SKU Stratification Methods in the Consumer Products Industry

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ABSTRACT

For companies with a large number of Stock Keeping Units (SKUs), it is extremely challenging, if not impossible, to manage the SKUs individually. Therefore, companies stratify SKUs into different classes and manage them by class. Currently, most companies identify SKU stratification based on the single factor of sales volume. This thesis explores more comprehensive analysis methods that can consider multiple SKU characteristics. We applied four methods (Single Factor Analysis, Dual-Matrix Analysis, Analytical Hierarchy Process, and Cluster Analysis) to the data of a company in the Consumer Packaged Goods industry. The factors considered were velocity, volatility, and profit margin. Our research indicates that the Analytical Hierarchy Process is the most viable and comprehensive method for stratifying SKUs. It allows for a flexible number of stratification factors, different importance levels of the factors, and user control of the number of classes and class sizes. By applying the Analytical Hierarchy Process to SKU stratification, companies will be able to carry the right inventory for the right SKUs, and improve customer service.

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Table A.1. Pairwise Comparison Relationships ................................................................................. 41
Inventory management is not a new idea. Since the advent of mass markets, companies have searched for better ways to manage their inventory. Stock Keeping Unit (SKU) stratification is a widely-employed inventory management method. The idea comes from the Pareto Principle that 20% of SKUs account for 80% of revenue. That is, a small subset of products is more important to the company than the rest of the products. SKUs are ranked by importance from high to low and classified into group A, B, C etc. The A class requires the most management and control. The lower classes receive a decreasing level of control. Different inventory targets and replenishment policies can also be applied on different classes. This approach focuses management attention on the important products. It also reduces the number of items to be managed from hundreds, or even thousands, to a handful (usually 3-5). SKU stratification is also known as ABC analysis. In this thesis, we will use the terms SKU stratification, inventory stratification, and ABC analysis interchangeably.

Traditionally, it is common practice to stratify SKUs based on the single factor of dollar usage (annual demand times average unit price). This method allows businesses to prioritize to a limited degree. The problem is that it over-emphasizes the importance of those SKUs that have high dollar usage. Not all of these SKUs are as valuable to the operations and profitability of the company as others. One key reason that a SKU could have high dollar usage, but not be as important is high cost. Dollar usage does not consider the cost of the product, only the price. Conversely, this method de-emphasizes SKUs that have low dollar usage but demand management attention. SKUs with low dollar usage could require more attention because of the volatility of their demand. As a result, the use of a single factor may lead companies to mismanage its inventory assets.

Apart from dollar usage, other important factors should be considered in inventory stratification. The type of factors may vary across industries and companies. For example, in the high tech industry where technology rapidly changes, the risk of product obsolescence is a critical factor. In the health sector, whether the drug or equipment is life-saving is critical to determining how much inventory to hold.
The sponsor company for this thesis is a leader in the Consumer Packaged Goods (CPG) industry. They manage inventory at distribution centers for their retail chain customers. Their current inventory stratification method is single factor analysis based on sales volume. The motivation of this project is to identify more comprehensive stratification methods to manage their inventory more efficiently. Specifically, we are interested to know which factors to consider and how to combine the factors for inventory stratification.

This thesis synthesizes research on four methods—Single Factor Analysis, Dual-Matrix Analysis, Analytical Hierarchy Process, and Cluster Analysis, and applies those methods to a practical dataset. The four methods are applied to three relevant factors: velocity, volatility, and profit margin. Based on the results of our analysis, we recommend the use of Analytical Hierarchy Process in SKU Stratification.
2 LITERATURE REVIEW

Inventory stratification has been an area of active research since the 1990s. Methods of stratification vary widely. There are as many strategies as there are implementations. The strategies range from very simple to extremely complex. Depending on the purpose of stratification, different methods are appropriate. To identify appropriate modelling techniques for inventory stratification, we conducted a review of literature regarding related data analytics methods. We will first discuss the classic single criterion ABC analysis, then we will go into dual-criteria and multi-criteria methodologies.

2.1 Single Criteria Analysis

ABC analysis was first discussed in 1951 in the article “ABC Inventory Analysis Shoots for Dollars Not Pennies” (Dickie, 1951). The article described how General Electric, as the first company ever, applied ABC analysis in inventory optimization. Traditionally, ABC analysis is based on the single criterion of dollar usage, which is annual demand times average unit price (Ramanathan, 2006). Products are ranked by dollar usage from high to low and categorized into class A, B and C. While single criterion ABC analysis is easy to understand and implement, it is successful only when products are fairly homogeneous. It has been recognized that other criteria such as inventory cost, lead time, etc. are also important in inventory stratification.

2.2 Dual Criteria Analysis

To address the need of including other important criteria, Flores and Whybark (1989) proposed a dual criteria approach. They used dollar usage and criticality as the two criteria, and applied standard ABC analysis to each of them. The two ABC groupings were then cross tabulated into a matrix form. From the matrix there are 9 possible combinations, which can be further grouped into ABC categories (Flores & Whybark, 1989). As a first attempt at ABC analysis beyond single criterion, this approach has its limitations. First, it is difficult to extend the method to include three or more criteria. Second, the two criteria are treated as equally important, which often is not the case in reality (Partovi & Burton, 1993).
2.3 Multi-Criteria Analysis

Flores and Whybark (1989) first proposed the use of more than one criterion. Since then, several multi-criteria decision-making methods have been employed to address the problem of inventory stratification. The methodologies fall into three broad categories: subjective weighting, linear optimization, and clustering. What the first two categories have in common is that they both involve three main steps. The first step assigns weights to different criteria. The second step scores each product on each criterion. The third step gives a weighted score. The two categories differ in how the weights are derived.

2.3.1 Subjective Weighting

The first category of methods is based on subjective weighting of criteria, which employs the Analytical Hierarchy Process (AHP). AHP first was developed by Saaty (1980) to help decision makers combine multiple objectives. Flores, Olson, and Dorai’s (1992) work is representative of the body of research using AHP. Other researchers such as Partovi and Burton (1993) later constructed similar AHP models. In AHP, criteria are arranged into a hierarchy of one or more levels. Pairwise comparison of relative importance is then evaluated based on the judgment of the decision maker. From the pairwise comparison, weights of each criterion can be derived by eigenvector or by software such as Expert Choice (Flores, Olson, & Dorai, 1992).

2.3.2 Linear Optimization

The second category of methods is linear optimization. Criticism of the AHP method stems from its subjectivity (Ramanathan, 2006). Linear optimization methods remove this subjectivity by deriving the weights of criteria from mathematical models. Ramanathan (2006) constructed a linear programming model for each product in inventory. The weights are determined from optimization subject to constraints that the weighted sum is less than or equal to one. Despite being a simple model, it is cumbersome and time-consuming to solve a linear optimization problem for every product. Building on Ramanathan’s model, Ng (2007) proposed a transformation technique so that the problem can be solved without a linear optimizer. Ng’s model is an extension to Ramanathan’s model and a simplification to Ramanathan’s method. However, Ng’s model requires the decision maker to rank the criteria. Therefore, it does involve a certain degree of
subjectivity. In addition, the score of each item is independent of the weights obtained from the model. Such independence may lead to inappropriate classification.

2.3.3 Clustering

2.3.3.1 Clustering Techniques

Cluster analysis is a bit of a misnomer. The term “cluster,” Everitt, Landau, Leese, and Stahl (2011) argue, reduces complexity of an advanced concept to a more palatable level. Such a characterization is strikingly appropriate, given the purpose of the analysis itself. According to Everitt et al. (2011), cluster analysis considers two primary factors in determining the clusters: homogeneity and separation (Everitt, Landau, Leese, & Stahl, 2011). Clustering groups items together based on their similarity to each other within given measures. Some methods also consider their distance from other points.

While the concept of clustering sounds fairly intuitive, the practice of clustering data points is complicated. Bandyopadhyay and Saha (2013) separated clustering methods into four main categories, with multiple methods within each. The four categories are hierarchical, density-based, grid-based, and partitional. The common purpose, they claim, is to identify a matrix where

\[ \Sigma_{j=1}^{n} u_{kj} \geq 1 \text{ for } k=1, 2, 3\ldots K, \]
\[ \Sigma_{k=1}^{K} u_{kj} = 1 \text{ for } j=1, 2, 3\ldots n, \text{ and} \]
\[ \Sigma_{k=1}^{K} \Sigma_{j=1}^{n} u_{kj} = n \text{ (Bandyopadhyay & Saha, 2013)}. \]

Next, we will briefly review the four clustering methods and their limitations.

a Hierarchical Clustering

Hierarchical clustering groups items into a classification tree based on similarity. At the top, there is a single cluster inclusive of all items. At the bottom, each item is a single cluster. This methodology does not allow for overlapping clusters and it becomes prohibitively complex as dimensions are added (Bandyopadhyay & Saha, 2013).
b Density-Based Clustering

Density-based clustering operates exactly as it is named. The proximity and separation of points determines a cluster (Bandyopadhyay & Saha, 2013). Therefore, clusters can take on any shape, which means a cluster could stretch across an entire dataset. It is true that points within any small segment of the cluster would be similar. However, points at opposite ends of the cluster could be very different.

c Grid-Based Clustering

Grid-based clustering considers the data overlaid onto a map of the total dataset. This grid is used to identify regions of concentrated data. Once the regions are identified, the clusters are developed. This grid-based approach is most useful to simplify clustering for extremely large datasets (Bandyopadhyay & Saha, 2013).

d Partitional Clustering

Partitional clustering groups points into convex clusters, often based on a centroid. In K-means clustering, a specified number of centroids are placed in the dataset randomly. Then, the distance from every data point to the nearest centroid is measured. The centroid then is moved to minimize the average distance from all those points. Now that the centroids have moved, the process is repeated. And it continues iteratively until the centroids do not move. At this point, the clusters are defined as the groups of points associated with each centroid (Bandyopadhyay & Saha, 2013). K-medoid clustering is a variation of K-means. Instead of randomly-placed centroids, the analysis begins with randomly-selected points within the dataset (Bandyopadhyay & Saha, 2013). “Fuzzy” clustering is an additional layer of complexity overlaid on either of these two methods. In fuzzy clustering, clusters are permitted to overlap slightly. Overlap means that points on the fringes may belong to more than one cluster (Ravinder & Misra, 2014). The results from partitional clustering are dependent upon the initialization of the centroids. Depending upon where the centroids begin, the resulting clusters can be different for the same dataset.

2.3.3.2 Challenges in Clustering

Some of the difficulties of clustering are pointed out by Kyan et al. (2014). The two most glaring challenges are anchoring and evaluation. When it comes to clustering, a clear problem is anchoring.
Anchoring means that these methods require a predetermined number of clusters to identify. Another challenge with clustering is evaluating the quality of the solution (Kyan, Muneesawang, Jarrah, & Guan, 2014). Put simply, it is difficult to determine how well the clusters represent the dataset. This is true inherently of unsupervised classification models because there is no labelled data with which to verify the model. Also, datasets with more dimensions than can be depicted visually present difficulties because clustering is based on visual techniques.

According to Ravinder and Misra (2014), when considering inventory, there is inherent value in subjective analysis by management (Ravinder & Misra, 2014). Management has insights such as human intuition, which analytics has yet to duplicate. The way that models account for such insights are through subjective inputs. Clustering does not allow for this sort of subjective input. It is our expectation that methods which do permit subjective weights will be more valuable in this practical application.

2.4 Summary

Research in ABC analysis evolved from single criterion to dual-criteria and multi-criteria. In multi-criteria analysis, different methodologies have been applied, including subjective weighting, linear optimization, and clustering. In our thesis, we will conduct single factor analysis, dual matrix analysis, AHP, and clustering. Based on the results of our analysis, we make a recommendation on the best method for SKU stratification.
3 METHODOLOGY

The objective of our thesis is to identify and test methods for SKU stratification. We applied these methods to data from distribution centers in the consumer packaged goods (CPG) industry. We analyzed four methods: single factor, dual matrix, AHP, and clustering.

3.1 Tools

We conducted our analysis in Microsoft Excel 2016, with the exception of the clustering technique. We elected to utilize this platform because of its versatility, ease of use, and ubiquity. Each of these characteristics will facilitate reproduction of our analysis.

For cluster analysis, we used SAS JMP Pro 13, obtained using the institutional license. We chose to use this software because it possesses an excellent clustering tool. Just as important, it is easy to install and use, and is readily available to our sponsor company.

3.2 Relevant Factors

We identified four relevant factors for our analysis of SKU stratification: velocity, volatility, profit margin, and lead time.

Velocity was an obvious choice to include because it represents sales volume – the single factor that is considered most often. When considering sales or shipment data, there is a measured volume moving in a set time period. This volume per time actually is velocity. Sales volume is a misnomer. To be more precise in the language of this thesis, the term velocity is used. Velocity is an important factor to consider because it represents demand. When demand is high, sales are high, so velocity is high. Conversely, when demand is low, sales are low, and velocity is low. Companies clearly ought to consider demand when managing their inventory.

Volatility was the next logical factor to include. Any time that a company considers demand, they should look beyond the average demand – which is represented by velocity. The next level of consideration for demand is how much it fluctuates around the mean. The term volatility is used to represent this measure. If a product has high volatility, that means that the demand varies a lot around the mean. With high
fluctuations in demand, it is wise to maintain higher levels of inventory. Therefore, volatility ought to be considered in inventory management.

In a for-profit company, a very important consideration for inventory management is the profit margin on each product. A company could improve management of their inventory based on velocity and volatility, and still be unprofitable. This is because neither of those factors considers the financial implications of individual products. Profit margin is included to account for the profitability of each product in the inventory management decisions.

Lead time is a factor that ought to be included when order fulfillment is a primary concern. Having the product in stock is an important aspect of the inventory manager’s ability to fulfill incoming orders. Without stock, the order cannot be fulfilled. Thus, the time required between requesting replenishment and receiving the product in inventory is important. Therefore, lead time ought to be considered in inventory management.

3.3 Data Acquisition

The data was provided by the sponsor company in the form of Excel spreadsheets. The decision was made to acquire the data this way for three reasons. First, it allowed us to focus on analyzing the data. We did not have to learn where and how to obtain the data from the sponsor company’s internal databases. Second, it permitted the contacts from the sponsor company to stay involved intimately in the research. Any time that we requested data, our contacts would provide guidance and insight. Third, it increases the ease of reproduction of this research because Excel is a ubiquitous platform.

For velocity and volatility, data was provided that reflected sales volume. In this application, sales volume is the volume sold by the manufacturer (our sponsor company) to the customer (a retailer). From volume, we calculated velocity and volatility. We requested two years of data, to account for seasonal variation. Initially, the data provided was reported by month. We requested that the data be broken down by week. Separating the data to the weekly level allowed us to account better for volatility in the sales volume. The data also was segmented by product, allowing us to conduct our analysis at the level of each individual SKU. Our sponsor requested that we separate our analysis by distribution center; they segmented the data accordingly.
For lead time, our contacts supplied review time, pick days, transit days, and receipt days for each shipping lane.

We also requested price and cost data in order to calculate profit margin, service level, and inventory value. This information was segmented by SKU.

3.4 Data Scrubbing

Once the data was provided, we identified extraneous data and determined how to treat that data.

The most obvious problem was SKUs that had no or very little data – insufficient for analysis. This problem arose from new or promotional products. Both of these categories lacked sufficient data to conduct meaningful analysis. We excluded offending SKUs from our analysis.

Another problem we encountered was extreme values at the beginning of a SKU’s lifecycle. This problem was attributed to initial stocking orders. When a product is new, stores must order a large quantity to create their initial inventory. Orders after that simply reflect sales to consumers. We addressed this problem by removing extreme values from the data. Our logic identified the maximum sales volume for each SKU over the two years of our dataset. Then we determined whether that maximum occurred in the first 10% of the data points (by count). If the maximum did occur in the first 10%, all data up to that point was discarded. This approach ensured that we also eliminated extraneous sales prior to the initial inventory order.

A concern arose when we identified products that appeared to have extremely high profit margins. Those products were determined to include additional supplies (such as displays). The basic product in a display already is included in our analysis under its own SKU. Therefore, we removed these display SKUs from our analysis.

We also discovered products with zero or negative profit margins. These items were identified as promotional items. Promotional items, like display items, consist of SKUs already present in our analysis. Thus, we removed promotional SKUs.
3.5 Calculation of Relevant Factors

3.5.1 Velocity

Velocity of inventory movement is volume per time. We calculated the average velocity in terms of order volume per week for each SKU over our two-year timeframe. Items that have a higher velocity have a greater impact on inventory management. Therefore, we will treat velocity such that higher velocities are of greater importance.

3.5.2 Volatility

We defined volatility as the coefficient of variation (c_v) of our dataset. The coefficient of variation is the ratio of the standard deviation (\( \sigma \)) to the mean (\( \mu \)):

\[
c_v = \frac{\sigma}{\mu}
\]

SKUs that have high volatility require more attention. In our analyses, we will handle volatility in a manner that assigns greater importance to higher volatilities.

3.5.3 Profit Margin

Profit margin was calculated as the difference between price and cost for each SKU. For any business, products with a higher profit margin are more important. Our analyses will reflect this reality by considering higher profit margins to be more important.

3.5.4 Lead Time

Order lead time was calculated as the sum of pick days, transit days, and receipt days. Total lead time was calculated as the sum of review time and order lead time. Analysis of the lead time data revealed that the lead time was dependent only upon facility, but not on SKU. Because our analysis was separated by facility, it would not add value to our analysis. Therefore, we dismissed lead time from our analysis.

3.6 Data Analysis

Having calculated our relevant factors, we applied our identified analysis methods.
3.6.1 Single Factor

For single factor analysis, first we calculated the values for each of our relevant factors for every SKU. Then we ranked all SKUs based on each of those factors separately.

Once the SKUs were ranked, we charted the values in order to identify the natural breaks in the data. These natural breaks would help us to identify the stratifications. To ensure consistency between methods, we also identified stratifications based on percentages of SKUs. We set the percentage of the SKUs that ought to be classified as A, B, C, etc.

3.6.2 Dual Matrix

For our dual matrix analysis, we began with the single factor analyses. Each SKU is given a classification by a single factor 1, and then another classification by a single factor 2. We combined the strata from two of the single factor analyses at a time. The combinations resulted in strata as shown in Table 1.

Table 1. Dual Matrix Key
The classification from factor 1 is read from the top of the table. The classification from factor 2 is read from the left of the table. The final classification is identified as the intersection of these two strata.

<table>
<thead>
<tr>
<th></th>
<th>Factor 1</th>
<th>Factor 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>A</td>
<td>A</td>
</tr>
<tr>
<td>B</td>
<td>A</td>
<td>B</td>
</tr>
<tr>
<td>C</td>
<td>B</td>
<td>C</td>
</tr>
<tr>
<td>D</td>
<td>D</td>
<td>E</td>
</tr>
</tbody>
</table>

For example, say product X had been identified as a B product for factor 1 and C for factor 2. This means that product X corresponds to the second column (labeled ‘B’ at the top) and the third row (labeled ‘C’ to the left). The intersection of the second column and the third row is labeled ‘C’. In this analysis, product X would be classified as a C product.

We conducted dual matrix analysis using all combinations of our three relevant factors: velocity & volatility, volatility & profit margin, and profit margin & velocity.
3.6.3 Analytical Hierarchy Process

The Analytical Hierarchy Process (AHP) requires a subjective weighting to be applied to the relevant factors. To obtain this weighting, we asked for input from our contacts at our sponsor company. They performed a pairwise comparison between our three relevant factors. This approach helped us to reflect the true importance of each factor to the business. A sample pairwise comparison can be seen in Table 2.

Table 2. Pairwise Comparison
Factor 1 is read from the left; factor 2 is read from the top. At the intersection of the two factors, a comparison is made, according to Table A.1.

<table>
<thead>
<tr>
<th></th>
<th>Velocity</th>
<th>Profit Margin</th>
<th>Volatility</th>
</tr>
</thead>
<tbody>
<tr>
<td>Velocity</td>
<td>1</td>
<td>1</td>
<td>3</td>
</tr>
<tr>
<td>Profit Margin</td>
<td>1</td>
<td>1</td>
<td>3</td>
</tr>
<tr>
<td>Volatility</td>
<td>1/3</td>
<td>1/3</td>
<td>1</td>
</tr>
</tbody>
</table>

In this example, velocity and profit margin have been identified as being equal in importance. Volatility was determined to be of one-third the importance of the other two factors. From the pairwise comparison matrix, we calculated an eigenvector to capture the relationships between the three factors.

Then we normalized the eigenvector to 1. The normalized value is the ratio of the differences between the current value and the minimum, and maximum and minimum:

\[
\text{Normalized value} = \frac{\text{current value} - \text{minimum}}{\text{maximum} - \text{minimum}}.
\]

The result is that the maximum is set equal to 1 and the minimum is set equal to 0. All other values fall in between. Normalization reduces the size of the numbers being handled, but maintains the relationships between values. Our normalized eigenvector provides the subjective weighting to apply to each of the factors. With normalization, the total weight clearly is seen to be equal to 100%.

With the weights prepared, we normalized our three relevant factors. Each factor was normalized to a scale between 0 and 1. In the case of the factors, normalization allows for direct comparison of values that otherwise would be incomparable. For example, consider factor 1 that has a range of 0 to 1,000. In contrast, factor 2 has a range from 0 to 5. A direct sum of these two factors will render factor 2 nearly (if not completely) impotent. However, by normalizing the ranges both factors can be compared on an equal scale.
Once the factors were normalized, the weights were applied and a composite sum was calculated. Simply put, the value for each factor was multiplied by the corresponding weight. The results then were summed for each SKU.

Earlier, we established that for each of our relevant factors, higher values are more important. We also calculated our weights to reflect higher values for higher importance. Therefore, the new composite was assigned increasing importance as the value increases. Thus, the SKUs were ranked in terms of the composite from highest to lowest. With this ranking, strata were identified based on the desired percentages of SKUs.

3.6.4 Clustering

Clustering is a machine-learning technique performed by specialized software. As mentioned above, we chose to use JMP. We chose K-Means clustering (a partitional clustering technique) because it is the most appropriate method for this kind of problem. It allows the number of clusters identified to be determined by the user. The resulting clusters will be the classification strata. Thus, by setting the number of clusters to be identified, the number of strata also is set. What is more, K-Means clustering is the most commonly used and well-documented method (Kyan, Muneesawang, Jarrah, & Guan, 2014). Our relevant factors and the desired number of clusters were provided as the inputs to the clustering tool. We chose to run separate analyses to identify 3, 4, and 5 clusters (strata).

3.7 Service Level Analysis

With the standard equations below, we calculated the desired service level by SKU. In order to represent demand in the calculations, we used sales volume as a proxy. This assumption could be challenged, because true demand is the sum of sales volume and unfulfilled orders due to shortage. However, for our analysis it gives us a good approximation. For holding cost and order cost, we requested and acquired data from our
sponsor company. To consider shortage cost, we utilized profit margin as a stand in. In other words, for every item that a company is short, it loses the profit margin on that item:

\[
Q^* = \sqrt{\frac{2c_c D}{c_e}}
\]

\[
P(\text{Stockout}) = \frac{Qc_e}{Dc_s}
\]

\[
\text{Service Level} = 1 - P(\text{Stockout}).
\]

With those numbers, we calculated the economic order quantity, \(Q^*\), for each item. With \(Q^*\) we were able to calculate the desired probability of stocking out. The probability of stocking out then allowed us to calculate the desired service level for each SKU. With the individual service levels, we identified the maximum, minimum, and average for each classification.

3.8 Summary

In summary, we obtained data from our sponsor company, cleaned the data and selected the relevant stratification criteria. We then chose four stratification methods of increasing complexity and comprehensiveness, and applied all four methods to our data. The following section details the results of our analyses.
4 RESULTS

The output of SKU stratification is an assigned class (A, B, C, D, etc.) for each SKU. This section presents the results of applying the four methods: single factor, dual matrix, AHP, and clustering. We applied these methods to our three relevant factors: velocity, volatility, and profit margin.

4.1 Single Factor

As presented in section 3.6.1, for each of the three relevant factors, we conducted a single factor stratification. Figure 1 charts the ranked velocity data. Initially, we identified the natural breaks and turning points in the data to be at approximately 750 and 100. Therefore, SKUs with velocity higher than 750 units per week were classified as A SKUs. SKUs with velocity between 100 and 750 were classified as B SKUs. SKUs with velocity below 100 were classified as C SKUs. The same analysis was done for volatility and profit margin respectively (Appendix B. Single factor distributions).

![Velocity Distribution](image)

**Figure 1.** Velocity Distribution in Single Factor Analysis
The velocity for each SKU in the dataset. Very few SKUs have high velocity (> 500 units/week), while many have velocity < 100 units/week. The natural shape of the curve can be used to identify classifications.

However, due to limitations in identifying natural breaks and turning points (see section 5.1.5), we determined the size of the strata based on percentage of SKUs. We specified the top 20% of SKUs as A. The next 25% we labeled as B. We set the next 25% as C. And the final 30% were identified as D.
Of 80 SKUs classified as A based on velocity, only 7 (8.75%) were classified as A for volatility and profit margin. Of 100 SKUs classified as B based on velocity, only 10 (10%) were classified as B for volatility and profit margin. In short, the classifications were very different for each of the three factors.

4.2 Dual Matrix

In dual matrix analysis, we overlay the results of two single factor stratifications to derive a new stratification (see section 3.6.2). This means that the size of each class was influenced, but not determined by the distribution of single factor results. Table 3 shows class size comparison in terms of percentage of SKUs between single factor and dual matrix stratification.

Table 3. SKU Percentage Comparison of Single Factor (Velocity) and Dual Matrix (Velocity and Profit Margin)
The percentage of SKUs in each class from single factor analysis based on velocity and dual matrix analysis based on velocity and profit margin.

<table>
<thead>
<tr>
<th>Class</th>
<th>Single Factor</th>
<th>Dual Matrix</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>20%</td>
<td>14%</td>
</tr>
<tr>
<td>B</td>
<td>25%</td>
<td>16%</td>
</tr>
<tr>
<td>C</td>
<td>25%</td>
<td>22%</td>
</tr>
<tr>
<td>D</td>
<td>30%</td>
<td>27%</td>
</tr>
<tr>
<td>E</td>
<td>22%</td>
<td>22%</td>
</tr>
</tbody>
</table>

Figure 2 shows that in dual factor classification, there were 64 SKUs classified as B. However, these 64 SKUs came from all four classes in the single factor results. 15 were A (blue), 20 were B (orange), 15 were C (grey), and 14 were D (yellow). SKUs classified in each stratum in the dual matrix method come from every class in the single factor method.
4.3 Analytical Hierarchy Process (AHP)

As discussed in section 3.6.3, we obtained from our sponsor company the pairwise comparison of the importance of the factors. By providing the comparison data (Table 2) to an online eigenvector calculator, we derived the following weightage (Table 4). Velocity and profit margin each carry 43% weight in the overall ranking, while volatility carries 14% weight.

Table 4. Factor Weightage

<table>
<thead>
<tr>
<th>Factor</th>
<th>Weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>Velocity</td>
<td>0.43</td>
</tr>
<tr>
<td>Profit Margin</td>
<td>0.43</td>
</tr>
<tr>
<td>Volatility</td>
<td>0.14</td>
</tr>
</tbody>
</table>

The resulting stratification from AHP was compared with single factor and dual matrix results. Figure 3 shows the comparison with results from single factor analysis based on velocity.
Figure 3. AHP vs Single Factor (Velocity) Stratification Comparison
Comparison of the results from single factor (velocity) and AHP analyses. Each color represents one class from single factor analysis; each stacked bar is one class from AHP analysis.

Clearly, AHP gives very different results than single factor analysis. At first glance, it is clear that the greatest number of SKUs in each classification remained in the same class. The bulk of the SKUs were not reclassified. This makes sense because the single factor analysis was based on velocity, and velocity received the heaviest weightage in the AHP analysis.

In contrast, the AHP and dual matrix results are more similar. Figure 4 shows the comparison between AHP and dual matrix based on velocity and profit margin. A SKUs given by AHP method are either A or B SKUs from dual matrix method. In addition, the lowest class from AHP (D) overlaps with the lowest class from dual matrix (E) by more than 90%. The similarity is expected given that velocity and profit margin account for 86% of the weightage on the inputs to AHP.
Figure 4. AHP vs Dual Matrix (Velocity & Profit Margin) Stratification Comparison
Comparison of the results from dual factor (velocity and profit margin) and AHP analyses. Each color represents one class from dual factor analysis; each stacked bar is one class from AHP analysis.

4.4 Clustering

Using the clustering analysis function in the software JMP (see section 3.6.4), we obtained results of 3, 4 and 5 clusters. Table 5 shows the resulting number of SKUs in each cluster.

Table 5. Clustering Output
The resulting number of SKUs in each cluster, using the K-Means clustering technique with the indicated number of predetermined clusters.

<table>
<thead>
<tr>
<th>Cluster #</th>
<th>3 Clusters</th>
<th>4 Clusters</th>
<th>5 Clusters</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>11</td>
<td>11</td>
<td>11</td>
</tr>
<tr>
<td>2</td>
<td>275</td>
<td>277</td>
<td>100</td>
</tr>
<tr>
<td>3</td>
<td>118</td>
<td>3</td>
<td>283</td>
</tr>
<tr>
<td>4</td>
<td></td>
<td>113</td>
<td>3</td>
</tr>
<tr>
<td>5</td>
<td></td>
<td></td>
<td>7</td>
</tr>
</tbody>
</table>

The number of SKUs in a cluster is determined entirely by the algorithms – we have no influence over class size. When identifying 3 clusters, the number of SKUs in clusters 1, 2, and 3 are 11, 275, and 118.
respectively. When the number of clusters is changed from 3 to 4 or 5, the 11 SKUs in cluster 1 remain unchanged. All other clusters are regrouped.
5 DISCUSSION

In this section, we will discuss the implications of our results and their applications. Due to the qualitative nature of the problem, comparisons between methods are based on qualitative properties, rather than quantitative analysis. Nevertheless, our analysis can provide insights into the advantages, limitations and applicability of each method.

5.1 Implications

We first consider each method individually. Then we compare all four methods. Finally, we provide our recommendation.

5.1.1 Single Factor

Our results showed that applying single factor analysis to different factors leads to very different classification. Therefore, stratification based on any single factor would lead to decisions that neglect the implications of other relevant factors. For example, using stratification based on velocity alone could place focus on products with high demand, but low profitability. By focusing on those products, the company would ignore its products with low demand, but high profitability. We conclude that single factor analysis is not a comprehensive method of SKU stratification. This result confirms our hypothesis that more comprehensive methods are required.

5.1.2 Dual Matrix

In Figure 2 we compared the results of single factor and dual matrix analyses. There are major differences in the stratifications. This finding reinforces our observation from single factor analysis. Stratification based on any single factor will not account for the impact of the other factors.

If our results had been very similar, the additional complexity of the dual matrix method would not add value. If the additional complexity added no value, then we would recommend the use of single factor analysis. However, our results confirm that the additional complexity does add value in the way of increased comprehensiveness.

Although derived from single factor results, dual matrix class size is not in direct proportion to single factor class size. For example, consider the case with no overlap between the A and B classifications of the
two factors analyzed. There would be zero SKUs classified as A in the dual matrix results. It would be difficult for such a result to add value. The inflexibility in class size of the dual matrix method limits its applicability.

5.1.3 AHP

As we observed in Figure 3, the results from the single factor method and the AHP method are very different. SKUs from each classification as determined by single factor analysis are identified in every other classification when submitted to AHP. These differences indicate that the additional factors included in AHP cause significant changes in classification. This fact confirms the importance of considering more than one important factor in SKU stratification. Once more, this confirms that the use of a single factor is insufficient for SKU stratification.

Figure 4, on the other hand, demonstrates that dual matrix analysis and AHP analysis have similar results. There are differences, which follows our hypothesis that more comprehensive methods are necessary to capture the impacts of more factors. However, the differences are not so large that they show AHP to be the obvious selection. Therefore, let us consider other benefits of the AHP method.

The AHP method also is extremely flexible. We considered only three relevant factors, but AHP theoretically has the flexibility to include infinite factors. However, identifying and calculating additional factors quickly can become cumbersome and tedious. What is more, the AHP method can be scaled back such that it is dual matrix or single factor analysis. This could be done by changing the weightage on the factors. For single factor analysis, set the weightage of the chosen factor to 1.0 and of other factors to 0.0. For dual matrix analysis, set the weightage of the two chosen factors to 0.5 and other factors to 0.0.

5.1.4 Clustering

We saw in Table 5 that the class sizes from the clustering method are unpredictable. In practical applications, this sort of unpredictability will create unnecessary and resource-consuming issues.

5.1.5 Class Sizes

While it is intuitive to use natural breaks and turning points to stratify data, this method has its limitations. First, the identification of breaks or turning points presents challenges. Second, it is possible
that some data have no natural break or turning point. Third, for the purpose of this study, using natural breaks does not allow for comparison across different methods.

The easiest way to identify a turning point is human judgment, which carries its own limitations. A more analytically robust method of identifying a turning point requires significant calculations. In effect, analytically identifying natural breaks is cluster analysis. By employing this tool, we change the method being used into the more complex cluster analysis. As we discussed in section 4.4, the class sizes in cluster analysis are unpredictable.

Also, if we identify stratifications in different ways for different methods, our comparison of the resulting stratifications will be invalid. To ensure consistency, we should identify the stratifications in a common manner across methods. Therefore, we determined the size of the strata based on percentage of SKUs. We outlined those breaks in section 4.1.

5.1.6 Summary

Each of the four methods analyzed in our project has its own strengths and weaknesses. Table 6 presents a comparison of the methods in five key areas. These areas were selected based on the practical considerations a practitioner would have when implementing a SKU stratification method.

Table 6. Method Comparison
Comparison of the four methods based on five key characteristics.

<table>
<thead>
<tr>
<th>Method</th>
<th>Factors Considered</th>
<th>Comprehensive ness</th>
<th>Ease of Implementation</th>
<th>Ability to Customize Class Size</th>
<th>Software Required</th>
</tr>
</thead>
<tbody>
<tr>
<td>Single Factor</td>
<td>1</td>
<td>Low</td>
<td>High</td>
<td>High</td>
<td>-</td>
</tr>
<tr>
<td>Dual Matrix</td>
<td>2</td>
<td>Medium</td>
<td>Medium</td>
<td>Medium</td>
<td>-</td>
</tr>
<tr>
<td>AHP</td>
<td>3 or more</td>
<td>High</td>
<td>Medium Low</td>
<td>High</td>
<td>Eigen Vector Calculator</td>
</tr>
<tr>
<td>Clustering</td>
<td>3 or more</td>
<td>High</td>
<td>Medium</td>
<td>Low</td>
<td>JMP</td>
</tr>
</tbody>
</table>

As their names imply, single factor and dual matrix methods can only consider 1 and 2 factors, respectively. In contrast, AHP and clustering can consider 3 or more factors. Thus, AHP and clustering are more comprehensive than single factor and dual matrix methods.
Regarding ease of implementation, AHP was the most labor-intensive method when we started the analysis from scratch. This was a result of the normalization of the factors and the process of obtaining the factor weights.

In terms of ability to customize class size, single factor method and AHP allow any class size. The reason is that in these two methods, classes are derived from a single ranked score. In dual matrix method, we can alter the single factor class sizes to adjust the final class size. That gives us a small degree of control over the class size. As discussed in section 4.4, clustering does not allow any adjustment on class size.

Lastly, regarding software required, Microsoft Excel was used to conduct spreadsheet analysis for every method. Single factor and dual matrix methods do not require any specialized software. For AHP, an eigenvector calculator is needed to transform pairwise comparison to weightage. Such calculators are readily available online. To do clustering, we need data analysis software with machine learning capability. JMP is one such software available.

5.1.7 Recommendation

The main goal of this research was to identify a suitable SKU stratification method for our sponsor company’s inventory management. Our recommendation is to apply the AHP method.

First, AHP is a comprehensive method. With the ability to include an infinite number of factors, none of the other methods were more comprehensive. (Granted, clustering was equally comprehensive.) Second, AHP allows subjective input on the relative importance between factors. This is critical because it enables the customization of the stratification based on different purposes of analyses. For example, analyses that focus on cost savings will have different emphases than analyses that focus on customer service. Finally, AHP has the flexibility to become both single factor and dual matrix analyses by adjusting weightage of factors accordingly. In other words, AHP is an all-encompassing model, more flexible and powerful than the other models.
6 APPLICATIONS, LIMITATIONS, & NEXT STEPS

In this section, we will apply SKU stratification to inventory value management and service level generation. Then we will discuss the limitations and broader applicability of our research. Finally, we will propose a few potential next steps.

6.1 Inventory Value Management

With the stratification result, we can calculate the total inventory value in each class. We took a snapshot of the inventory quantity by SKU. Then we multiplied the inventory quantity by product cost for each SKU. The resulting inventory value was then grouped by the AHP SKU stratification.

As shown in Figure 5, from A class to D class, total inventory value was in decreasing order. Although A SKUs were only 20% in terms of SKU count, they made up 47% of total inventory value. This was a rough indication that our sponsor company was holding inventory for the right SKUs.

![Inventory Value By Class](image)

**Figure 5.** Inventory Value by Class
The total value of inventory for every SKU in each class, based on AHP stratification.

Starting from SKU stratification, our sponsor company will be able to set an inventory value target for each class. They can then monitor actual inventory value by class to ensure optimal working capital management. Our SKU stratification method will build a solid basis for inventory value allocation.
6.2 Service Level Generation

Using the recommended service level for each SKU (section 3.7), the maximum, minimum, and average for each classification was calculated. These values will allow management decisions to be made about service level at an aggregate level of the stratifications. Table 7 shows the minimum, maximum, and average service level for each classification.

Table 7. Recommended Service Level Metrics by Classification
The minimum, maximum, and average service level for each classification as determined by the AHP method. Recommended service level was calculated for each SKU. These metrics were aggregated based on the classifications from the AHP method.

<table>
<thead>
<tr>
<th></th>
<th>Min</th>
<th>Max</th>
<th>Avg</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>69%</td>
<td>100%</td>
<td>95%</td>
</tr>
<tr>
<td>B</td>
<td>70%</td>
<td>97%</td>
<td>91%</td>
</tr>
<tr>
<td>C</td>
<td>28%</td>
<td>95%</td>
<td>84%</td>
</tr>
<tr>
<td>D</td>
<td>12%</td>
<td>90%</td>
<td>72%</td>
</tr>
</tbody>
</table>

The service level calculations include demand, which is proportional to velocity, and cost, which is weakly positively correlated with profit margin. In other words, the factors in the service level calculation and stratification analysis are related. Therefore, it was expected that the service level for SKUs in the same classification would be similar. SKUs in higher classifications were expected to have higher recommended service levels. This turned out to be partially accurate.

The stratification analysis included volatility while the service level calculations did not. Therefore, volatility was the primary cause of differences between the two. Most SKUs in a classification would form a logical distribution about the mean service level. Volatility caused outliers; sometimes extreme outliers. The outliers were created in two ways: boosting and sandbagging.

For example, a SKU may have low velocity and profit margin, which result in a low service level. But that same SKU could have a high volatility that boosts the classification higher. In this way, the SKU has a high classification with a low service level. The SKU becomes an outlier and a minimum service level for that classification. Boosting is why the minimum service level for the A classification is so low at 69%.

The opposite also could be true. A SKU could have a high velocity and profit margin, and therefore a high service level. The SKU also could have an extremely low volatility which drags down the classification.
The SKU has a low classification and a high service level. This SKU has become an outlier and a maximum for that classification. Sandbagging is why the maximum for the D classification is so high at 90%.

6.3 Limitations and Broader Application

While this project used data from one distribution center, the stratification methods can be easily applied to other distribution centers. We also do not foresee a problem with using the stratification methods on a store level. For other Consumer Packaged Goods (CPG) companies, the relevant factors may be slightly different from our sponsor company. For example, lead time may differ significantly across products such that it needs to be considered as another relevant factor. However, the logic of the methods remains the same. Beyond the CPG industry, our research might need to be further extended to accommodate industry specific characteristics. For example, many companies have products that are always or often sold together. SKU stratification may then need to take into account the relationship among products.

6.4 Potential Next Steps

This project has the potential to be extended in several directions. We suggest the following research areas.

First, further research can be done to explore methods to identify strata cut-offs. In this thesis project, we dictated the class sizes as percentage of total number of SKUs. The decision on the exact percentages more or less was arbitrary. An interesting research topic would be how to determine the appropriate cutoffs for the strata.

Another interesting topic would be research on the optimal reanalysis frequency. Once the initial SKU stratification has been determined, it must be decided when next to refresh the data and analysis. More frequent reanalysis will obviously require more effort and time. How the additional effort compares with the marginal benefit remains an open question.

Also, there is the question of how to handle new products, promotional items, and other exceptions in SKU stratification. While we outlined the general approach to SKU stratification, a supplemental study for exception handling could be beneficial.
SKU stratification has applications in working capital management, service level generation, omni-channel distribution, and beyond. It is applicable to not only our sponsor company, but also other Consumer Packaged Goods (CPG) companies and other industries.
CONCLUSION

Our research identified the SKU stratification method that works best for our sponsor, a Consumer Packaged Goods company. We applied and compared four methods: Single Factor Analysis, Dual-Matrix Analysis, Analytical Hierarchy Process, and Cluster Analysis. The analysis indicates that different methods give very different SKU stratification results. We found that the Analytical Hierarchy Process is the most viable and comprehensive method among the four. It allows for a flexible number of stratification factors, different importance levels of the factors, and user control of class sizes.

Several related questions remain uninvestigated in this research. One important research topic will be the identification of strata cut-offs and class sizes. Another area of interest is the appropriate re-generation frequency of SKU stratification. Finally, new products and exception handling can be further researched.

Our research indicates that it is practical for companies to employ multi-criteria stratification methods to manage inventory more comprehensively, and AHP is the method that we recommend for such an application.
REFERENCES

APPENDIX A. PAIRWISE COMPARISON RELATIONSHIPS

Table A.1. Pairwise Comparison Relationships
When comparing two factors, the value corresponding to the determined relationship is applied to Table 2.

<p>| | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>1/7</td>
<td>Significantly Less Important</td>
</tr>
<tr>
<td>1/5</td>
<td>Less Important</td>
</tr>
<tr>
<td>1/3</td>
<td>Slightly Less Important</td>
</tr>
<tr>
<td>1</td>
<td>Equally Important</td>
</tr>
<tr>
<td>3</td>
<td>Slightly More Important</td>
</tr>
<tr>
<td>5</td>
<td>More Important</td>
</tr>
<tr>
<td>7</td>
<td>Significantly More Important</td>
</tr>
</tbody>
</table>
APPENDIX B. SINGLE FACTOR DISTRIBUTIONS

Volatility Distribution

Natural Breaks / Turning Points:
CV = 0.9 and CV = 0.5

Figure B.1. Volatility Distribution in Single Factor Analysis
The volatility for each SKU in the dataset. The natural shape of the curve is less conducive to identifying the second break than the first.

Profit Margin Distribution

Natural Breaks / Turning Points:
PM = 10 and PM = 4.5

Figure B.2. Profit Margin Distribution in Single Factor Analysis
The profit margin for each SKU in the dataset. Very few SKUs have high profit margin (> 10 $/unit), while many have profit margin < 4.5 $/unit. The natural shape of the curve can be used to identify classifications.
APPENDIX C. STRATIFICATION RESULTS COMPARISON ACROSS METHODS

Dual Matrix vs Single Factor Stratification Comparison

Single Factor Classification

<table>
<thead>
<tr>
<th></th>
<th>A</th>
<th>B</th>
<th>C</th>
<th>D</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of SKUs</td>
<td>120</td>
<td>100</td>
<td>80</td>
<td>60</td>
</tr>
</tbody>
</table>

Dual Matrix Classification

Figure C.1. Dual Matrix (Velocity and Volatility) vs. Single Factor (Velocity) Stratification Comparison
Comparison of the results from single factor (velocity) and dual factor (velocity and volatility) analyses. Each color represents one class from single factor analysis; each stacked bar is one class from dual factor analysis.

Dual Matrix vs Single Factor Stratification Comparison

Single Factor Classification

<table>
<thead>
<tr>
<th></th>
<th>A</th>
<th>B</th>
<th>C</th>
<th>D</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of SKUs</td>
<td>120</td>
<td>100</td>
<td>80</td>
<td>60</td>
</tr>
</tbody>
</table>

Dual Matrix Classification

Figure C.2. Dual Matrix (Volatility and Profit Margin) vs. Single Factor (Velocity) Stratification Comparison
Comparison of the results from single factor (velocity) and dual factor (Volatility and Profit Margin) analyses. Each color represents one class from single factor analysis; each stacked bar is one class from dual factor analysis.
**Figure C.3.** Dual Matrix (Volatility and Velocity) vs Single Factor (Volatility) Stratification Comparison
Comparison of the results from single factor (volatility) and dual factor (volatility and velocity) analyses. Each color represents one class from single factor analysis; each stacked bar is one class from dual factor analysis.

**Figure C.4.** Dual Matrix (Volatility and Profit Margin) vs Single Factor (Volatility) Stratification Comparison
Comparison of the results from single factor (volatility) and dual factor (volatility and profit margin) analyses. Each color represents one class from single factor analysis; each stacked bar is one class from dual factor analysis.
Figure C.5. Dual Matrix (Velocity and Profit Margin) vs. Single Factor (Volatility) Stratification Comparison
Comparison of the results from single factor (volatility) and dual factor (velocity and profit margin) analyses. Each color represents one class from single factor analysis; each stacked bar is one class from dual factor analysis.

Figure C.6. Dual Matrix (Profit Margin and Velocity) vs. Single Factor (Profit Margin) Stratification Comparison
Comparison of the results from single factor (profit margin) and dual factor (profit margin and velocity) analyses. Each color represents one class from single factor analysis; each stacked bar is one class from dual factor analysis.
**Figure C.7.** Dual Matrix (Profit Margin and Volatility) vs. Single Factor (Profit Margin) Stratification Comparison
Comparison of the results from single factor (profit margin) and dual factor (profit margin and volatility) analyses. Each color represents one class from single factor analysis; each stacked bar is one class from dual factor analysis.

**Figure C.8.** Dual Matrix (Velocity and Volatility) vs. Single Factor (Profit Margin) Stratification Comparison
Comparison of the results from single factor (profit margin) and dual factor (velocity and volatility) analyses. Each color represents one class from single factor analysis; each stacked bar is one class from dual factor analysis.
**Figure C.9. AHP vs. Single Factor (Volatility) Stratification Comparison**
Comparison of the results from single factor (volatility) and AHP analyses. Each color represents one class from single factor analysis; each stacked bar is one class from AHP analysis.

**Figure C.10. AHP vs. Single Factor (Profit Margin) Stratification Comparison**
Comparison of the results from single factor (profit margin) and AHP analyses. Each color represents one class from single factor analysis; each stacked bar is one class from AHP analysis.
**Figure C.11. AHP vs. Dual Matrix (Velocity & Volatility) Stratification Comparison**
Comparison of the results from dual factor (velocity and volatility) and AHP analyses. Each color represents one class from dual factor analysis; each stacked bar is one class from AHP analysis.

**Figure C.12. AHP vs. Dual Matrix (Volatility & Profit Margin) Stratification Comparison**
Comparison of the results from dual factor (volatility and profit margin) and AHP analyses. Each color represents one class from dual factor analysis; each stacked bar is one class from AHP analysis.