11
30-44 (Adults)
36.67%
11
45-59 (Middle Aged)
23.33%
7
Churn Percentage (Map)
7.955%
Harapan Baru
Indonesia
6.818%
Lingga
5.682%
Lingga
© 2025 Mapbox © OpenStreetMap
Churn by Store Type
Type
General Trade
Modern Trade
Value
400
200
0
Active Customers
Churn Customers
Store-wise Churn Rate
Store Name
Churn Rate
5%
0%
Harapan Baru
Priangan
Sinar Harapan
Bonafid
Prima Kelapa Dua
Prestasi Utama
Lingga
Prima Kota
Prima Tendean
Buana
Buana Indah
Gita Ginara
Churn by Product Category
Product Name
Churn Rate
5%
0%
Coffee Candy
Crackers
Oat
Yoghurt
Thai Tea
Ginger Candy
Cheese Stick
Choco Bar
Cashew
Potato Chip
PDF

CHURN & CLV ANALYSIS

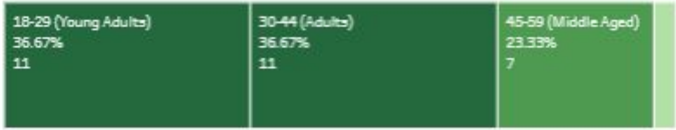
RETENTION RATE	CHURN RATE	USERS	ACTIVE CUSTOMER	CHURN CUSTOMER	CLV	REVENUE IMPACT OF CHURN	AVERAGE PURCHASE VALUE	AVG CUSTOMER LIFESPAN (M)	AVG CUSTOMER LIFESPAN (D)	PURCHASE FREQUENCY
66.4%	6.7%	447	417	30	3,613,391	8,291,300	32,279	9.667	299.0	11.23

Churn Rate Over Time

Churn Demography



Churn by Age



Customers show **strong retention (66.4%)** and **high CLV (3.61M),** indicating long-term value, but **churn (6.7%) is rising mid-year, especially among younger segments (18-44) and in key store (Harapan Baru dan Priangan). Action:** Strengthen early engagement, target high-churn locations, and optimize product offerings to sustain loyalty.

Churn Percentage (Map)

Churn by Store Type

Store-wise Churn Rate

Churn by Product Category

5. Business Recommendation

Business Recommendation

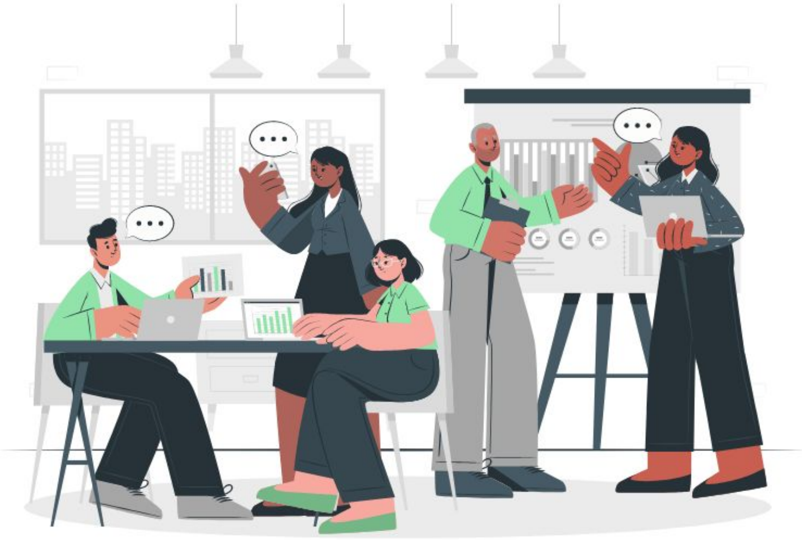
Recomm.	Insights	Actionable Items
Expand High-Sales Regions	Eastern Indonesia & Sulawesi lead sales, while Jakarta & Java have potential for growth	1. Strengthen distributor partnerships in top regions. 2. Invest in marketing to boost Jakarta & Java performance. 3. Explore expansion in Sumatra & Kalimantan.
Boost Retention & Reduce Churn	Retention is **66.4%**, but churn (6.7%) is rising, especially among **18-44-year-olds** and in **Harapan Baru & Lingga**.	1. Implement **personalized retention campaigns**. 2. Re-engage **high-churn locations** with exclusive offers. 3. Strengthen onboarding & loyalty programs.
Enhance RFM-Based Customer Engagement	**Big Spenders (21.92%) & Loyal Customers (10.96%)** drive sales, while **Almost Lost (17.23%)** are at risk.	1. Offer **VIP perks** for top customers. 2. **Run win-back campaigns** for Almost Lost. 3. Convert **Recent Shoppers (25.5%)** into repeat buyers..
Optimize Product & Pricing Strategy	**High AOV (31,867)** but churn on certain products (e.g., Coffee Candy & Choco Bar).	1. **Upsell premium products** like Cashew & Oat. 2. Reduce churn on low-retention products with **bundles/discounts**. 3. **Implement repeat purchase incentives (e.g., buy 3x, get 1 free).**
Leverage Best-Selling & High-Priced Products	**Yoghurt, Oat, & Crackers** lead in sales, while **Potato Chips, Coffee Candy, & Choco Bar are high-priced**.	1. **Promote best-sellers** with targeted ads & bundling. 2. **Introduce premium packaging & branding** for high-priced products. 3. **Offer trial packs or discounts** to drive demand for premium items.
Increase Sales of Low-Performing Products	These products (Thai Tea, Cashew, Ginger Candy) have lower sales and need better positioning.	1. **Bundle Thai Tea with best-sellers (e.g., Coffee Candy).** 2. **Rebrand Cashew as a premium snack** with gift-worthy packaging. 3. **Position Ginger Candy for health-conscious consumers** with immunity-boosting messaging.
Encourage Repeat Purchases	Cheese Stick is the **top-selling product**, but can be optimized further.	1. **Exclusive Cheese Stick multipacks (e.g., family-size or snack packs)** to drive bulk purchases. 2. **Limited-edition seasonal flavors** to create excitement & urgency. 3. **Loyalty points for frequent buyers (e.g., buy 5, get 1 free).**

Thank You !

Any QUESTIONS ?

hijirdw@gmail.com
https://www.linkedin.com/in/hijirdella/

https://github.com/hijirdella/Kalbe-Nutritionals-BI-Final-Project-Sales-RFM-Cohort-Churn-CLV-Optimization



6. Appendix

DATASET OVERVIEW

Case Study - Customer

	A	B	C	D	E
1	CustomerID	Age	Gender	Marital Status	Income
2	1	55	1	Married	5,12
3	2	60	1	Married	6,23
4	3	32	1	Married	9,17
5	4	31	1	Married	4,87

Case Study - Store

	A	B	C	D	E	F
1	StoreID	StoreName	GroupStore	Type	Latitude	Longitude
2	1	Prima Tendean	Prima	Modern Trade	-6,2	106,816,666
3	2	Prima Kelapa Du	Prima	Modern Trade	-6,914,864	107,608,238
4	3	Prima Kota	Prima	Modern Trade	-7,797,068	110,370,529
5	4	Gita Ginara	Gita	General Trade	-6,966,667	110,416,664

Case Study - Product

	A	B	C
1	ProductID	Product Name	Price
2	P1	Choco Bar	8800
3	P2	Ginger Candy	3200
4	P3	Crackers	7500
5	P4	Potato Chip	12000

Case Study - Transaction

	A	B	C	D	E	F	G	H
1	TransactionID	CustomerID	Date	ProductID	Price	Qty	TotalAmount	StoreID
2	TR11369	328	01/01/2022	P3	7500	4	30000	12
3	TR16356	165	01/01/2022	P9	10000	7	70000	1
4	TR1984	183	01/01/2022	P1	8800	4	35200	4
5	TR35256	160	01/01/2022	P1	8800	7	61600	4

DATASET PROFILE – CUSTOMER

	CustomerID	Age	Gender	Marital Status	Income
0	1	55	1	Married	5,12
1	2	60	1	Married	6,23
2	3	32	1	Married	9,17
3	4	31	1	Married	4,87
4	5	58	1	Married	3,57

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 447 entries, 0 to 446
Data columns (total 5 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   CustomerID      447 non-null    int64
 1   Age             447 non-null    int64
 2   Gender          447 non-null    int64
 3   Marital Status  444 non-null    object
 4   Income          447 non-null    object
dtypes: int64(3), object(2)
memory usage: 17.6+ KB
```

	CustomerID	Age	Gender
count	447.000000	447.000000	447.000000
mean	224.000000	39.782998	0.458613
std	129.182042	12.848719	0.498842
min	1.000000	0.000000	0.000000
25%	112.500000	30.000000	0.000000
50%	224.000000	39.000000	0.000000
75%	335.500000	50.500000	1.000000
max	447.000000	72.000000	1.000000

	Marital Status	Income
count	444	447
unique	2	369
top	Married	0
freq	340	16

Recommended Data Improvements:

- **Fix the income format** (replace commas with dots if necessary to ensure numerical accuracy).
- **Handle missing marital status values**, potentially using mode imputation.
- **Investigate age 0 entries** to check for data entry errors.

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DATASET PROFILE – STORE

	StoreID	StoreName	GroupStore	Type	Latitude	Longitude
0	1	Prima Tendean	Prima	Modern Trade	-6,2	106,816,666
1	2	Prima Kelapa Dua	Prima	Modern Trade	-6,914,864	107,608,238
2	3	Prima Kota	Prima	Modern Trade	-7,797,068	110,370,529
3	4	Gita Ginara	Gita	General Trade	-6,966,667	110,416,664
4	5	Bonafid	Gita	General Trade	-7,250,445	112,768,845
5	6	Lingga	Lingga	Modern Trade	-5,135,399	11,942,379
6	7	Buana Indah	Buana	General Trade	3,316,694	114,590,111
7	8	Sinar Harapan	Harapan Baru	General Trade	554,829	95,323,753
8	9	Lingga	Lingga	Modern Trade	-3,654,703	128,190,643
9	10	Harapan Baru	Harapan Baru	General Trade	3,597,031	98,678,513
10	11	Sinar Harapan	Prestasi	General Trade	533,505	101,447,403
11	12	Prestasi Utama	Prestasi	General Trade	-2,990,934	104,756,554
12	13	Buana	Buana	General Trade	-126,916	116,825,264
13	14	Priangan	Priangan	Modern Trade	-5,45	10,526,667

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 14 entries, 0 to 13
Data columns (total 6 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   StoreID     14 non-null     int64
 1   StoreName   14 non-null     object
 2   GroupStore  14 non-null     object
 3   Type        14 non-null     object
 4   Latitude    14 non-null     object
 5   Longitude   14 non-null     object
dtypes: int64(1), object(5)
memory usage: 804.0+ bytes
```

	StoreID
count	14.0000
mean	7.5000
std	4.1833
min	1.0000
25%	4.2500
50%	7.5000
75%	10.7500
max	14.0000

	StoreName	GroupStore	Type	Latitude	Longitude
count	14	14	14	14	14
unique	12	7	2	14	14
top	Lingga	Prima	General Trade	-6,2	106,816,666
freq	2	3	8	1	1

Recommended Data Improvements:

- **Fix latitude and longitude formatting** (convert commas to dots for numerical consistency).
- **Check for duplicate stores** in `StoreName` and `GroupStore`, as "Lingga" and "Sinar Harapan" appear multiple times.
- **Analyze store type distribution** to see if "Modern Trade" and "General Trade" differ significantly in geographical placement.

Google Collab [here]

DATASET PROFILE – PRODUCT

	ProductID	Product Name	Price
0	P1	Choco Bar	8800
1	P2	Ginger Candy	3200
2	P3	Crackers	7500
3	P4	Potato Chip	12000
4	P5	Thai Tea	4200
5	P6	Cashew	18000
6	P7	Coffee Candy	9400
7	P8	Oat	16000
8	P9	Yoghurt	10000
9	P10	Cheese Stick	15000

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10 entries, 0 to 9
Data columns (total 3 columns):
 #   Column        Non-Null Count  Dtype 
---  ------        --------------  ----- 
 0   ProductID     10 non-null     object
 1   Product Name  10 non-null     object
 2   Price         10 non-null     int64 
dtypes: int64(1), object(2)
memory usage: 372.0+ bytes
```

	Price
count	10.000000
mean	10410.000000
std	4890.455557
min	3200.000000
25%	7825.000000
50%	9700.000000
75%	14250.000000
max	18000.000000

	ProductID	Product Name
count	10	10
unique	10	10
top	P1	Choco Bar
freq	1	1

Recommended Data Improvements:

- **Further categorize products** into types (e.g., snacks, beverages, dairy) for better segmentation.
- **Analyze price segmentation** to identify pricing trends and potential product bundling opportunities.

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DATASET PROFILE – TRANSACTION

	TransactionID	CustomerID	Date	ProductID	Price	Qty	TotalAmount	StoreID
0	TR11369	328	01/01/2022	P3	7500	4	30000	12
1	TR16356	165	01/01/2022	P9	10000	7	70000	1
2	TR1984	183	01/01/2022	P1	8800	4	35200	4
3	TR35256	160	01/01/2022	P1	8800	7	61600	4
4	TR41231	386	01/01/2022	P9	10000	1	10000	4

	TransactionID	Date	ProductID
count	5020	5020	5020
unique	4908	365	10
top	TR71313	02/03/2022	P5
freq	3	31	814

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5020 entries, 0 to 5019
Data columns (total 8 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   TransactionID  5020 non-null   object
 1   CustomerID     5020 non-null   int64
 2   Date           5020 non-null   object
 3   ProductID      5020 non-null   object
 4   Price          5020 non-null   int64
 5   Qty            5020 non-null   int64
 6   TotalAmount    5020 non-null   int64
 7   StoreID        5020 non-null   int64
dtypes: int64(5), object(3)
memory usage: 313.9+ KB
```

	CustomerID	Price	Qty	TotalAmount	StoreID
count	5020.000000	5020.000000	5020.000000	5020.000000	5020.000000
mean	221.263745	9684.800797	3.644622	32279.482072	7.489841
std	129.672955	4600.708780	1.855295	19675.462455	4.028502
min	1.000000	3200.000000	1.000000	7500.000000	1.000000
25%	108.000000	4200.000000	2.000000	16000.000000	4.000000
50%	221.000000	9400.000000	3.000000	28200.000000	7.000000
75%	332.000000	15000.000000	5.000000	47000.000000	11.000000
max	447.000000	18000.000000	10.000000	88000.000000	14.000000

Recommended Data Improvements:

- **Check for duplicate transactions** (since there are 4,908 unique TransactionIDs but 5,020 rows).
- **Analyze product demand trends** to see which items drive the most sales.
- **Investigate high-value transactions** to understand customer purchasing behavior.
- **Segment transactions by store** to identify top-performing locations.

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Customer Segmentation

1. **Best Customer** (R=1, F=1, M=1)
   Highly engaged, frequent buyers with high spending. Prioritize loyalty programs and exclusive rewards.
2. **Potential Customers** (R=1, F=1, M=2) or (R=1, F=2, M=2) or (R=2, F=1, M=1) or (R=2, F=2, M=2)
   Emerging valuable customers. Encourage repeat purchases with personalized offers.
3. **Lost Cheap** (R=4, F=4, M=4 or 3)
   Inactive, low-value buyers. Low priority for retention, but could be re-engaged with discounts.
4. **Big Spender** (M=1)
   High-value customers regardless of frequency. Offer premium deals and upsell opportunities.
5. **Loyal Customers** (F=1)
   Frequent buyers with consistent purchases. Strengthen relationships through VIP programs.
6. **Others/Recent Shopper** (R=1 or R=2)
   New or occasional buyers. Encourage further engagement through follow-ups and promotions.
7. **Almost Lost** (R=3)
   Customers showing decreased engagement. Use retention strategies like personalized reactivation campaigns.
8. **Lost Customers** (R=4)
   Inactive buyers. Re-engage with strong incentives like exclusive discounts or special deals.

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