Strategy Formulation for SKU Rationalization using Financial and Bill of Material Metrics

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Strategy Formulation for SKU Rationalization using Financial and Bill of Material Metrics

For Newell Brands

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Submitted to the Program in Supply Chain Management
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ABSTRACT

As Newell Brands expanded its SKU portfolio to drive business growth and cater to diverse consumer needs, the resulting increase in complexity began to hinder supply chain efficiency, profitability, and effective inventory management. To address these challenges, the company sought to develop a methodology for SKU rationalization that would enable them to streamline their product offerings, reduce costs, and improve overall supply chain performance. This capstone project developed a strategy for SKU rationalization for Newell Brands by integrating financial and bill of material (BOM) complexity metrics. The methodology employed a rating system to evaluate SKUs based on total annual sales, total annual margin, number of child components, minimum clan rank, and number of unique components. A three-step filtering procedure identified SKUs as candidates for rationalization under various business scenarios. Applying the procedure to multiple scenarios demonstrated that adjusting filtering criteria enabled the company to control the number of SKUs flagged. The principles can be extended to other companies facing similar challenges in product proliferation and supply chain operations in their industries.

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1. Introduction

1.1. Motivation

Newell Brands, the sponsor company of this capstone project, is a conglomerate boasting a diverse portfolio of over 100 consumer-oriented brands. With a dedicated workforce of 26,000 employees, its commitment to innovation and quality is reflected in its $9.5 billion net sales (Newell Brands, 2023). Newell derives 35% of its revenue from international sales, highlighting its successful expansion into global markets. Newell Brands is organized into three distinct operating segments—home, learning and development, and outdoor—and is well-positioned to cater to a broad spectrum of consumer needs, making it a prominent player in the ever-evolving consumer goods industry.

Being a conglomerate, Newell Brands has traditionally allowed each brand to operate independently. Over time, these brands have introduced new products to attract customers and drive business growth. However, this expansion of its business operations has increased the complexity within its supply chain system. A diverse product portfolio can bring benefits such as increased revenue, market expansion, and risk mitigation. However, it can also come with drawbacks, including reduced efficiency, elevated expenses, extended lead times, and instances of stockouts.

Newell Brands initiated a Stock-Keeping Units (SKU) rationalization analysis for the entire product portfolio, which contained over 100,000 individual SKUs, to identify products with high manufacturing costs and low-profit margins. Currently, the portfolio has been streamlined to contain fewer than 26,000 products. The company aims to reduce the number of SKUs to below 10,000. However, achieving this target has become increasingly challenging, as easily attainable improvements have already been implemented in SKU optimization efforts over the past 5 to 10 years. Therefore, the company intends to take a fresh approach by examining the product portfolio from a bill of material (BOM) perspective; that is, by analyzing each product's complexity and commonality at the components and sub-components levels. They plan to develop a procedure involving metrics to enable business leaders to assess product complexity and identify potential improvement opportunities in manufacturing, planning, and forecasting that could help in SKU rationalization.

1.2 Problem Statement & Research Questions

As Newell Brands grows, its expansion into various product segments has introduced greater complexity to its business management. This complexity has manifested in several ways, including challenges in forecasting demand and managing inventory efficiently, reduced visibility into operations, and a more inflexible supply chain. Their primary goal is to address these issues by rationalizing the SKUs from a BOM perspective. The analysis will incorporate data visualizations that capture complex relationships and dependencies between components and subassemblies. This will enable stakeholders to understand the product portfolio's structure and identify critical areas for improvement in forecast accuracy and holding costs. Newell Brands can focus its resources on high-value offerings by eliminating redundant or low-performing SKUs.

To develop a comprehensive SKU rationalization strategy, it is essential to address the following key questions:

1. What metrics can characterize SKUs in Newell Brands portfolios regarding similarity or uniqueness among the SKUs?
2. What are some possible ways to combine financial and complexity metrics to infer the criteria for SKU portfolio optimization?
3. Will the strategy apply to different product portfolios within Newell Brands?

1.3 Scope: Project Goals & Expected Outcomes

The capstone project aims to develop an SKU rationalization methodology using the sponsor company's bill of material (BOM) for the "Writing Pen" family. It focuses on characterizing SKUs in terms of metrics that can capture complexity and similarity from the standpoint of the BOM. The BOM for "Writing Pen" consists of 390 SKUs and 2,427 unique child components comprising eight product families and 46 product lines. This project will investigate the complexity of BOM and formulate an intuitive method to analyze it. This analysis will allow the sponsor company to identify opportunities for portfolio rationalization, cost optimization, and improving supply chain efficiency.

We hypothesize that the sponsor company can make informed choices regarding complexity reduction, cost optimization, and efficiency enhancement using the complexity metrics generated by the bill of material analysis.

The deliverables to the sponsor company will include:

1. Identification of relevant metrics to characterize BOM according to properties such as level of complexity, similarity, or financial metrics.
2. Identification of a methodology for computing those metrics using the BOM of "Writing Pens" that can be applied to different product portfolios.
3. Strategy formation of SKU rationalization incorporating the relevant metrics for business purposes.

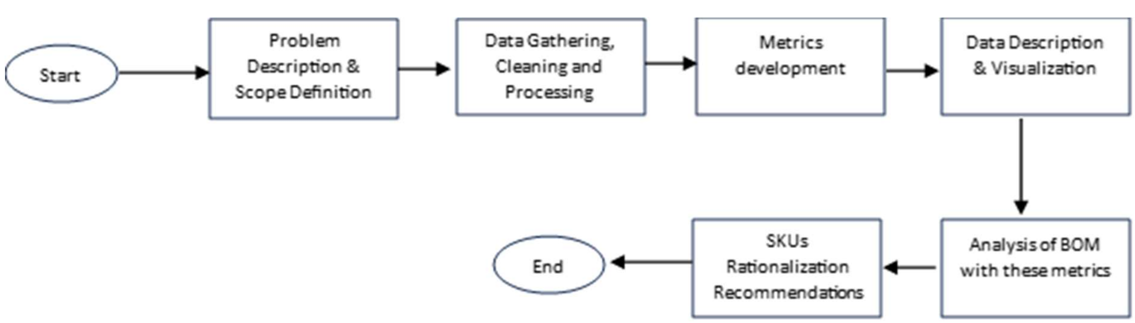
Once these metrics are defined based on analysis of the BOM, the sponsor company expects to utilize them to improve supply chain efficiency, reduce lead times, and minimize stockouts. This information will help the sponsor company target cost-reduction initiatives and optimize the overall product portfolio. Furthermore, it can help the sponsor company with component standardization, strategic sourcing, or product design.

1.4 Plan of Work

Our project plan included the following steps to build the complexity metrics and recommend rationalizing the SKUs to reach our sponsor company's goal. First, we reviewed the literature regarding the methodologies to represent complex BOM and the most relevant metrics. Second, we formulated complexity metrics for the sponsor company's BOM data based on uniqueness, similarity, or financial metrics. Third, we identified a methodology for analyzing and visualizing the sponsor company's BOM data with these metrics. This helped us run our preliminary analysis, which was input to our hypothesis validation. Lastly, we synthesized information and provided SKU rationalization recommendations to our sponsor company. Figure 1 represents the main steps that were carried out in this capstone.

Figure 1

Plan of Work



2. State of the Practice

As companies grow, they add more product variations to enter new markets, yet these choices can complicate the supply chain and lead to increased expenses in production, inventory, and management (McCord, 2015). According to RSR Research, 40% of retailers highlighted SKU rationalization as one of the top three supply chain challenges (Hoffman, 2008). Reduced product variety allows executives to oversee better product sales, forecasting, and manufacturing more effectively. Thus, our capstone's central problem is identifying opportunities for product rationalization by analyzing the company's BOM. Therefore, we examined the following areas to address the issue of SKU rationalization from the BOM perspective: SKU rationalization methodologies, followed by an analysis of metrics that assess product similarities in the given BOM.

2.1 SKU Rationalization Methodologies

SKU rationalization is a strategic technique in product management where a company assesses and refines its product mix by reviewing its SKUs. SKU rationalization aims to optimize a company's offerings for greater efficiency. It provides many supply chain benefits: streamlining product selection, reducing costs, and allowing better focus of resources. The process involves a data-driven approach to analyzing different metrics. By carefully evaluating the performance of each SKU, companies can determine which items should remain widely available and which ones to discontinue. The result is an improved, tighter product portfolio aligned to consumer demand and companies' goals.

There are two main approaches for rationalizing a product portfolio. First, redundant-product rationalization eliminates SKUs by identifying those that do not directly address a documented customer need, with the expectation that their sales will shift to the remaining products in the portfolio. For example, a pharmaceutical company offers two SKUs of Brand X in the same market: one-month and two-month packs. Although both products have strong sales, it is revealed that patients using Brand X require monthly check-ups, and providers decide whether to continue the treatment. The customer's needs can be met with just the one-month pack, making the two-month pack redundant. Rationalizing the two-month pack has significant benefits, such as streamlining sales and operations efforts, improving patient care, and potentially transferring 100% of the sales from the two-month pack to the one-month pack (Leiter, 2011). The second approach is "tail-end pruning," the common and traditional product rationalization method (Leiter, 2011), and Newell Brands has practiced it in its SKU rationalization. Tail-end pruning eliminates the worst-performing products at the bottom of the initial Pareto analysis of the portfolio. Pareto's analysis illustrates an 80/20 rule: 80% of its revenue comes from 20% of the products. Some companies may also have negative sales volumes and returns from their worst products due to excessive returns. Pruning these products will reduce overall revenue and margins, but the aim is for the cost reductions to outweigh the losses (Gilliland, 2011).

2.2 Similarity metrics based on BOM

A BOM network shows a detailed framework or system that delineates the components, parts, sub-assemblies, and raw materials needed for manufacturing a specific product. This structure highlights the hierarchical connections and dependencies among these elements, demonstrating how they link together and are assembled to form the product (Schmidt et al., 2017). Analyzing BOM networks allows companies to make more informed decisions about which products to keep or eliminate, ultimately leading to a more streamlined and profitable product portfolio.

The BOM network approach is a method that analyzes the similarities and relationships between the product structures of different products within a complex product family using network analysis techniques. This approach helps to identify opportunities for SKU rationalization. The approach models BOM data as tree graphs and compares the trees using two algorithms: the Common Parts Algorithm (CPA) and the All-Path Tree Edit Distance Algorithm (APTED). These two algorithms quantify the similarity between component variants to find clusters of high commonalities. The CPA algorithm measures how alike two SKUs are based on their components. The APTED algorithm is used to identify the minimum-cost sequence of transforming operations when converting the BOM of one product to another (Schmidt et al., 2017).

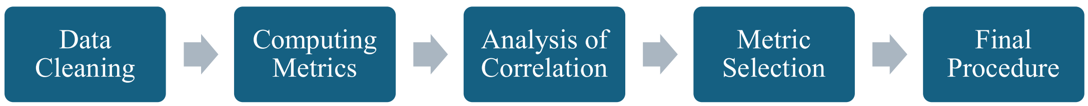
Identifying similarities between products helps to capture the potential candidates of SKU rationalization based on the assumption that the sales will shift from the removed SKUs to the existing ones when all other factors are the same.

3. Methodology

After defining the research problem and reviewing state-of-the-practice methodologies, we concluded that no single metric could effectively quantify the complexity of the entire BOM network. Instead, we focused on developing a procedure to segment SKUs based on complexity-related parameters such as similarities, sales volume, margin percentage, component uniqueness, and node centrality. Hence, the methodology aims to address the complexity of the BOM network and develop a procedure for SKU rationalization. The methodology encompasses five key steps, as shown in Figure 2.

Figure 2

Steps in Methodology



- **Step One**: Data Cleaning

The raw data was analyzed to identify product lines and families, providing insights into the portfolio's diversity. Relevant metrics for SKU rationalization, such as sales, margin, and BOM features (e.g., bom_level, finished_good_material, parent_component_material, and component_material), were retained, while others were dropped. Details of this analysis are shown in Section 3.1

- **Step Two**: Computing Complexity Metrics

In this step, we calculated eight metrics using the BOM Network graph to build a strategy for SKU rationalization. These include metrics relevant to the number and hierarchy of components in the SKU (e.g., number of child components, number of parent components, number of unique components), those relevant to the structure of the BOM (e.g., in-degree centrality, out-degree centrality, number of edges), and cost per component. Details of this analysis are provided in Section 3.2

- **Step Three**: Analysis of Correlation

We created a heatmap to calculate the correlation among different financial and complexity metrics to understand the most critical metrics that can be chosen for our final analysis. The heatmap and details of the analysis are shown in section 3.3.

- **Step Four**: Metric Selection

We chose three complexity metrics for our final SKU rationalization strategy. The selection was based on the following criteria:

1. Correlation between metrics
2. Interpretability of metrics in the business context for our capstone company
3. Including top-down approach metric along with bottom-up approach metric

Details of this analysis are shown in Section 3.4

Step Five: Final Procedure

A rating system was employed before developing a final procedure to categorize SKUs based on the above-chosen metrics during the SKU rationalization analysis. This rating system helped sort SKUs into buckets, provide quantitative measurements for decision-making, and standardize the review process. Within the rating system, each SKU is assigned a rating from 1 to 5 for each criterion, with lower ratings indicating a reduced likelihood of the SKU being removed from the BOM network.

The procedure for SKU rationalization consists of three main steps. This approach allows for identifying potential candidates, considering factors such as low sales performance, high complexity, and product similarity. This procedure comprises three steps where different SKUs are assessed and filtered according to financial and BOM complexity metrics previously identified based on BOM analysis and correlation matrix. This procedure is explained in detail in Section 3.5

Sections 3.1 through 3.5 outline the comprehensive, step-by-step procedure for developing the SKU rationalization strategy. Each step will help the audience understand the methodology and its application in more detail within the context of this project.

3.1 Data Cleaning and Feature Engineering

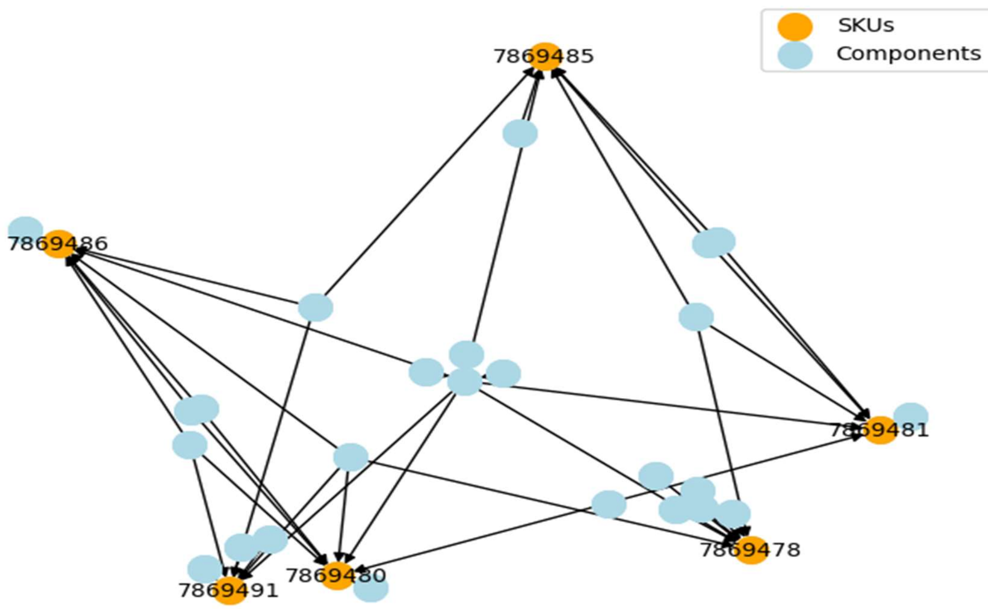
The raw data was analyzed to identify the product lines and product families, providing insights into the diversity of the given portfolio. We decided to use SKU sales and margin to build our strategy for SKU rationalization. We did not use the revenue column in our analysis because our sponsor company focuses on improving sales and total margin and rationalizing SKUs at the expense of a slight revenue loss.

3.2 Computing Metrics

We created a BOM network of the "Writing Pens," as shown in Figure 3, to compute metrics for our analysis. Figure 3 is a sample of a small network created from BOM data for only six SKUs to illustrate a visualization of the BOM.

Figure 3

Sample Bill of Material Network



The orange dots represent SKUs, and the blue represents components or sub-components. The figure shows edges representing the connection between components, parent components, and SKUs. The arrow in the figure represents the edges of the BOM and shows the direction of connection between components, parent components, and the end node of an SKU. This network helped us visualize the BOM network and calculate metrics for our analysis. All the metrics mentioned from this point are visualized and calculated using this BOM network.

Table 1 shows all the metrics we calculated for the analysis and briefly describes them.

Table 1

Calculated Metrics

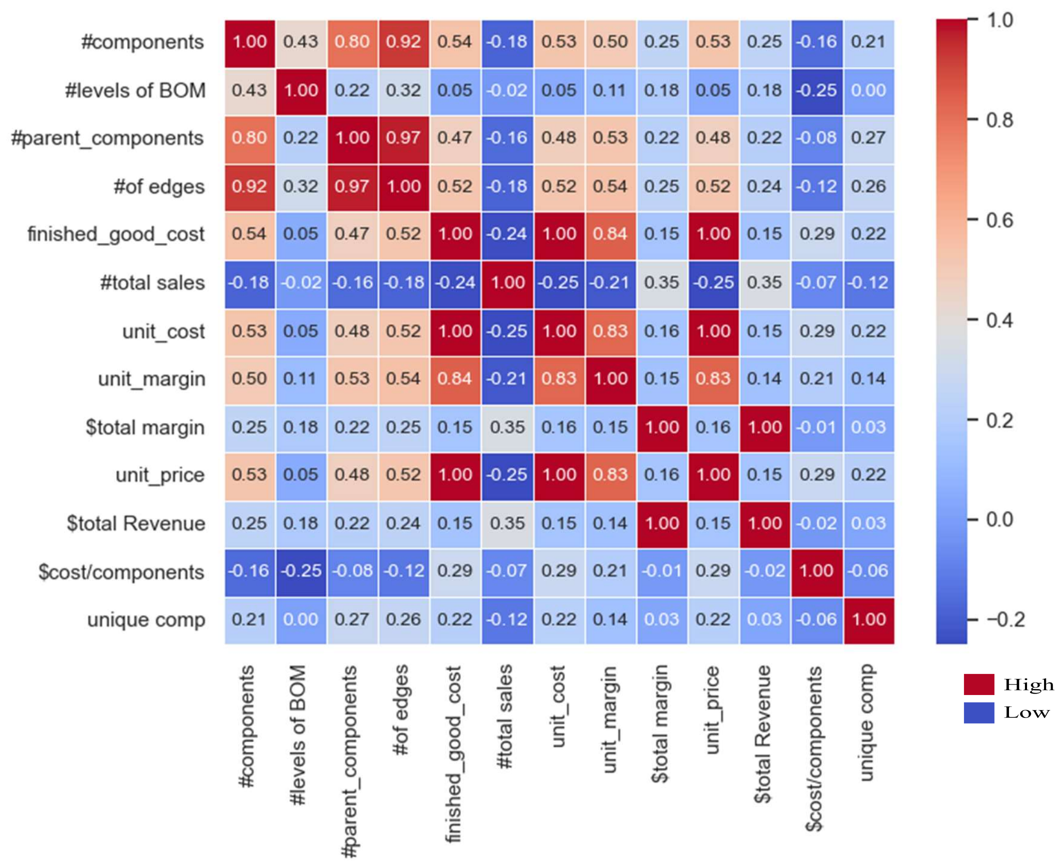
Metric Name	Description
Number of Child Components	A child component refers to the lowest-level individual parts or components that make up a larger assembly or product.
Number of Parent Components	The number of the highest-level components in a BOM that consists of other components or subassemblies
Minimum Clan Rank	The lowest rank among all the clans (groups of SKUs sharing a common component) to which the SKU belongs, with lower ranks indicating higher complexity due to the associated component's limited usage and low aggregated sales
Number of Unique Components	The number of components that are consumed by only 1 Finished Good
In-degree Centrality of Nodes	A ratio of the number of incoming edges, which are the connections between nodes, to the total number of nodes in the network
Out-degree Centrality of Nodes	A ratio of the number of outgoing edges to the total number of nodes in the network
Number of Edges	The direction of connection between components, parent-components, and end node of an SKU
Cost per Component	The individual cost of each component used in the manufacturing of a product

3.3 Analysis of Heatmap

As shown in Figure 4, we created the correlation matrix for all the complexity and financial metrics. The following heatmap shows the correlation among all the metrics. This heatmap is one of the key factors considered to finalize the complexity metrics used in our methodology.

Figure 4

Heatmap for Analyzing Correlation



3.4 Metric Selection

We calculated eight different complexity metrics that can be used for SKU rationalization but finalized three complexity metrics based on the correlation graph.

Table 2 gives brief reasons for choosing these metrics.

Table 2

Final Complexity Metrics for Analysis

Metric Name	Reason for Selection
Number of Child Components	It has a medium correlation with SKU cost metrics, is more interpretable than other metrics like out-degree centrality or cost per component, and is highly correlated with various complexity metrics such as the number of edges, parent components, and BOM levels.

Number of Unique Components	It identifies SKUs with inherent supply chain risks, such as low order volumes, potential supplier disinterest, and uncertain component availability, which can add complexity to the supply chain.
Minimum Clan Rank	It is a bottom-up approach that captures component-level complexity and translates it into an SKU-level metric, providing visibility into the most complex components within the BOM network.

Further, this section will explain the importance of all the metrics chosen and give the reasons in detail. We found the following three metrics helpful for our SKU rationalization purpose- number of child components, minimum clan rank for SKUs, and number of unique components in an SKU:

1. Number of child components

An SKU is composed of child components and parent components. Child components are at the bottom of the BOM chart and can be visualized as SKU's building blocks. Parent components are made up of child components.

We hypothesize that the greater the number of child components, the more complex an SKU is because the higher the number of child components, the more steps in manufacturing and assembly are involved. For example, an SKU with 50 components is more complex than an SKU with 20.

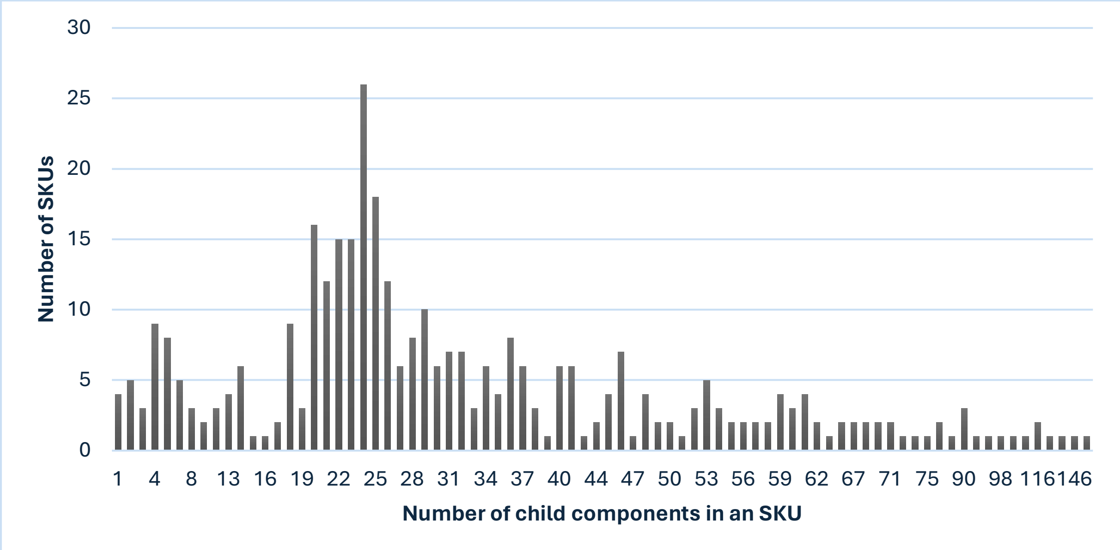
We chose the number of child components as crucial for our analysis for three main reasons:

- It has a medium correlation with the cost metrics of the SKU.
- It is more interpretable than metrics such as out-degree centrality, number of nodes, number of edges, cost per component, etc.
- It has a high correlation to many complexity metrics, such as the number of edges, the number of parent components, the level of BOM, etc.

Figure 5 shows the descriptive analysis of the number of SKUs vs. the number of child components. This capstone project focuses on SKUs with many child components to flag them for rationalization.

Figure 5

Number of SKUs vs Number of Child Components



2. Minimum Clan Rank for SKUs

This metric was calculated by analyzing the BOM network with a "bottom to top" analysis. We started our study from the component level and made conclusions at the SKU level. This analysis helped us capture the intricacies of the BOM network that cannot be visualized if we view the problem from the top level to the bottom level, i.e., if we explain the behavior of components by using metrics from the SKU level.

We have a total of 1,271 components in our BOM. We found two parameters linked to components that helped us analyze the BOM from the "bottom to top" approach:

1. Total number of SKUs that a component goes into.
2. Total aggregated sales of all the SKUs the component goes into.

We sorted the SKUs in ascending order using the above two parameters. We then arranged the components in order, where the component that goes into the lowest number of SKUs and has the lowest aggregated sales for those SKUs will be ranked higher than the components that go into a higher number of SKUs and have high aggregated sales for the SKUs linked to that component.

We introduced a new term called "clan" to simplify our metric calculation. We defined "clan" as a list of SKUs into which a particular component goes. The clan with a component that goes into the lowest number of SKUs and has the lowest aggregated sales for those SKUs is assigned a Rank of 1. We then calculate ranks from 1 to 1,271 for all the clans. Each clan can contain one or more SKUs, depending on how many SKUs the linked component goes into.

Since an SKU comprises one or more components, there can be repeated SKUs in different clans. Intuitively, the component linked to Rank 1 is a prime candidate for component rationalization, but our project is focused on SKU rationalization. From this analysis, we need to assign a number to each SKU that can capture its complexity. Hence, we decided to create our second important metric for our analysis: Minimum clan rank for each SKU.

We hypothesized that the SKUs ranked towards the top are the most complex ones. Accordingly, we picked the minimum clan rank an SKU is linked to as a complexity metric. We calculated the minimum clan rank for each of the SKUs. For example, an SKU with a minimum Clan Rank of 10 is more complex than an SKU with a minimum Clan Rank of 50.

The two main reasons to choose the minimum clan rank as a complexity metric are:

1. It is a bottom-up approach where component-level complexity is captured and translated into an SKU-level metric.
2. It provides visibility into the most complex components in the BOM network.

Figure 6 shows the clan rank linked with a list of SKUs in the column "Associated SKUs (CLAN)." For our analysis, we calculated the minimum clan rank linked to each SKU. Also, Figure 6 represents how many SKUs a component goes into and the clan to which it is linked.

Figure 6

Clan Rank linked to each SKU (A Sample from the Complete Table)

Component No	No. of SKUs	Associated SKUs (CLAN)	Total Sales	Clan Rank
7871676	2	7875493, 7857734	111	517
7871677	2	7875490, 7857733	222	518
7858402	2	7869481, 7869485	333	519
7855706	2	7869481, 7869485	333	520
7851840	2	7870571, 7814614	555	521
7851841	2	7870571, 7814614	555	522

7851818	2	7870571, 7814614	555	523
7851817	2	7870571, 7814614	555	524
7851839	2	7870571, 7814614	555	525
7861612	2	7869480, 7869481	666	526
N82509809394	2	OZ6147, 7814614	777	527
N82509809398	2	OZ6147, 7814614	777	528
N82509809391	2	OZ6147, 7814614	777	529
N82509809396	2	OZ6147, 7814614	777	530
N82509809392	2	OZ6147, 7814614	777	531

3. Number of unique components in an SKU

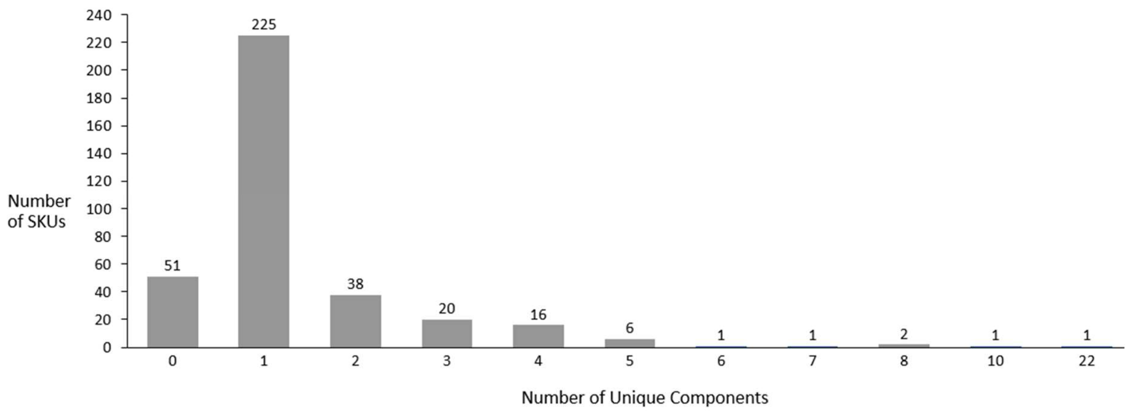
We used the number of unique components in an SKU as a complexity metric for our SKU rationalization because of the ease of understanding this metric. When the sponsor company's procurement team buys a component exclusive to a particular SKU, it adds complexity to the supply chain. If the volume ordered for that unique component is low, the supplier may look for another buyer. Alternatively, the supplier may not be incentivized to fulfill the order if that component represents a small portion of their revenue. There is always a risk attached when a product has a unique component, as the availability and supply of that component can be uncertain. Using the number of unique components per SKU as a complexity metric helps identify SKUs with this inherent supply chain risk.

We hypothesized that the more unique components an SKU has, the more complex it is. For instance, an SKU containing ten unique components would be considered more complex than one with only three unique components.

Figure 7 shows a bar graph for the number of unique components vs. the number of SKUs. It also shows that 225 SKUs have one unique component. Over 40 SKUs have more than four unique components, while 51 have no unique ones. Our capstone project focuses on SKUs with three or more unique components to flag them for rationalization.

Figure 7

Number of Unique Components vs Number of SKUs



The other complexity metrics that we calculated and did not use in our final procedure are as follows:

1. In-degree centrality of nodes (a ratio of the number of incoming edges, which are the connections between nodes, to the total number of nodes in the network). We did not use this because this metric is myopic and does not capture the complete complexity of the BOM network. It only considers the number of components directly attached to the end node of the SKU and leaves out the components that are not directly attached to that node.
2. Out-degree centrality of nodes (a ratio of the number of outgoing edges to the total number of nodes in the network) at the component level to find the number of SKUs linked to a component. This metric also suffers from the same drawbacks as in-degree centrality. Out-degree centrality only considers components that directly connect to a node and ignores the components that are not directly connected to the node. Also, it is not as interpretable as the number of components comprehensively capturing complexity.
3. The number of edges in an SKU's BOM is highly correlated with the number of components in an SKU; hence, only one of them was used, although this could also explain the complexity on its own.
4. The number of parent components in a BOM network is highly correlated to the number of child components. Hence, using the number of components as a complexity metric would be redundant.

5. Cost/component is a metric calculated based on the unit cost of an SKU and the number of components in that SKU. We did not select this metric for our methodology because, as seen in Figure 4, it is not correlated to any financial metric.

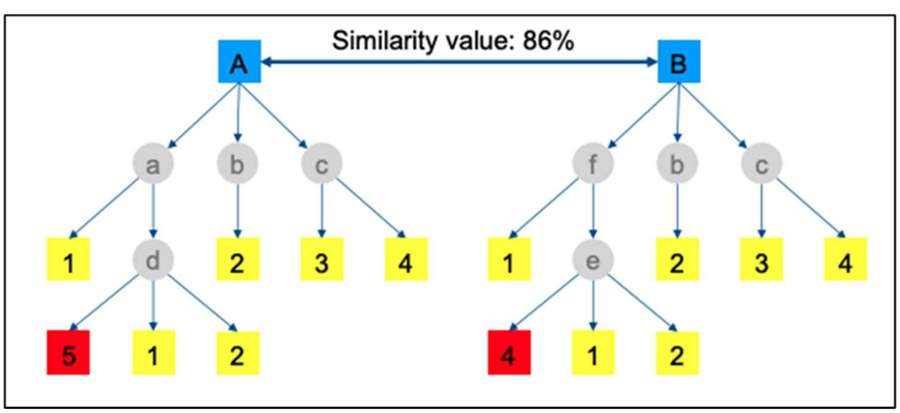
After analyzing the complexity metrics, we will now explain similarity metrics. Equation 1, “Similarity,” explains the calculation of the Common Parts Algorithm (CPA). It finds a score as a percentage that reflects how many unique components are shared between two SKUs.

$$Similarity = \frac{2 * Number\ of\ Common\ Parts}{Sum\ of\ all\ Parts} \tag{1}$$

Similarity value ranges from 0 to 1. A return value of 1 indicates that the two assemblies have the same parts, whereas a return value of 0 signals no shared parts. This comparison is automatically made once for each pair of assemblies. In Figure 8, the Similarity metric is applied to compare the two BOM tree structures, "A" and "B." Having six common parts (yellow) and 14 parts in total, the similarity is 0.86, or 86%. Parts that do not exist in both trees are highlighted in red. The grayed-out assembly nodes are not compared by the algorithm (Schmidt et al., 2017) because they are not the components that go into the SKU; instead, they combine two or more components. Hence, it is excluded to avoid redundancy in similarity calculations.

Figure 8

Similarity Calculation using CPA



Color	Detail
Yellow	Common Parts
Red	Uncommon Parts
Grey	Not a raw material

Figure 9 shows some of the results of similarity calculations using Equation 1. We have 390 SKUs that we are using to calculate the similarity between each pair of SKUs. Hence, we calculated 75,855 similarity value pairs for each SKU pair.

Figure 9

Similarity Values of SKU-Pairs (A Sample from the Complete Table)

sku1	sku2	similarity
7836803	7874586	0.984
7972263	7972264	0.977
7864648	8043720	0.975
8040697	8048363	0.974
7836806	7874591	0.974
7867983	7867984	0.971
7836804	7874640	0.970
8040690	8048286	0.969
7911583	7912895	0.969
10533	7993173	0.968
7969077	7972938	0.968
7836805	7874585	0.966
8002816	8048280	0.961
7837722	7847065	0.961
7967629	7967634	0.960
7836808	7874592	0.959
7851672	7937774	0.959
7818994	7821421	0.958
8061833	8210552	0.958
7886441	7904532	0.957
8061831	8229298	0.957
7828144	7828146	0.956
7851672	7911583	0.955

3.5 Final Procedure

Before we develop a final procedure, a rating system is needed to bucket SKUs for further analysis. Hence, during the SKU rationalization analysis, a rating system was used to categorize SKUs into groups based on key metrics. The rating system serves several vital purposes. Firstly, Newell Brands can sort their SKUs into buckets according to each assessed metric. Secondly, it provides a quantitative measurement to facilitate decision-making by assigning numerical ratings to each SKU. Lastly, the rating system helps standardize the review process and guide the analysis. Each SKU is assigned a rating from 1 to 5 for each criterion within the rating system. A lower rating indicates a reduced likelihood of the SKU being removed from the portfolio.

- **The rating system for financial metrics**

I. Total annual sales

For this financial measure, the SKUs with the higher annual sales figures were given lower ratings since the sponsor company prefers higher sales for an SKU in the portfolio. For our capstone purpose, the SKU with a higher rating is more likely to be removed than an SKU with a lower rating. Hence, we assigned lower ratings to SKUs with higher sales to lower the chances of those SKUs being removed from the portfolio.

To assign ratings to all the SKUs related to this financial metric, we arranged them in ascending order based on their total annual sales. We assigned Rating 1 to the 20% of the SKUs with the highest total annual sales. Similarly, we assigned Rating 5 to the 20% of the SKUs with the lowest total annual sales. We then assigned ratings to the rest of the SKUs, creating buckets of SKUs based on total sales figures.

Table 3 shows the number of SKUs for each rating based on the total annual sales.

Table 3

Number of SKUs in each Rating Bucket for Total Annual Sales

Ratings	Number of SKUs
1	74
2	72
3	72
4	72
5	72

II. Total annual margin

Like the criterion of total annual sales, higher values for total annual margin correspond to lower ratings. Specifically, the SKUs generating the top 20% of annual margins were classified as Rating 1, while those in the bottom 20% annual margin range were assigned a rating of 5. Table 4 illustrates the SKU distribution across each rating level, determined by their respective total annual margin performance. This rating system allows for a quantitative evaluation and comparison of SKUs based on their margin contributions.

Table 4

Number of SKUs in each Rating Bucket for Total Annual Margin

Ratings	Number of SKUs
1	74
2	72
3	72
4	72
5	72

- **The rating system for complexity metrics**

I. Minimum clan rank

The minimum clan rank metric measures the complexity based on two factors: the total number of SKUs a component is used in and the total aggregated sales of all those SKUs containing that component. It assigns a quantitative value to each SKU that measures complexity. The lower the minimum clan rank of an SKU, the more complex it is considered, as it contains components involved in fewer SKUs and is associated with lower sales volumes. The top 20th percentile of SKUs, characterized by the highest minimum clan rank values, were designated a rating of 1. This rating reflects a lower level of complexity associated with these SKUs. In contrast, the bottom 20th percentile of SKUs, exhibiting the lowest minimum clan rank values, were assigned a rating of 5, indicating higher complexity. The SKUs that did not fall into the top or bottom 20th percentiles based on minimum clan rank were grouped into separate buckets or segments, with the allocation determined by the minimum clan rank values within each bucket. Table 5 illustrates the number of SKUs in each rating bucket for minimum clan rank.

Table 5

Number of SKUs in each Rating Bucket for Minimum Clan Rank

Ratings	Number of SKUs
1	74
2	72
3	72
4	72

5	72

II. The number of child components

The rating system for the number of child components metric aims to capture the increased operational complexity of having more components. This complexity stems from challenges related to assembly processes, inventory management, and supplier management. However, segmenting the product portfolio based on this metric deviates from the previous methods. Assigning ratings solely based on percentile rankings could result in SKUs with an identical number of child components receiving different ratings, which would be an arbitrary distinction.

To address this concern, the rating assignment for the number of child components metric was based on defined ranges of component quantities. This approach ensured that SKUs with equal child components were consistently assigned the same rating. The specific rating criteria are explained in Table 6.

Table 6

Number of SKUs in each Rating Bucket for Number of Child Components

Ratings	Number of Child Components	Number of SKUs
1	1-18	71
2	19-23	61
3	24-29	80
4	30-46	77
5	47-149	73

III. The number of unique components

The rating system for the number of unique components in an SKU aims to capture the complexity that arises in supply chains due to the uniqueness of components. If a component is solely used in one SKU, then the order quantity will be less for that component, and our sponsor company will lose the leverage of buying in higher volumes. This leads to a supply chain challenge due to component shortages, posing a constant risk to their availability. This is due to the inability to onboard multiple suppliers for that component.

The distribution of SKUs in terms of unique components was not symmetrical in our data set. Hence, we used a rating system that was different from the one we used for other metrics. We assigned Rating 1 to the SKUs that have zero unique components, Rating 2 to the SKUs that have one unique component, Rating 3 for the ones with two unique components, Rating 4 for those with three unique components, and Rating 5 for the SKUs that have four or more unique components. The data in Table 7 indicates how many different SKUs received each rating level.

Table 7

Number of SKUs in each Rating Bucket for the Number of Unique Components

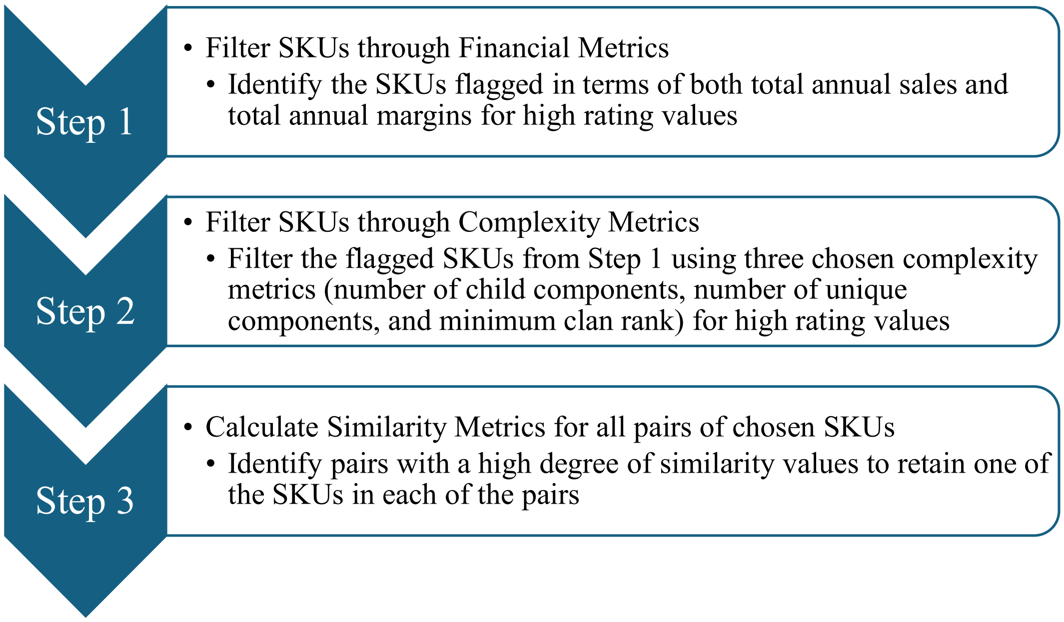
Ratings	Number of SKUs
1	51
2	225
3	38
4	20
5	28

- **3-step Procedure**

We finalized our procedure for SKU rationalization using the metrics chosen from the previous sections and the ratings developed for each SKU earlier in this section. Figure 10 provides an overview of the final procedure, which shows a three-step procedure for the SKU rationalization strategy.

Figure 10

Three-step Final Procedure for SKU Rationalization



Further, this section illustrates the three-step procedure in detail.

***Step 1*:**

We used the ratings derived from the financial metrics, namely, total annual sales and total annual margin, to identify a list of SKUs exhibiting low annual sales and low annual margin performance. This is the first filter through which all the SKUs were passed.

First, the SKUs were flagged as highly complex in terms of total annual sales and margins. Next, we found the SKUs flagged as highly complex regarding total annual margins. Further, we unified both lists and identified a list of SKUs flagged for SKU rationalization.

***Step 2*:**

We ran a second round of filtering on the flagged SKUs from Step 1. The complexity metric ratings were used to filter SKUs, and a list of SKUs characterized by high complexity for these metrics was flagged.

Three specific complexity metrics were selected: the number of child components, unique components, and the minimum clan rank of each SKU. The SKUs were filtered independently based on each of these complexity metrics. Those SKUs exhibiting high complexity values across all three metrics were identified and flagged for potential rationalization.

***Step 3*:**

We ran the third step on the SKUs flagged in step 2. The similarity metric for all pairs of SKUs after step 2 was used to identify pairs with a high degree of similarity based on the BOM analysis. This step further evaluated whether both SKUs within a similar pair should be rationalized or if one should be retained to maintain product portfolio continuity based on the business needs of our sponsor company.

After completing these three steps of evaluation based on financial, complexity, and similarity metrics, the final flagged SKUs are considered potential candidates for SKU rationalization, having filtered through the various screening criteria.

4. Results and Discussion

The procedure for SKU rationalization described in Section 3.5 was employed to execute multiple simulations by adjusting the filtering criteria at each stage of the procedure. Each simulation yielded a distinct set of SKUs identified as potential candidates for rationalization, contingent upon the predetermined business requirements that governed the selection of the filtering metrics. This adaptability in modifying the filters for the various metrics provides our corporate sponsor company the flexibility to tailor the procedure to their diverse business needs. This section presents a comprehensive illustration of the procedure's application employing a specific configuration of filters, accompanied by the results of executing multiple scenarios.

As an illustrative case, consider the scenario presented in Table 8, where the first filtering step identified SKUs based on their total annual sales or total annual margin, achieving a rating of 5. The second step filtered SKUs contingent on each complexity metric scoring 4 or above. The third phase involved calculating similarity values between each pair of these six SKUs, as shown in Table 9. An examination of Table 9 indicates that none of the rationalization candidate SKUs exhibited extremely high similarity, with all pairwise values below 0.90. Consequently, based on the criteria defined in this scenario, the recommendation is to eliminate the six SKUs listed in Table 10.

Table 8

Sample Rating Criteria Filter for SKU Rationalization

Name of metric	Total Annual Sales	Total Annual Margin	No of the child components	Minimum Clan rank	The number of unique components
Rating	Either one of them 5		4 and above	4 and above	4 and above

Table 9

Similarity Value Comparison for Flagged SKUs for Rationalization

SKU1	SKU2	Similarity value
7874590	5348	0.70
7829158	7829156	0.60
7829158	8014518	0.54
7829156	5348	0.51
7874590	7829156	0.46
7818905	5348	0.42
7818905	7874590	0.41
7829156	8014518	0.40
7818905	7829156	0.34
7818905	8014518	0.09
7818905	7829158	0.09
7829158	7874590	0.07
7829158	5348	0.07
8014518	5348	0.07
7874590	8014518	0.06

Table 10

List of SKUs Flagged for Rationalization

SKU No.	Sales Rating	Margin Rating	Child comp. Rating	Unique Comp. Rating	Clan Rank Rating
7818905	5	5	5	5	5
7829158	5	5	5	4	5
7874590	5	4	5	5	4
7829156	5	3	5	5	4
8014518	5	3	5	5	4
5348	5	3	5	5	4

Table 11 presents the results of different scenarios run using the three-step procedure for SKU rationalization. The SKUs flagged in each scenario are listed in Appendix A.

Table 11

Results From Different Scenarios

Scenario Number	Total Annual Sales Rating	Total Annual Margin Rating	The Number of the Child Components Rating	Minimum Clan Rank Rating	The Number of Unique Components Rating	Number of SKUs Flagged
1a	5	5	5	5	5	1
1b	Either one of them 5		4+	4+	4+	6
1c	Either one of them 5		3+	3+	3+	11
2a	Either one of them 5		5	5	Not considered	5
2b	Either one of them 5		4+	4+	Not considered	29

From Table 11, we conclude that as we relaxed the ratings for filtering SKUs, more and more SKUs were recommended for rationalization. Our sponsor company can use this procedure and results to rationalize SKUs based on their business needs. They can keep tighter ratings as filters to remove fewer SKUs. In contrast, if they want to remove a significant number of SKUs, they can relax the filters and get the most appropriate list for rationalization.

For scenarios 2a and 2b, we have excluded the number of unique components as a factor in this scenario. This helped us explore which SKUs are recommended for rationalization if we do not factor in the number of unique components. This approach to SKU rationalization can be practical when the number of unique components is not a critical factor in determining complexity or when the organization has a relatively standardized product portfolio with fewer unique components. By focusing on the financial and complexity metrics of clan rank and the number of child components, the organization can still identify and rationalize unprofitable SKUs that contribute to operational complexity.

5. Conclusion

Companies strive to optimize their product portfolios and streamline operations to maintain a competitive advantage in today's highly competitive business landscape. This pursuit is particularly crucial for consumer-packaged goods (CPG) companies like Newell Brands, which offer diverse consumer-oriented brands spanning multiple product categories. As companies expand their product offerings, they often face increased complexities in managing supply chains, forecasting demand accurately, and maintaining operational efficiency. The proliferation of SKUs can lead to higher costs, extended lead times, and stockouts, ultimately affecting profitability and customer satisfaction. Recognizing these challenges, our sponsor company, Newell Brands, initiated multiple SKU rationalization initiatives in the past to identify and eliminate redundant or low-performing SKUs based on financial metrics, enabling them to focus their resources on high-value offerings.

Motivated by this pressing need, the primary objective of this capstone project was to formulate a strategy for SKU rationalization for our sponsor company using financial metrics and metrics derived from bill of material (BOM) analysis. Our approach centered around developing a robust methodology that integrated financial metrics, namely total annual sales and total annual margin, with complexity metrics derived from the BOM analysis. These complexity metrics, including the number of child components, minimum clan rank, and the number of unique components, provided critical insights into the intricacies of Newell Brands' product offerings.

A salient strength of our methodology lies in its adaptability and capacity for customization. By integrating these diverse metrics into a rating system, we established a quantitative framework for evaluating and comparing SKUs across multiple dimensions. Through a three-step procedure for SKU rationalization, we demonstrated how Newell Brands can modify the filtering criteria based on their specific business priorities and desired outcomes. This flexibility helps our sponsor company tailor the SKU rationalization process to align with their strategic objectives, prioritizing profitability, reducing operational complexities, or striking a balanced approach considering financial and operational considerations.

Section 4 illustrates the practical application of our methodology through various scenarios. By progressively relaxing the filtering criteria, we showcased how the number of SKUs identified for potential rationalization can be varied, enabling Newell Brands to make informed decisions based on their risk appetite and resource allocation strategies. This versatility ensures that the proposed approach remains relevant and valuable regardless of the company's evolving business landscape or shifting market dynamics.

The capstone project has delivered an adaptable framework for SKU rationalization tailored to Newell Brands. The principles and techniques outlined in this study can be extended to other organizations grappling with similar challenges, making it a valuable contribution to supply chain management and product portfolio optimization. Ultimately, this capstone project empowers companies like Newell Brands to tackle the complexities of product proliferation, enabling them to maintain agility, responsiveness, and a competitive edge in their respective industries.

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Appendix A

Scenario 1a results

Flagged SKU No.	Sales Rating	Margin Rating	Child comp. Rating	Unique Comp. Rating	Clan Rank Rating
7818905	5	5	5	5	5

Scenario 1b results

Flagged SKU No.	Sales Rating	Margin Rating	Child comp. Rating	Unique Comp. Rating	Clan Rank Rating
7818905	5	5	5	5	5
7829158	5	5	5	4	5
7874590	5	4	5	5	4
7829156	5	3	5	5	4
8014518	5	3	5	5	4
5348	5	3	5	5	4

Scenario 1c results

Flagged SKU No.	Sales Rating	Margin Rating	Child comp. Rating	Unique Comp. Rating	Clan Rank Rating
7818905	5	5	5	5	5
7829158	5	5	5	4	5
7874583	5	5	4	3	5
H9231719	3	5	3	3	4
7874590	5	4	5	5	4
8166058	5	4	4	3	4
7829156	5	3	5	5	4
8014518	5	3	5	5	4
5348	5	3	5	5	4
7851677	5	4	5	3	3
7831336	5	3	5	5	3

Scenario 2a results

Flagged SKU No.	Sales Rating	Margin Rating	Child comp. Rating	Clan Rank Rating
7818905	5	5	5	5
7829158	5	5	5	5
7815405	5	5	5	5
7837184	5	5	5	5
7837185	5	5	5	5

Scenario 2b results

Flagged SKU No.	Sales Rating	Margin Rating	Child comp. Rating	Clan Rank Rating
7818905	5	5	5	5
7972810	5	5	5	4
7829158	5	5	5	5
7829150	5	4	5	4
8014383	5	5	5	4
7815405	5	5	5	5
8048970	5	5	5	4
7819372	5	4	4	4
7874583	5	5	4	5
7861525	5	5	5	4
7836805	5	5	5	4
7874590	5	4	5	4
7864648	5	4	5	4
7819373	5	5	4	5
7836807	5	5	4	4
7837184	5	5	5	5
7828144	5	5	4	5
8166058	5	4	4	4
7814618	5	5	4	4
7899087	5	5	4	5
7837185	5	5	5	5
7904553	5	5	4	5
7814660	4	5	4	4
7829156	5	3	5	4
8040685	4	5	4	4
7907596	5	4	4	5
7847656	4	5	4	4
8014518	5	3	5	4
5348	5	3	5	4