Developing a Portfolio Segmentation Model for Medical Devices

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Medical device companies often manage a wide array of products and markets, each with unique supply chain needs that cannot be met by a uniform operating approach. In partnership with a leading medical device company, our project aimed to refine product segmentation based on financial performance and develop frameworks to identify tailored strategies for each segment. We implemented five segmentation approaches: traditional two-dimensional frameworks, Pareto segmentation for sales and gross profit, a category role matrix adapted from the retail industry, the BCG matrix focusing on growth potential, and regional segmentation by country's financial performance. Additionally, we used K-means clustering to provide a comprehensive multidimensional view of the segments. For each segment, we recommended specific strategic operations including product discontinuation, cost reduction in goods sold, product replacement, introduction of new products, sales promotions, and market expansion. Then, we focused particularly on the cost of goods sold and product discontinuation strategies. We suggested prioritizing material spend management, identifying key suppliers for procurement negotiations, and revising the make-or-buy decision process for more accurate comparisons. We also developed a heuristic weighted scoring system to rank products from the highest to lowest priority for discontinuation.

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1 INTRODUCTION

The COVID-19 pandemic has highlighted the importance of supply chain management in the medical device industry. The disruptions caused by the pandemic have forced organizations to reassess their operational resilience and robustness. Many firms have experienced sales disruptions due to inaccurate forecasting, which has led to higher end-to-end costs. Additionally, the cost of goods sold (COGS) has increased due to insatiable demand and inflationary pressures (O'Dea et al., 2022). This phenomenon can be linked to a snowball effect, a situation in which one action or event causes many other similar actions or events in a dynamic system, highlighting supply chains' inherent complexity.

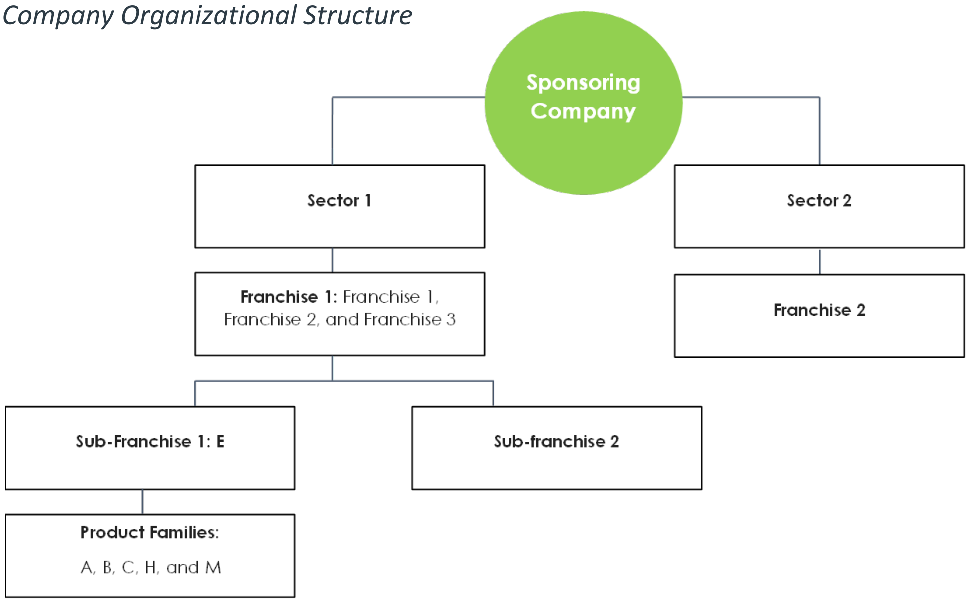
The sponsoring company, a leading medical device franchise, is recalibrating its focus to support growth and innovation in one of their business units, featuring product families such as: "A", "B", "C", "H", and "M". The anticipated growth and evolving customer service demands have presented a distinct challenge. The company's objective is to refine and implement efficient processes to drive sustainable profitability specifically across the previously mentioned products families.

However, since the onset of the COVID pandemic in 2020, the sponsoring company has witnessed a consistent decline in its profit margins. With diverse products, the franchise seeks enhanced products management to revert to its pre-pandemic profitability levels. Several factors contributed to the diminishing returns, including high inventory costs, complex sales operations, comprehensive end-to-end expenses, and challenges managing a product portfolio – all the products and services offered by the company – with a high degree of complexity.

The sponsoring company is motivated to pinpoint these profit-depleting elements within their product families – a product family is a subset of closely related products within a larger product portfolio (Refer to Figure 1). They aim to mitigate end-to-end costs, augment product portfolio efficiency, and overcome overstock issues. By implementing these measures, the company aspires to achieve the desired profitability benchmarks for its portfolio.

Figure 1

Sponsoring Company Organizational Structure



1.1. Problem Statement and Research Questions

Our sponsor company aims to boost its profits by a certain percentage and revert to its pre-COVID financial performance. A significant rise in end-to-end costs, particularly in material and inventory expenses, has reduced the profit margins for their product range.

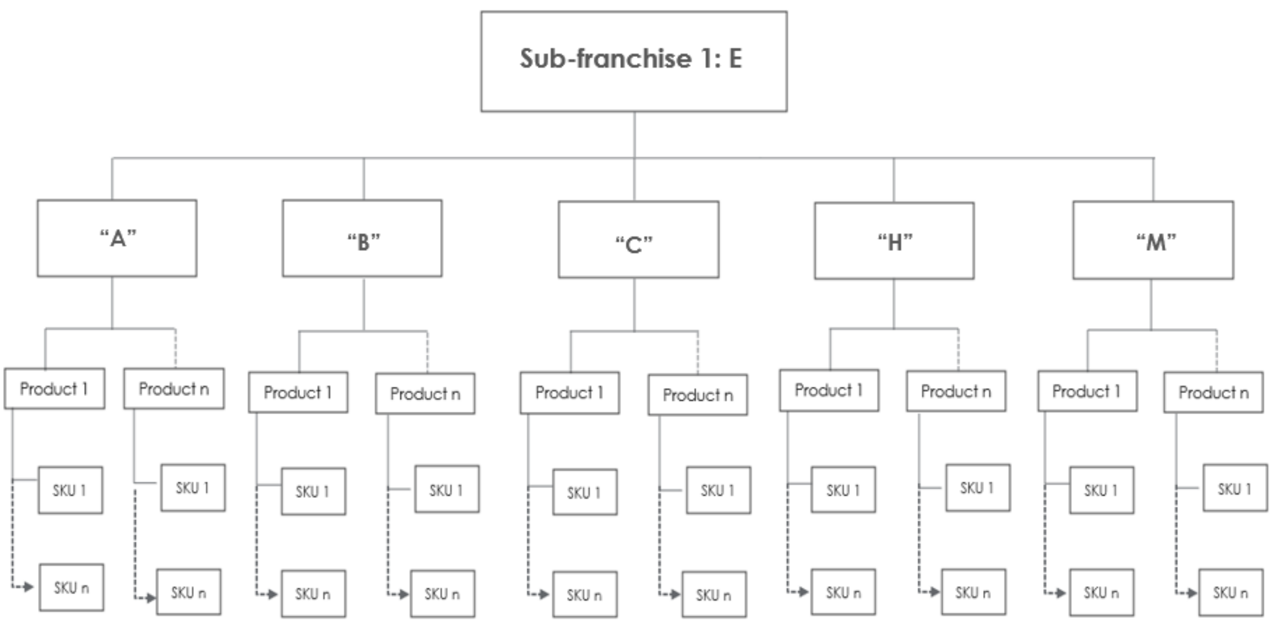
The product families consist of multiple medical devices used to perform surgical procedures in various medical applications (Refer to figure 2). Products in these families lack a streamlined segmentation, which prevents the Sponsoring Company from effectively driving finished goods productivity, enhancing net trade sales, and improving gross profit margins.

Addressing these challenges requires thoroughly exploring the following research questions:

- How can the company effectively segment and get profit-maximizing recommendations for the products under scope?
- What are the primary factors affecting the profitability of the products?
- Can unsupervised machine learning provide a more comprehensive clustering of the products' financial performance than the BCG and Category Role matrix frameworks?

Figure 2

Product Family Layout



1.2. Project Goals and Expected Outcomes

The sponsoring company faced the significant challenge of returning the gross profit margin to levels seen before the COVID pandemic. Practically they are seeking to understand and operationalize a solution that will facilitate pragmatic decision-making processes within sales and operations.

In this capstone project, we initially applied traditional segmentation approaches such as Pareto Analysis, Category Role Matrix, BCG Matrix, and a Regional View to identify products that are not meeting the company's gross margin profit targets. To complement this analysis, we employed an unsupervised machine learning technique, k-clustering, which provided a multi-dimensional view of the product portfolio.

Following this segmentation, we conducted a detailed examination of the production cost structure for the underperforming products to pinpoint areas for profitability improvement. This involved analyzing the Cost of Goods Sold (COGS) to identify the primary cost drivers associated with each product.

Using the insights gained from the cost analysis, we formulated specific recommendations aimed at enhancing profitability. The project concluded with exploring strategies for product elimination, cost reduction, and simplification of the product portfolio.

The proposed solution to address the research questions can be summarized in three main outcomes: The first involves harmonizing data between multiple systems, which includes ensuring consistency (Data cleaning), compatibility (Validation), and aggregation of data across various formats and systems. The second outcome focuses on the creation of homogeneous clusters between products, utilizing both traditional methods and unsupervised machine learning to enhance operational decision-making and financial performance. The third outcome entails an assessment of cost drivers within these clusters, aimed at providing tactical and strategic recommendations to the sponsoring company.

Potential practical examples of this solution's capabilities are:

- Complexity reduction or product codes elimination proposal based on the company's gross profit target of 70%.
- Identifying the factors impacting profitability for product codes in scope.
- Conducting an analysis of the product portfolio sales, profitability, and cost of goods sold.
- Provide a recommendation of how to segment the product portfolio using traditional and machine learning methods.

2 STATE OF THE PRACTICE

The State of the Practice outlines the process defined to address the research questions linked to the Portfolio Segmentation Model capstone project:

- How can the company effectively segment and get profit-maximizing recommendations for the products under scope?
- What are the primary factors affecting the profitability of the Endosurgery products?
- Can unsupervised machine learning provide a more comprehensive clustering of the products' financial performance than the BCG and Category Role matrix frameworks?

The sponsoring company's primary objective for this project is to receive recommendations to improve the gross profit percentage within its product families by providing visibility of the proposed segments recommendations based on the products financial performance.

The initial step to define the problem was to understand which are the variables used to calculate the gross profit percentage for each product. The formula to calculate gross profit percentage is the following:

$$(Net\ Trade\ Sales\ -\ Cost\ of\ Goods\ Sold)\ \div\ Net\ Trade\ Sales\ =\ Gross\ Profit\ \%$$

In an effort to refine the portfolio segmentation strategy for classifying products based on their contribution to profitability within the business, a thorough literature review was undertaken. This review sought to identify best practices employed across diverse industries. Four distinct methodologies were scrutinized to better align with the primary objective of segmenting products based on variables such as Net Trade sales per product, Gross Profit %, and Growth. The following section is dedicated to presenting a high-level overview of each methodology's objectives, approach, and expected outcomes.

1.3. Supply Chain Segmentation Approaches

The extensive literature on product segmentation management is too vast to be covered comprehensively in this summary. Instead, this overview provides a concise examination of various methodologies for product segmentation, particularly within the context of a medical device company. These approaches play a critical role in enabling companies to optimize inventory levels, minimize costs, and grow profitability, and revenue. Understanding these strategies is essential for medical device companies due to the critical nature of their products and the stringent regulatory compliance requirements they must adhere to.

For organizations with vast product ranges, such as the sponsoring company, managing individual products can become impractical. Grouping similar products into categories allows for the implementation of standardized policies for each group, simplifying management oversight. This aggregation provides a structured approach to specifying, monitoring, and controlling performance across different product families. Recommendations for managing these groups can range from general guidelines, such as enhanced managerial oversight, to more specific strategies.

In the literature, various approaches for product segmentation are discussed. In this project, following the sponsoring company's guidelines, we simplified the segmentation approach based on the variables at hand. We selected three traditional segmentation methods suitable for our research questions: Pareto Analysis, the Category Role Matrix, and the BCG Matrix. These methods aim to clearly identify SKUs that do not meet targets for gross profit, net sales, and growth.

Next, we employed a clustering method using unsupervised machine learning to form homogeneous clusters of products with similar characteristics based on the raw data received. This step's goal is to group similar products to analyze their impact on gross profit independently. For this analysis, we utilized feature engineering, defined as the process of using domain knowledge to select, modify, or create new features from raw data to increase the predictive power of machine learning algorithms (Zheng & Casari, 2018). Then, we performed a cost of goods sold analysis to identify the factors impacting gross profit within each cluster. The subsequent section will provide a literature review of the tools and models used in this execution.

1.3.1. Pareto Analysis

Pareto analysis forms a cornerstone of strategic management, finance, manufacturing, and quality control. Underpinning this analysis is the concept of an unequal distribution of inputs and outputs, commonly known as the "80/20 rule" (Koch, 2011), which suggests that a small percentage of causes often lead to a large percentage of effects (Foss & Hallberg, 2013).

In strategic management, the essence of Pareto analysis lies in identifying and prioritizing those few inputs that produce the most significant outcomes, whether in terms of revenue, profits, or return on investment (Pareto, 1964). This involves pinpointing the critical few efforts that generate the greatest benefit and focusing on these while minimizing less productive endeavors. This approach can be applied to various aspects of a business, from finance and management to supply chains and marketing, enabling the identification of strengths, weaknesses, and opportunities for creating a competitive advantage.

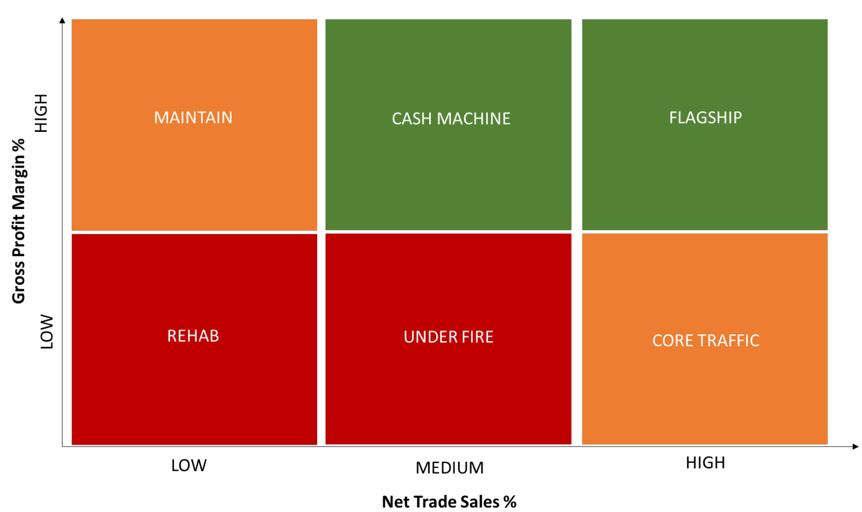
The application of the Pareto principle empowers businesses to streamline their product lines and customer base, guiding them towards eliminating obsolete or unprofitable elements. Pareto analysis ensures that resources are allocated efficiently, preventing the replication of inefficiencies, and maximizing the utilization of the most effective aspects of the business.

1.3.2. Category Role Matrix

The Category Role Matrix proposed by Dr. Robert Blattberg focuses on dividing the products portfolio on a two dimensional model of ‘2 by 3’ using gross Profit % and sales combined to optimize creation of value and responsiveness (Blattberg & Subrata, 1976). The main categories created within the matrix responds to categorization of products based on Sales (High, Medium, and Low) and Gros Profit % (High and Low) (see Figure 3).

Figure 3

Category Role Matrix



Note. Low, medium, and high thresholds are defined by an organization’s net trade sales and gross profit targets (financial targets). From *Category role matrix* by Stray Partners, 2023. *Available at: https://www.straypartners.com/cases/category-role-matrix* .

Once the two dimensional model is constructed considering Gross Profit Margin % and Net Trade Sales % for each product within the product families, there are two main strategic recommendations that can be provided in order to improve profitability for the whole portfolio. The first one is focused on increasing sales and maintaining margin and the second one is focused on increasing margin while maintaining sales. Criteria need to be defined to allocate each of the products within the applicable category based on thresholds defined along with sponsoring company for GP% and Sales %. An aggregated view for all the portfolio as well as the individual product family views are recommended to be developed to provide visibility at the portfolio and at the product family level. High level recommendations can be provided for each of the segments with the main objective of maximizing profitability. Below is a non-exhaustive list of examples from the recommendations that can be explored by each of the segments once visibility of products profitability profile is understood:

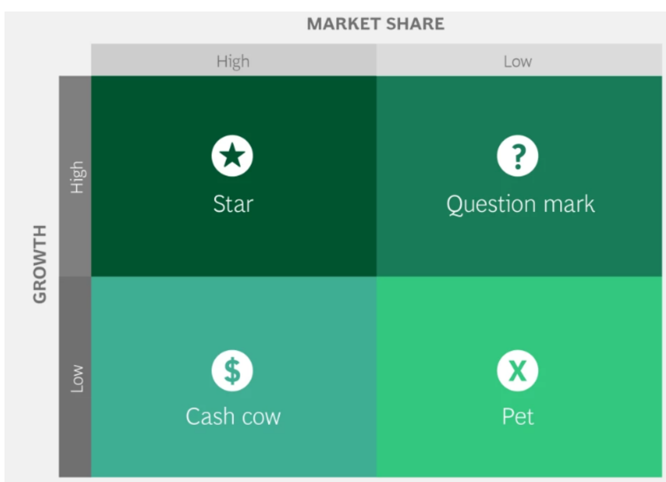
- **Rehab and Under Fire Categories**: Increase Gross Profit Margin %, Potential replacement, elimination or de-listing
- **Cash Machine and Flagship Categories**: Sustain and Drive More Revenue (Sales)
- **Maintain Category**: Increase Promotion Effectiveness and Distribution, explore opportunities to expand distribution of code
- **Core Traffic Category** Evaluate Price Increases and Product Architecture or Design (Cost of Goods Sold improvement)

1.3.3. BCG Matrix

The Boston Consulting Group (BCG) Matrix, also known as the Growth-Share Matrix (David, 2021), is a strategic framework that helps companies manage their product portfolios (Henderson, 1970). It categorizes products or business units into four quadrants based on two key dimensions: relative market share and market growth rate, refer to Figure 4 for the BCG Matrix visual.

Figure 4

BCG Matrix



Note. What is the growth share matrix? (no date). From *BCG Global, https://www.bcg.com/about/overview/our-history/growth-share-matrix*

By understanding the position of each product or business unit within the BCG Matrix, organizations can make informed decisions about resource allocation, market positioning, and investment strategies. Description for each of the BCG Matrix quadrants can be found below:

- **Stars:** represent products with high market growth and high market share. These products often require substantial investment to sustain their growth and maintain market leadership. With effective strategic management, Stars have the potential to mature into Cash Cows as market growth stabilizes.
- **Question Marks:** represents the products with high market growth but low market share. They present significant opportunities for growth but also pose risks due to their weak competitive position. Strategic decisions regarding Question Marks are crucial, as they may require considerable investment to increase market share and potentially become Stars.
- **Cash Cows:** They generate consistent cash flow that can be reinvested in Stars and Question Marks, supporting the overall portfolio's growth and balance.
- **Dogs:** represent products with low market growth and low market share. They often generate little profit and offer limited growth prospects. Decisions regarding Dogs may involve divestment or discontinuation, as they may no longer align with the company's strategic objectives.

The BCG Matrix remains a valuable tool for strategic management, providing a simplified framework for analyzing and managing product portfolios. However, it is important to note that the matrix is a simplified model and should be used in conjunction with other strategic considerations, such as product life cycles, competitive analysis, and financial projections.

The BCG Matrix dimension that we are incorporating within the tool view is the expected volume growth including 3-year demand forecast input. This will inform the organization about which of the codes are expected to grow, which ones are expected to experience neutral growth, and which ones are expected to decline. This data input can help link segmentation recommendations to future growth expectations for the product codes in scope to improve profitability.

1.3.4. Clustering: Unsupervised Machine Learning

Multiple unsupervised machine learning approaches can be implemented for product segmentation to help understand common features between products in scope. The most used machine learning technique is Machine Learning K-Clustering Analysis (Jackson, 2022). The main objective of implementing this method is to identify supply chain segments based on product and supply characteristics and help the organization design a tailored supply chain strategies for each of the segments to help on drive operational efficiency.

The first step in performing unsupervised machine learning k-clustering is to complete an exploratory data and factor analysis to identify potential segmentation criteria and select the most relevant factors to create the product segments (Jackson, 2022). These factors can have multiple types, which ranges within three main categories: continuous (numeric variables that have infinite values between any two values), discrete (numeric variables that have finite values between any two values), or categorical (non-numerical variables).

The second step is to complete a data scaling process. The main objective of this step is to normalize the data points. K-clustering methods such as k-means and k-prototypes use distances between the data points to determine de similarity that exists between them. This distance calculation and comparison is sensitive to the factors scaling. While implementing the scaling process, the independent variables (factors) are standardized to make sure they can be allocated within a fixed range. If this step is not completed, the k-clustering algorithm will tend to weight variables with greater absolute values higher impacting the clustering outcome (Jackson, 2022).

In data preprocessing for K-means or K-prototypes clustering, scaling techniques are crucial because they ensure that each variable contributes equally to the distance calculations, which are fundamental to the clustering process (Natarajan, 2023). According to Hvitfeldt (2024), several common scaling techniques are used to standardize or normalize the independent variables before applying K-means or K-prototypes clustering:

1. **Logarithmic Scaling**
   - **Definition**: Applies the logarithm function to each data point, effective for handling right-skewed data.
   - **Pros**: Reduces the impact of outliers and decreases skewness, making data more normally distributed.
   - **Cons**: Not applicable to zero or negative values without adding a constant prior to transformation.
2. **Square Root Scaling**
   - **Definition**: Takes the square root of each data point, effectively reducing the range and diminishing the effect of outliers.
   - **Pros**: Reduces skewness and mitigates the influence of outliers.
   - **Cons**: Less effective than logarithmic scaling for handling highly skewed data.
3. **Box-Cox Transformation**
   - **Definition**: A parametric transformation aiming to normalize data. Applicable only to positive data.
   - **Pros**: Can address a broader range of skewness compared to logarithmic scaling.
   - **Cons**: Limited to positive data and requires determination of an optimal lambda parameter.
4. **Yeo-Johnson Transformation**
   - **Definition**: Modifies Box-Cox to accommodate both positive and negative data by adapting the transformation.
   - **Pros**: Supports data with both positive and negative values.
   - **Cons**: Requires finding an optimal lambda parameter, which can be computationally intensive.
5. **Percentile Scaling (Rank Scaling or Quantile Scaling)**
   - **Definition**: Scales features based on their percentile or quantile rank, typically to a range between zero and one.
   - **Pros**: Useful for scaling features to a bounded interval and less sensitive to outliers.
   - **Cons**: Can distort the distances between points and might not be suitable if preserving the original data distribution is crucial.
6. **Normalization (L2 Normalization)**
   - **Definition**: Scales input vectors to have a unit norm, ensuring equal contribution of features to distances between data points.
   - **Pros**: Promotes feature equality in influence.
   - **Cons**: Can be influenced by outliers, potentially skewing the scaled data.
7. **Range Scaling**
   - **Definition**: Scales data to a specified range, not limited to [0, 1].
   - **Pros**: Allows flexibility in choosing the target range.

- **Cons**: Like MinMax Scaling, it is sensitive to outliers, which can affect the scaling range.

8. **Max-Abs Scaling**
   - **Definition**: Divides each feature by its maximum absolute value, scaling them within the range of [-1, 1].
   - **Pros**: Maintains the sign of the data and is generally less influenced by outliers than MinMax Scaling.
   - **Cons**: If negative values are rare or absent, the scaling range can be inconsistent.
9. **Robust Scaling**
   - **Definition**: Utilizes the median and interquartile range for scaling, diminishing the impact of outliers.
   - **Pros**: Particularly effective for datasets with outliers.
   - **Cons**: Unlike some other methods, it does not scale data to a fixed range.
10. **Binning**
    - **Definition**: Segregates data into bins or intervals, effectively transforming numerical variables into categorical ones.
    - **Pros**: Minimizes the effect of small observation errors and outliers.
    - **Cons**: Involves loss of information and can reduce data variability.
11. **Splines**
    - **Definition**: Employs piecewise polynomial functions for data fitting and transformation, useful for data smoothing.
    - **Pros**: Offers flexible fitting capabilities, excellent for capturing nonlinear relationships.
    - **Cons**: Can lead to model complexity and risk of overfitting.
12. **Polynomial Expansion**
    - **Definition**: Creates polynomial features by elevating existing features to various powers.
    - **Pros**: Enables modeling of feature interactions and nonlinear relationships.
    - **Cons**: Can dramatically increase the number of features, potentially leading to overfitting and computational challenges.

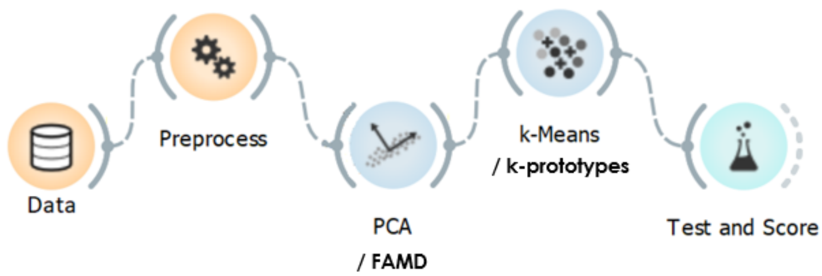
Once the scaling technique is selected and applied for the independent variables, the third step in performing unsupervised machine learning k-clustering is to select a method that can be used to reduce the number of independent variables prior to implementing the product segmentation method, generally known as dimensionality reduction techniques. These independent variables (factors) incorporate information related to each product characteristic that explains the products' behavior and requirements. To have an effective segmentation strategy, the process of segmenting the products should use a few related characteristics (Protopappa-Sieke & Thonemann, 2017).

The two dimensionality reduction techniques we evaluated for the capstone implementation were the Factor Analysis of Mixed Data (FAMD) and the Principal Component Analysis (PCA). The Factor Analysis of Mixed Data or FAMD is applied to understand how the different variables are related to each other and proceed to select a few variables as segmentation drivers when dealing with both numerical and categorical variables (*Protopappa-Sieke & Thonemann, 2017)*. The Principal Component Analysis (PCA) is useful to reduce the number of factors avoiding issues such as sensitivity to noise and multicollinearity and improve clustering results when dealing with numerical variables (Jackson ,2022).

The fourth step consists in applying the k-means (for numerical values) or k-prototypes (for numerical and categorical values) clustering algorithm using the selected factors to create the product segments and cluster products across multiple dimensions. The final step in the process is to evaluate the clustering results using the Silhouette score (Jackson, 2022). This metric calculates the distance between clusters, helping to assess how well-separated and cohesive the clusters are. Figure 5 depicts the typical pipeline for product segmentation while implementing k-Means in a standardized manner.

Figure 5

Typical Pipeline for Implementing K-clustering Algorithm



Note. This figure was modified to include Factor Analysis of Mixed Data (FAMD) and k-prototypes to account for methods used when dealing with categorical attributes. From Jackson, I. (2022) "AutoML Approach to Stock Keeping Units Segmentation" Journal of Theoretical and Applied Electronic Commerce Research 17, no. 4: 1512-1528. https://doi.org/10.3390/jtaer17040076

After evaluating the multiple segmentation, clustering, and descriptive analytics methods within the literature review, the data available from the sponsoring company, and the primary objective of segmenting the product portfolio, we decided to use the following methodologies, adjusting certain characteristics to better serve the sponsoring company's expectations:

1. **Descriptive Analytics:**
   a. **Pareto Analysis:** Using 2023 Net Trade Sales and Gross Profit contribution for the portfolio.
   b. **Category Role Matrix:** Using 4 quadrants instead of 6 quadrants to simplify the traditional segmentation process using Net Trade Sales and Gross Profit% thresholds provided by the sponsoring company.
   c. **BCG Matrix:** Inspired by the BCG Matrix, a view of Net trade sales, gross profit %, and expected growth for each of the product codes was pursued to link to segmentation recommendations. This was aligned with the sponsoring company as a result of infeasibility to obtain market share data at the product code level.

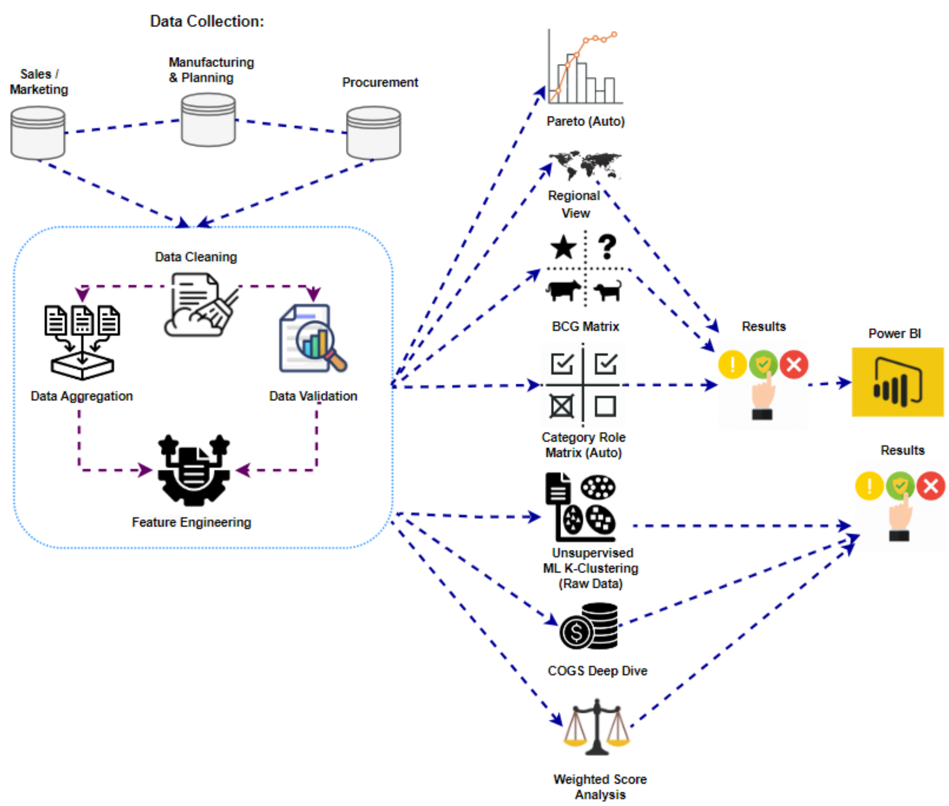
2. **Clustering Method: K-clustering Algorithm:** To provide the ability to segment recommendations considering multiple dimensions such as cost of goods sold, finished goods inventory, and raw material attributes, machine learning K-clustering algorithm was implemented.

3 DATA AND METHODOLOGY

Our methodology started by collecting data from multiple sources as explained in section 3.1. Once the required data was collected, a data cleaning process was completed to prepare the data sets for the subsequent process steps, as described in section 3.2. Once the data was cleaned, the assumptions included within the data cleaning process were aligned with the sponsoring company in a process known as data validation process, mainly described in section 3.2. The next step consisted in comparing the multiple data sets to serve as an input for the data aggregation process as described in section 3.3. Once the data was cleaned and validated with the sponsoring company, the aggregation process was completed. Aggregating the attributes linked to the product codes enabled the creation of a single source of truth. Once the single source of truth was created, feature engineering was applied to certain features to increase the predictive power of the machine learning algorithms as described in section 3.4. Once these data preparation process steps were completed, the analysis process started. The Pareto Analysis, Category Role Matrix, BCG Matrix (Growth Matrix), Regional View, and K-Clustering methods were applied to the data to get insights that helped respond the research questions from the Capstone Project as described in sections 3.5, 3.6, and 3.7. Section 3.8 describes the process steps completed while handling missing data in preparation to completing the analyses. A dynamic visualization using Microsoft Power BI tool was constructed for the BCG, Category Role Matrix, and Regional view analyses. Figure 6 provides a visual representation of the methodology process steps executed in this capstone project.

Figure 6

Data and Methodology Process Flow



Note. The unsupervised machine learning K-clustering analysis uses raw data as inputs to create the clusters or segments for the portfolio.

3.1 Data Collection

The data collection process was focused on collecting inputs to calculate gross profit % for each of the products in the Sub-franchise product families. Nine data sets were received from the company: Net trade sales (NTS), Gross Profit %, Average Selling Price, Cost of Goods Sold, Active products list, Finished Goods Inventory per product, Products discontinuation matrix, Long Range Financial Plan Demand Projections, and Component Procurement data including raw material prices. Refer to Tables 1 and 2 for details regarding data set attributes definitions, data sources, and data timeframe.

Table 1

Data Sets Dictionary

Data set	Definition
Net Trade Sales (NTS) per product	Total Revenue collected by the firm linked to each product during the time frame selected.
Gross Profit % (GP%) per product	Difference between the Net Trade Sales and the Cost of Goods sold divided by the Net Trade sales for each product.
Average Selling Price per product	Average Selling price for each individual product.
Cost of Goods Sold (COGS) by product	Aggregated Cost of Goods sold for each individual product
Active Product list	List of active products as of November 2023 (Assessment Start date)
Inventory by product: Global Distribution Hub (Units and $)	Quantity of Units and Inventory dollars at the Global Hub as of November 2023 (Assessment start date)
Products Discontinuation Matrix	Product list projected to be discontinued within the next 3 Years (2024 – 2026)
Products Long Range Financial Plan Demand	Yearly demand projection by product for years 2023 through 2026
Procurement Components Data	Components Suppliers Names, Components for each product, Cost breakdown per component, and Component Category

Table 2

Data Sets, Data Source, and Timeframe

Data set	Data Source	Timeframe
Net Trade Sales (NTS) per product	Financial Sales data system	2023 Actuals
Gross Profit % (GP%) per product	Gross Profit System	2023 Actuals
Average Selling Price per product	Financial Sales and Gross Profit Hub Systems	2023 Actuals
Cost of Goods Sold (COGS) per product	Financial Sales data system	2023 Actuals

Data set	Data Source	Timeframe
Active Product list	Enterprise Resource Planning (ERP) System	2023 Active codes
Inventory by Product: Memphis Global Hub (Units and $)	Enterprise Resource Planning (ERP) System	2023 Actuals
Products Discontinuation	Strategy Team input	Expected product discontinuations.
Products Long Range Financial Plan Demand	Enterprise Resource Planning (ERP) System	2023 - 2026
Component and Supplier Cost Data	JDE System	2023 Actuals

3.2 Data Cleaning and Validation

During the data set evaluation process, it was discovered that there were multiple ways to name a specific product base code depending on how the data sets were structured and the sources used to extract them. The data sets were extracted from four different systems: TM1 (Financial System), ERP (Enterprise Resource Planning) System, GP Hub (Gross Profit Common Data Tableau visualization tool used at Enterprise Level), and JDE System. The product names are divided into two main categories:

1. **Base code:** Includes base code identification for globally distributed product.
2. **Mod code:** a numeric pre-fix or suffix is added to the base code to identify a specific product distributed in a unique market or products containing minor changes in characteristics such as language in packaging and design change to meet regulatory or quality requirements. Table 3 provides additional details of the product names nomenclature embedded within each of the data sets.

Table 3

Data Sets with Their Respective Product Nomenclature

Data Set	Base Code	Mod base = PRODUCT number = Material Number
Inventory	Base Column X = Base code	Material No. Column E = Contains Base Codes and BaseCode-Mod Code suffix format within same column
Net Trade Sales, Gross Profit, Average Selling Price	No Base code listed in separate column	Product Column E = Contains Base codes and ModCode prefix followed by base code format within same column
Active Codes	Base Column B = Base code	MOD Base Column C = ModCode prefix followed by base code format

Data Set	Base Code	Mod base = PRODUCT number = Material Number
COGS breakdown	Base Column F = Base Code	Code Column E = Mod Code
Component and Supplier Cost Data	Product Family Name Summary Tab = Base Code	Column starting at J = Mod Code

The first step of the data cleaning process consisted of standardizing the base product codes across the multiple data sets received by the sponsoring company to enable the capability of aggregating the different attributes for each product code in preparation to the analysis. An automated approach with a Python code was tried, but character rules were diverse and were not applicable for the entire data sets, therefore a manual approach was followed to align product base codes across the files. As a result of this cleaning and manual encoding process, one single list of product base codes was created to standardize product identifications across the data sets. Table 4 shows standardization approach examples the original product base code format, the standardized product base code format, and an explanation of the changes.

Table 4

Standardization Approach Examples

Product Base Original Format	Product Code Standardized Format	Comment
9	0009	Standardized with Planning Active Codes list format
470	0470	
4025	004025	

The result of this standardization exercise enabled the creation of a single source of truth including standard product codes names. The original standard codes list included product codes under the portfolio representing $1.37B in Net Trade Sales. Refer to Appendix A for Net Trade Sales and GP% Baseline Distribution between product families. In alignment with the sponsoring company, there were codes that were removed from the baseline, which were not found when aggregating the reports. The items within the removed codes were not found within the active codes list due to multiple reasons such as: codes tied to financial plugs, codes linked to regional conversions, and codes tied to product services.

For the product codes left in scope, a cross check was performed against the discontinuation matrix input from the sponsoring company. Therefore, since these codes are already in process of being discontinued, codes were also eliminated from the overall assessment. After these two steps, a total of 665 product codes remained as part of the scope of the project execution representing $1.2B in Net Trade Sales for 2023. Refer to Appendix B for the reference of product codes included as part of this project execution.

In preparation for data aggregation, the procurement reports cleaning was performed. The procurement reports included the bill of materials for product codes in scope, the price for each raw material, a flag confirming if raw material had a dual source strategy in place, and data linked to the raw material category. The main cleaning step performed on these reports was to consolidate the data, which was received in separate scattered tables, within a single table. Additionally, for the Megadyne product codes procurement information, the product codes were within a single cell. This represented a potential problem for future coding functionalities; therefore, the product codes list was separated into individual cells.

Once a single and standardized list of product codes was created, the subsequent step consisted in aggregating the data sets to link each of the data attributes to its corresponding product base code. For the aggregation purposes two main observations were made regarding the data sets. The first observation was that the product families names (Known by the sponsoring company as Majors) were not standardized between the GP Hub system and the Planning Active codes list. The Planning Active codes list product family names (Majors) was used as a single source of truth for the aggregation step. Also, “C” and “BE” products were aggregated within the same product family category. Once this process step was completed, the data set was ready to be used to perform the Pareto Analysis and Category role matrix.

The process steps performed during the data cleaning process and the assumptions for missing data and non-standard codes were shared with the sponsoring company to make sure those assumptions were following a logical approach and their business rules. This confirmation step is commonly known as the data validation step. Once this step was completed, the data set was ready to be used for aggregation purposes.

3.3 Data Aggregation

After standardizing the product codes list and completing the cleaning process for all reports, the final objective was to create a single standard source of truth (global table) that gathered all the features linked to the individual product codes. This global table includes verified information with the following features: Sales, Gross Profit, Growth, average inventory 2022 and 2023 as a proxy of the working capital, and supply chain value stream mapping steps.

3.4 Feature Engineering:

In the feature engineering phase of the project, we implemented one-hot encoding on the "make or buy" variable to better structure the data for analysis. This method involved creating two separate columns: one for "make" and another for "buy" In this setup, if a product is manufactured in-house, the "make" column is marked with a '1' and the "buy" column with a '0'. Conversely, if a product is sourced externally, the "buy" column is marked with a '1' while the "make" column is set to '0'. This binary encoding technique simplifies the representation of categorical data, enabling the machine learning models to process each option distinctly, thereby enhancing the clarity and effectiveness of the model's predictions.

3.5 Segmentation Approaches: Pareto Analysis, Category Role Matrix, BCG Matrix, and Regional View

Four different segmentation approaches were performed using the portfolio cleaned data sets. The first analysis consisted on constructing a visual to provide visibility of which were the product codes driving the majority of the net trade sales and gross profit within the product portfolio. The results of this analysis provides a high level understanding of which codes have greater impact to the portfolio’s profitability based on the net trade sales and gross profit quantity and percentage contributions.

The sponsoring company was also in need of getting visibility of which codes were driving were complying with the thresholds of 70% gross profit and $100K of Net Trade Sales. The Category role matrix provides a simple visual representation of the segments using these thresholds to divide the different product codes in four different segments, which are described in section 3.5.2. A view portraying the expected growth for each of the product codes and the product families (Minors) was performed to link the segmentation recommendations to the growth expectations for the product codes in scope. The following sections (3.5.1, 3.5.2, and 3.5.3) provide details regarding the Pareto Analysis, Category Role Matrix, and Expected growth views for the Sub-franchise products portfolio. Lastly, a Regional view including the gross profit % and expected growth by Country was constructed to provide visibility of which countries are driving accretive and dilutive gross profit % as well as expected growth per country. Section 3.5.4 provides the Regional View details and visual representation.

3.5.1 Pareto Analysis

The Pareto Analysis view was constructed for the Net Trade Sales attribute. The sum of 2023 Net Trade Sales and the Cumulative percentage representation from Total sales per product code was calculated for each of the product base codes to identify the product codes representing the 80% of the total volume for the product families. Refer to Results section for graphical representation of the Pareto view using Net Trade Sales.

The Pareto Analysis view was also constructed for the Gross Profit Volume attribute. The 2023 Gross Profit percentages and the Cumulative percentage representation from Gross Profit per product code was calculated for each of the product base codes to identify the product codes driving the 80% of the total gross profit for the product families. Refer to Results section for graphical representation of the Pareto view using Gross Profit in Volume.

3.5.2 Category Role Matrix:

The following section summarizes the steps undertaken to construct the Category role matrix view including steps such as Data Scaling and Data Visualization.

3.5.2.1 Data Scaling for Visualization in Category Role Matrix

In preparing to create the Category Role Matrix visualization, a scaling update was performed to include the Net Trade Sales versus Gross Profit percentage attributes within a single graph. The main reason for performing this transformation was to ensure the unit of measurement for these product attributes was standardized between Net Trade Sales and the gross profit percentage. The following scaling methods were evaluated:

- **Logarithmic Transformation**: The logarithmic transformation becomes negative when values are between 0 and 1. Since the Gross Profit is represented as a percentage, when converting the values into decimals they become decimals (values between 0 and 1), converting the results of the transformation into negative numbers for gross profit percentages (Hvitfeldt, 2024). After evaluating this transformation proposal, it was decided to not include it as part of the visualization.

- **Square Root Transformation**: The square root transformation does not provide the same scale between Net Treade Sales and Gross Profit % to create quadrants including both attributes within the same side (Hvitfeldt, 2024). After evaluating this transformation proposal, it was decided to not include it as part of the visualization.
- **Percentile Transformation:** Transforms values from 0 to 1 for Net Trade Sales and from 0 to 1 for Gross Profit (Hvitfeldt, 2024). The percentile transformation does not impact the ranking and quadrant position of the PRODUCT's, it in fact maintains the ranking and no information is lost for segmentation purposes. After evaluating this transformation proposal, it was decided to include it as part of the visualization for the Category Role Matrix.

3.5.2.2 Category Role Matrix Data Visualization

Once the Net Trade Sales and GP% data scaling process was performed for the product codes in scope, the percentile GP vs Percentile Net Strade Sales scatter plot view was created using Microsoft Power BI tool. To define the segments, thresholds were defined with input from the sponsoring company were provided using Net Trade Sales and Gross profit % target requirements. Table 6 shows the thresholds used to categorize each of the product base codes within the category role matrix.

Table 6

Net Trade Sales and GP% Thresholds

Threshold	Nominal Value	Percentile
Net Trade Sales	$100,000	0.649
Gross Profit Percentage	70%	0.320

To simplify the segmentation process and reduce the cognitive load required to interpret the segments using the Category Role Matrix as a framework, the number of segments to be used for the visual representation within the tool was reduced to four. The visual representation created consisted of a 2x2 graph with Net Trade Sales Percentile as the x axis and GP Percentile as the y-axis. This visualization enables clear differentiation between the products in each segment. Four main segments created based on Net Trade Sales and GP Percentiles:

1. High Sales, High GP Percentiles represented by dark green
2. Low Sales, High GP Percentiles represented by light green
3. High Sales, Low GP Percentiles represented by light red
4. Low Sales, Low GP Percentiles represented by dark red

The following steps were undertaken to create the visualization using Power BI software:

1. The harmonized and clean data from Net Trade Sales and GP% was transformed using Percentile calculation outlined in section 3.5.
2. Harmonized, clean, and transformed data was loaded in Power BI. Data coming from Data Aggregation after Transformation including all the codes and attributes were uploaded following the below steps:
   a. File > Get Data > Upload
   b. Data Tab > Right Click > New Measure > Name: Quadrant Color Category
3. Variables were created to differentiate the segments. This steps provide the capability to visualize the segments and thresholds based on the GP% Target = 70% (0.320 percentile) and NTS = $100,000 (0.649 percentile).
   a. Four variables were created: Sales %, GP%, Treshold Sales Percentile = 0.649, Treshold GP Percentile = 0.320
   b. DAX code was created within PowerBI to visualize each of the segments. Refer to Appendix C for DAX code details.
   c. The switch function was added to change the color of each quadrant based on thresholds defined. HEX codes were selected to use for each quadrant. The tool created includes two different Category role matrices visualizing the data. The first view includes the graphed Net Trade Sales and GP percentiles, including 4 different colors representing each of the segments.

3.5.3 BCG Matrix: Growth View

To complement the Category Role matrix view, a dashboard including the expected growth for each product code was created. This view allows the sponsoring company to identify which product families and which specific product codes are expected to be growing in volume within the next 3 years horizon based on data provided from their most recent long range financial planning exercise.

The first view that was constructed included data from gross profit % and expected growth at the product code level. The codes represented in green, complies with the minimum of 70% Gross Profit target. Product codes represented in dark red are codes that are declining in volume (Negative growth) or maintained flat over the next three years horizon (2023 – 2026). The product codes represented in pink are codes that are expected to grow between 0% and 5% over the next three years horizon (2023 – 2026). The product codes represented in orange are codes that are expected to grow between 5% and 10% over the next three years horizon (2023 – 2026). And product codes represented in yellow are codes that are expected to grow 10% or more within the next three years horizon (2023 – 2026). Visual representation was generated using Microsoft Power BI tool. Refer to Appendix D for Power BI DAX Code used to differentiate product codes within each of the growth buckets.

The second growth view created incorporated data tied to expected volume growth within the x-axis, gross profit % within the y-axis and Net Trade Sales represented by the size of the bubble for each of the product families within the portfolio as per Figure 13 (Expected growth at the Minor level).

3.5.4 Regional View

To provide visibility to the sponsoring company about which countries were driving accretive GP% (≥70%) and which countries were driving dilutive GP% (<70%) during 2023 for the entire product portfolio, a regional view was constructed using Microsoft Power BI tool. A world map was added as part of the view for the user to scroll over it and select specific countries of interest and show aggregated view of the total Net Trade Sales for the Country during 2023, Gross Profit % for the Country at the end of 2023, and the expected growth for the country from 2023 to 2026. Visual filters, commonly known as slicers were created to filter the type of data the user wants to see. Slicers created for the Regional view included the following attributes to provide filtering functionality within the view:

- Gross Profit % – Low (<70% represented in red in Figure 16) and High (≥70% represented in green in Figure 16)
- Growth Category – High and Medium (≥5% represented in green in Figure 16), Low (0% - 5% represented in orange in Figure 16), Negative (<0% represented in red in Figure 16)

3.6 Unsupervised Machine Learning Clustering Method: K-Clustering

After completing the traditional segmentation framework, we applied an unsupervised machine learning technique, K-clustering to the raw data. This step aimed to verify whether additional insights could be gleaned from the attributes associated with each product code within the project's scope. The features chosen for the K-clustering analysis, as detailed in the Global table (the source of truth), were as follows:

- Net Trade Sales – Numerical.
- Gross Profit – Percentage.
- Expected Growth – Percentage.
- Average cost of inventory for 2022 and 2023, used as a proxy for working capital – Numerical.
- Make or buy - Binary.

These features were exclusively used to form the clusters; no additional or composite features were employed in this analysis. The goal was to utilize the raw data provided by the sponsoring company to explore if clustering the product codes by the mentioned features could reveal any further insights.

For the scaling of data in the K-clustering, we adopted min-max scaling, as recommended in the literature (Jackson, 2022). The min-max scaling was executed using the following formula, where xx is the original value of the feature, and $x'x'$ is the normalized value:

$$x' = \frac{x - \min(x)}{\max(x) - \min(x)'}$$

No dimensionality reduction was applied before the K-clustering, as the data was not high-dimensional (less than 10 features). We used the PCA technique solely for the purpose of visualizing the clusters, not for the clustering process itself.

3.7 Weighted Score

To propose a heuristic for product rationalization, we used a weighted scoring system to evaluate each product based on three key metrics: Sales, Gross Profit (GP), and Growth. Initially, we assigned weights to these metrics to reflect their importance to the organizational goals. Specifically, Sales and Gross Profit each received a weight of 0.4, while Growth was assigned a weight of 0.2, highlighting the emphasis placed on each metric in the scoring system.

We then applied the min-max scaling technique to normalize the data for Sales, GP, and Growth, adjusting each metric to a uniform scale from 0 to 1. This normalization uses the same formula typically employed in K-clustering in 3.6. This step is crucial as it ensures all metrics are on a comparable scale, accommodating different scales and distributions.

Following the normalization, we computed the composite score for each product by multiplying the normalized values by their designated weights and summing the results. The formula for calculating the score is:

$$\text{Score} = (0.4 \times \text{Normalized Sales}) + (0.4 \times \text{Normalized GP}) + (0.2 \times \text{Normalized Growth})$$

Finally, the products were ranked from lowest to highest based on their scores. A lower score indicates that a product contributes less effectively to the three key metrics: Sales, Gross Profit, and Growth.

3.8 Handling Missing Data

The dataset had missing data for certain mode codes, specifically regarding the average inventory for 2022 and 2023. Since inventory data was available at the base product level, we used sales figures as a proxy to estimate the inventory for each mode code. For example, if a base code had three associated mode codes and we only had inventory information at the base level, we calculated the sales percentage of each mode code relative to the base code. We then applied these percentages to the base code's inventory to estimate the inventory for each mode code. This method provided a proportional estimate of inventory at the mode code level based on their sales figures.

4 RESULTS and DISCUSSION

Results and discussion chapter provides details on the results obtained from the different methodologies execution. Section 4.1 includes the Pareto analysis results including both Net Trade Sales and Gross Profit $ for the product portfolio. The Category Role Matrix results can be found in section 4.2 including visual representation using data set at the Product Code level. Subsequent section 4.3 includes results from the BCG growth matrix including visuals representing data at the product code level and at the product Minor level (Product sub-categories within each of the product families are commonly know by the sponsoring company as Minors). The Regional View results can be found in section 4.4 including a visual representation of the countries and their respective Net Trade Sales, GP%, and expected growth. The K-Clustering unsupervised machine learning results can be found in section 4.5, including visual representation and details for each of the clusters obtained after running the model. Section 4.6 includes results from the weighted score analysis. Lastly, the cost of goods sold deep dive analysis results can be found as part of the section 4.6.

4.1 Pareto Results

The Net Trade Sales attribute Pareto Analysis view using the sum of 2023 Net Trade Sales and the cumulative percentage representation from Total sales per product code provided insights into which product codes were driving 81% of the portfolio total sales. Table 7 shows the 21 product codes driving 80% of the Total Net Trade Sales, the percentage of Net Trade Sales driven by each code, and product families linked to each product code (Major and Minor).

Table 7

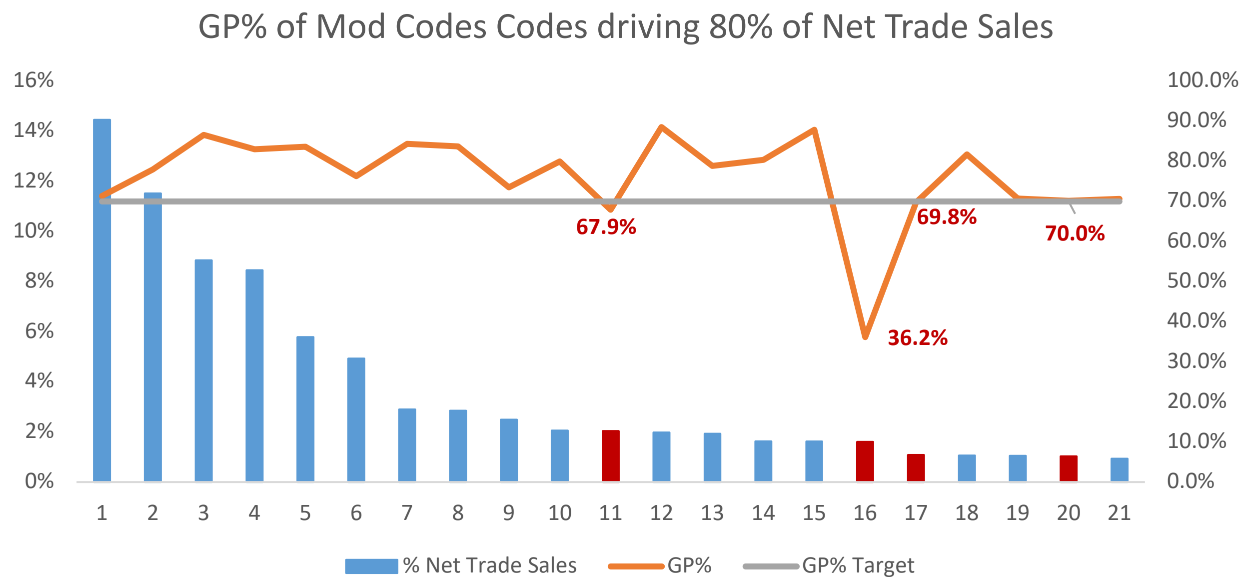
Product Codes Driving 81% of Net Trade Sales

SKU Number	CY Sales $ 2023	Major	Minor	% Portfolio NTS	GP%
1	$ 174,089,922	"H"	H+7	14%	71%
2	$ 138,767,538	"H"	H11	12%	78%
3	$ 106,565,981	"H"	HA+	9%	87%
4	$ 101,779,035	"H"	H+7	8%	83%
5	$ 69,614,729	"H"	HF+	6%	84%
6	$ 59,437,077	"H"	H+7	5%	76%
7	$ 34,861,543	"H"	HF+	3%	84%
8	$ 34,268,892	"H"	H+7	3%	84%
9	$ 30,028,167	"A"	AL	2%	74%
10	$ 24,821,550	"H"	H11	2%	68%
11	$ 24,520,196	"A"	AC	2%	89%
12	$ 23,864,971	"H"	HA+	2%	79%
13	$ 23,281,170	"H"	H11	2%	80%
14	$ 19,583,503	"H"	HF+	2%	88%
15	$ 19,494,715	"H"	HA+	2%	36%
16	$ 19,324,947	"M"	SE	2%	80%
17	$ 13,030,110	"H"	HCN	1%	70%
18	$ 12,782,571	"H"	HFL+	1%	82%
19	$ 12,632,497	"C"	G	1%	71%
20	$ 12,379,209	"A"	AC	1%	70%
21	$ 11,267,719	"A"	AL	1%	71%

Figure 7 offers a graphical representation of the Pareto view using Net Trade Sales for 2023.

Figure 7

Pareto Chart for Net Trade Sales 2023



Note. Pareto chart showing the sum of 2023 Cumulative Net Trade Sales on the left y-axis, the product codes on the x-axis, and the Gross Profit percentage on the right y-axis.

The Net Trade Sales attribute Pareto Analysis view using the sum of 2023 Gross Profit Volume and the cumulative percentage representation from Total gross profit volume per product code provided insights of which product codes were driving 80% of the portfolio total gross profit volume. Table 8 shows the 18 product codes list driving 80% of the Total Gross Profit volume, the percentage of gross profit volume driven by each code, and product families linked to each product code (Major and Minor).

Table 8

Product Codes Driving 80% of Gross Profit Volume

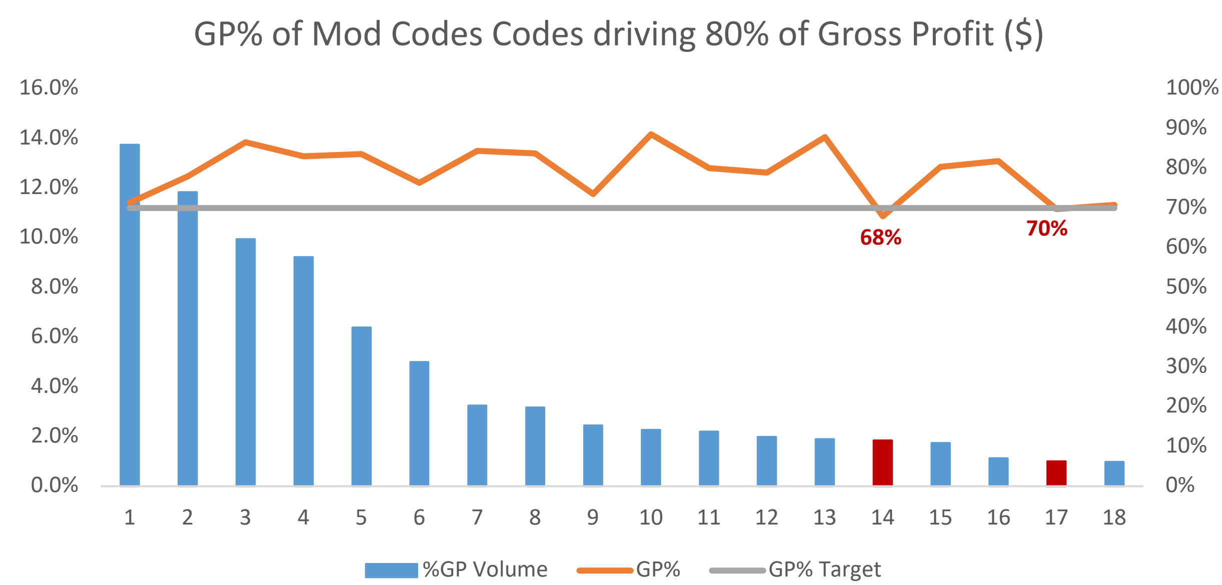
SKU Number	GP$ 2023	Major	Minor	% Portfolio GP$	GP%
1	$ 118,962,292	“H”	H+7	13.8%	71%
2	$ 98,287,181	“H”	H11	11.8%	78%
3	$ 84,593,687	“H”	HA+	9.9%	87%
4	$ 72,683,250	“H”	H+7	9.2%	83%
5	$ 51,873,603	“H”	HF+	6.4%	84%
6	$ 42,606,985	“H”	H+7	5.0%	76%
7	$ 26,029,158	“H”	HF+	3.3%	84%
8	$ 26,306,423	“H”	H+7	3.2%	84%
9	$ 19,699,764	“A”	AL	2.4%	74%
10	$ 19,138,335	“H”	HA+	2.3%	89%
11	$ 15,940,587	“H”	H11	2.2%	80%

SKU Number	GP$ 2023	Major	Minor	% Portfolio GP$	GP%
12	$ 16,477,857	“H”	H11	2.0%	79%
13	$ 15,475,398	“H”	HA+	1.9%	88%
14	$ 15,074,676	“A”	AC	1.8%	68%
15	$ 13,424,150	“H”	HF+	1.7%	80%
16	$ 9,990,699	“H”	HFL+	1.1%	82%
17	$ 8,904,519	“H”	HCN	1.0%	70%
18	$ 7,973,591	“C”	G	1.0%	71%

Refer Figure 8 for graphical representation of the Pareto view using Gross Profit Volume for 2023.

Figure 8

Pareto Chart for Gross Profit 2023



Note. Pareto chart showing the 2023 Cumulative Gross Profit on the left y-axis, the product base codes on the x-axis, and the Gross Profit % on the right y-axis.

4.2 Category Role Matrix Results

The Category Role Matrix View shows a graphical representation of the portfolio proposed segments, including a plot of the Net Trade Sales and Gross Profit Percentiles for each product code within the scope of the project (Figure 9). As a reminder, thresholds used to create segments within this view provided by the company were: GP% of 70 and Net Trade Sales of $100,000. Appendix B includes product codes details: product codes list, net trade sales, and GP% for data set used to construct the Category Role Matrix.

Figure 9

Category Role Matrix for 2023

Note. Figure 9 provides a visual representation of the Category Role Matrix using a 2x2 view, Gross Profit percentile is included within the y-axis and Net Trade Sales is included within the x axis including product codes representing 90% of the total sales for the business for 2023.

The following section provides a description of each of the segments represented within the Category role matrix depicted in Figure 9:

1. High Sales (Yearly Sales >$100K), High GP Percentiles (>70% GP) represented by dark green

A total of 109 product codes belong to this segment. Out of the 109 codes within the segment, the split of the codes within this segment belong to the product families (Major) shown in Table 9.

Table 9

High Sales (Yearly Sales >$100K), High GP Percentiles (>70% GP) Product Codes Details

Product Code Quantity	Product Family: Major	Total Sales within Segment
52 Product Codes	"M"	$ 36,020,556
37 Product Codes	"H"	$ 895,694,363
10 Product Codes	"A"	$ 71,686,684

Product Code Quantity	Product Family: Major	Total Sales within Segment
10 Product Codes	“C”	$ 35,195,380

2. Low Sales (Yearly Sales <$100K), High GP Percentiles (>70% GP) represented by light green
A total of 118 product codes belong to this segment. Out of the 118 codes within the segment, the split of the codes within this segment belong to the product families (Major) shown in Table 10.

Table 10

Low Sales (Yearly Sales <$100K), High GP Percentiles (>70% GP) Product Codes Details

Product Code Quantity	Product Family: Major	Total Sales within Segment
83 Product Codes	“M”	$ 1,529,269.60
19 Product Code	“H”	$ 359,560.60
5 Product Codes	“A”	$ 196,576.40
11 Product Codes	“C”	$ 352,928.60

3. High Sales (Yearly Sales >$100K), Low GP Percentiles (<70% GP) represented by light red
A total of 115 product codes belong to this segment. Out of the 115 codes within the segment, the split of the codes within this segment belong to the product families (Major) shown in Table 11.

Table 11

High Sales (Yearly Sales >$100K), Low GP Percentiles (<70% GP) Product Codes Details

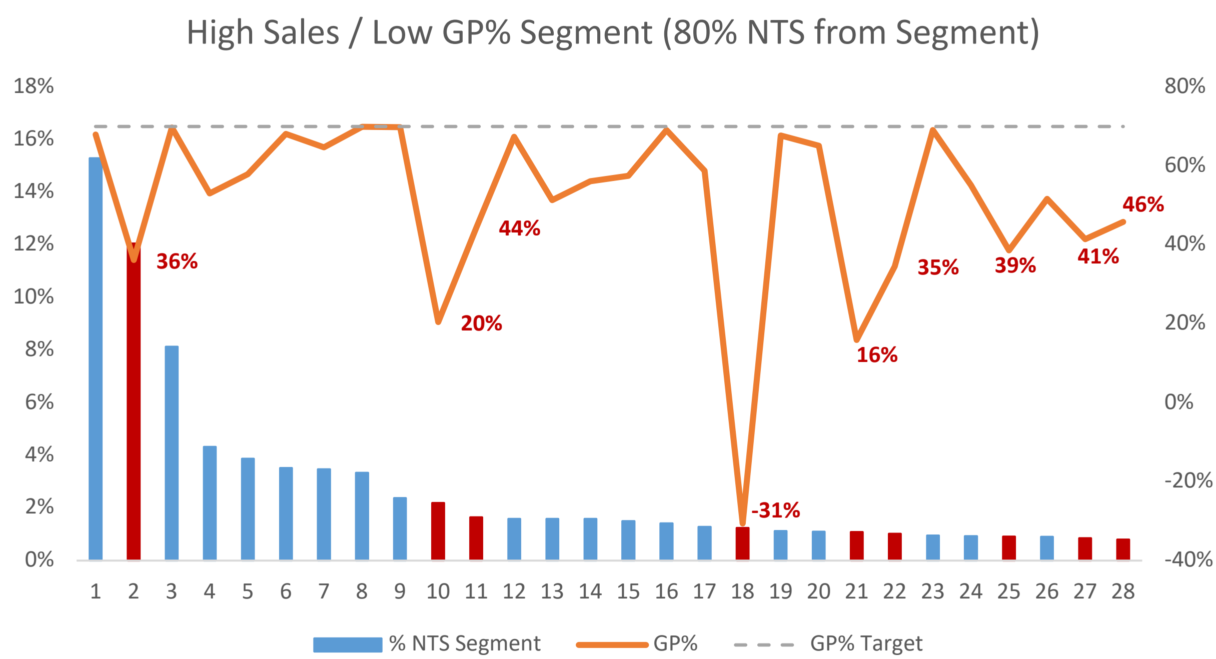
Product Code Quantity	Product Family: Major	Total Sales within Segment
68 Product Codes	“M”	$ 63,225,262
11 Product Codes	“H”	$ 26,635,390

Product Code Quantity	Product Family: Major	Total Sales within Segment
19 Product Codes	“A”	$ 61,818,486
17 Product Codes	“C”	$ 8,637,077

Figure 10 provides a graphical representation of the codes driving 80% of the sales within the High Sales/Low Gross Profit Segment.

Figure 10

Codes Driving 80% of the Net Trade Sales in 2023 within High Sales / Low GP% Segment



4. Low Sales (Yearly Sales <$100K), Low GP Percentiles (<70% GP) represented by dark red
A total of 323 base codes fall within this segment. Out of the 323 codes within the segment, the split of the codes within this segment belong to the product families (Major) shown in Table 12.

Table 12

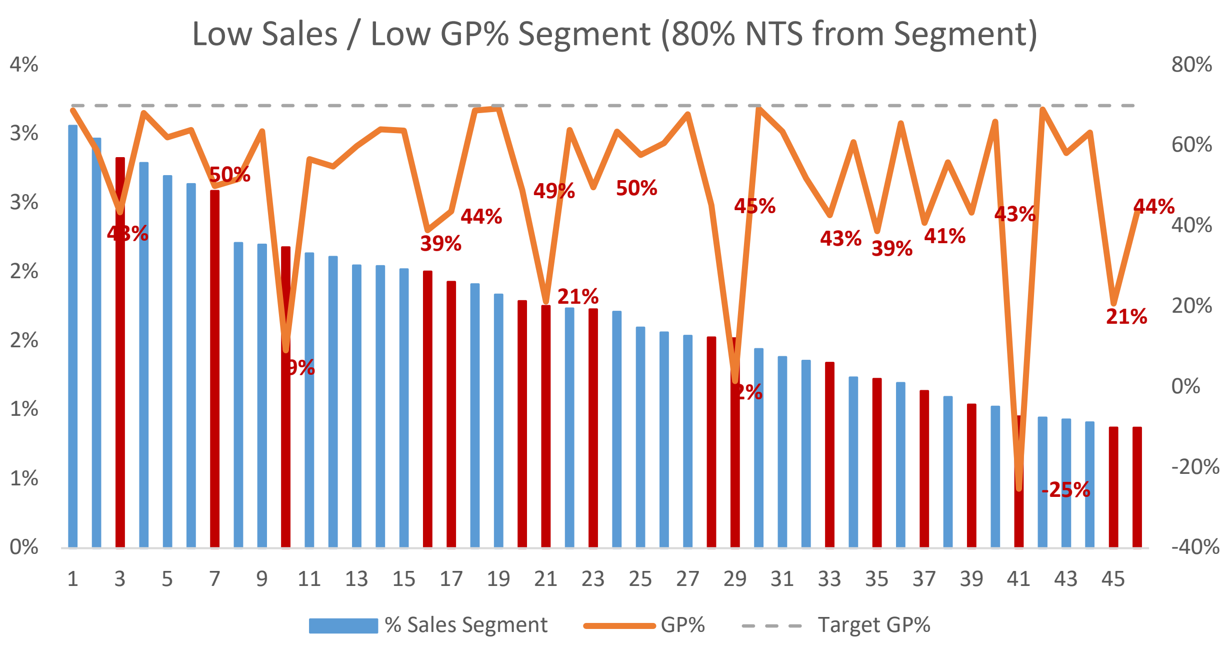
Low Sales (Yearly Sales <$100K), Low GP Percentiles (<70% GP) Product Codes Details

Product Code Quantity	Product Family: Major	Total Sales within Segment
226 Product Codes	"M"	$ 2,599,229.30
34 Product Codes	"H"	$ 112,425.50
22 Product Codes	"A"	$ 258,907.90
41 Product Codes	"C"	$ 194,836.00

Figure 11 provides a graphical representation of the codes driving 80% of the sales within the Low Sales/Low Gross Profit Segment.

Figure 11

Codes Driving 80% of the Net Trade Sales in 2023 within Low Sales / Low GP% Segment



4.3 BCG: Growth Results

The growth view using the expected volume growth from end of year 2023 through 2026 for product codes provided insights into which product codes were expected to grow within the strategic horizon of the next three years, based on the most recent long range financial planning exercise performed by the sponsoring company. There were 5 segments created by the growth view within Figure 12. The first segment in Figure 12 portrays which codes comply with the minimum of 70% GP% highlighted in green color. For the product codes that are not complying with the 70% GP% threshold, 4 segments were created to be able to differentiate codes that are expected to grow in volume versus codes that are expected to decline or remain flat. Refer to Figure 12 for a graphical representation of the product codes view Gross Profit % versus growth view. The results obtained within each of these segments included within the growth view in Figure 12 are the following:

1. **Product codes with GP% of 70% or higher represented in green** - A total of 227 product codes were part of this segment, aligned with the product codes included within sections 4.2.1 and 4.2.2.
2. **Expected Growth of 10% or higher represented in yellow –** A total of 118 codes were part of this segment. Refer to Appendix B for the full list of codes. The product codes within this segment are not driving an accretive gross profit for the portfolio, but are expected to be growing within the next three years. Out of the 118 codes within the segment, the split of the codes within this segment belong to the product families (Major) shown in Table 13.

Table 13

Product Codes Quantity with expected Growth of 10% or higher

Product Code Quantity	Product Family: Major
92 Product Codes	“M”
8 Product Code	“H”
18 Product Codes	“A”

3. **Expected Growth of 5% to 10% represented in orange -** A total of 74 codes were part of this segment. Refer to Appendix B for the full list of codes. The product codes within this segment are not driving an accretive gross profit% for the portfolio, but are expected to be growing at a rate between 5% and 10% within the next three years. Out of the 74 codes within the segment, the split of the codes within this segment belong to the product families (Major) shown in Table 14.

Table 14

Product Codes Quantity with expected Growth of 5% to 10%

Product Code Quantity	Product Family: Major
54 Product Codes	“M”
7 Product Codes	“H”
3 Product Codes	“A”
10 Product Codes	“C”

4. **Expected Growth of 0% to 5% represented in pink -** A total of 135 codes were part of this segment. Refer to Appendix B for the full list of codes. The product codes within this segment are not driving an accretive gross profit% for the portfolio and are expected to grow at a rate between 0% and 5% within the next three years. Out of the 135 codes within the segment, the split of the codes within this segment belong to the product families (Major) are shown in Table 15.

Table 15

Product Codes Quantity with expected Growth of 0% to 5%

Product Code Quantity	Product Family: Major
99 Product Codes	“M”
9 Product Code	“H”
27 Product Codes	“C”

5. **Expected Negative growth or decline represented in red** - A total of 111 codes were part of this segment. Refer to Appendix B for the full list of codes. The product codes within this segment are not driving an accretive gross profit for the portfolio and are expected to decline in volume within the next three years. Out of the 111 codes within the segment, the split of the codes within this segment belong to the product families (Major) shown in Table 16.

Table 16

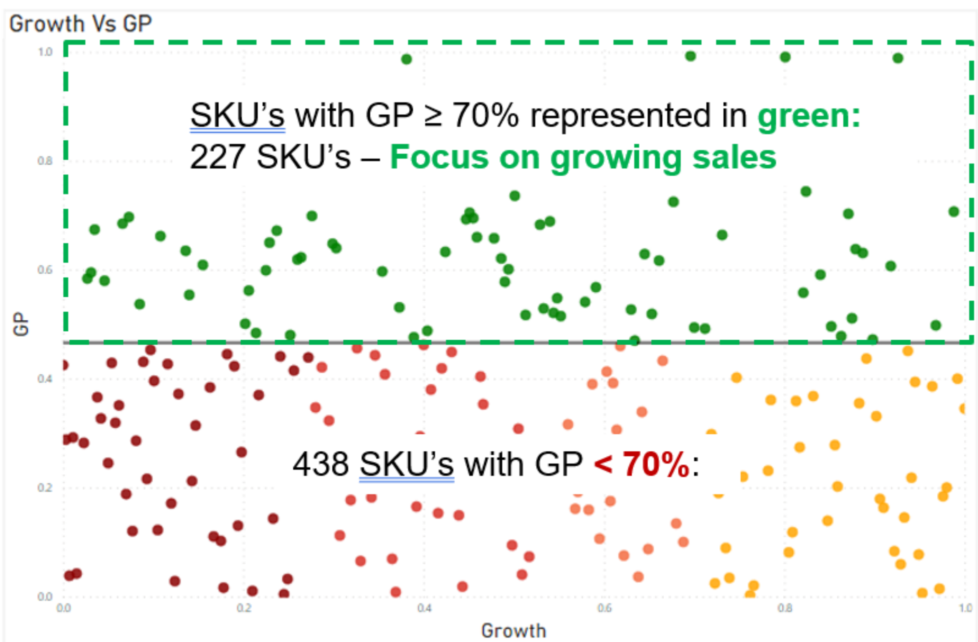
Product Codes Quantity with expected Negative growth or decline

Product Code Quantity	Product Family: Major
26 Product Codes	"M"
7 Product Codes	"A"
10 Product Codes	"C"

Figure 12 provides a visual representation of the Growth view, with Gross Profit percentile is included within the y-axis and the expected growth rate included within the x axis. Horizontal line represents 70% Gross Profit threshold.

Figure 12

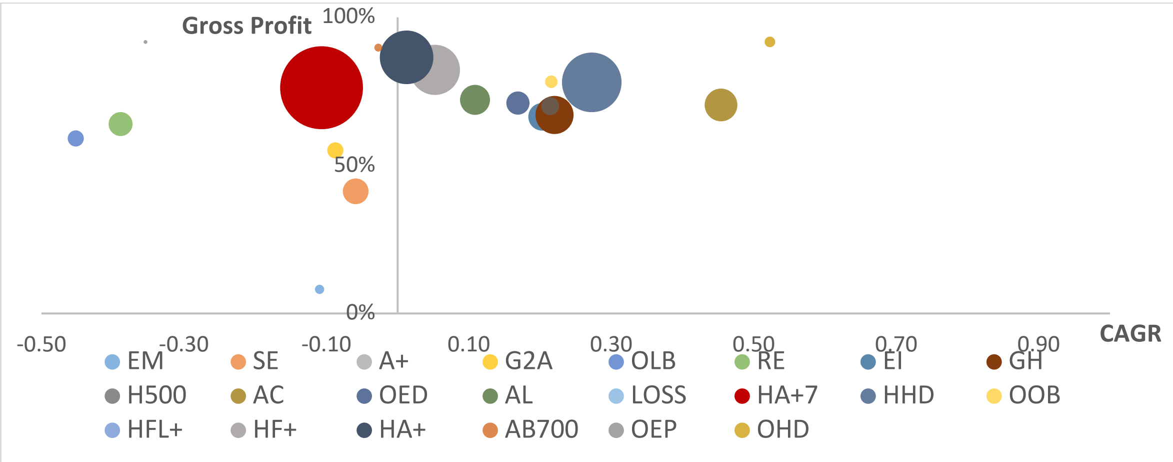
Expected Growth Visual (Product Code Level)



The expected growth visual in Figure 13 incorporates data related to expected volume growth within the x-axis, gross profit % within the y-axis and Net Trade Sales represented by the size of the bubble for each of the product families within the portfolio. Figure 13 provides a graphical representation of the Expected growth visual at the product family level (Minor level). The Expected growth visual in Figure 13 allows the sponsoring company get a high-level overview of the net trade sales generated by each of the product families during 2023, the families' (Minors) expected growth within the next three years (2023 – 2026) and the gross profit % of each of the product families within the portfolio. Appendix E includes data set used to generate the product families' growth view.

Figure 13

Expected Growth Visual (Product Family – Minor Level)



4.4 Regional View

The Regional View results contain the Total 2023 Net Trade Sales by Country, GP% by Country, and Expected Growth by Country within the same visualization. Refer to Figure 14 for the visual representation of the Regional View. Fifty-seven countries are represented within the regional view depicted in Figure 14, in which 47 of them have an accretive GP% (>70%) represented in green within Figure 14. The remaining 10 Countries have a dilutive GP% (≤70%) represented in red within Figure 14. The Countries with dilutive GP% can be found within Table 17. Refer to Appendix F for data used to construct the Regional View visualization.

Table 17

Countries with Dilutive GP% (≤70%)

Countries	Sales 2023	GP%
BELGIUM	$ 11,065,100	67.85%
BRAZIL	$ 31,306,300	69.96%
CHILE	$ 5,133,300	66.68%
COLOMBIA	$ 10,110,800	69.83%

Countries	Sales 2023	GP%
DENMARK	$ 2,555,300	69.00%
MISSA	$ 1,537,500	65.88%
NETHERLANDS	$ 10,377,000	66.37%
NORWAY	$ 614,000	66.97%
PORTUGAL	$ 6,160,300	69.00%
SWEDEN	$ 4,018,200	66.39%

Out of the 57 countries, 20 of them are expected to decline in volume as per the latest long range financial plan from the sponsoring company. The Countries with expected volume declines can be found in Table 18.

Table 18

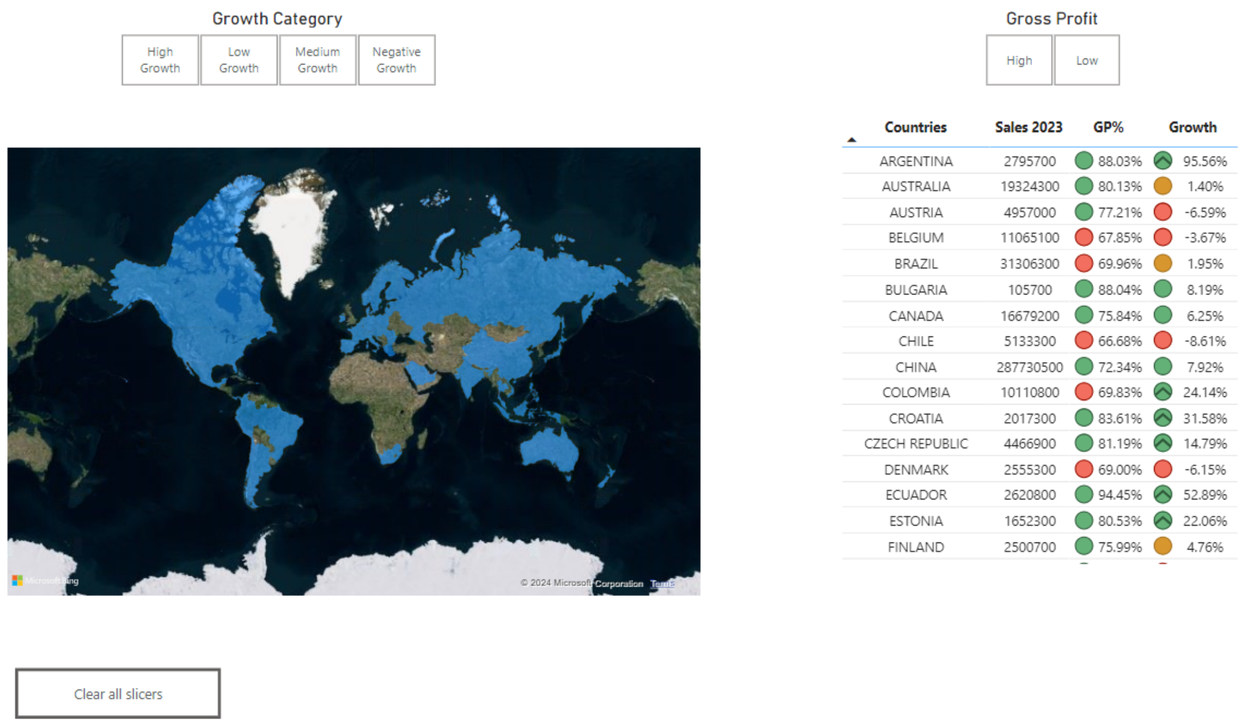
Countries with declining volume (2023 – 2026)

Countries	Sales 2023	GP%	Growth
AUSTRIA	$ 4,957,000	77.21%	-6.6%
BELGIUM	$ 11,065,100	67.85%	-3.7%
CHILE	$ 5,133,300	66.68%	-8.6%
DENMARK	$ 2,555,300	69.00%	-6.2%
FRANCE	$ 34,168,000	76.55%	-6.6%
ITALY	$ 53,829,500	83.32%	-3.9%
LATVIA	$ 1,282,000	78.35%	-0.2%
NETHERLANDS	$ 10,377,000	66.37%	-4.3%

Countries	Sales 2023		GP%	Growth
NORWAY	$	614,000	66.97%	-17.8%
PANAMA	$	2,412,200	82.17%	-1.3%
PERU	$	2,273,900	95.88%	-2.4%
PORTUGAL	$	6,160,300	69.00%	-11.2%
RUSSIAN FEDERATION	$	4,428,900	85.30%	-76.4%
SOUTH AFRICA	$	6,114,100	83.97%	-9.7%
SPAIN	$	23,041,400	79.59%	-7.7%
SWEDEN	$	4,018,200	66.39%	-6.5%
SWITZERLAND	$	10,262,700	79.98%	-0.1%
TAIWAN	$	14,949,300	86.38%	-4.4%
UNITED ARAB EMIRATES	$	61,471,700	80.10%	-2.0%
UNITED STATES	$	382,516,100	71.20%	-4.1%

Figure 14

Regional View: 2023 Net Trade Sales, GP%, and Growth



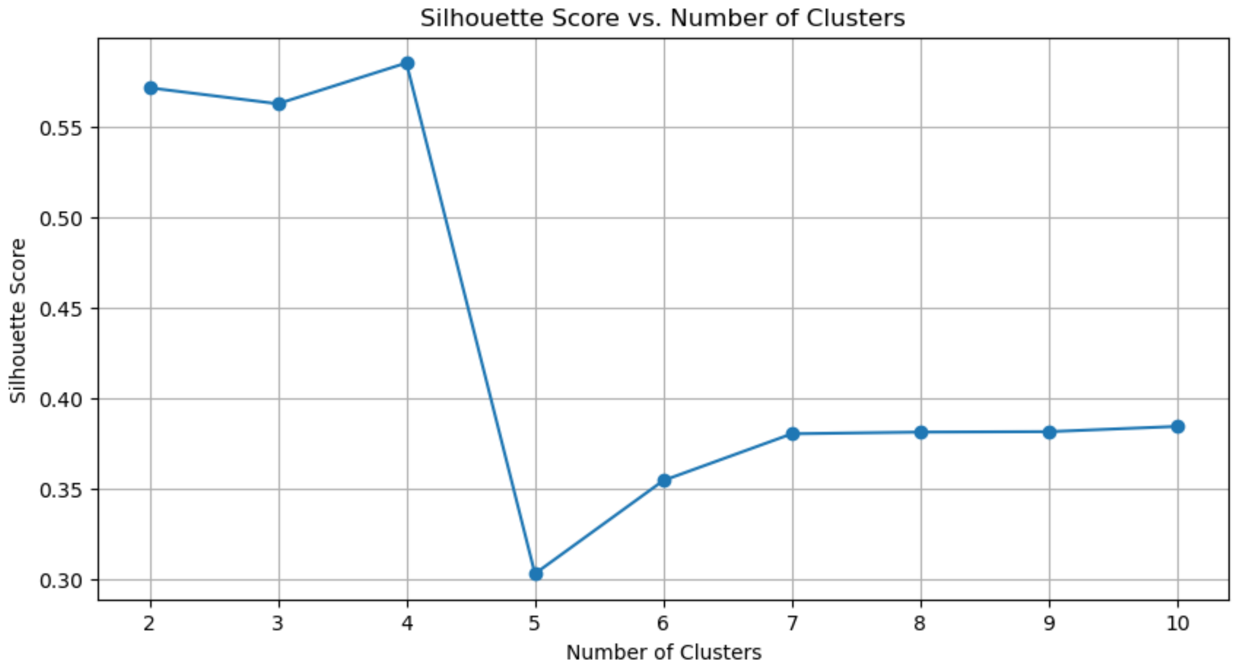
Note. The growth category slicer can be found in the top left corner of the Regional View. Gross Profit Slicer can be found in the top right corner of the Regional View. In the bottom left corner, a bottom to clear all slicers was created to facilitate the removal of all filters from the view. Table included within Regional View includes the Country, Total Net Trade Sales for 2023 by Country, GP% by Country, and Expected growth by Country.

4.5 K-Clustering: Unsupervised Machine Learning Results

The results of the K-clustering analysis on the dataset were derived using a combination of the silhouette score and Principal Component Analysis (PCA) visualization techniques as described in the methodology section. The silhouette score analysis revealed that the optimal number of clusters for our dataset is four (Refer to Figure 15), achieving the highest silhouette score of 0.58. This indicates a good separation and cohesion within the clusters.

Figure 15

Silhouette Score



The summary of the clusters' characteristics are as follow as per **Table 19**:

- **Cluster 0:** Dominated by products fully manufactured in-house (100% 'Make' and 0% 'Buy'), this cluster accounts for $428 million in sales and has a GP of 73%. It has moderate high sales (28.20%), high GP% (33.74%), and growth (20.93%) percentages.
- **Cluster 1:** This cluster features the highest percentage of high sales (90.48%) and shows substantial percentages in high GP (52.38%) and growth (42.86%). It primarily consists of in-house production (95.24% 'Make') with minimal outsourcing (4.76%), yet it records relatively low total sales of $2 million and a GP of 48%.
- **Cluster 2:** Exclusively composed of outsourced products (100% 'Buy'), this cluster presents moderate to high percentages in sales (42.70%) and GP (25.84%) and a relatively strong growth rate of 35.96%. It shows $155 million in sales with a GP of 71%.
- **Cluster 3:** Marked by the highest performance across all metrics—100% in both high sales and high GP, with a growth rate of 20%. This cluster has a balanced make or buy strategy (40% 'Make', 60% 'Buy') and boasts the highest sales figures at $590 million, along with the highest GP percentage of 78%.

Table 19

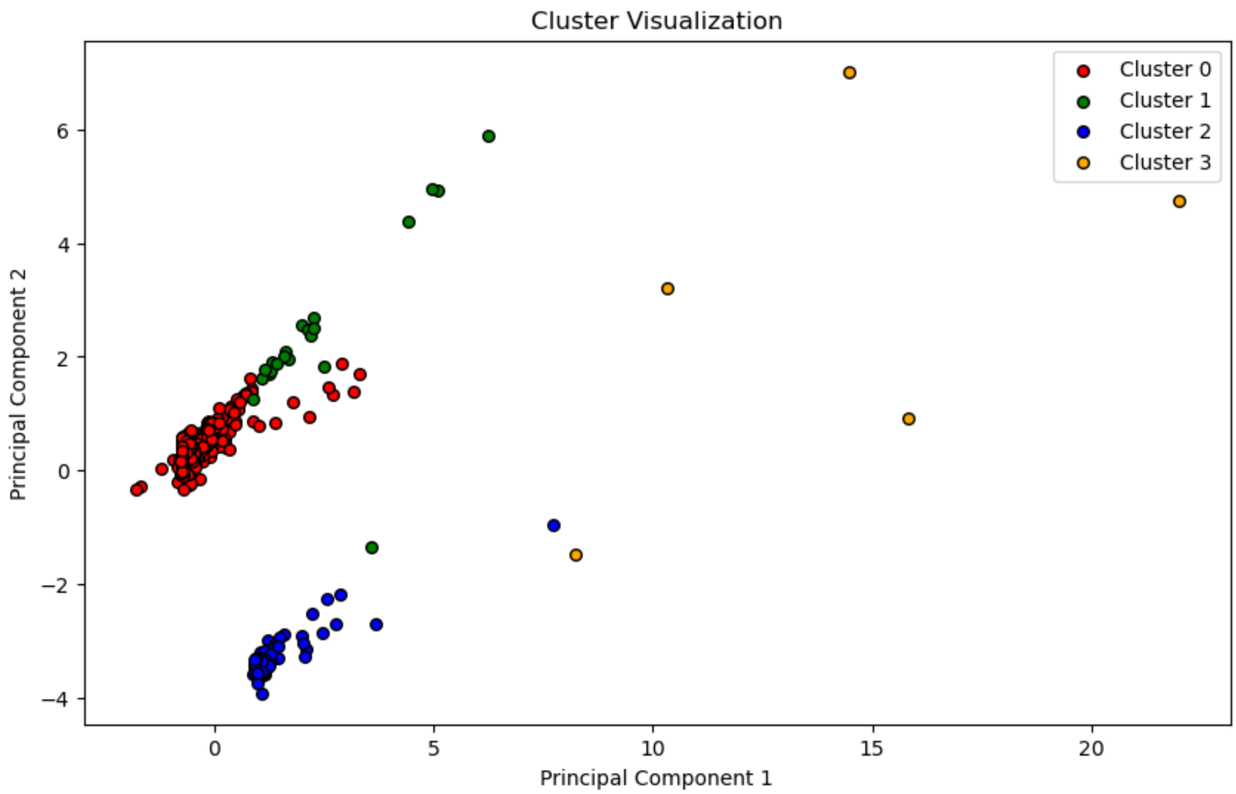
K-Clustering Results

Cluster Number	% High Sales	% High GP%	High Growth %	Make %	Buy %	Sales	GP%
0	28.20%	33.74%	20.93%	100.00%	0.00%	$428 M	73%
1	90.48%	52.38%	42.86%	95.24%	4.76%	$2 M	48%
2	42.70%	25.84%	35.96%	0.00%	100.00%	$155M	71%
3	100.00%	100.00%	20.00%	40.00%	60.00%	$590 M	78%

Finally, Figure 16 provides a PCA visualization that clearly displays the four clusters. This visualization helps to easily distinguish and understand the relationships between them in a reduced dimensional space.

Figure 16

K-Clustering: K-means Results Visualization (Cluster 0, 1, 2 and 3)

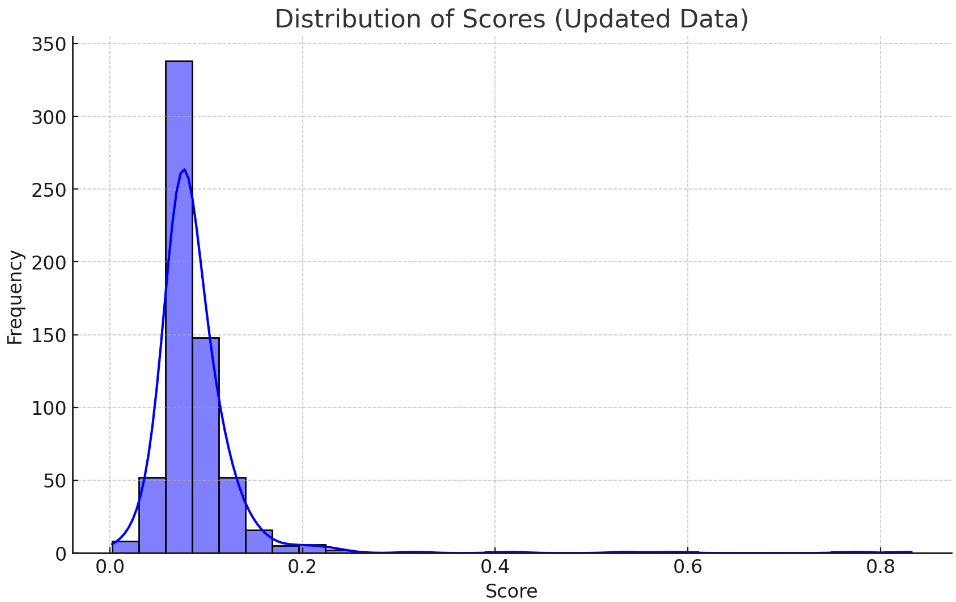


4.6 Weighted Score Results

The weighted score analysis results clearly points to a significant variation in performance across the product portfolio. Most products maintain moderate performance levels around a median a weighted score of 0.09, while some achieve scores as high as 0.832. This distribution underscores the presence of both underperformers and top performers within the portfolio (Refer to Figure 17).

Figure 17

Distribution of Scores



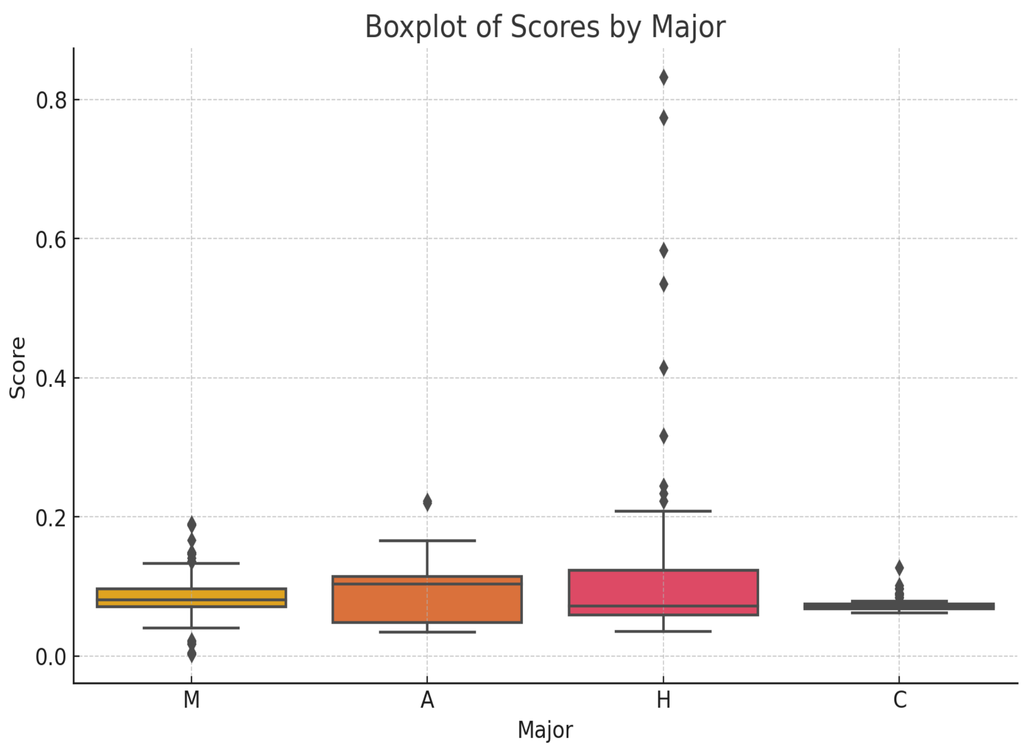
Each product type exhibits its own range of scores (Refer to Figure 18), indicating different levels of performance within the categories:

- **Major A**: The scores for Major A range from a minimum of 0.034 to a maximum of 0.223, with a median at 0.103. The 25th percentile is at 0.048 and the 75th percentile at 0.114. This significant variability suggests that while some products are performing well, others are substantially underperforming, making Type A a primary target for rationalization by identifying and potentially discontinuing its lower-scoring products to improve overall profitability.
- **Major C**: Products in Major C show more consistent performance but on the moderate to lower end, with scores ranging from 0.062 to 0.128 and a median of 0.070. The interquartile range is tight, from 0.068 to 0.074, indicating uniformity in lower performance. This group could benefit from a comprehensive review to determine if any products should be improved significantly or phased out to allocate resources more effectively.
- **Major H**: This Major includes the highest scores in the dataset, stretching from 0.035 to a maximum of 0.832, with a median at 0.072. The interquartile range from 0.059 to 0.123 points to a presence of high-performing products. However, the wide range of scores also suggests variability, with some products potentially underperforming. Strategic decisions here might involve focusing on enhancing or capitalizing on the high performers and reconsidering or eliminating the low scorers.

- **Major M**: Containing the majority of products, Major M shows moderate variability with scores ranging from 0.003 to 0.191 and a median score of 0.081. The interquartile range is from 0.071 to 0.096. Given its size and the breadth of performance, Type M might contain several underperformers that, if discontinued, could significantly enhance the overall score average and reduce costs.

Figure 18

Score distribution by Major



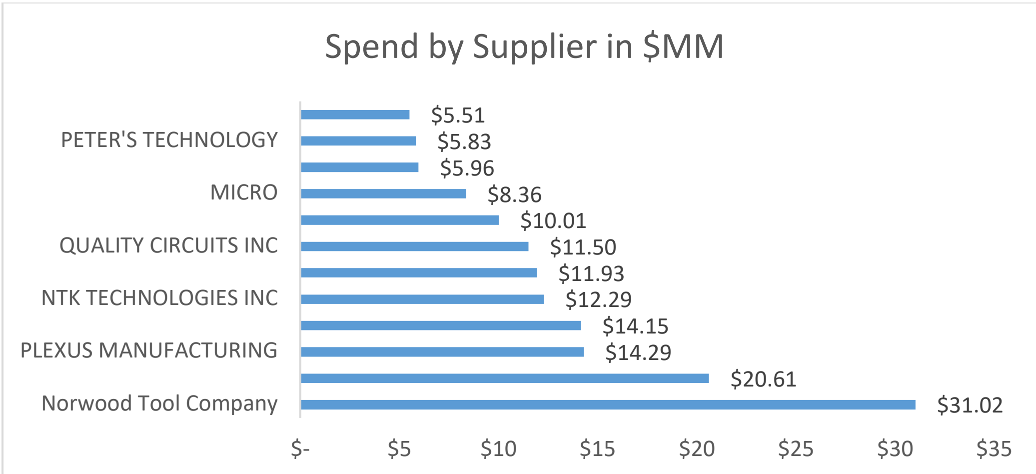
Given this variability, the company should prioritize the discontinuation of the lowest-scoring products within each product type (Major). By eliminating these underperformers, resources can be reallocated to support and enhance products with higher scores, potentially increasing overall efficiency and profitability of the product portfolio. This targeted approach to product rationalization will help in streamlining operations and focusing on areas that offer the most significant returns.

4.7 Cost of Goods Sold (COGS) Results

4.7.1 A cost of goods sold analysis was performed to identify factors affecting the profitability of codes with dilutive GP%. While assessing cost of goods sold data, it was found that ~80% of the total cost of goods sold from the codes within scope comes from the raw material spending account. In Figure 19, Norwood Tool Company is identified as the leading supplier in terms of spending for cluster 0.

Figure 19

Spend by Supplier in $MM



4.7.2 In addition to spending per supplier, notable differences were observed in the total cost of goods sold between internal and external manufacturing sites for products made in both types of supply chain networks. Table 20 display these differences for products with the same base codes and comparable modification codes.

Table 20
Base Code H36 Actual Cost of Good Sold (Internal vs External)

Mod Base	External	Internal	Sales ($MM)	GP%	Material Cost ($)	Transformation Cost	Production Cost
H361		X	$101	82%	$60.19	$7.68	$67.87
H362	X		$174	71%	$65.24	$4.58	$69.82

4.7.3 A simulation was conducted to explore the impact of transferring all production of product code H361 to internal manufacturing, where production costs are lower compared to external sites. By excluding overhead costs in the calculation of the cost of goods sold for this code, the simulation indicated a potential improvement in gross profit by 3.5%. For additional details refer to Table 21.

Table 21
Potential Improvement in Gross Profit from Volume Transfer to Internal Manufacturing

Mod Base	External	Internal	Sales ($MM)	GP%	Material Cost ($)	Transformation Cost	Production Cost
H362	X		$174	74.5% (+3.5%)	$60.19	$3.12	$64.52

4.7.4 The key outcomes of our detailed analysis highlight the critical role of procurement in the cost structure, pinpointing specific suppliers for potential cost reductions. Additionally, the comparison between in-house production ('make') and external purchasing ('buy') revealed that in-house production is more cost-effective. The next section will outline recommendations based on these insights.

4.8 Recommendations

This section presents our recommendations, derived from various methods we implemented. Our suggestions primarily aim to identify improvement opportunities within the product portfolio, which might assist the sponsoring company in making decisions to enhance their portfolio's profitability.

4.8.1 Segmentation Recommendations:

Based on the four segmentation methods we used, we can derive specific recommendations for each cluster that might help the company improve its financial performance. Table 22 provides additional details linked to the recommendations from each segmentation method.

Table 22

Recommendations per Segmentation Method

Segmentation Method	Recommendation
Pareto	- Focus on reducing costs for the most dilutive codes, H11, HA+, HCN, AC of Net Trade Sales Pareto and the 2 codes, AC, HCN from the Gross Profit Pareto to improve profitability. - Explore new markets, pricing promotions and marketing for the 80% per cent of the product constituting 20% of total sales.
Category Role Matrix	- For the High Sales Segment (Yearly Sales >$100K) with Low Gross Profit (GP) Percentages (<70% GP), which is a critical segment in the category role matrix, the focus should be on the product codes in the lower 50%. Reducing the cost of goods sold (COGS) for these products could potentially enhance profitability. - For the Low Sales Segment (Yearly Sales <$100K) with Low Gross Profit Percentages (<70% GP): We recommend addressing products in this segment by either reducing the cost of goods sold (COGS) or considering discontinuation to potentially enhance profitability.
BCG Matrix	The focus on the BCG Matrix should be in the lower half for all stock keeping units lower than 70 percent GP%. In this segment we recommend: - For the 118 codes expected to grow at a rate of 10%: reduce the cost of goods sold.

Segmentation Method	Recommendation
BCG Matrix	- For the 74 codes expected to grow between 5% and 10% b: reduce the cost of goods sold. - For the 135 codes expected to grow between 0% and 5%: Reduce the cost of goods sold and Introduce replacement in the product map to replace them with higher growing products. - For the 111 codes that has negative growth: we recommend considering discontinuation and product replacement by new technology introduction.
Regional View	- It is advisable to collaborate with the commercial organization to explore potential negotiations for increasing the average selling prices of the products sold in the 10 countries with dilutive gross profit percentages (≤70%), as listed in Table 17. - Focus on promotion and aggressive pricing in the countries exhibiting negative growth, as detailed in Table 18.
Unsupervised Machine learning – k Clustering	The results from the analysis of the four clusters provide insights on how to strategically focus on each cluster: - **Cluster 0:** Comprising entirely 'Make' products, this cluster might benefit from a reduction in the cost of goods sold (COGS) through enhanced production efficiency. Consideration of discontinuation is advisable for products, as only 28% of this cluster achieves high sales. - **Cluster 1:** With half of its products anticipated to grow by more than 10%, consider cutting COGS and refining cost management strategies to capitalize on expected growth. - **Cluster 2:** Exclusively produced by external manufacturers, this cluster might benefit from negotiating better pricing with these manufacturers to decrease costs, crucial for supporting its high-sales products that are expected to grow. - **Cluster 3:** As the leader in revenue and profit but with low growth, this cluster might look into product enhancements, exploring new markets, and increasing promotional efforts to stimulate growth.

4.8.2 Weighted score and Cost of Goods Sold Deep Dive and recommendation:

The weighted score analysis prioritized products for rationalization based on three key criteria: sales, gross profit, and growth. We recommended initiating discussions with the sales and marketing teams to consider discontinuing the top 20% of products on this list. This action is projected to improve gross profit margins by 0.8%.

For the make-or-buy analysis, we recommend consulting the detailed comparison provided in the table below. This robust comparison is inspired by "Production Economics: Evaluating Costs of Operations in Manufacturing and Service Industries (Industrial Engineering) " by Anoop Desai and Aashi Mital, which evaluates the financial fundamentals of comparing the buy and the make solutions (Desai & Mital, 2018).

Table 23
Make versus Buy comparison recommendation

Category	Buy (External)	Make (Internal)
Gross local purchases	X	X
Logistics on local purchases	X	X
Taxes on local purchases	X	X
Logistics on imported purchases	X	X
Taxes and custom clearance expenses on imported purchases	X	X
Customs duties on imported purchases	X	X
Re-sale of materials for recycling	X	X
Scrap and reworked parts on purchases	X	X
Indirect purchasing expenses	X	X
Purchasing cost	**Buy (External)**	**Make (Internal)**
Production Direct Labor	X	X
Operating and maintenance costs	X	X
Depreciation of Plant Capacity means	X	Not to include
Scrap and reworked parts on production	X	X
Indirect factory costs	X	X
Infrastructure	X	X
Taxes on activity	X	X
Production cost	**Buy (External)**	**Make (Internal)**

Packaging	X	X
Cost of downstream logistics	X	X
Overheads	X	Not to include
Amortization of specific expenses for the product	X	Not to include
Financial charges	X	Not to include
Margin before tax	X	Not to include
Selling Price	**Purchasing Price**	**Production Cost**

5 CONCLUSION

To conclude this capstone project report, we would like to do a recap of the research questions we were trying to assess by the execution of the project. The first research question talked about how can the company effectively segment and get profit-maximizing recommendations for the products under scope? We can conclude that there are multiple methods that can be used to segment the product portfolio to prioritize strategic and operational actions for each cluster that potentially help the company improve financial performance of the product portfolio. Traditional methods such as the Pareto Analysis, the Category Role Matrix, and the BCG: Growth Matrix can be used to have a holistic descriptive view of the portfolio financial performance and drive recommendations for improvement.

The second question we were trying to address with this capstone project was tied to which were the primary factors affecting the profitability of the products? After completing the capstone project, we can conclude these are the main factors driving the profitability of the portfolio: Material cost, High complexity and High production costs linked to the M Major, External Manufacturing costs are higher when compared with internal manufacturing for the examples explored within capstone project. To expand on these factors, additional insights were found within the analysis which can help the sponsoring company prioritize efforts moving forward to improve profitability:

- Material Spending cost represents an area of opportunity for the business as ~80% of the total cost of goods sold cost comes from the raw material spending.
- There is a high number of product codes (high complexity) from the M Major with low gross profit % reducing the overall portfolio's profitability.
- The internal versus external production costs plays a role in the profitability of the portfolio, it is recommended to perform a comprehensive assessment of make versus buy and it is generally recommended to internalize high-runners and externalize low runners.

Lastly, we implemented a machine learning algorithm to confirm if it could provide a more comprehensive clustering of the products' financial performance than the BCG and Category Role matrix frameworks. It can be concluded that the machine learning algorithm in fact can provide additional insights while clustering product codes using a multi-variable analysis. Multiple variables can be used in conjunction to provide a more holistic approach to segment the portfolio as previously discussed within this report.

As part of the closing section of this report, we would also like to discuss the limitations identified for each of the methods applied in this Capstone Project execution. The limitations identified can be found within Table 24. This section can help inform the sponsoring company which additional areas of focus might be identified for future research to continue enhancing the financial performance of their portfolio. The limitation section also provides insights on how each of the methods can complement each other to make decisions for the portfolio using a holistic approach.

Table 24

Capstone Project Methods' Limitations

Method	Study Limitations
Pareto Analysis	Two-dimensional descriptive analysis which considers 2 variables: Net Trade Sales and Gross Profit % or Gross Profit $ and Gross Profit % for the top 20% of the codes from the portfolio. Interactions with other variables such as expected growth for the product codes is not part of the analysis. Focus is on the top 20% of the codes driving 80% of the value for the business, the analysis is not focused on the 80% of the codes driving 20% of the revenue (High variability and complexity side of the portfolio).
Category Role Matrix	Two-dimensional descriptive analysis which considers 2 variables: Net Trade Sales and Gross Profit % per product code. Additional variables such as expected growth for the codes is not part of the analysis. Provides a descriptive view of historical financial performance for the product codes, lacking visibility of expected future performance.
BCG: Growth Matrix	Two-dimensional descriptive analysis which considers 2 variables: GP% and Expected Growth. Expected growth values used for the execution of the project comes from the latest long range financial plan exercised performed by the organization. When calculating forecast accuracy between the forecasted values from that exercise and actual values, the forecast mean average percentage error was 29.32%. Overall recommendations from this view are based on the expected growth forecasted values. BCG Matrix provides visibility of expected growth based with an error of 29%. It is recommended to look for ways to improve MAPE error and re-run growth view to proceed with decision making.
Regional View	Regional View provides visibility to the total sales, GP%, and expected growth linked to each specific countries where the products from the sponsoring company are distributed. Additional analysis should be performed at the product family level complementing this view to understand drivers of the countries' sales, GP%, and/or growth performance.

Method	Study Limitations
Unsupervised Machine Learning: K-clustering	Data available for the analysis included Net Trade Sales for 2023, Gross Profit for 2023, Expected Growth (2023 – 2026), Average Inventory for 2022 and 2023, and products manufacturing locations (internal versus external). Analysis was limited to these variables to generate the clusters. To understand more complex dynamics and behaviors between the product codes within the portfolio, additional variables such as engineering specifications, distribution network setup, raw materials locations precedence could have helped identify more complex patterns within the data to drive end to end insights.
COGS Deep Dive	Material spending contributes to approximately 80% of the total cost of goods sold for the product portfolio. Additional granularity on data available such as top spending components, synergies between product families, expected volume growth by component can help compliment this analysis. The cost of goods sold deep dive was focused on data available from the manufacturing nodes. Overhead costs within the cost of goods sold within the data was not granular enough to be able to split between fixed and variable overhead. Fixed overhead should be removed from the analysis when performing make or buy assessments, as fixed overhead is considered a sunk cost. Additional information such as raw material suppliers locations, distribution network data, transportation routes, and transportation costs are not part of the analysis. Opportunities for network optimization can be obtained expanding data sets to consider some of these variables.
Weighted Score Analysis	It relies heavily on the precise and unbiased allocation of weights to each criterion, which can introduce significant subjectivity if not grounded in empirical evidence. Moreover, the method presupposes that all criteria are independent, potentially overlooking the complexities of interrelated factors.

To conclude this capstone project's report we would like to recommend the sponsoring company to focus future efforts on additional research to complement this study. Additional insights can be obtained to contribute to the continuous improvement of the financial performance of this business taking these suggested actions: Performing activity-based costing effort where allocated costs use cost drivers and consider activities involved and resources used to produce their products across all manufacturing locations. It is also recommended to extend the make or buy analysis for the entire portfolio and complement analysis with installed and staffing capacity assessments for each of the manufacturing locations as well as integrate the know-how capabilities for each of those teams as an input for volume transfer recommendations.

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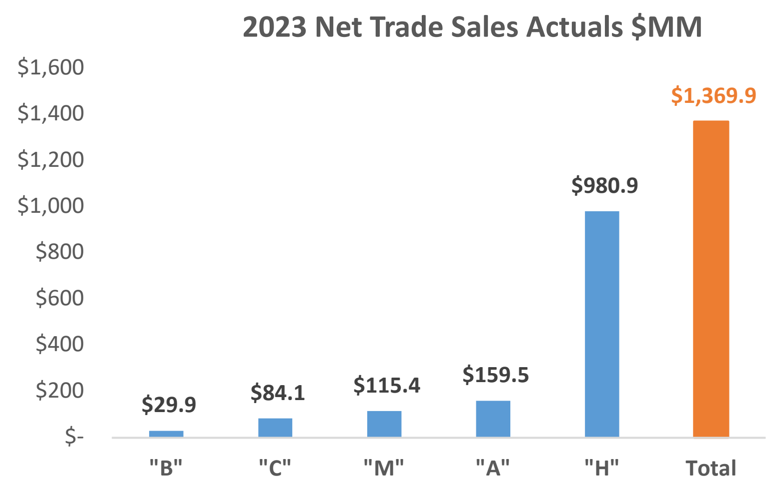
APPENDICES

Appendix A - Net Trade Sales and GP% Baseline Distribution between product families

Figures A1 and A2 include Net Trade Sales and Gross Profit % baseline information for each of the product families (Majors) within the scope of the Capstone Project.

Figure A1

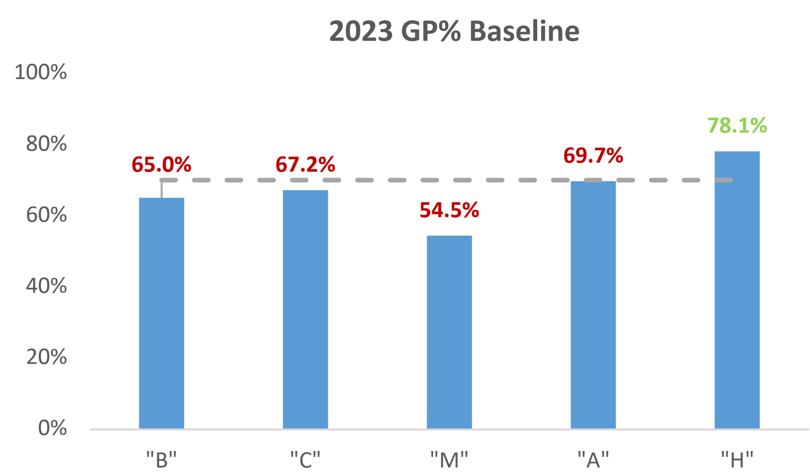
2023 Net Trade Sales Actuals in Millions of Dollars



Note. Product families are represented along the x-axis and net trade sales in millions of dollars is represented along the y-axis.

Figure A2

2023 Gross Profit Percentage (GP%) Baseline



Note. Product families are represented along the x-axis and gross profit % is represented along the y-axis.

Appendix B - Product Codes List in Scope

Table B1 includes the list of product codes within the scope of the Capstone Project. Table B1 includes the Net Trade Sales, the Gross Profit %, the Gross Profit in Volume ($), the Major, the Average Inventory for 2022 and 2023, and the Compound Annual Growth Rate % (CAGR%) for each product code within the scope of the Capstone Project. Product codes within baseline data were defined to maintain confidentiality from company's data. The product codes numbering does not follow a logical approach when compared to the labels within Figures across the document.

Table B1

Product Codes list in scope for Analysis: Baseline Data

Product Code	NTS ($) 2023	GP in volume	GP %	Major	Average Inventory 2022	Average Inventory 2023	CAGR	Clusters
1	174089921.7	124459312	71%	"H"	3601	7783	-13.7%	3
2	138767538.3	107198294.2	77%	"H"	2603	655	18.4%	3
3	106565981.2	89987334.84	84%	"H"	163	41	-7.0%	3
4	101779034.8	83471964.32	82%	"H"	1354	10405	-13.7%	3
5	69614728.6	57854457.43	83%	"H"	223	52	0.8%	3
6	59437077.1	45279806.03	76%	"H"	1596	708	-13.4%	2
7	34861543.4	29442221.04	84%	"H"	0	463	0.8%	0
8	34268891.6	28650512.77	84%	"H"	155	825	-13.2%	0
9	30028166.6	22146407.83	74%	"A"	77	995	6.2%	0
10	23864971	20581815.95	86%	"H"	182	31	-6.2%	0
11	24821549.6	19904146.21	80%	"H"	361	298	18.4%	0
12	23281169.6	17964528.09	77%	"H"	745	179	17.9%	2
13	19494715.3	17166429.56	88%	"H"	108	657	-7.0%	0
14	19583503.1	15713478.89	80%	"H"	421	33	0.8%	0
15	12782571	10196459.77	80%	"H"	264	241	-2.5%	0
16	12632496.7	8895117.586	70%	"C"	97	120	0.9%	2
17	12379208.8	8395812.605	68%	"A"	291	1502	17.2%	0
18	11267719	7726070.608	69%	"A"	96	7	6.2%	2
19	10190996.9	7266033.894	71%	"H"	93	80	17.9%	2
20	7916191.3	5971845.329	75%	"C"	278	393	-1.6%	0
21	7566269.5	5850116.368	77%	"H"	2	145	17.9%	0
22	7030141.9	4911740.592	70%	"M"	93	150	5.3%	0
23	5639160.7	4855564.581	86%	"A"	0	0	17.2%	0
24	6194174.7	4400928.042	71%	"C"	177	1073	0.6%	0
25	4936921.2	3864198.766	78%	"M"	25	70	10.1%	0
26	4064021.5	3102077.985	76%	"H"	151	91	1.7%	0
27	4316772.9	3009418.745	70%	"A"	162	313	16.8%	0

Product Code	NTS ($) 2023	GP in volume	GP %	Major	Average Inventory 2022	Average Inventory 2023	CAGR	Clusters
28	3439156.5	2772922.105	81%	"H"	0	101	0.8%	0
29	3835327.3	2739441.507	71%	"A"	129	37	6.2%	2
30	3084098.7	2519153.675	82%	"H"	421	33	0.8%	0
31	2845994.7	2463006.026	87%	"H"	133	930	-6.2%	0
32	3477038.6	2462720.973	71%	"H"	171	1254	11.5%	2
33	3418727	2325365.929	68%	"C"	536	195	0.3%	0
34	2558195.7	2070560.184	81%	"H"	0	0	-7.0%	0
35	2422559.8	2006733.641	83%	"H"	424	204	-13.7%	0
36	1903875.2	1599234.721	84%	"H"	264	241	-2.5%	0
37	2256491	1571123.728	70%	"C"	298	136	0.3%	0
38	1886143.1	1513373.093	80%	"H"	122	17	0.8%	0
39	2021925.5	1435639.703	71%	"M"	0	0	5.3%	2
40	1613483.9	1363624.132	85%	"M"	1262	593	4.7%	0
41	1689366.6	1227061.544	73%	"A"	0	0	14.2%	0
42	1468340.3	1153093.843	79%	"H"	60	100	1.7%	0
43	1021511.4	1141119.803	112%	"M"	0	0	15.0%	1
44	1620159.3	1139702.311	70%	"M"	11	31	19.1%	0
45	1287016.7	1107489.034	86%	"H"	24	44	-2.5%	0
46	1619988.9	1104086.036	68%	"C"	296	140	0.4%	0
47	1463243.4	1100854.707	75%	"H"	84	18	-1.1%	0
48	1394255.6	1082086.725	78%	"M"	2900	3453	1.0%	1
49	1206092.7	1022175.989	85%	"M"	1724	284	5.8%	0
50	1132610.5	1012601.447	89%	"A"	0	3	16.8%	0
51	1189169.6	950602.8113	80%	"H"	19	0	1.7%	0
52	1107660.9	793423.0293	72%	"H"	0	0	17.9%	0
53	992082.7	725045.0361	73%	"M"	8575	8206	6.2%	1
54	795220.6	699852.8834	88%	"M"	600	43	4.4%	0
55	916963.8	651690.5245	71%	"M"	2092	200	3.5%	0
56	849819.2	603606.4035	71%	"A"	0	0	17.2%	0
57	792720.4	599098.2051	76%	"M"	1979	5034	4.0%	1
58	648304.3	576369.9665	89%	"M"	250	276	4.6%	0
59	584818.9	516625.6799	88%	"M"	0	0	5.8%	0
60	738517.9	515060.1284	70%	"M"	0	0	10.1%	2
61	615907	457061.7611	74%	"M"	2081	1410	20.5%	1
62	530641.4	455753.0421	86%	"H"	0	0	-6.2%	0
63	628382.3	449007.2332	71%	"H"	431	75	54.8%	0
64	585288.4	410973.9748	70%	"M"	0	0	19.1%	2
65	380478.2	392881.9576	103%	"M"	0	78	3.1%	0
66	548532.7	392156.3154	71%	"A"	0	0	17.2%	0
67	449069.1	342668.7723	76%	"C"	0	0	0.6%	0

Product Code	NTS ($) 2023	GP in volume	GP %	Major	Average Inventory 2022	Average Inventory 2023	CAGR	Clusters
68	197413.6	327237.9014	166%	"M"	485	809	10.5%	0
69	420399.8	309190.7728	74%	"M"	1564	1889	9.8%	0
70	185066.4	302019.0704	163%	"M"	20	14	1.2%	0
71	364692.9	301966.8138	83%	"M"	1230	278	5.8%	0
72	361931.4	294854.1703	81%	"H"	90	4	-6.2%	0
73	280174.2	288092.9764	103%	"M"	11	148	4.7%	0
74	364939.6	277739.5958	76%	"M"	0	0	3.0%	0
75	329484.3	269102.4024	82%	"H"	0	0	-13.2%	0
76	336077.4	264695.1453	79%	"M"	95	1273	5.2%	0
77	329374.7	256917.5137	78%	"M"	0	1216	5.3%	0
78	231737.4	250882.973	108%	"M"	17	17	16.9%	0
79	141171	242575.1688	172%	"M"	16	12	10.5%	0
80	305070.6	237784.3187	78%	"C"	19	5	-1.6%	0
81	313161.9	235981.6851	75%	"M"	0	127	-10.6%	0
82	286727.6	233662.8562	81%	"M"	1	7	6.2%	0
83	286016.7	232987.6939	81%	"M"	242	0	4.0%	0
84	298203.1	231243.8011	78%	"M"	4	3	1.1%	0
85	312385.8	225785.3842	72%	"M"	1531	0	2.9%	0
86	269124.8	224560.135	83%	"H"	0	0	-13.7%	0
87	233252.4	212912.1369	91%	"M"	232	137	4.6%	0
88	253974.5	198354.0845	78%	"H"	19	29	-13.2%	0
89	245729.3	197706.6271	80%	"M"	0	0	1.0%	0
90	253292.4	185289.1	73%	"M"	0	0	12.6%	2
91	217305.5	173433.0877	80%	"M"	585	438	16.2%	0
92	200829.7	173194.7967	86%	"M"	4	2	9.8%	0
93	212871.4	171018.3926	80%	"M"	504	939	9.8%	0
94	225508.1	167358.2861	74%	"M"	606	2509	4.0%	0
95	207396.7	164907.3226	80%	"M"	2	1	20.5%	2
96	229889.1	162187.4805	71%	"M"	7055	5399	10.2%	1
97	210176.5	156140.1167	74%	"C"	913	913	1.6%	0
98	101165.6	154882.5816	153%	"M"	94	316	1.2%	0
99	204751.4	154738.1671	76%	"M"	714	3871	-1.2%	1
100	192994.2	151212.4584	78%	"C"	232	232	1.6%	0
101	192449	150077.0658	78%	"M"	15	0	2.0%	0
102	248067.1	145378.5799	59%	"M"	0	0	4.4%	2
103	188295.5	139211.0121	74%	"M"	4301	2755	16.2%	1
104	181698.3	138119.4779	76%	"M"	0	0	4.8%	0
105	187236.9	137447.9931	73%	"M"	0	0	-1.7%	2

Product Code	NTS ($) 2023	GP in volume	GP %	Major	Average Inventory 2022	Average Inventory 2023	CAGR	Clusters
106	184652.8	134221.2876	73%	"M"	1504	3065	9.2%	1
107	153847.2	129539.3424	84%	"H"	97	21	-7.0%	2
108	136722	109325.5615	80%	"M"	0	0	4.6%	2
109	127106.6	95475.5773	75%	"M"	1	4	0.7%	1
110	84727.7	93379.0136	110%	"M"	7	9	4.7%	0
111	74545.6	74545.6	100%	"C"	0	0	0.9%	0
112	74345.1	73819.301	99%	"M"	566	582	15.4%	0
113	97916.8	73468.6749	75%	"C"	0	0	0.3%	0
114	83684.6	70826.9574	85%	"H"	0	0	-13.7%	0
115	97064.5	69411.9706	72%	"M"	2326	130	8.5%	0
116	86538	68378.9591	79%	"M"	637	529	7.6%	0
117	86342.6	62062.4495	72%	"M"	1	0	6.4%	0
118	79454.8	60208.7203	76%	"M"	728	69	5.3%	0
119	79601.1	57770.3528	73%	"M"	0	47	3.2%	0
120	75505.5	57128.9589	76%	"M"	220	0	3.5%	0
121	62787.8	55002.1128	88%	"H"	525	45	0.8%	2
122	72858.1	52896.7667	73%	"M"	0	75	1.0%	0
123	64383.5	51674.2528	80%	"H"	0	0	-13.4%	0
124	66941.4	49399.2775	74%	"M"	0	0	8.1%	1
125	61152.6	47816.3167	78%	"A"	181	0	15.8%	0
126	37111.4	47193.7727	127%	"H"	1	0	-1.1%	0
127	61627.3	44432.3581	72%	"A"	0	0	18.6%	0
128	58443.3	43218.0609	74%	"M"	0	0	7.9%	0
129	52451.2	40068.8332	76%	"C"	91	11	2.9%	0
130	45102.3	37912.5951	84%	"M"	4	3	1.1%	0
131	53253.9	37741.629	71%	"A"	180	137	18.6%	0
132	39886.6	32313.3833	81%	"H"	421	33	0.8%	0
133	81804.8	31374.2966	38%	"M"	0	0	4.6%	2
134	33559.5	31321.1836	93%	"C"	0	0	-1.6%	0
135	16944.1	30573.3609	180%	"M"	82	135	21.2%	0
136	31887.8	30284.38	95%	"M"	0	0	0.7%	0
137	27768.3	30158.5609	109%	"M"	31	477	5.4%	0
138	42101.7	30122.5146	72%	"H"	0	0	1.3%	0
139	35664.8	28400.251	80%	"H"	0	0	-13.4%	0
140	39675.3	28152.8585	71%	"M"	0	0	7.6%	2
141	7350.5	28046.1852	382%	"C"	0	0	0.6%	0
142	32696.6	28003.7639	86%	"M"	105	0	12.1%	0
143	28505.3	22656.4759	79%	"C"	0	0	0.3%	0

Product Code	NTS ($) 2023	GP in volume	GP %	Major	Average Inventory 2022	Average Inventory 2023	CAGR	Clusters
144	23914.5	19718.5256	82%	"M"	150	1	5.8%	0
145	25155.2	19206.0467	76%	"M"	3	0	21.2%	2
146	27124.4	18414.0874	68%	"M"	48	29	9.5%	0
147	24504.4	18059.1834	74%	"M"	0	8	32.2%	0
148	20892.9	16994.6738	81%	"C"	0	0	-2.4%	0
149	21601.4	16971.8186	79%	"H"	264	241	-2.5%	0
150	19908.8	15459.8468	78%	"M"	361	0	9.9%	0
151	21705.5	15302.7866	71%	"M"	0	68	3.3%	0
152	16953.6	15065.4816	89%	"M"	340	118	5.4%	2
153	16875.4	14153.033	84%	"H"	77	0	1.7%	0
154	18484.6	13667.1187	74%	"C"	348	348	1.6%	0
155	15172.2	12946.1182	85%	"A"	1	0	-13.8%	0
156	17420.9	12721.9308	73%	"C"	0	0	0.4%	0
157	14005.7	12198.9647	87%	"H"	114	5	6.0%	2
158	11850.7	12020.6931	101%	"M"	0	0	15.4%	0
159	14717.7	10699.8383	73%	"M"	44	46	22.8%	2
160	27488.2	9335.9011	34%	"M"	195	68	9.2%	2
161	12160.6	9157.0159	75%	"M"	0	0	3.3%	2
162	10923.8	8769.4669	80%	"M"	203	128	4.8%	0
163	4871.8	8635.4699	177%	"M"	39	33	11.5%	0
164	6779.3	8505.8553	125%	"M"	670	46	4.7%	2
165	7971.8	8452.3061	106%	"M"	0	120	0.2%	0
166	11811.9	8314.2971	70%	"M"	231	0	-10.6%	0
167	8369.3	7261.6031	87%	"H"	0	0	0.8%	0
168	9540.1	6854.2748	72%	"M"	114	105	5.5%	0
169	8914.8	6694.535	75%	"M"	0	42	1.4%	0
170	9093.4	6402.9114	70%	"M"	261	9	2.6%	0
171	7918.7	5975.2782	75%	"M"	48	0	5.3%	0
172	8311.1	5940.6228	71%	"M"	0	5	-9.9%	0
173	7413.7	5626.3336	76%	"M"	0	0	5.1%	0
174	7671.2	5410.8096	71%	"M"	0	108	1.0%	0
175	5809.4	4530.3683	78%	"M"	15	0	2.0%	0
176	5213.3	4429.1856	85%	"H"	0	0	-2.5%	0
177	5203.8	4230.8974	81%	"M"	380	0	-2.9%	0
178	4761.1	3930.7345	83%	"M"	0	26	2.3%	0
179	5370.4	3822.4623	71%	"A"	0	0	6.2%	0
180	4808.1	3745.8672	78%	"H"	0	0	1.3%	0
181	3409.7	3190.6313	94%	"M"	1	0	1.0%	0
182	4292.4	3180.3041	74%	"M"	495	432	15.3%	0

Product Code	NTS ($) 2023	GP in volume	GP %	Major	Average Inventory 2022	Average Inventory 2023	CAGR	Clusters
183	3903.1	2836.74	73%	"M"	36	36	5.9%	0
184	2956.1	2356.0117	80%	"M"	0	26	8.7%	0
185	2528.1	2310.6834	91%	"M"	904	53	4.6%	0
186	2487.2	2230.9078	90%	"H"	0	0	-13.4%	0
187	2726.3	2223.1946	82%	"M"	220	1	3.1%	0
188	2885.7	2181.1749	76%	"M"	48	41	-4.8%	0
189	2887.4	2055.1075	71%	"H"	0	0	-1.1%	0
190	1836.7	1979.8519	108%	"M"	0	103	5.1%	0
191	2641.9	1962.7367	74%	"M"	0	91	32.8%	0
192	1611.6	1578.2694	98%	"M"	0	49	11.6%	0
193	1683.9	1428.4509	85%	"M"	220	0	3.5%	0
194	1682.5	1366.9622	81%	"C"	0	0	0.3%	0
195	1445.9	1295.4344	90%	"M"	0	0	6.5%	0
196	1566	1294.7515	83%	"M"	63	0	17.7%	0
197	1511	1161.5343	77%	"M"	16	3	1.0%	0
198	1123.8	1051.5011	94%	"M"	1826	960	6.2%	0
199	1212.7	1030.5609	85%	"M"	242	0	4.0%	0
200	1259.7	1019.9781	81%	"M"	0	0	1.0%	0
201	797.8	904.5068	113%	"H"	0	0	-13.2%	0
202	874.8	843.1442	96%	"M"	0	0	0.9%	0
203	882.8	801.5824	91%	"M"	4	2	9.8%	0
204	962.3	746.865	78%	"M"	119	107	4.0%	0
205	926.3	658.2306	71%	"M"	0	0	17.7%	0
206	827.1	592.577	72%	"M"	59	5	5.1%	0
207	822.2	591.5758	72%	"M"	0	0	-4.8%	0
208	809.3	570.5565	71%	"M"	168	0	5.2%	0
209	563.1	563.1	100%	"M"	0	0	5.5%	0
210	722.7	554.0473	77%	"M"	0	80	49.3%	0
211	466	363.3318	78%	"M"	0	0	8.8%	0
212	433	331.3101	77%	"M"	0	0	-20.5%	0
213	381.7	281.4405	74%	"M"	307	1	5.3%	0
214	279.3	279.3	100%	"M"	505	624	16.2%	0
215	341.6	274.3627	80%	"M"	0	0	9.6%	0
216	208	208	100%	"M"	389	0	9.9%	0
217	275.1	201.7904	73%	"M"	19	9	16.2%	0
218	277	201.7792	73%	"M"	0	0	5.4%	0
219	204.6	179.4291	88%	"M"	1144	1097	40.4%	2
220	118.8	118.8	100%	"C"	0	0	0.4%	0

Product Code	NTS ($) 2023	GP in volume	GP %	Major	Average Inventory 2022	Average Inventory 2023	CAGR	Clusters
221	105.2	105.2	100%	"M"	8	0	1.1%	0
222	-3.2	-3.2	100%	"M"	81	80	5.5%	0
223	27.1	-9.2573	-34%	"M"	6	7	3.0%	0
224	-199.5	-488.6646	245%	"H"	0	0	1.7%	0
225	108.2	-491.1099	-454%	"M"	8	1	3.5%	0
226	-40808	-41257.9911	101%	"H"	0	0	-13.2%	0
227	-42097.9	-42097.9	100%	"H"	0	0	-7.0%	0
228	24520196.3	16688301.71	68%	"A"	534	1761	17.2%	0
229	19324947	7138512.624	37%	"M"	1334	3023	22.6%	1
230	13030109.6	9072378.077	70%	"H"	627	622	8.7%	2
231	6931773.7	3697241.607	53%	"A"	400	347	-13.8%	0
232	6216489.4	3606593.019	58%	"A"	145	648	14.2%	0
233	5651419.7	3839538.345	68%	"A"	0	0	6.2%	0
234	5560093.5	3595986.985	65%	"A"	574	534	16.8%	0
235	5346763.9	3685949.954	69%	"H"	0	0	18.4%	0
236	3807394.2	2651947.644	70%	"A"	506	533	18.6%	0
237	3513316.3	742211.6774	21%	"M"	692	1651	25.4%	0
238	2639916.5	948141.4095	36%	"C"	751	2630	7.9%	2
239	2543557.4	1714674.888	67%	"M"	0	324	0.0%	0
240	2541931.4	1273274.798	50%	"M"	0	0	22.6%	2
241	2534188	1441391.167	57%	"A"	67	135	-8.6%	0
242	2416131.5	1396758.513	58%	"A"	122	144	-10.7%	0
243	2275243.6	1581375.721	70%	"M"	1323	1572	2.0%	0
244	2061501.6	1197915.319	58%	"H"	428	232	1.3%	0
245	1991276.3	-538206.5276	-27%	"M"	217	345	-20.7%	0
246	1809126.3	1224089.02	68%	"M"	21	53	-4.3%	0
247	1761046.7	1146348.035	65%	"M"	0	284	2.9%	0
248	1741789.6	319978.7592	18%	"M"	776	1683	5.5%	0
249	1637149.3	547846.3531	33%	"M"	0	0	-20.7%	2
250	1530515.1	1065356.4	70%	"M"	587	3542	4.8%	1
251	1497445.5	862029.7325	58%	"C"	2	0	0.9%	0
252	1464861.2	565081.4403	39%	"H"	34	658	33.2%	0
253	1459152.7	757382.5578	52%	"H"	371	1674	54.8%	0
254	1366270.8	573595.3655	42%	"M"	4310	2541	20.2%	1
255	1283650.8	590682.2235	46%	"M"	479	366	12.9%	0
256	1263640	629243.8051	50%	"M"	953	2427	1.9%	0
257	1175584.7	712713.5589	61%	"A"	74	187	-8.2%	0

Product Code	NTS ($) 2023	GP in volume	GP %	Major	Average Inventory 2022	Average Inventory 2023	CAGR	Clusters
258	1167340	777372.0116	67%	"H"	121	2	-7.0%	0
259	1116937.1	555710.931	50%	"M"	868	2063	1.1%	0
260	1090508.8	471167.2928	43%	"M"	409	399	16.9%	0
261	990612.8	657318.3416	66%	"M"	778	2059	1.1%	0
262	891053.6	335820.4246	38%	"M"	0	0	11.4%	2
263	852676.8	364264.2114	43%	"M"	145	228	20.2%	0
264	831669.9	394731.4091	47%	"H"	227	194	-4.0%	2
265	794380	512412.904	65%	"C"	169	98	-2.4%	0
266	784107.1	476941.5238	61%	"A"	226	258	15.8%	0
267	730000.2	384823.0299	53%	"M"	568	276	17.2%	0
268	722211	494356.7197	68%	"M"	0	0	-4.3%	2
269	653686.3	339896.6478	52%	"A"	0	0	- 13.8%	0
270	645365.3	256146.1741	40%	"H"	402	15	-5.8%	2
271	619218.4	406338.3076	66%	"M"	0	0	24.1%	2
272	571472.5	362795.3798	63%	"M"	0	0	4.7%	2
273	533493	321129.2887	60%	"C"	5	5	1.6%	0
274	526796.2	239784.1052	46%	"M"	55	208	7.2%	0
275	508611.8	288701.8288	57%	"C"	100	100	1.6%	0
276	476565.9	322599.3918	68%	"M"	976	1369	1.0%	0
277	476286.9	307878.3277	65%	"M"	0	460	8.5%	0
278	433665.7	154188.9339	36%	"C"	0	324	0.9%	2
279	430191.2	-23343.1536	-5%	"M"	253	477	11.4%	0
280	420065.2	226879.0415	54%	"C"	506	506	1.6%	0
281	404621.9	271081.9066	67%	"H"	963	0	33.2%	0
282	379828.8	-111379.4018	-29%	"M"	50	1388	3.0%	0
283	375712	213456.5461	57%	"M"	224	403	1.5%	0
284	365251.1	199401.2933	55%	"C"	219	219	1.6%	0
285	359520.9	168231.7005	47%	"M"	51	535	4.8%	0
286	349737.7	127747.9953	37%	"M"	884	1349	10.5%	0
287	343787	112441.7538	33%	"M"	342	340	1.2%	0
288	341720.9	70133.3463	21%	"M"	360	2201	5.5%	0
289	330684.3	228905.9364	69%	"M"	0	189	-3.1%	0
290	329522.9	113609.2074	34%	"M"	0	0	17.2%	2
291	328056.7	224165.167	68%	"M"	945	2200	3.0%	0
292	321064.4	158607.7272	49%	"A"	0	0	18.6%	0
293	313847.3	207560.8784	66%	"M"	0	0	10.2%	1
294	311444.1	213982.5167	69%	"M"	60	0	8.5%	0
295	305114.1	210161.7898	69%	"M"	756	3260	6.2%	1
296	299071.3	195777.5978	65%	"M"	0	119	-2.9%	0
297	288572.1	118243.0115	41%	"M"	0	0	12.9%	2

Product Code	NTS ($) 2023	GP in volume	GP %	Major	Average Inventory 2022	Average Inventory 2023	CAGR	Clusters
298	286214.2	147763.5362	52%	"M"	61	109	16.9%	0
299	278698.9	-141039.1746	-51%	"M"	93	115	0.9%	0
300	271867.4	151956.5046	56%	"C"	230	18	4.0%	0
301	265778.1	173704.6976	65%	"M"	3552	3554	1.1%	1
302	262889.6	81018.4943	31%	"M"	0	0	9.9%	2
303	253747.1	253747.1	100%	"A"	0	0	0.0%	0
304	246740.9	167299.8706	68%	"A"	0	0	15.8%	0
305	236273.1	124795.3288	53%	"M"	556	666	15.3%	0
306	232620.7	161576.5324	69%	"M"	0	126	0.0%	0
307	221777.3	130672.4093	59%	"C"	0	0	0.4%	0
308	203583	111740.2929	55%	"M"	7972	6282	12.6%	1
309	195431.2	84690.2285	43%	"M"	1015	557	7.1%	0
310	194099.5	89847.5143	46%	"M"	666	1074	-1.2%	0
311	193880.2	91739.5784	47%	"C"	222	32	8.7%	0
312	185309.6	112495.1439	61%	"M"	0	319	5.0%	0
313	175454.1	122315.9783	70%	"M"	39	522	6.4%	0
314	172430.6	86250.8469	50%	"A"	0	0	-13.8%	0
315	170321.3	100626.4838	59%	"M"	0	0	5.5%	2
316	164158.6	81901.8025	50%	"A"	0	0	-10.7%	1
317	164114.8	85185.3206	52%	"C"	6945	6945	1.6%	1
318	161547.5	75235.4061	47%	"A"	0	0	-10.7%	0
319	154553.2	64662.8134	42%	"M"	69	93	3.2%	0
320	148931.4	61613.0089	41%	"C"	0	0	0.9%	0
321	141303.1	65657.5432	46%	"M"	47	367	-1.7%	0
322	136724.2	83534.0652	61%	"M"	0	0	3.6%	2
323	136417.5	-58101.4339	-43%	"M"	583	980	0.9%	0
324	131374.6	83305.0928	63%	"M"	0	0	-1.7%	2
325	96876.6	67152.7307	69%	"M"	0	181	2.6%	0
326	131234.8	89876.0046	68%	"A"	0	0	16.8%	0
327	121391.6	84696.9337	70%	"M"	0	59	4.2%	0
328	119080.7	55946.753	47%	"M"	92	277	23.2%	0
329	88408.9	59946.3914	68%	"A"	0	3	16.8%	0
330	118800.4	83319.1074	70%	"C"	0	0	0.3%	0
331	117747.8	47313.2564	40%	"M"	0	0	25.4%	2
332	116497.9	77165.7378	66%	"A"	0	0	-13.8%	0
333	93991.5	55529.4097	59%	"M"	0	119	15.3%	0
334	85400.6	53245.8176	62%	"M"	0	96	0.4%	0
335	112999.2	13073.9216	12%	"H"	0	0	1.8%	0

Product Code	**NTS ($) 2023**	**GP in volume**	**GP %**	**Major**	**Average Inventory 2022**	**Average Inventory 2023**	**CAGR**	**Clusters**
336	111532.7	76639.3636	69%	"M"	0	0	10.5%	2
337	69669.6	44362.9603	64%	"M"	0	376	7.9%	0
338	83543.6	41277.5144	49%	"C"	0	0	0.9%	0
339	60557.9	41224.6057	68%	"M"	147	2	15.3%	0
340	81973	40897.634	50%	"M"	0	334	5.1%	0
341	58186.7	40624.7844	70%	"M"	1	0	9.6%	0
342	64018.3	40424.299	63%	"C"	143	143	1.6%	0
343	64871.7	38877.6314	60%	"A"	254	117	14.2%	0
344	89502	38770.1975	43%	"M"	0	186	7.1%	0
345	67639.7	38343.5425	57%	"M"	854	349	15.3%	0
346	66838.2	37127.9113	56%	"C"	1254	1254	1.6%	0
347	55006.5	34243.5544	62%	"M"	1	1	5.2%	2
348	54241.9	33772.4299	62%	"M"	1	4	16.9%	2
349	48728.5	33070.3863	68%	"M"	2092	779	16.2%	0
350	111004.3	3431.5829	3%	"H"	310	715	1.8%	2
351	45685.8	31567.5962	69%	"M"	3	0	1.0%	0
352	50605.4	29247.6145	58%	"C"	123	162	8.7%	0
353	49497.4	29124.176	59%	"A"	122	0	14.2%	0
354	43860.5	27859.9018	64%	"M"	0	88	3.1%	0
355	54798.5	27243.1886	50%	"M"	131	216	3.3%	0
356	56691.2	26904.0118	47%	"M"	12	236	12.0%	0
357	61104.4	26713.9025	44%	"M"	119	188	-6.3%	0
358	25161	25161	100%	"C"	0	0	0.0%	0
359	63469.6	25052.8508	39%	"M"	57	59	3.9%	0
360	37883.7	24699.8118	65%	"M"	1233	266	6.4%	0
361	70031.6	24437.2893	35%	"M"	0	0	8.3%	2
362	39171.3	23700.5284	61%	"M"	0	0	4.8%	0
363	22483.8	22483.8	100%	"C"	0	0	0.0%	0
364	48353	21978.9803	45%	"M"	0	153	9.6%	0
365	32455.5	21476.4617	66%	"M"	0	362	9.9%	0
366	20896.5	20896.5	100%	"C"	0	0	0.0%	0
367	29973	20698.6641	69%	"M"	0	8	-26.7%	0
368	34691.5	19386.1969	56%	"M"	77	63	-1.2%	0
369	27031.4	19077.3379	71%	"M"	89	48	11.6%	0
370	42528.3	18396.4865	43%	"M"	0	0	4.3%	2
371	28841.2	17977.7016	62%	"M"	0	0	2.0%	0
372	64724.8	17258.5434	27%	"M"	4	0	0.9%	2
373	42995.6	16942.4095	39%	"M"	0	0	20.2%	2
374	29494.4	16548.8921	56%	"A"	0	0	-10.7%	0

Product Code	NTS ($) 2023	GP in volume	GP %	Major	Average Inventory 2022	Average Inventory 2023	CAGR	Clusters
375	24297.2	16259.6341	67%	"M"	2	5	1.0%	2
376	23901.9	15947.5921	67%	"M"	1	0	1.2%	2
377	15525.4	15525.4	100%	"C"	0	0	0.0%	0
378	24734.5	15384.436	62%	"C"	0	0	0.3%	0
379	32948.1	15068.9365	46%	"M"	120	228	2.6%	0
380	36062.7	14798.4842	41%	"M"	1	0	3.1%	0
381	21292	13616.865	64%	"M"	335	141	-1.2%	0
382	24261.8	13422.1891	55%	"M"	288	107	7.6%	0
383	110969.9	76573.7249	69%	"M"	333	109	3.2%	0
384	19142.4	12519.5902	65%	"M"	127	35	1.4%	0
385	27646.8	12490.2381	45%	"C"	90	10	-0.6%	2
386	55575	12415.875	22%	"H"	144	579	-5.8%	0
387	21313.6	12183.7823	57%	"A"	0	0	-10.7%	0
388	24858.1	12165.3593	49%	"M"	1	0	5.3%	2
389	20416.3	11987.955	59%	"C"	789	789	1.6%	0
390	21762.3	11215.0476	52%	"M"	29	29	8.3%	0
391	16653.1	10931.7948	66%	"M"	0	0	12.1%	0
392	15530.4	10830.4958	70%	"M"	81	32	-9.1%	0
393	25899.4	10794.2276	42%	"M"	239	113	-2.0%	0
394	10743.9	10743.9	100%	"C"	0	0	0.0%	0
395	27304.6	9938.8744	36%	"M"	1483	1469	16.5%	0
396	9874.1	9874.1	100%	"C"	0	0	0.0%	0
397	15519.4	9866.7398	64%	"M"	0	0	-3.1%	0
398	9627.3	9627.3	100%	"C"	0	0	0.0%	0
399	14110.6	9287.6235	66%	"M"	128	102	9.5%	0
400	15339.2	8820.7174	58%	"M"	0	0	6.5%	0
401	14177.7	8771.444	62%	"M"	229	85	0.4%	0
402	16643.1	8755.2756	53%	"M"	101	50	-5.4%	0
403	17597.7	8482.656	48%	"M"	254	61	6.5%	0
404	15313.1	8242.3914	54%	"H"	637	776	-4.0%	0
405	8156	8156	100%	"C"	0	0	0.0%	0
406	12356.5	8136.9839	66%	"M"	0	578	22.8%	0
407	8033.2	8033.2	100%	"M"	0	0	0.0%	0
408	38838.8	7387.5948	19%	"M"	0	0	5.3%	2
409	10313.6	7048.3564	68%	"M"	0	111	14.1%	0
410	12842.2	6942.329	54%	"C"	248	248	1.6%	0
411	10530.5	6770.1769	64%	"A"	0	0	14.2%	0
412	10144.9	6687.2844	66%	"M"	92	73	-9.1%	0
413	9603	6274.2852	65%	"A"	0	0	-8.2%	0
414	9247.6	6244.0241	68%	"M"	0	1	4.2%	0

Product Code	NTS ($) 2023	GP in volume	GP %	Major	Average Inventory 2022	Average Inventory 2023	CAGR	Clusters
415	19025.5	5888.8092	31%	"H"	105	0	9.5%	0
416	13238.1	5338.8129	40%	"M"	0	0	15.3%	2
417	7750.2	5305.3998	68%	"A"	0	0	-8.2%	0
418	9553.7	5277.2069	55%	"M"	25	6	-1.2%	2
419	5598.1	5247.4981	94%	"M"	683	956	5.4%	0
420	18628.3	5201.5971	28%	"M"	0	37	8.3%	0
421	7314.3	5105.8148	70%	"M"	82	8	3.3%	0
422	8702.5	5091.9446	59%	"M"	18	0	3.5%	0
423	110900.2	57008.2004	51%	"C"	347	347	1.6%	0
424	9119.4	4712.5313	52%	"A"	1	1	-8.6%	0
425	69042.7	4619.8611	7%	"M"	788	740	2.9%	0
426	9857.7	4337.2885	44%	"M"	13	0	0.2%	0
427	6811	4261.9101	63%	"H"	0	0	1.8%	0
428	4170.3	4170.3	100%	"M"	0	0	0.0%	0
429	7121	4169.6006	59%	"M"	346	0	10.5%	0
430	7894	4109.3843	52%	"M"	43	0	-20.5%	0
431	6486.4	3888.1745	60%	"M"	3	0	32.2%	0
432	7010.1	3797.4637	54%	"M"	0	0	-1.0%	2
433	20773	3694.8479	18%	"C"	0	0	-0.6%	0
434	11080.1	3653.1588	33%	"M"	61	218	4.3%	0
435	16200.9	3588.5722	22%	"M"	0	0	2.9%	2
436	6325.3	3554.2722	56%	"M"	258	221	20.0%	2
437	110285.7	-47889.9367	-43%	"M"	97	220	4.3%	0
438	10004.2	3300.1637	33%	"M"	178	117	8.8%	0
439	10232.1	3270.2298	32%	"M"	44	2	-9.9%	0
440	8096.8	2993.4955	37%	"M"	29	42	0.2%	0
441	4809	2914.5489	61%	"M"	273	248	22.8%	0
442	7314.2	2883.4016	39%	"C"	104	0	8.7%	2
443	2668.5	2668.5	100%	"C"	0	0	0.0%	0
444	3551.3	2513.6347	71%	"M"	15	13	4.3%	2
445	8983.6	2213.9836	25%	"M"	1239	43	7.9%	0
446	4470.6	2188.3785	49%	"H"	0	0	22.6%	0
447	5698.3	2185.9114	38%	"M"	0	14	0.7%	0
448	3965.2	2118.5597	53%	"M"	3	0	-5.4%	0
449	3726.4	2042.675	55%	"M"	112	105	-25.9%	0
450	10969.3	2025.7316	18%	"M"	8	3	-1.2%	2
451	4873.7	1892.4276	39%	"M"	25	0	8.3%	0
452	6610.8	1764.365	27%	"M"	1	1	20.2%	2
453	3745.2	1711.6864	46%	"M"	647	11	3.5%	0

Product Code	NTS ($) 2023	GP in volume	GP %	Major	Average Inventory 2022	Average Inventory 2023	CAGR	Clusters
454	4398.1	1669.858	38%	"M"	0	34	-2.6%	0
455	2579.5	1597.1628	62%	"M"	8	0	1.9%	2
456	1569.5	1569.5	100%	"C"	0	0	0.0%	0
457	2382.4	1558.5933	65%	"M"	204	33	11.6%	0
458	2700	1514.5591	56%	"M"	0	0	1.0%	0
459	2959.3	1427.9152	48%	"M"	9	7	6.4%	0
460	12672	1373.8549	11%	"M"	533	375	8.8%	0
461	5486.9	1316.5956	24%	"M"	25	0	9.2%	0
462	1861.3	1232.0366	66%	"M"	29	14	18.2%	2
463	8279.6	1225.1744	15%	"M"	1134	257	0.2%	0
464	1587.4	1159.4941	73%	"C"	104	0	8.7%	0
465	3317.8	1125.3642	34%	"M"	145	92	1.9%	0
466	48161.8	1046.3988	2%	"M"	1859	1217	2.3%	0
467	4285.4	939.5658	22%	"M"	474	240	14.1%	0
468	2090.2	915.8005	44%	"M"	0	0	7.9%	0
469	1709.1	890.7828	52%	"M"	178	201	18.2%	0
470	1305.1	855.8146	66%	"M"	0	0	49.3%	2
471	1681.6	821.8191	49%	"M"	96	110	15.1%	0
472	2095.7	803.9683	38%	"M"	156	0	0.0%	0
473	903.7	771.7598	85%	"C"	3	1	-2.4%	0
474	1453.3	764.9563	53%	"M"	26	0	3.1%	0
475	1154.6	748.9888	65%	"A"	0	0	15.8%	0
476	1440.8	738.7344	51%	"M"	21	0	3.3%	0
477	1046.6	718.5007	69%	"C"	0	0	4.0%	0
478	1954.3	665.0375	34%	"H"	0	0	9.5%	0
479	984.2	657.2949	67%	"M"	202	159	27.7%	0
480	1255.8	653.0024	52%	"M"	91	7	-1.2%	0
481	2896.5	640.0676	22%	"M"	0	1	14.1%	0
482	978.4	626.0249	64%	"H"	0	0	22.6%	0
483	974.7	616.257	63%	"M"	0	0	-11.4%	2
484	1276.8	609.5587	48%	"M"	116	104	11.5%	0
485	927.8	583.3166	63%	"M"	428	382	15.2%	0
486	3084.2	541.06	18%	"M"	527	5	3.1%	0
487	1153.9	531.6484	46%	"M"	0	0	12.3%	0
488	863.4	513.9825	60%	"M"	58	52	-11.4%	0
489	876.5	456.9797	52%	"M"	2098	939	15.1%	2
490	806.5	449.3588	56%	"M"	59	76	49.3%	0
491	1452.7	440.83	30%	"C"	0	0	-0.6%	0
492	729.2	433.4677	59%	"M"	0	0	21.2%	2

Product Code	NTS ($) 2023	GP in volume	GP %	Major	Average Inventory 2022	Average Inventory 2023	CAGR	Clusters
493	1154.7	415.019	36%	"M"	7	0	0.2%	0
494	801.2	404.683	51%	"M"	0	0	-2.0%	0
495	575.2	349.4278	61%	"M"	25	6	-1.2%	0
496	1529.5	336.1289	22%	"M"	58	28	21.2%	0
497	553.9	328.5284	59%	"C"	0	0	7.9%	0
498	707.8	308.4976	44%	"M"	0	278	1.9%	0
499	307.2	307.2	100%	"C"	0	0	0.0%	0
500	3372.6	301.2588	9%	"M"	3943	1456	15.1%	1
501	643.7	273.5607	42%	"M"	3	0	2.6%	0
502	371.3	254.7143	69%	"M"	181	230	32.8%	0
503	2042.5	206.1711	10%	"H"	0	0	-0.1%	0
504	274	187.7928	69%	"M"	102	88	20.0%	0
505	1436	182.2578	13%	"M"	11	0	4.8%	0
506	1288.7	176.7526	14%	"M"	36	11	12.0%	0
507	307.6	164.164	53%	"M"	18	4	32.2%	0
508	9010.6	156.3218	2%	"M"	1431	1213	5.4%	0
509	285	130.6703	46%	"M"	21	16	-4.8%	0
510	1099.3	128.5144	12%	"M"	10	7	-2.6%	0
511	464.1	118.4925	26%	"M"	6	9	20.2%	0
512	2552.1	104.7308	4%	"M"	101	53	8.7%	0
513	232.6	81.7237	35%	"M"	30	25	10.6%	0
514	130.7	64.4148	49%	"M"	0	0	15.3%	2
515	804.6	48.6387	6%	"M"	25	0	-26.7%	0
516	235.5	45.1112	19%	"M"	381	1	9.6%	0
517	88.4	15.5108	18%	"M"	70	44	8.7%	0
518	93.1	9.634	10%	"M"	72	0	0.9%	0
519	439.2	4.2026	1%	"M"	27	0	1.0%	0
520	10.5	3.8955	37%	"M"	0	0	15.1%	0
521	49.6	3.84	8%	"M"	30	8	27.7%	0
522	0	0	0%	"M"	2.904761905	0	10.6%	0
523	0	0	0%	"M"	6	0	5.4%	0
524	0	0	0%	"M"	48.47169811	28.7690583	-10.6%	0
525	0	0	0%	"H"	0	0	-4.0%	0
526	0	0	0%	"C"	0	0	0.9%	0
527	0	0	0%	"A"	0	0	-8.2%	0
528	0	0	0%	"M"	1.24	0	16.2%	0
529	0	0	0%	"M"	0.777777778	0	2.0%	0
530	0	0	0%	"M"	65.59574468	0	2.0%	0
531	0	0	0%	"M"	31.84782609	0	6.4%	0

Product Code	NTS ($) 2023	GP in volume	GP %	Major	Average Inventory 2022	Average Inventory 2023	CAGR	Clusters
532	0	0	0%	"M"	20.28571429	0	5.1%	0
533	0	0	0%	"M"	23.26086957	0	1.0%	0
534	0	0	0%	"M"	97.33333333	0	5.4%	0
535	0	0	0%	"M"	13.53846154	0	-26.7%	0
536	0	0	0%	"M"	4	0	3.9%	0
537	0	0	0%	"M"	24.52083333	0	-1.2%	0
538	0	0	0%	"M"	0	0	12.0%	0
539	0	0	0%	"M"	10.22058824	1	-1.7%	0
540	0	0	0%	"M"	26.375	0	9.8%	0
541	0	0	0%	"M"	100.25	0	32.2%	0
542	0	0	0%	"M"	35.25	27	5.9%	0
543	0	0	0%	"C"	0	0	-0.6%	0
544	0	0	0%	"M"	30.70833333	3.113960114	49.3%	0
545	0	0	0%	"M"	25.59574468	0	18.2%	0
546	0	0	0%	"M"	10.76923077	0	22.8%	0
547	0	0	0%	"A"	0	0	16.8%	0
548	0	0	0%	"A"	0	0.242152466	17.2%	0
549	0	0	0%	"A"	0	0	18.6%	0
550	0	0	0%	"M"	24.09090909	0	3.9%	0
551	0	0	0%	"M"	6.1875	0	3.3%	0
552	0	0	0%	"M"	10	0	20.2%	0
553	0	0	0%	"H"	0	0	-4.0%	0
554	0	0	0%	"C"	0	0	0.9%	0
555	0	0	0%	"H"	0	0	-13.4%	0
556	0	0	0%	"A"	0	0.034759358	-8.2%	0
557	0	0	0%	"H"	0	3	1.7%	0
558	0	0	0%	"H"	0	1	1.7%	0
559	0	0	0%	"M"	1101.16	1035.565022	-11.4%	0
560	0	0	0%	"M"	1.357142857	1	-20.7%	0
561	0	0	0%	"M"	2	2	11.4%	0
562	0	0	0%	"A"	92.57142857	0	17.2%	0
563	0	0	0%	"C"	0	0	7.9%	0
564	0	0	0%	"C"	0	0	2.9%	0
565	0	0	0%	"C"	0	0	8.7%	0
566	0	0	0%	"C"	0	0	0.6%	0
567	0	0	0%	"C"	35.55813953	0	2.9%	0
568	0	0	0%	"C"	0	0	4.0%	0
569	0	0	0%	"C"	0	0	0.3%	0

Product Code	NTS ($) 2023	GP in volume	GP %	Major	Average Inventory 2022	Average Inventory 2023	CAGR	Clusters
570	0	0	0%	"H"	0	0	1.3%	0
571	0	0	0%	"H"	0	0	0.8%	0
572	0	0	0%	"C"	0	0	7.9%	0
573	0	0	0%	"C"	0	0	4.0%	0
574	0	0	0%	"C"	0	0	-2.4%	0
575	0	0	0%	"H"	0	0	6.0%	0
576	0	0	0%	"H"	0	0	-6.2%	0
577	0	0	0%	"H"	0	0	-7.0%	0
578	0	0	0%	"H"	0	0	6.0%	0
579	0	0	0%	"H"	0	0	-13.7%	0
580	0	0	0%	"A"	0	0	-13.8%	0
581	0	0	0%	"H"	0	0	6.0%	0
582	-4	-4	100%	"M"	12	13	-25.9%	0
583	68.8	-4.7865	-7%	"H"	0	0	-0.1%	0
584	-12.3	-12.3	100%	"M"	1	0	0.2%	2
585	-17.2	-17.2	100%	"M"	87	0	2.0%	0
586	-28.1	-28.1	100%	"H"	121	112	22.6%	0
587	1097.9	-34.7138	-3%	"M"	240	296	12.3%	0
588	-35.1	-35.1	100%	"M"	1	0	3.3%	2
589	-38.4	-38.4	100%	"M"	22	12	13.0%	0
590	-40.1	-38.6564	96%	"M"	307	17	9.2%	0
591	-61.3	-61.3	100%	"M"	0	0	12.0%	2
592	1057.5	-61.7254	-6%	"M"	195	92	11.5%	0
593	1360.1	-78.9067	-6%	"H"	0	0	-4.0%	0
594	-82.8	-82.8	100%	"M"	2	0	1.1%	0
595	-122.8	-122.8	100%	"M"	1	0	16.2%	0
596	492.9	-142.1596	-29%	"M"	65	2	26.1%	0
597	-146.6	-146.6	100%	"M"	0	0	4.8%	0
598	-188	-188	100%	"M"	292	0	9.2%	0
599	174.8	-212.1643	-121%	"M"	703	563	21.2%	0
600	-97.9	-243.5464	249%	"M"	0	0	3.9%	2
601	-270.5	-270.5	100%	"M"	97	0	1.9%	0
602	-311.5	-311.5	100%	"M"	271	0	-3.1%	0
603	4308.9	-333.6491	-8%	"M"	654	47	2.3%	0
604	1707	-366.4893	-21%	"M"	77	64	13.0%	0
605	72.1	-367.2162	-509%	"M"	13	0	3.5%	0
606	605.2	-374.3631	-62%	"M"	16	6	32.2%	0
607	-401.4	-401.4	100%	"M"	66	0	4.0%	0

Product Code	NTS ($) 2023	GP in volume	GP %	Major	Average Inventory 2022	Average Inventory 2023	CAGR	Clusters
608	860.4	-415.0046	-48%	"M"	0	0	15.2%	2
609	5900.6	-540.4678	-9%	"M"	1583	1414	17.7%	0
610	-569.3	-569.3	100%	"M"	205	0	3.2%	0
611	5061.2	-612.0104	-12%	"M"	981	173	5.4%	0
612	-231.9	-715.0316	308%	"M"	263	1	-1.2%	0
613	-744.3	-744.3	100%	"H"	0	0	-1.1%	0
614	-792.9	-792.9	100%	"M"	555	0	1.0%	0
615	1256.5	-853.3423	-68%	"M"	44	33	12.0%	0
616	-1013.9	-1013.9	100%	"M"	7	0	6.2%	0
617	-1036.2	-1036.2	100%	"M"	72	0	3.6%	0
618	-1100.4	-1100.4	100%	"M"	58	0	1.2%	0
619	-1196.6	-1196.6	100%	"M"	86	0	1.1%	0
620	-1308.1	-1308.1	100%	"M"	0	0	-1.7%	0
621	-1367.6	-1548.3548	113%	"M"	534	0	1.0%	0
622	2886.7	-1561.7934	-54%	"M"	351	10	26.1%	0
623	887.8	-1597.0358	-180%	"M"	0	0	1.1%	0
624	4160.1	-1598.2292	-38%	"H"	417	277	-0.1%	0
625	-1687.9	-1687.9	100%	"M"	976	546	4.0%	0
626	-1800	-1800	100%	"M"	12	0	0.9%	0
627	-1425.9	-1805.046	127%	"M"	208	0	1.0%	0
628	4813.9	-1886.8148	-39%	"M"	182	114	32.8%	2
629	-2018.8	-2018.8	100%	"M"	184	0	4.8%	0
630	-2124.1	-2161.7488	102%	"M"	419	0	4.8%	0
631	15062.1	-2289.1809	-15%	"M"	94	23	5.3%	0
632	-2368.6	-2368.6	100%	"A"	0	0	-8.2%	0
633	-2427.5	-2427.5	100%	"M"	216	0	-10.6%	0
634	4278.8	-2434.9135	-57%	"H"	393	301	22.6%	0
635	-2703	-2703	100%	"H"	0	0	1.7%	0
636	-2875.9	-2875.9	100%	"M"	0	0	6.2%	0
637	-3023.9	-3053.8338	101%	"M"	313	2	5.2%	0
638	-3335.9	-3335.9	100%	"H"	284	0	-13.4%	0
639	-3301.3	-3373.9744	102%	"M"	113	5	2.0%	0
640	1644.6	-3626.0689	-220%	"M"	0	0	0.0%	0
641	4134.3	-3747.5817	-91%	"M"	0	0	3.0%	2
642	-3843.5	-3843.5	100%	"M"	130	0	2.0%	0
643	-4080.6	-4080.6	100%	"M"	11	0	12.0%	0
644	-4573.3	-4573.3	100%	"H"	0	0	-1.1%	0
645	-4623.9	-4623.9	100%	"A"	405	71	15.8%	0
646	-5166.2	-5166.2	100%	"M"	2	0	3.0%	0

Product Code	NTS ($) 2023	GP in volume	GP %	Major	Average Inventory 2022	Average Inventory 2023	CAGR	Clusters
647	-5897.8	-5897.8	100%	"M"	248	0	1.0%	0
648	-7104.9	-7104.9	100%	"H"	58	0	-7.0%	2
649	-5619.8	-7384.4172	131%	"A"	0	0	6.2%	0
650	-7860.8	-7728.0992	98%	"M"	110	0	16.9%	2
651	-8026.5	-8026.5	100%	"A"	0	0	-8.6%	0
652	-3920.6	-8121.3425	207%	"H"	402	15	-5.8%	0
653	30243.5	-8802.7861	-29%	"H"	74	200	9.5%	0
654	-9776.8	-9776.8	100%	"M"	15	0	25.4%	0
655	-11446.1	-11446.1	100%	"H"	198	6	-6.2%	2
656	-12197	-12197	100%	"A"	18	0	6.2%	0
657	27668.7	-13391.0007	-48%	"C"	120	109	-0.6%	0
658	-15475.4	-15475.4	100%	"M"	3798	381	22.6%	0
659	110041.4	31901.2953	29%	"C"	31	121	-0.8%	2
660	106789.6	45942.8945	43%	"M"	0	2	11.9%	2
661	103934.8	67752.8032	65%	"C"	0	0	-1.6%	0
662	102160.8	5026.2139	5%	"M"	179	112	9.9%	0
663	101825.6	68607.1776	67%	"M"	175	595	3.6%	0
664	-344122.7	-470998.989	137%	"C"	1	0	7.9%	0
665	101819.4	56890.2551	56%	"M"	0	84	5.4%	0

Appendix C – Power BI DAX Code for Category Role Matrix

Please find below Code included within DAX function for the Category Role Matrix view performed in Microsoft PowerBI software. The function contains lines of code to define Net Trade Sales and Gross Profit % Targets, as well as the lines of code to categorize each product code using a pre-defined color based on the Net Trade Sales and Gross Profit % Features.

```
Quadrant colorpercentil23U =
VAR Sales23U = SELECTEDVALUE(Sheet3[Percentile Sales Scale])
VAR GP23U = SELECTEDVALUE(Sheet3[Percentile GP Scale ])
VAR Treshsales = 'Sales Target'[Test Value]
VAR TreshGP = 'GP Target'[Parameter Value]
RETURN
SWITCH(

    TRUE(),

  Sales23U < Treshsales && GP23U < TreshGP, "#A80000",
  Sales23U < Treshsales && GP23U > TreshGP, "#73B761",
  Sales23U > Treshsales && GP23U > TreshGP, "#536F18",
  Sales23U > Treshsales && GP23U < TreshGP, "#bf1b1b",
   "#000000")
```

Appendix D – Power BI DAX Code for BCG Growth Matrix

Please find below Code included within DAX function for the BCG Growth Matrix view performed in Microsoft PowerBI software. The function contains lines of code to define Growth and Gross Profit Targets, as well as the lines of code to categorize each product code using a pre-defined color based on the growth feature.

```
Growth Quadrant =
VAR Growth22 = SELECTEDVALUE(Sheet1[Growth percentile])
VAR GP = SELECTEDVALUE(Sheet1[Percentile GP Scale ])
VAR Treshgrowth = 0.6950
VAR Treshgrowth1 = 0.5290
VAR Treshgrowth2 = 0.2760
VAR GPTreshold = 0.466
RETURN
IF(
    GP >= GPTreshold,
    "#008000",
    SWITCH(
        TRUE(),
        Growth22 <= Treshgrowth2, "#8B0000",
        Growth22 <= Treshgrowth1, "#D73027",
        Growth22 < Treshgrowth, "#F46D43",
        "#FFA500"
    )
)
```

Appendix E - Expected Growth Visual (Product Family – Minor level)

Table E1 includes the list of product families sub-categories (Minors) within the scope of the Capstone Project. Table E1 includes the 2023 Net Trade Sales, the Gross Profit %, and the Compound Annual Growth Rate % (CAGR%) for each product family sub-category (Minor) within the scope of the Capstone Project.

Table E1

Expected Growth Visual Baseline data (Minor Level view)

Minor	Sum of 2023 Sales $	GP %	CAGR
EM	$ 4,320,492	8%	-0.11
SE	$ 33,354,472	41%	-0.06
A+	$ 65,727	47%	2.00
G2A	$ 13,124,880	55%	-0.09
OLB	$ 1,814,052	59%	-0.45
RE	$ 28,953,211	64%	-0.39
EI	$ 38,407,739	66%	0.20
GH	$ 73,150,209	67%	0.22
H500	$ 16,180,198	70%	0.21
AC	$ 54,035,384	70%	0.45
OED	$ 27,160,242	71%	0.17
AL	$ 45,345,539	72%	0.11
LOSS	$ 1,403,059	74%	1.41
HA+7	$ 346,570,221	76%	-0.11
HHD	$ 179,079,445	78%	0.27
OOB	$ 7,897,756	78%	0.22
HFL+	$ 15,271,981	82%	0.05
HF+	$ 126,642,953	82%	0.05
HA+	$ 144,761,872	87%	0.01
AB700	$ 3,174,933	90%	-0.03
OEP	$ 718,514	92%	-0.35
OHD	$ 5,662,096	92%	0.52

Appendix F – Regional View Data

Table F1 includes data utilized for the construction of the regional view within Microsoft PowerBI tool. Dataset includes aggregated data from Total Net Trade Sales for 2023 by Country, GP% by Country, and expected growth by country.

Table F1

Regional View Data: Country, Total 2023 Net Trade Sales, GP%, and Growth by Country

Countries	Sales 2023	GP%	Growth
ARGENTINA	$ 2,795,700	88.03%	95.6%
AUSTRALIA	$ 19,324,300	80.13%	1.4%
AUSTRIA	$ 4,957,000	77.21%	-6.6%
BELGIUM	$ 11,065,100	67.85%	-3.7%
BRAZIL	$ 31,306,300	69.96%	2.0%
BULGARIA	$ 105,700	88.04%	8.2%
CANADA	$ 16,679,200	75.84%	6.3%
CHILE	$ 5,133,300	66.68%	-8.6%
CHINA	$ 287,730,500	72.34%	7.9%
COLOMBIA	$ 10,110,800	69.83%	24.1%
CROATIA	$ 2,017,300	83.61%	31.6%
CZECH REPUBLIC	$ 4,466,900	81.19%	14.8%
DENMARK	$ 2,555,300	69.00%	-6.2%
ECUADOR	$ 2,620,800	94.45%	52.9%
ESTONIA	$ 1,652,300	80.53%	22.1%
FINLAND	$ 2,500,700	75.99%	4.8%
FRANCE	$ 34,168,000	76.55%	-6.6%
GERMANY	$ 44,977,600	73.69%	1.1%
GREECE	$ 10,286,400	71.16%	40.5%
HONG KONG	$ 6,718,800	83.88%	4.7%
HUNGARY	$ 1,587,600	74.75%	30.1%
INDIA	$ 21,571,100	72.93%	2.4%
INDONESIA	$ 4,083,600	86.21%	19.3%
IRELAND	$ 3,732,100	81.06%	15.6%
ISRAEL	$ 6,313,100	86.77%	0.8%
ITALY	$ 53,829,500	83.32%	-3.9%
JAPAN	$ 122,549,800	72.51%	2.3%
KOREA	$ 38,264,700	73.99%	8.2%
LATVIA	$ 1,282,000	78.35%	-0.2%
LITHUANIA	$ 590,600	83.41%	12.9%
MALAYSIA	$ 6,195,300	84.12%	29.0%
MEXICO	$ 18,094,900	83.13%	12.7%
MISSA	$ 1,537,500	65.88%	23.7%

Countries	Sales 2023	GP%	Growth
NETHERLANDS	$ 10,377,000	66.37%	-4.3%
NEW ZEALAND	$ 4,181,200	79.15%	10.2%
NORWAY	$ 614,000	66.97%	-17.8%
PANAMA	$ 2,412,200	82.17%	-1.3%
PERU	$ 2,273,900	95.88%	-2.4%
PHILIPPINES	$ 2,789,200	82.13%	53.4%
POLAND	$ 5,060,100	79.16%	6.3%
PORTUGAL	$ 6,160,300	69.00%	-11.2%
PUERTO RICO	$ 3,561,000	72.28%	11.3%
ROMANIA	$ 1,127,700	84.94%	73.5%
RUSSIAN FEDERATION	$ 4,428,900	85.30%	-76.4%
SAUDI ARABIA	$ 27,523,100	82.71%	27.6%
SINGAPORE	$ 3,569,100	86.44%	4.8%
SLOVAKIA	$ 2,020,300	79.20%	7.0%
SLOVENIA	$ 5,266,000	79.11%	38.4%
SOUTH AFRICA	$ 6,114,100	83.97%	-9.7%
SPAIN	$ 23,041,400	79.59%	-7.7%
SWEDEN	$ 4,018,200	66.39%	-6.5%
SWITZERLAND	$ 10,262,700	79.98%	-0.1%
TAIWAN	$ 14,949,300	86.38%	-4.4%
THAILAND	$ 11,581,500	81.46%	29.9%
UNITED ARAB EMIRATES	$ 61,471,700	80.10%	-2.0%
UNITED STATES	$ 382,516,100	71.20%	-4.1%
VIETNAM	$ 5,022,900	80.63%	31.3%