Quantifying packaging material complexity to improve portfolio management

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ABSTRACT

Product portfolio complexity poses a significant challenge for many consumer packaged goods (CPG) manufacturers, resulting in higher costs, risks, and production time. This work aims to assist the sponsor company in managing and measuring its complexity and determining the financial impact of delisting complex SKUs. We used a four-phase methodology involving data collection and mapping, analytics, complexity analysis, and financial analysis to achieve this. The complexity analysis was applied to the primary and secondary packaging for a variety of product SKUs using the commonality index metric, which indicates the frequency of components present in an SKU. We then connected this metric with aggregated and granular financial metrics to identify the relationships between complexity and costs. Our results showed that SKUs with a low commonality index exhibit an average total cost 40.8% higher than those with a high commonality index. Additionally, our results found that SKUs with a low commonality index had a packaging materials cost that was 105% greater than SKUs with a high commonality index. Therefore, modifying specific SKU components with low commonality makes cost savings possible. We suggest using the commonality index and aggregated and granular financial metrics as a guideline for delisting and introducing new products to effectively manage and reduce supply chain complexity in the CPG industry.

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1. INTRODUCTION

Many businesses are struggling with portfolio complexity, resulting from globalization and the growing demand for customized offerings. This complexity is often costly, but difficult to identify due to the lack of accounting transparency around niche offerings and products with small sales quantities. This leads to poor decisions and investments, as companies may not be aware of the true costs of their specialized product configurations (Bannasch & Bouché, 2016).

Adams et al. (2016) state that "complexity among food-and-beverage manufacturers...is costing them as much as $50 billion in gross profit in the US market alone". Much of this complexity is driven by increased product assortment in a manufacturer's portfolio. Adding a new product to the portfolio, while potentially beneficial to meet customer demands, may also lead to operational challenges such as warehousing constraints, co-manufacturing needs, or profit cannibalization for other stock-keeping units (SKU). While companies acknowledge the problem, traditional approaches to portfolio simplification, such as cutting the lowest-volume SKUs, can produce unintended downstream consequences. Companies need to find ways to reduce complexity without negatively impacting their strategic assortment (Adams et al., 2016).

This project's sponsor company is a consumer packaged goods (CPG) manufacturer that maintains a 38.6% market share in their sector and produces over 500 iconic brands (NBWA, 2022). Our project aims to help the sponsor company measure complexity and manage its product portfolio and quantifying the financial impact of delisting complex stock-keeping units (SKUs).

The company actively delists materials that experience low or declining profitability; however, the financial business case for this action can be challenging. This process is constantly evaluated as the company releases innovative products and develops growing brands. The project focuses on measuring financial and operational complexity in the primary and secondary packaging SKUs within the European core portfolio. The team will identify critical cost drivers to reduce complexity and improve profitability. The deliverable will be a methodology that measures product complexity in terms of component uniqueness and relevant costs, such as production, primary warehousing, and transportation, thus enabling the sponsor company to build stronger business cases and improve decision making for portfolio management.

1.1. Motivation

Supply chain complexity is a major problem for many CPG manufacturers. The CPG industry is constantly launching new products to win shelf space and capture growth, particularly in fast-growing regional markets. However, manufacturing more SKUs leads to increased complexity in the supply chain, which can be a significant challenge for CPG companies already under pressure to cut costs and improve efficiency. This complexity includes increased costs, risks, and production time throughout the supply chain, making it crucial for CPG companies to find ways to manage and reduce complexity while continuing to innovate and capture new markets (Adams et al., 2016).

In the case of the sponsor company, complexity issues arise in their production facilities, given that high product variety contributes to an increase in cost and overall production time. Production capabilities depend on a large number of upstream suppliers being able to successfully fulfill their orders in a timely manner. Additionally, introducing innovative products often means adding new raw materials, packaging materials, and supplier relationships. For that reason, the company tries to limit the increase of new product components by relying on their in-house or vertically integrated production capabilities. However, sales and marketing do not always consider all downstream operational impacts (inventory, production, distribution) when releasing a product to a new market segment.

The company has developed for all their products a circular continuous-improvement process managing complexity that involves three main phases: a) prevent complexity, b) create transparency, and c) reduce complexity. The prevent complexity phase focuses on developing component and product launch rules, ensuring that cross-functional teams keep complexity prevention in mind. The create transparency phase aims to create visibility in the supply chain to identify key complexity drivers by understanding the components and dependencies for their finished goods. Finally, the reduce complexity phase seeks to eliminate unique or poorly performing products from the portfolio in order to add value to customers and maintain strategic priorities. Currently, the sponsor company measures complexity by using its key performance indicator (KPI), margin after cost of operating (MACO), which is then paired with supply chain losses (SCL) to capture aggregated cost totals related to keeping a product in their portfolio. However, MACO and SCL do not holistically capture all production costs and trade-offs stemming from the opportunity cost of producing a different SKU with their available capacity. To realize the opportunity cost of manufacturing another product, the companies should conduct a granular cost-to-serve analysis focused on individual bill of materials (BOM) components to better understand the impact of customization and the cost profile of each product rather than distributing component costs across the entire portfolio (Bannasch & Bouché, 2016).

1.2. Problem Statement and Scope

We work with the company's portfolio management, procurement, production, and global logistics teams to solve the main research questions: *How can the sponsor company measure complexity and manage its product portfolio? What is the financial impact of delisting complex* *stock-keeping units (SKUs) from the core portfolio?* The team will focus on measuring the economic complexity of the primary and secondary packaging SKUs since they account for a significant percentage of the total costs and add complexity to the production processes. The sponsor company specifically chose to focus on primary and secondary packaging for this analysis, given that these components represent a major driver in component variety, cost, and lead time. For instance, simplifying packaging configurations can lead to cost savings and shorter lead times, thus improving production efficiency. The project was scoped within the core portfolio of their European region, which is composed of Belgium, Netherlands, France, and Luxembourg. This region was selected because it includes several major production facilities and maintains accurate and accessible data.

We will examine two main complexity perspectives: operational and financial. The main financial KPI our team will analyze is MACO. MACO can be viewed as a product's gross margin multiplied by its production volume in hectoliters (HL). The sponsor company considers a reduction in SKUs with low MACO (whether via material reduction or production efficiency) as cost savings, thus improving profitability for each product line. For this reason, MACO will serve as a baseline for our analysis. However, we believe this can be augmented by examining granular costs at the BOM component level. As mentioned previously, the complexity management process of the sponsor company focuses on three main phases: prevention, transparency, and reduction. In this analysis, our primary focus will be on the reduction stage. However, we will develop a methodology that offers operational and financial insights into the existing complexity. This approach will also enhance the sponsor company's understanding of existing complexity during the prevention phase, enabling them to adopt a proactive approach rather than a reactive one.

1.3. Project Goals

The proposed methodology for this project is first to analyze datasets related to the company's production, materials and resource costing, packaging, supply chain design, suppliers, warehouses, and distribution channels. These data will enable us to better understand production volumes, production costs, customer demand, and how each contributes to complexity from a cost-to-serve perspective. We believe that complexity's operational and financial impacts can be measured with a Commonality Index (CI) derived from a Compatibility Matrix built using the company's bill of materials. The next step is to match product components with associated costs to quantify the cost of material complexity for both unique and standard components. Our team developed a cost comparison analysis for a provided subset of high-performing and poorly-performing SKUs to develop a more robust analysis beyond a MACO comparison utilizing cost data and our commonality index. Ultimately, our team aims to help quantify the financial opportunity of delisting SKUs with low degrees of component commonality and profitability.

The outcome is a methodology that measures product complexity regarding component uniqueness, enabling the sponsor company to make managerial decisions around the estimated profitability and material complexity. The upcoming methodology chapter (Chapter 3) will discuss the steps we deployed to develop these insights and the results achieved after each milestone (Chapter 4). These chapters will explain the development of our commonality index metric and the key finding that products with low commonality index scores have a total average cost that is 40.8% greater than products with high commonality index scores. Additionally, our discussion chapter (Chapter 5) will discuss management recommendations relative to different profitability scenarios and future research that can be realized with more granular data. Ultimately, we anticipate that this information will help our sponsor company make more robust portfolio management decisions by pairing financial outcomes with measured operational complexity.

2. STATE OF THE ART

To address the research questions, this study proposes a methodology to measure complexity from an operational perspective and integrates the decision-making process with financial metrics. To develop this methodology, we have reviewed literature in the following areas: (1) the drivers of supply chain complexity and portfolio proliferation; (2) methodologies to measure portfolio complexity; (3) methodologies to reduce portfolio complexity; and (4) methodologies to measure the cost to serve within the supply chain accurately.

2.1. Drivers of Supply Chain Complexity and Portfolio Proliferation

A supply chain is a complex network of business entities exchanging products/services, information, and money (Serdarasan, 2013). Supply chain complexity is a problem many industries face and is caused by various factors. According to Adams et al. (2016), complexity can be positive or negative. Positive supply chain complexity can lead to a diverse product assortment that meets the needs of various customer segments. Whereas negative supply chain complexity often creates stress on production and operations. In these negative scenarios, complexity often "erodes profit, increases inventory, and [creates a less agile supply chain]" (Adams et al., 2016). While firms aim to gain a competitive advantage by creating efficiencies within their network, complexities often arise that negatively impact their operations and financial performance (Serdarasan, 2013).

Zhang et al. (2019) also discussed positive and negative complexity regarding commonality and distinctiveness. Commonality refers to the reuse of assets across product families, whereas distinctiveness refers to having unique components used for one product in a product family to meet customer demand better and stand out in the marketplace. The commonality is linked to strategies for improving a firm's profitability by lowering costs; however, manufacturing costs will likely increase if too many products are distinct (Zhang et al. 2019). This idea proposes that firms evaluate the trade-off between commonality and distinctiveness when making portfolio management decisions considering product attractiveness and manufacturing efficiency.

The operational complexity drivers, as discussed by Serdarasan (2013), resulting from portfolio growth can be classified into three main categories: (1) static complexity; (2) dynamic complexity; and (3) decision-making complexity). Static complexity is driven by a business's operational limitations, which constrain the flexibility of supply chain networks, such as the number of production lines or inventory capacity. Dynamic complexity refers to the reactions to randomness or unpredictable consumer behavior a business aims to serve. Finally, decision-making complexity comes from the interaction between static and dynamic complexity when a human has to intervene and make a business decision (Serdarasan, 2013). Decision-making complexity is often amplified when the ultimate goal of a business differs across departments. For instance, sales and marketing may want to introduce a new product category to meet an emerging market segment. However, a new product category often leads to an increase in machine downtime, change over time, and lower production yields.

The financial complexity driven by portfolio growth is often hidden when adding a new product/service. Bannasch and Bouché (2016) described a case when a manufacturing executive pushed to manufacture a new product claiming it would reduce costs by 10%, yet in reality; the venture increased the firm's cost by 20%. In order to fully evaluate the actual cost of portfolio expansion, the authors suggest that a firm must deep dive into their financials and granularly assess the cost profile of each individual component before considering the addition or removal of a new SKU.

Since our project works with a global manufacturer, who often adds new products to their portfolio, we focus on measuring and reducing the negative impact of static complexity connected to these additions. This will be done by quantifying the operational and financial costs of adding new products to the portfolio.

2.2. Methodologies to Measure Portfolio Complexity

Portfolio proliferation is a pain point felt by many firms across several industries, given that it is difficult to quantify and manage. SKU proliferation leads to inflated portfolios composed of products with poor performance, yet the profit margin by SKU does not tell the whole story. Trattner et al. (2019) suggest that product complexity metrics can be classified into five categories: (1) structural metrics, (2) composite metrics, (3) demand distribution measures, (4) production measures, and (5) product customization (Trattner et al., 2019). This research focuses on structural and composite product complexity, given that these categories contain single and multi-dimensional metrics relevant for product portfolio complexity measurement. We also examine operational and financial methodologies to quantify portfolio complexity.

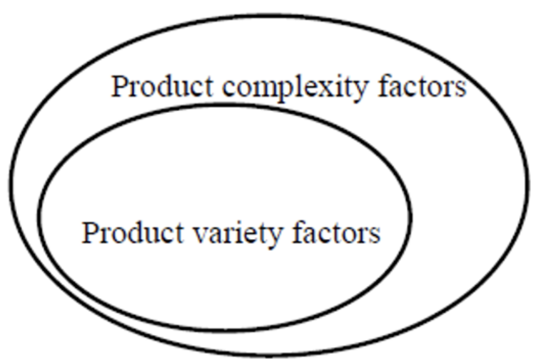
Structural product complexity comprises single-dimension metrics such as product variation (SKUs) and components (Trattner et al., 2019). Structural metrics are often used as a variant that quantifies the impact of product complexity in operational performance metrics such as inventory levels (Wan & Sanders, 2017) and risk for disruption (Inman & Blumenfeld, 2014). An analysis conducted by Wan and Sanders (2017) determined that over time, a higher product variety, or an increased SKU level, leads to greater forecast bias and higher inventory levels.

During this time, the firm used the same forecasting methods and software, yet their results led to a significant increase in the level of held inventory. This analysis shows how structural product complexity, or a single metric (i.e., number of SKUs), can help uncover underlying product complexity factors (See Figure 1).

For this project, we care about two metrics: SKU variation and component variation, given that they are correlated (Sun, 2005) and directly impact the company's innovation goals and portfolio mix. Measuring SKU variation and component variation will ultimately give the sponsor company a better understanding of the products and associated components they will delist into their decomplexity initiatives or add when introducing a new product to their portfolio.

Figure 1

Relationship Between Product Complexity and Product Variety



Note. Product variety factors help uncover deeper product complexity factors. From "Manufacturing System and Supply Chain Analyses Related to Product Complexity and Sequenced Parts Delivery," by Sun, H, 2005, [Doctoral dissertation, University of Tennessee – Knoxville]. Tennessee Research and Creative Exchange. https://trace.tennessee.edu/utk_graddiss/2297/

Composite product complexity is composed of multi-dimensional metrics such as component variability (Trattner et al., 2019) or the Generalized Complexity Index (GCI), as suggested by Jacobs (2013). The Generalized Complexity Index (GCI) considers three dimensions: (1) multiplicity, (2) diversity, and (3) interrelatedness of elements in a product line. Multiplicity refers to the number of different SKUs, while diversity is the degree of difference among those SKUs. Interrelatedness is the interacting functions or processes among elements. The GCI is calculated by multiplying the measures of the previously measured dimensions. By mapping product portfolios with an unbiased metric, such as GCI, decisions can be made to optimize product configurations.

Zhang et al. (2019) discussed measuring portfolio complexity in terms of commonality and distinctiveness. Measuring commonality involves developing a commonality index that quantifies the number of shared BOM components across products in the same product family. In turn, distinctiveness is considered low commonality or components unique to specific products. This process is taken a step further by applying weights to component types that have been identified as drivers of complexity to ensure that their commonality is properly represented in the overall product commonality index (Zhang et al. 2019). Zhang et al.'s commonality index methodology will be particularly useful in measuring the sponsor company's portfolio complexity from an operational perspective.

2.3. Methodologies to Reduce Portfolio Complexity

Many firms first look to a Pareto analysis and aim to cut the tail, removing the SKUs with the lowest profit or volume, but this can often lead to unexpected downstream consequences such as increasing the per-unit cost of adjacent items made on the same production line or eliminating a complimentary portfolio item (Adams et al., 2016). Portfolio simplification must be a cross-functional effort where operations, finance, and marketing are aligned to a common goal centered on explicit metrics (Yu, 2016). When deciding which SKUs to delist, the cross-functional team needs to consider the peripheral supply chain impacts that removing certain SKUs may cause. According to Yu (2016), "It is also important to evaluate [how removing an SKU may] contribute to complexities, such as changeover, failures, scrap, unique material, and packaging format." To properly conduct this process, there are two main steps: (1) formulate a qualitative complexity analysis process to identify SKU reduction candidates and (2) quantify the potential additional complexities and cost or operational improvements that may result from removing that SKU.

According to Staskiewicz et al. (2020), a simple Pareto analysis "tends to be a one-time event… [and] does not address the supply chain complexity [or] operational performance." To achieve a true complexity reduction outcome, they proposed a two-phase process: (1) an "AS-IS" analysis and (2) a "TO-BE" design. The AS-IS analysis is centered around "analyzing product variety, costs, delivery performance, quality, and other performance data from production and assembly for each product family." This allows for developing a robust understanding of the peripheral factors that drive value and cost at the product family level. Aggregating to a product family level rather than an SKU level allows for portfolio decisions within the category, ultimately minimizing any product variety erosion.

Additionally, the TO-BE design process can be appropriately evaluated after this analysis. The TO-BE design phase consists of two main steps: (1) identify possible SKU reduction initiatives and (2) select an SKU reduction initiative. Ultimately Staskiewicz et al.'s (2020) work serves as a framework for process designs that take thorough analysis and managerial design decisions into account.

When discussing reducing complexity, several works use clustering analysis for product variety management and portfolio de-complexification, employing basic structural or composite metrics. Hochdorffer et al. (2017) developed a methodology that groups products with similar production requirements, mapping each product variety and assigning a binary variable to the production systems required. This produces a matrix of distances, including all products and production technologies, representing differences between pairs of product variants. Finally, an algorithm runs that groups products with similar requirements into a cluster to determine a core set of materials and products.

Moon et al. (2006) proposed a method to cluster products based on functional features and integration rules, therefore determining common production abilities, or modules, that could be used as a starting point for future product designs. Dai and Scott (2007) highlighted using clustering for product platform optimization. Their method involves grouping standard platform product components into clusters to optimize product configurations. However, a technique to measure or reduce complexity is incomplete if it is not connected to the impact it may have on performance. Therefore, the following subsection discusses how to calculate the cost of complexity.

2.4. Methodologies to Quantify Costs of Complexity

Many firms use activity-based costing (ABC) to allocate production costs to their products at various stages of the manufacturing process. Thyssen et al. (2005) examined the use of ABC to assess the economic benefits of modularization. Modularization breaks down a more extensive cycle into smaller "modules" that can easily be switched, managed, and cost. They argued that modularization could lead to significant cost savings, but these benefits are difficult to quantify using traditional cost accounting methods. Yet, ABC provides a more accurate and detailed process for measuring the costs and benefits of modularization. Under this model, ABC provides a detailed understanding of the actual cost of a process and ultimately allows for better decision-making.

Activity-based costing is relevant because it aims to assign costs per unit based on the manufacturing or production activities associated with each SKU (Minjares, 2008). According to Mejía-Argueta et al. (2015), cost-to-serve is another way to consider financial impact. Cost to serve is a metric based on a 12-step process of evaluating the company's financial statements and obtaining a detailed ABC that analyzes the impact of logistics and commercial operations. Cost-to-serve is a more suitable metric than net margin because net margin does not consider commercial and logistics costs that can increase with complexity. Also, cost-to-serve methodology suggests integrating the metric into a multi-criteria decision-making process that considers qualitative aspects, such as the product life cycle and strategic goals.

In addition to ABC costing and cost-to-serve analysis, den Hartog (2012) suggests that a sensitivity analysis can be conducted to measure the Portfolio Value of a Product (PVP) to determine if the added complexity of a new SKU is profitable or costly. PVP is calculated by subtracting the Total Portfolio Value (TPV), which is Total Received Benefits (TRB) - Total Invested Resources (TIR), for the portfolio with and without a given product. The delta of those two values will determine the value added for the given SKU in focus (den Hartog, 2012). This practice may be especially relevant for the sponsor company, given that their current delisting metric is driven off margin by SKU before operational cost. With this information, determining a

PVP for various SKUs will be beneficial for understanding the impact of removing Total Invested Resources and Total Received Benefits before making a delisting decision.

Companies can reduce complexity when any financial metrics are combined with postponement or modularization. Modularization examines process steps individually, simplifying the scope when gathering resource input costs. Thyssen et al. (2005) used ABC to analyze the costs associated with the traditional versus modular approach in a manufacturing company case study. The case concluded that the modular approach was more cost-effective due to reduced overhead and setup costs and create opportunities to eliminate inefficient process steps.

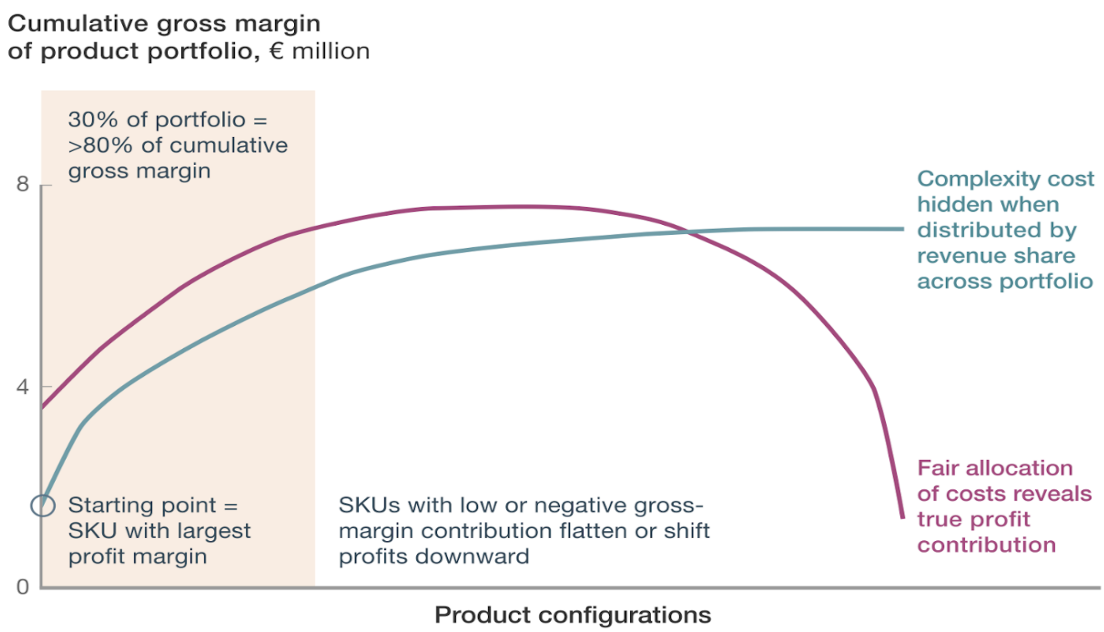
In addition to modularization, Zheng & Abu (2019) discussed using ABC costing to derive an accurate view of Malaysian palm oil production. As the dependence on Malaysian palm oil grew, it became increasingly important for the government to accurately capture the costs associated with production and better understand the amount of profit realized. Even though the authors did not consider complexity in the framework, they used data to cost each manufacturing process step, create insights, expose process inefficiencies to leadership, and calculate accurate profitability figures.

Bannasch & Bouche (2016) use a fair allocation of cost (similar to ABC costing) rather than a traditional cost approach (allocating costs relative to revenue generation), enabling leadership to understand portfolio costs of complexity better. Using a conventional approach to low-margin items hides the actual cost of production in the financials of high-margin items, which creates a distorted picture of portfolio profitability. When using an ABC or another costing method, leaders can realize the actual cost and true margin of all products in their portfolio. Ultimately this can better enable portfolio management and decision-making. This idea is well illustrated in

Figure 2, where the gross margin curve with the traditional costing method is flattened towards the tail. However, the gross margin sharply dips using a fair cost allocation approach. The sharp dip in gross margin is due to the allocation of actual production cost per SKU, which enables leadership to understand true per-unit profitability.

Figure 2

Complexity Costs Distributed by Revenue vs Fair Allocation

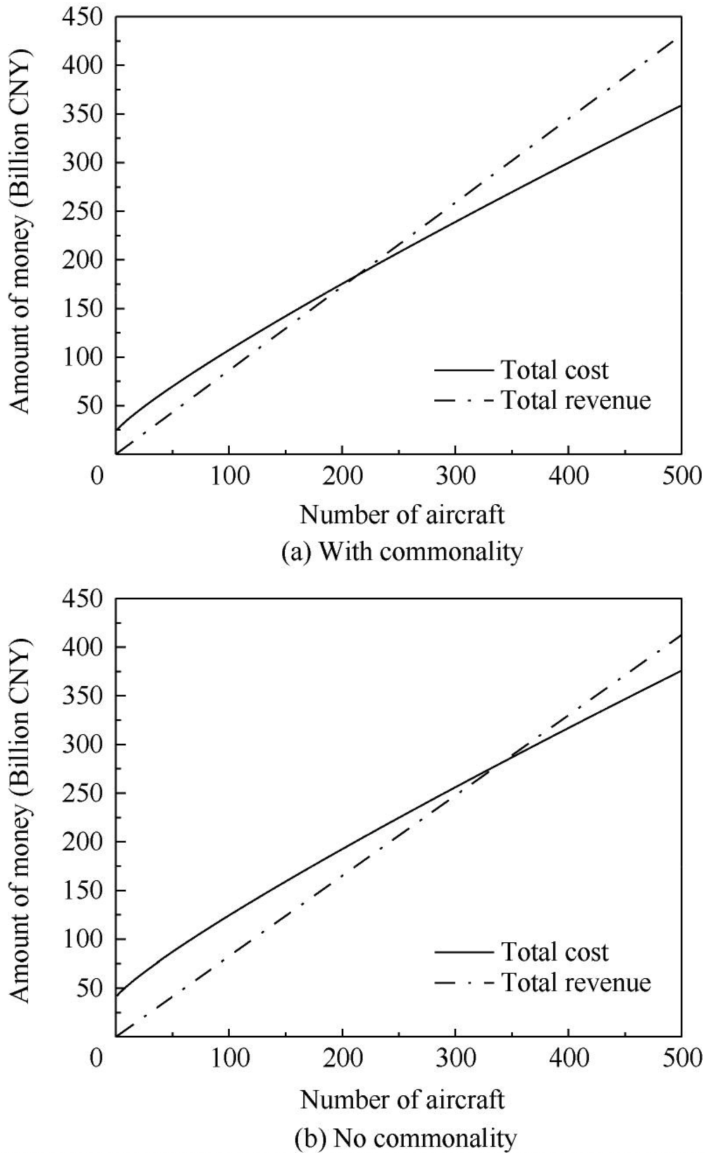


Note. Fair allocation of costs reveals true margin per product compared to a distributed cost model. Adapted from "*Finding the true cost of portfolio complexity*," by Bannasch, F., & Bouché, F. (2016, September 19), Mckinsey & Company. https://www.mckinsey.com/industries/automotive-and -assembly/our%20insights/finding-the-true-cost-of-portfolio-complexity

In addition to ABC costing, Zhang et al. (2019) examined commonality metrics across aircraft manufacturing components and assigned costs to each element to quantify the costs of materials complexity. This study involved the development of a commonality index that quantifies which parts are shared across product lines and product families. After examining associated product costs, the research showed that parts with a high degree of commonality were less cost intensive to the aircraft design and manufacturing process when compared to parts that were unique across product lines. Zhang et al.'s (2019) work serves as a model for value comparison beyond raw material costs, given that it also considers the material's compatibility to produce additional products in other product families. Furthermore, it was found that products with commonality have a lower cost, higher margin, and lower break-even volume when compared to products without commonality (see Figure 3).

Figure 3

Break-Even Analysis for Products with and without Commonality



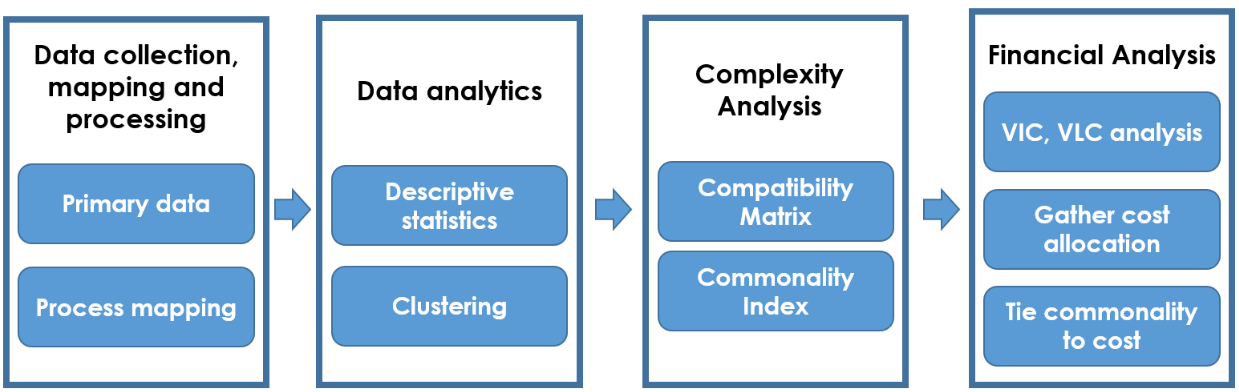
Note. Products with commonality had a lower breakeven point compared to products without commonality. From "Exploration and implementation of commonality valuation method in Commercial aircraft family design," by Zhang, Y. et al. (2019), *Chinese Journal of Aeronautics.* https://doi.org/10.1016/j.cja.2019.05.005.

3. METHODOLOGY

After reviewing the information gathered in the State of the Art, the methodology for measuring and reducing complexity at the sponsor company will be structured in four main phases (see Figure 4). The first phase involves data collection, mapping, and processing, the second phase focuses on analytics, the third phase is about developing a complexity analysis, and the fourth phase focuses on financial analysis.

FIGURE 4

Methodology Process



3.1. Phase 1: Data Collection, mapping, and processing

Our methodology begins with gathering data to gain insights into manufacturing processes, stakeholder interactions, and policies. This involves collecting information from four sources: (1) the company's process handbooks; (2) interviews with stakeholders; (3) on-site visits; and (4) spreadsheets containing the bill of materials and data for each SKU.

3.1.1. Primary Data

The primary data was obtained through semi-structured interviews with decision-making stakeholders who shared their perspectives on complexity dimensions, functions of their area, supply chain integration, measurements, and Key Performance Indicators (KPIs), as well as suggestions for improvement. In addition, primary data was collected through direct observations during a site visit to a manufacturing plant.

3.1.2. Secondary Data

The secondary data was sourced from company process handbooks on Material Planning, Supply Network Planning, and Portfolio Management. This was supplemented by spreadsheets containing information on the Bill of Materials of the entire product portfolio, and other spreadsheets with information on aggregated financial metrics and descriptions of the SKUs.

3.1.3. Process and Stakeholder Mapping

We created a process map that outlines the relevant processes, problematic areas, and metrics related to product complexity based on the primary and secondary data sources. This helped us identify the appropriate stakeholders for each process and understand how products flow through the company's supply chain.

3.2. Phase 2: Data Analytics

Descriptive analytics and clustering are useful techniques for extracting insights from unknown data sets. Descriptive analytics enables the team to understand the nature, distribution, and characteristics of the data to better inform our research methods and hypotheses. Clustering SKUs with similar product configurations also allow the team to identify products with similar levels of component commonality.

3.2.1. Descriptive Analytics

We analyze the data by identifying trends and dispersion measures such as mean, standard deviation, and distribution metrics for each dataset. Through this process, we can identify relationships between different factors across SKUs, such as margin vs. volume and the distribution of packaging configurations. Correlations observed in this analysis inform our hypothesis by identifying key relationships in product performance. Our team confirms outlier data points in our dataset with the company sponsor and refine our scope of relevant products in order to conduct a meaningful and accurate analysis across the portfolio.

3.2.2. Clustering

Given the literature reviewed in Chapter 2.3., we believe that products with similar levels of complexity can be identified with clustering techniques in product variety management. To achieve this, the configuration of each SKU is incorporated into a compatibility matrix. This is followed by identifying common product platforms, are be grouped into clusters, enabling us to visualize the relationships among products and components similar to the interconnectedness dimension proposed by Jacobs (2013). We utilize the K-Modes clustering methodology to analyze the data and predict clusters of related product configurations, as the majority of data concerning packaging materials consist of categorical variables. Moreover, numerical variables such as MACO, volume, and cost exhibit high correlation; thus, utilizing them with K-prototypes or K-Means may result in inconsistent outcomes. The resulting cluster information will enable the sponsor company to identify delisting candidates with similar product configurations and cost profiles.

3.3. Phase 3: Operational Complexity Analysis

This phase involves conducting a complexity analysis based on a compatibility matrix that links components with SKUs through binary variables. Subsequently, the commonality index (CI) for both components and SKUs is determined. The component commonality index is represented by an integer that indicates the number of SKUs in which a particular component is present. In contrast, the commonality index for SKUs indicates the frequency at which the components that make up a specific SKU occur.

3.3.1. Compatibility Matrix

A compatibility matrix was constructed using structural metrics such as product and component variety to map finished good SKUs to their corresponding components across the portfolio. This matrix assigns a binary variable to each SKU and component combination, covering the multiplicity and diversity components of Jacobs' (2013) complexity dimensions. See Figure 5 for an example of our Compatibility Matrix:

FIGURE 5

Example Compatibility Matrix

	Component 1	Component 2	Component 3	.	.	Component n
Material 1	1	1	0	0	0	1
Material 2	0	1	0	1	0	0
Material 3	0	1	1	0	0	0
.	0	0	0	1	0	1
Material n	0	1	0	0	1	1

3.3.2. Commonality Index Formation

After building the compatibility matrix, we develop a commonality index (CI) derived from the count of SKUs assigned to each component. This number is represented by a whole number.

$$Component\ Commonality\ index = \sum_{i=1}^{n} x_i \tag{1}$$

In this formula, x_i represents the binary variable for the *ith* row in the component column you want to sum, and *n* is the total number of materials. A low component commonality index indicates unique components used in a few SKUs, while a higher component commonality index indicates shared components across the portfolio.

The next step was to classify each component by category to normalize the component commonality index to take a value between 1 and 100 by using the following formula:

$$Normalized\ CI = \frac{CI - min\ CI\ of\ the\ category}{max\ CI - min\ CI} \tag{2}$$

Then we determined the SKU commonality index, which is an adaptation of the Percent commonality index (Zhang et al., 2019) and is calculated by a weighted average of the normalized component commonality index.

$$SKU\ Commonality\ Index = \frac{\sum_{i=1}^{m} CI_i * W_i}{\sum_{i=1}^{m} W_i} \tag{3}$$

Each component index is multiplied by a weight assigned to its category by the company and then summed. This sum is then divided by the total sum of weights, resulting in a number ranging from 0 to 100. This process indicated how common the components that conform to an SKU are. The category and that weight is incorporated into the Normalized CI and all the components. Therefore, an SKU that shares many elements with others will have a higher Commonality Index score. In contrast, an SKU that utilizes unique features will have a low Commonality Index score.

3.4. Phase 4: Financial Analysis

This section focuses on data selection, analysis, and cost allocation for a subset of the company's products to identify opportunities to reduce complexity and improve profitability. The following subsections describe the process of analyzing Variable Industrial Costs (VIC) and Variable Logistics Costs (VLC) for each product and gathering cost allocation per SKU. The aim was to tie commonality to cost and understand how unique components affect profitability, which can help reduce complexity. The chapter also highlights the relationship between material complexity and cost.

3.4.1. Data Selection

Given data constraints, cost information could not be requested for the entire portfolio. So, a subset of data was specifically selected by the sponsor company based on a delist/keep assessment they have previously performed to represent SKUs with measurable cost and bill of materials (i.e., BOM) components. We considered a subset of data containing healthy or high MACO per hectoliter, and unhealthy, low MACO per hectoliter, SKUs designated to be delisted or kept in the portfolio. This subset had 20 SKUs in the portfolio and represented products with varying Commonality Index scores and types, including A, B, C, and D types. The company makes the ABCD classification based on MACO and volume, where A shows the highest MACO and volume.

3.4.2. VIC analysis

We analyzed Variable Industrial Cost (VIC) for each SKU in our data to fully understand each product's unique cost drivers. VIC includes costs driven by:

- Raw Materials
- By-Products
- Bulk Transport
- Packaging
- Direct Wages & Salaries
- Energy & Fluids
- Environmental
- Auxiliary Materials
- Subcontracting
- License Fees
- Semi-Finished Materials
- Other Production Costs

An interesting feature of VIC is that it can possess negative values. This is because VIC incorporates the value of salable by-products that are generated during the production process. Several SKUs within our analysis are adjusted based on their production volume and the revenue generated from their by-products. VIC is a useful tool, similar to the cost of goods sold (COGS), for identifying direct and indirect costs associated with each SKU in our scope, given that VIC and COGS are directly related to components required to manufacture each product (Mejía-Argueta et al. 2015).

3.4.3. VLC analysis

We analyzed the Variable Logistics Costs (VLC) for each SKU in our data to understand each product's warehousing and logistics costs. VLC includes primary warehousing and transportation costs for products sold in the domestic market where they are produced and export goods sold in other markets in Europe. VLC has costs driven by the following components:

- Inbound and Outbound Distribution
- Reverse Logistics
- Warehousing
- Picking

3.4.4. Cost allocation per SKU

After gathering the required data about the company's products, components, and production costs, we estimate the actual cost of producing each SKU. Although VIC and VLC components do not replace the activity-based costing (ABC) or cost-to-serve analysis, we can use them to calculate a combined industrial and logistics cost to compare each product's net revenue and generate a figure that closely aligns with the product's MACO, yet examines financial elements for the complexity analysis. We expect any discrepancies that occur are likely the result of complexity costs caused by the uniqueness of the components used. By calculating the impact of complexity costs with this methodology, we can better understand how unique components affect profitability and identify opportunities to reduce complexity.

3.4.5. Tie Commonality to Cost

Costs are measured at each product's SKU level in the delist scope for the company. The cost measurement is derived from datasets pertaining to MACO, Bill of Materials Cost, VIC, and VLC. When comparing these cost calculations for products with a high Commonality Index score and products with a low Commonality Index score, we identify substantial differences in packaging and material costs. This expectation is supported by a study conducted on airplane manufacturing by Zhang et al. (2019), which found that costs with commonality were lower than costs for no commonality. This insight drives a better understanding of the relationship between material complexity and cost.

In summary, our methodology consists of four main phases: Data Collection, Data Analysis, Operational Complexity Analysis, and Financial Analysis. The following chapter discusses the outcomes from stakeholder mapping and resulting data sets, descriptive analytics and clustering results, the development of a compatibility matrix and commonality index, and the financial outcomes observed comparing high-commonality products and low-commonality products.

4. RESULTS

Our results section begins with a description of the supply chain process map and stakeholder analysis. The process map highlights the complexities and coordination challenges within the supply chain. Data analytics includes descriptive analytics and the result of the clustering algorithm using K-modes. The resulting clusters were analyzed to gain insights into critical characteristics and the commonality analysis. Next, the complexity analysis section includes a compatibility matrix, which identifies unique SKUs and components in the portfolio, and results in a commonality index for components and SKUs. This analysis helps to better understand the relationships between packaging materials and costs, suggesting a potential financial benefit of reducing product complexity.

4.1. Data Collection, Mapping, and Processing

This section focuses on the data collection process for the capstone project. A process and stakeholders mapping was created to identify relevant stakeholders and understand the supply chain processes. The chapter concludes with a detailed description of the packaging materials used by the company, which includes primary and secondary containers.

4.1.1. Primary Data

Through primary data collected from interviews and site visits, we received information about the sponsor company's current delisting process, the relation of complexity and innovation, and key metrics aside from MACO.

4.1.1.1. Current Delisting Process

Through primary data collected from interviews and site visits, we learned that several departments play a critical role in the company's delisting process. The most important departments are innovation, portfolio management, and supply network planning. These departments estimate the financial impact of delisting poorly performing SKUs using MACO as their main criteria. They create an assessment for each proposed SKU and give six months to reassess based on new analysis and results. The final decision is made only after approval from all teams involved in the process.

4.1.1.2. Innovations and Complexity

Innovations have been focused on developing products with new flavors, which often require unique packaging materials, leading to higher complexity and obsolescence. In addition, the department also develops new packages for seasonal and festive products. These complexity drivers increase the volume of different packaging materials used, leading to higher warehousing and transportation costs.

4.1.1.3. Other Key Performance Indicators (KPI)

The company uses several key performance indicators (KPIs), including MACO and Gross Line Yield (GLY). GLY measures the percentage of time the line is operating. The company's main stakeholders hypothesize that complexity negatively affects GLY. Therefore, reducing complexity in the supply chain may lead to an increase in GLY and, ultimately, improved performance.

4.1.2. Secondary Data

The main secondary data provided by the company comes from three spreadsheets. The BOM spreadsheet is a comprehensive dataset that includes all the SKUs in the company portfolio, along with the associated component and other data such as the production plant and component group. This dataset served as the primary input for the complexity analysis presented in chapter

4.3. The Portfolio spreadsheet is a dataset used for clustering analysis that is detailed in section 4.2.2. This dataset provides information about the packaging characteristics for each SKU, as well as aggregated financial metrics. The Costs Dataset includes detailed information about logistics, warehousing, and production costs. We received two cost datasets that provided a granular description of these costs for a pre-selected group of SKUs, which were used as inputs for the financial analysis presented in section 4.4.

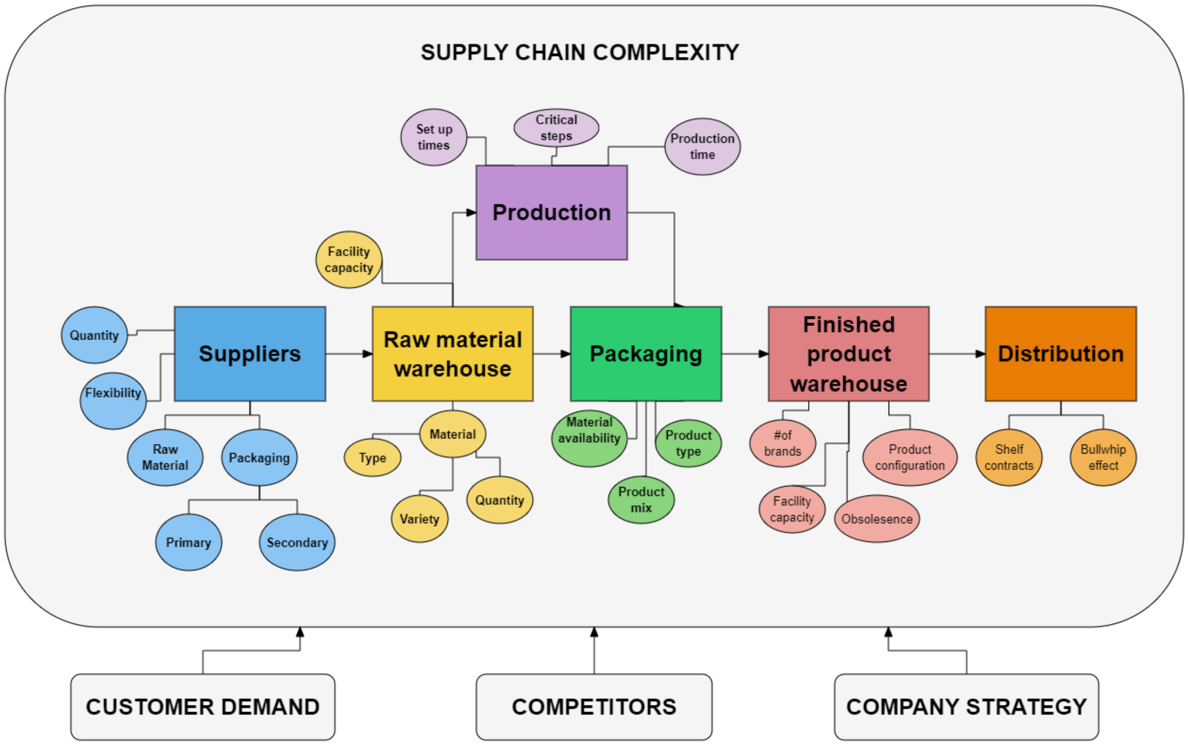
4.1.3 Process and Stakeholders Mapping

Figure 6 is a visual representation of the company's supply chain processes and stakeholders, which helps us identify the relevant stakeholders for process understanding and data clarification. The supply chain begins with suppliers, who contribute to complexity through volume, flexibility, and the type of materials supplied. There are separate suppliers for raw materials and primary and secondary packaging. Raw materials are stored in the warehouse according to their kind, variety, and quantity. The variety and amount of materials can create coordination challenges and add complexity.

From the warehouse, the product moves to production, where setup times, critical production steps, and production time can create bottlenecks and limit flexibility. The product then moves to packaging, where the availability of materials, product mix, and packaging type are the main contributors to complexity. Next, the product is sent to the finished product warehouse, where the number of brands, configuration, and capacity contribute to complexity. Allocating specific space for each SKU with a particular package configuration is necessary, and limited capacity means that the sponsor company must have different assortments in limited quantities. Finally, the product is distributed to customers, where the shelf contracts, and demand patterns across the supply chain nodes add complexity.

Figure 6

Supply Chain Process Map



Packaging materials are generally divided into primary and secondary types and depend on the type of container used for the product. There are three main types of containers: bottles, cans, and kegs. Bottles are typically made of glass and can vary in color, shape, and volume. Cans come in two versions, sleek and standard, and can also vary in volume. Kegs are large containers designed to hold bigger volumes. Additionally, secondary packaging materials like cartons vary in size depending on the product's size, container type, package configuration, and brand.

4.2. Data Analytics

We used descriptive analytics and clustering analysis to gain insights into the packaging materials of a particular product portfolio. The analysis utilized ten different categorical variables to identify common characteristics among SKUs through a K-modes clustering algorithm..

4.2.1. Descriptive Analytics

We analyzed the portfolio information to assess product characteristics and better understand MACO, volume, and primary packaging materials. We also identified inherent factors contributing to variabilities among the SKUs, such as container size, type, material, and packaging configuration. By analyzing the provided graphs (see Figure 7), we identified common characteristics among the SKUs. For instance, the most frequent container size is 12oz, which accounts for approximately 50% of all SKUs. This understanding of the data helped us identify which attributes would be valuable to utilize in our cluster analysis.

We analyzed 10 different categorical variables inherent to the products and the possible ranges of values, shown in Table 1. The dataset contains 211 SKUs, followed by the count of unique values found within the category. The row "freq" represents the frequency on which is repeated. In Figure 7 the distribution of all the values for the categorical variables are shown.

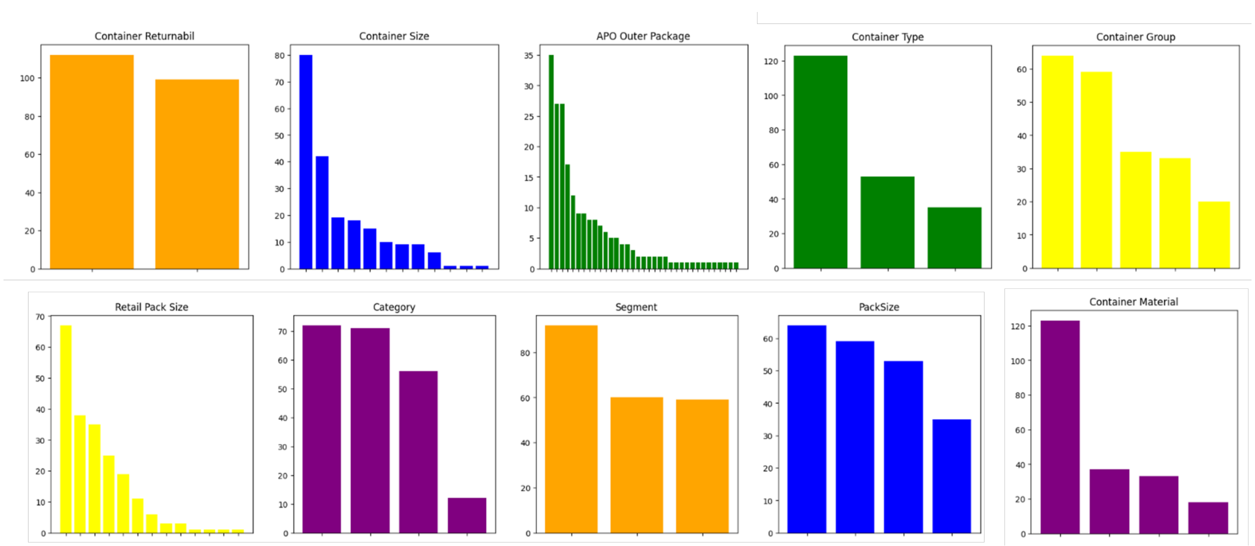
TABLE 1

Categorical Variable Summary Statistics

	Container Type	Container Group	Container Material	Container Returnability	Container Size	APO Outer Package	Retail Pack Size	Category	Segment	PackSize
unique	3	5	4	2	12	35	13	4	3	4
freq	123	64	123	112	80	35	67	72	92	64

FIGURE 7

Descriptive Analytics of the Packaging Materials



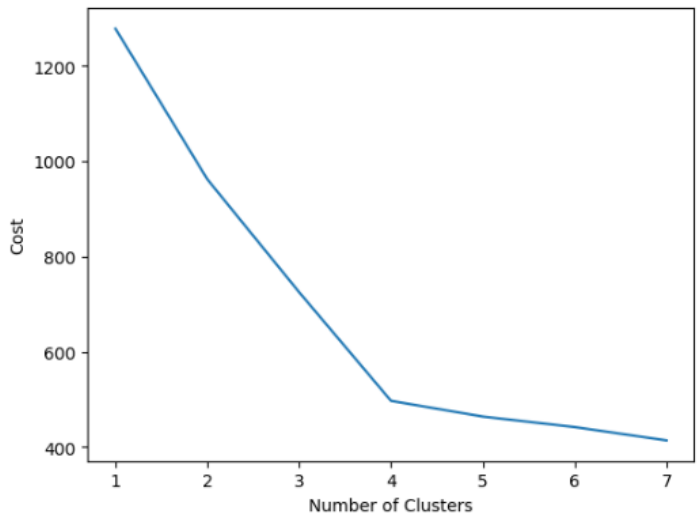
4.2.2. Clustering

The portfolio data served as the primary input for our clustering methodology, which aimed to categorize packaging materials into groups based on common attributes. To achieve this goal, we utilized categorical variables, such as “Container Type”, “Container Group”, “Container Material”, “Container Returnability”, “Container Size”, “Outer Package”, “Retail Pack Size”, “Category”, “Segment”, and “PackSize”. We used the K-Modes algorithm to conduct the analysis, which is well-suited for handling categorical data. By grouping similar packaging materials into distinct clusters, we can gain insights into critical characteristics that define each group. The resulting clusters will help inform our understanding of component relationships and commonality.

The clustering methodology began with data cleaning, leaving us with 210 SKUs and 10 different component categories. We then transformed the categorical data with a label encoder so that integers would represent every unique value from each category using the sklearn package. Then we used the K-Modes library in Python because it is specifically designed to perform this analysis. To determine the optimal number of clusters, we used Cao Initialization. The elbow graph is crucial for obtaining meaningful clusters that can be used for further analysis. Figure 8 indicates that the optimal number of clusters is 4.

FIGURE 8

Cao Initialization Elbow Graph



Once the clustering algorithm is executed, we can generate visualizations that allow us to compare the number of SKUs in a particular cluster across multiple categorical variables.

In Figure 9, we observe the clusters by container returnability; the graph is divided into two parts, each with two bars. We found that the red and the blue bars represent bottles, returnable and non-returnable, while the green bar contains the cans and the orange the kegs.

FIGURE 9

Clusters by Container Returnability

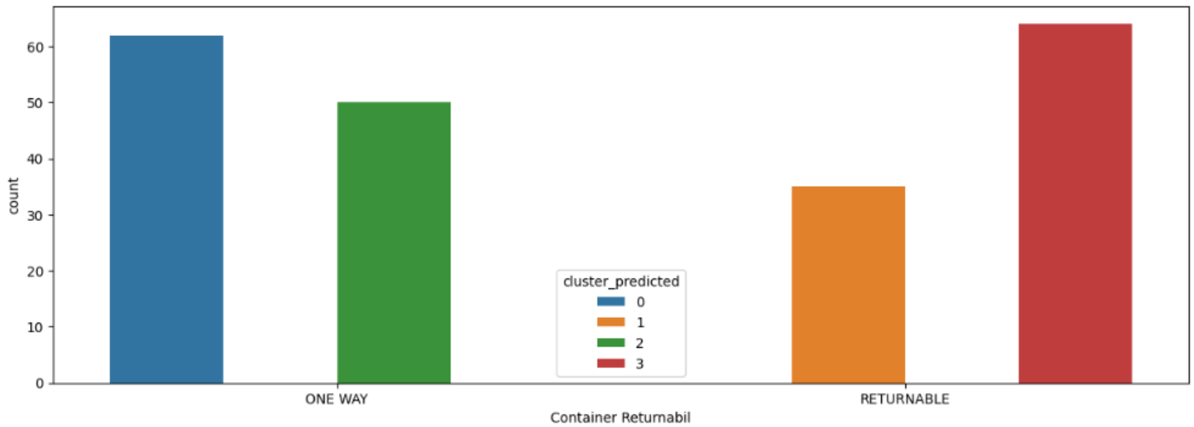
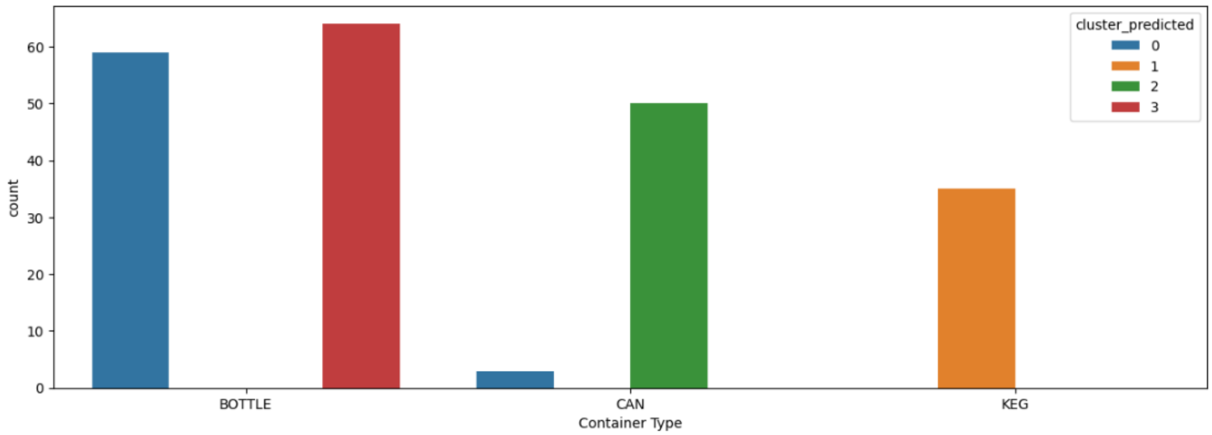


Figure 10 explains how the different containers are grouped into clusters based on their characteristics. The analysis shows that container type is a major factor in the clustering process. Specifically, bottles are divided into two distinct clusters, representing one way and returnable bottles while cans are grouped together in a single cluster. Kegs, on the other hand, form their own distinct cluster, given their unique features.

FIGURE 10

Clusters by Container Type



In conclusion, our clustering analysis yielded intuitive results, which we attribute to the values from the variables being specific for a particular type of container. For example, most bottles are made of glass, while kegs are typically made of stainless steel. However, to achieve more precise clusters, we must consider more specific attributes and incorporate other packaging components, such as labels, caps, and secondary packaging. Alternatively, we could conduct three separate clustering analyses on a significant sample of data for each type of container to gain a deeper understanding of the unique characteristics of each packaging type. However, we could not proceed this way due to the limited size of the dataset, which might not have been significant enough for each individual analysis. By refining our clustering methodology, we can gain a more nuanced understanding of our packaging materials and understand component relationships.

4.3. Complexity analysis

We conducted a complexity analysis that involved developing a compatibility matrix and a commonality index which was then strengthened by component category weights and yielded significant insights when paired with portfolio performance metrics.

4.3.1. Compatibility Matrix

The compatibility matrix we created is a valuable tool for identifying both unique and common components among the 8,623 unique SKUs and 17,432 unique components in the sponsor company's portfolio. The large size of the matrix highlights the complexity of the company's materials and configurations, making it crucial to simplify the understanding of SKUs and components. Utilizing this matrix can give us a more comprehensive understanding of the interplay between components and SKUs in the sponsor company's portfolio.

4.3.2. Commonality Index Calculation

We developed two commonality index metrics, one for individual components and one for SKUs. Then, we compared the metrics to financial dimensions through dispersion graphs to evaluate the relationships between the commonality index and profitability.

4.3.2.1 Bill of Material (BOM) Components

The commonality index was developed by taking the sum of the binary variables for each component within the compatibility matrix, representing the number of SKUs that include each specific component.

The distribution of the commonality index for company components is highly skewed to the left, with a median and 75th percentile value of 2 (See Table 2 and Figure 11 below). This indicates that most components in the BOM are used in only one or two finished goods out of over 7,000 SKUs. However, some materials have a high commonality index, with a maximum value of 5,141. This indicates that a single component can be present in as many as 5,141 SKUs (approximately 60% of the SKUs). This information suggests that while some components are used commonly across many products, most components in the bill of materials are unique to specific products.

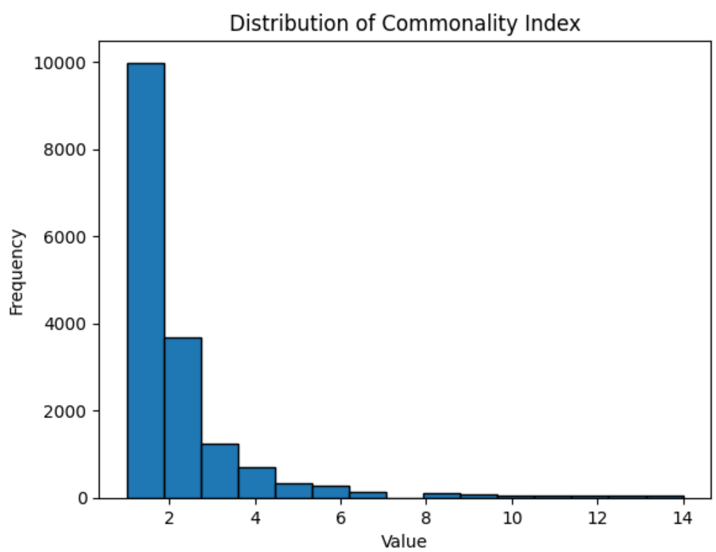
Table 2

Commonality Index Dispersion Summary Statistics

	Commonality Index
count	17432.000000
mean	5.574403
std	57.997556
min	1.000000
25%	1.000000
50%	1.000000
75%	2.000000
max	5141.000000

FIGURE 11

Commonality Index Dispersion Histogram



After obtaining the commonality index for every component, we mapped each component to its relevant component group. A component group is a category that classifies similar components together, for example, “cans” or “cartons”. The database contains 102 different component groups. However, we only considered groups the sponsor company prioritized and classified as suitable for this exercise. These component groups were selected due to their complexity and cost implications, thus narrowing the scope to 38 groups.

After selecting the 38 component groups, we worked with the sponsor company to categorize them into broader component categories. The resulting types were: Labels, Stretch Wrap, Secondary Packaging, Tertiary Packaging, Crowns, Stickers, Bottles, Cans, Can Ends, Crates, Keg Caps, Kegs, Sleeves, and Primary PET. Then, commonality index scores were computed for each category; the distribution of category scores can be observed in Figures 12 to 14.

FIGURE 12

Commonality Index Distribution for Bottles

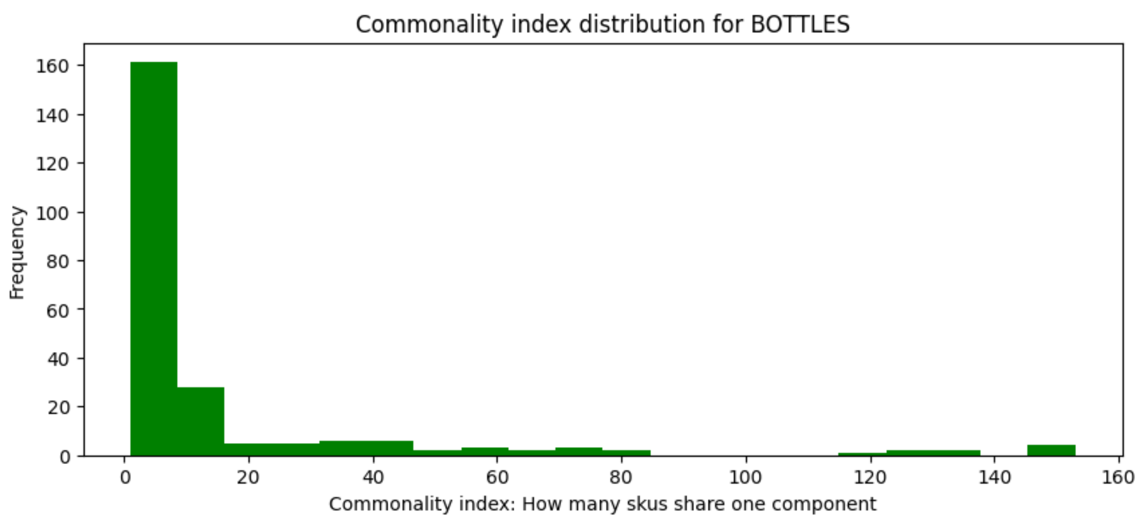


FIGURE 13

Commonality Index Distribution for Cans

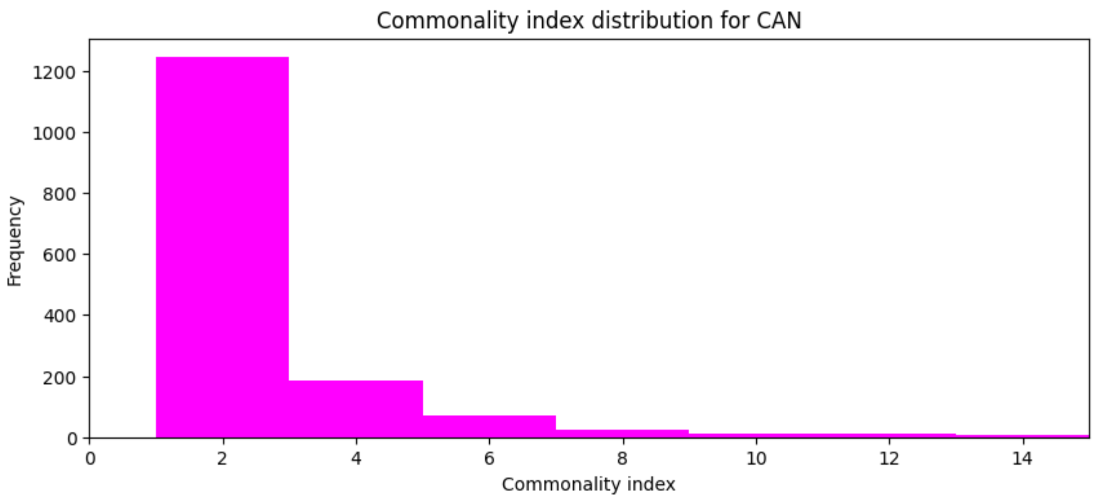
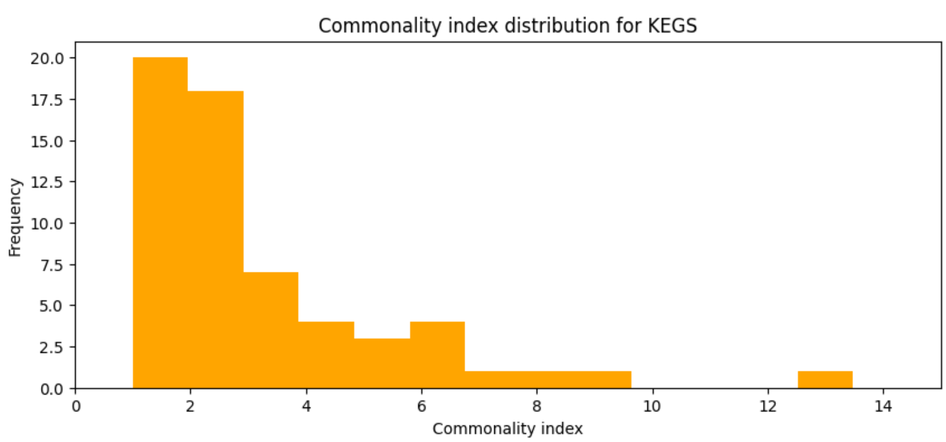


FIGURE 14

Commonality Index Distribution for Kegs



Since each category has its own CI distribution, we standardized the CI for each category to range from 0 to 100 within that category's specific component. This approach ensures that the

CI values are comparable across categories and facilitates a more accurate data comparison. To account for each component's varying contribution complexity, we worked with the company to assign weights based on the cost and complexity of the component. This approach is justified because not all categories have an equal impact on complexity, so this approach helps ensure that our complexity score accurately reflects the relative importance of each category.

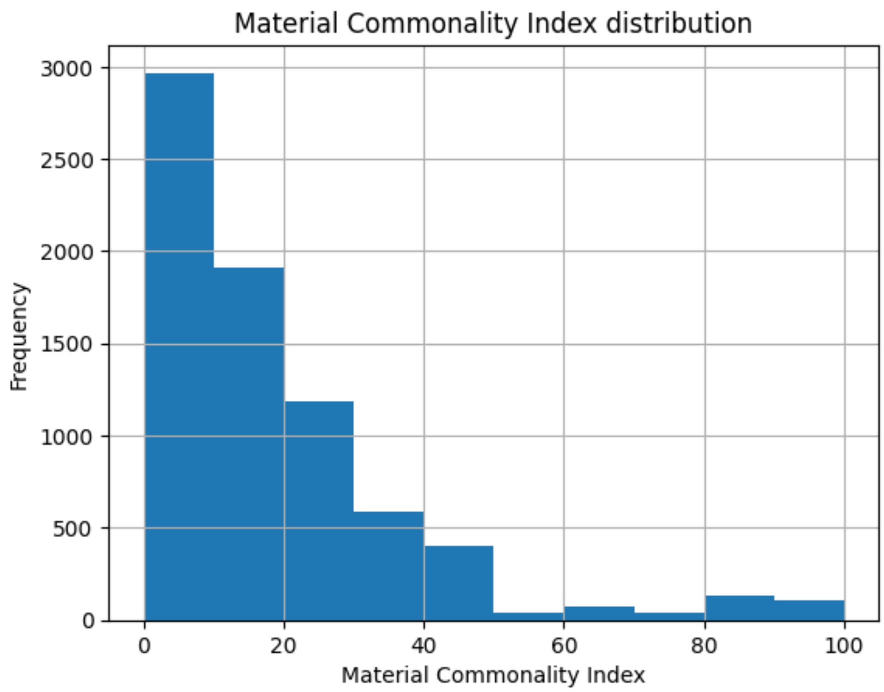
4.3.2.2. Finished Good Products

With the weights assigned, we can calculate the CI for each SKU by aggregating the CI of all the components that make up that product. We used a weighted average of the CI values, considering each component's cost and complexity. This approach allows us to accurately measure the degree of commonality across different SKUs and can help us identify products dependent on unique components.

To calculate the material weighted CI for a set of m components, we utilized equation 3 described in section 3.3.2. Specifically, we obtained the individual CI (CIi) for each component i and its corresponding weight (Wi). We arrived at the material-weighted CI by multiplying each CI by its weight and summing up the results for all m components. The resulting product CI is then normalized to a value between 0 and 100. Our analysis identified approximately 3,000 SKUs with a high level of uniqueness, achieving the minimum commonality score. We observed that Kegs tended to have the highest commonality index, requiring fewer packaging materials. The same applies to pre-manufactured products that often only use a label or secondary packaging. For fully in-house manufactured products, we considered an excellent commonality index to be in the range of 30 or higher (see Figure 15).

FIGURE 15

Weighted Material Commonality Index Distribution



4.3.2.3. Commonality Index Relationships

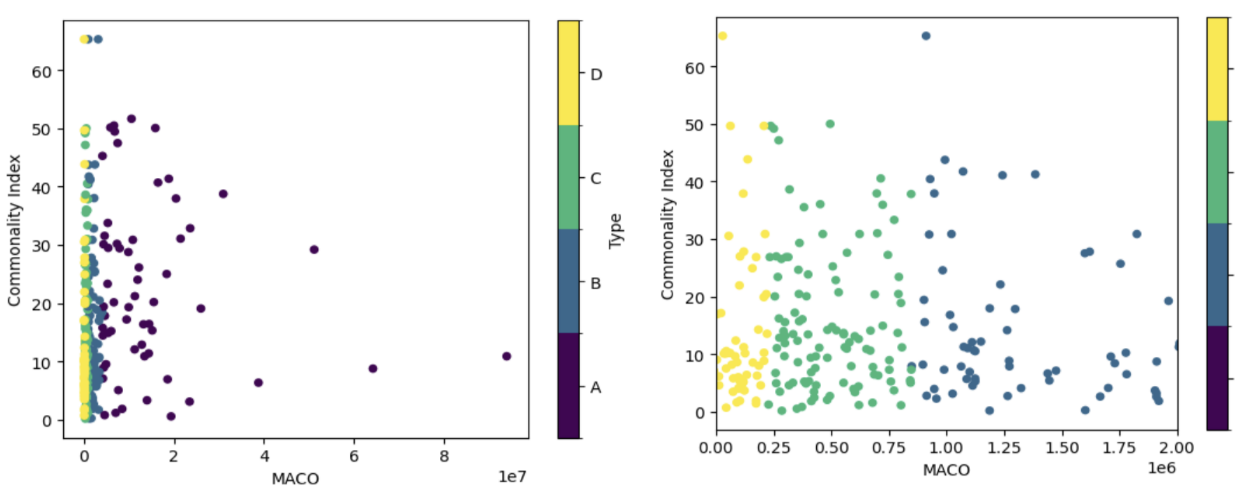
After calculating the weighted commonality index for each product, we joined the CI per SKU to the portfolio dataset to evaluate the relationships between CI and other metrics that are relevant to product performance.

4.3.2.3.1. MACO vs. Commonality Index

The graph presented in Figure 16 shows the relationship between MACO and CI, classified by type according to the company's portfolio classification. Figure 16 A and B are the same graph, however, Graph B is zoomed in on the X-axis for a better appreciation of the dispersion of the data. The portfolio is divided into different types based on the total MACO. Upon analyzing the graph, we do not find a clear correlation between MACO and Commonality index. However, there is a clear separation based on the type classification. This implies that MACO has the most substantial impact on each type classification and material complexity is not considered when assigning each product to a type category.

FIGURE 16

MACO vs. Commonality Index



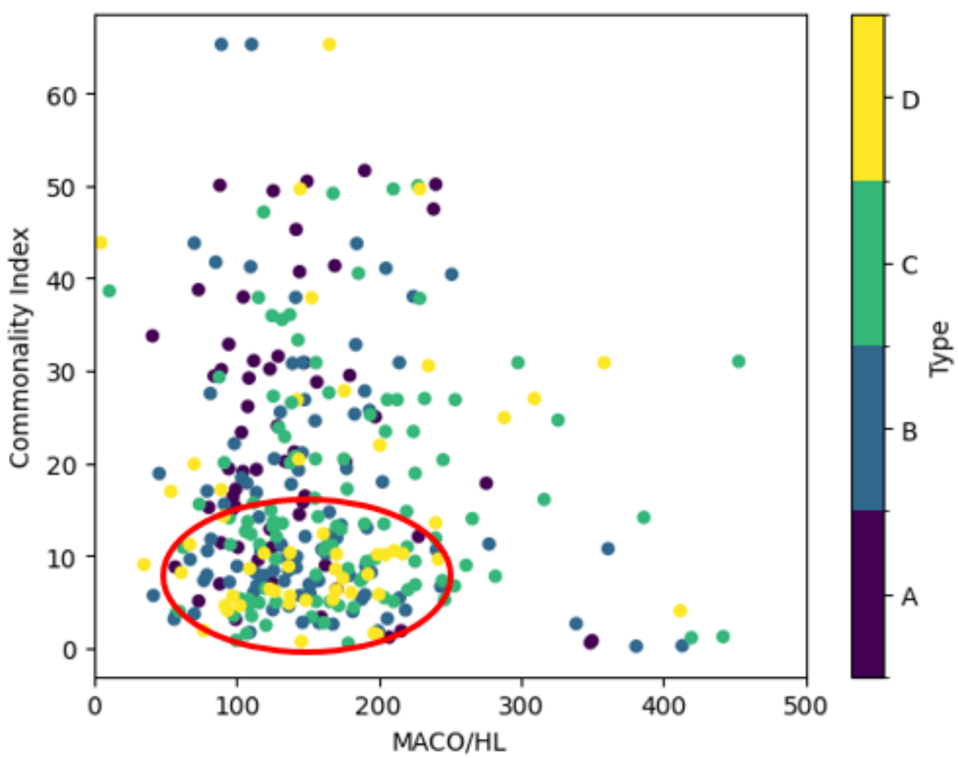
A **B**

4.3.2.3.2. MACO/HL vs. Commonality Index

The MACO per hectoliter (MACO/HL) is a profitability metric the company uses that adjusts for volume. The graph shows no clear correlation between MACO/HL and the Commonality index when including this metric. However, the data does indicate that products classified as Type D are primarily located in the bottom left corner of the graph, indicating that they generally have a low Commonality index and a low MACO/HL value (see Figure 17).

FIGURE 17

MACO/HL vs. Commonality Index



4.3.2.3.2.1. Variance analysis with Analysis of Variance (ANOVA)

We conducted an ANOVA variance analysis to test our hypothesis that there may be a significant difference in the mean MACO of products based on their type. ANOVA is a statistical tool that allows us to compare the means of multiple groups and identify any significant differences between them. By using ANOVA, we could determine whether there were any significant differences in the mean MACO and MACO/HL of type A, B, C, and D products and whether these differences were statistically significant. Our analysis showed that with a significance level of 0.05, there was a considerable difference between the mean MACO of types A, B, C, and D. At the same time, there was no significant difference between the mean MACO/HL of the different types. These findings confirm the relationships we observed in Figures 16 and 17, which suggested that MACO is based on volume and revenue rather than granular cost drivers. These results also indicate that volume plays a significant role in classifying the company's products for types. Our findings may also suggest that other approaches, such as a bottom-up analysis of costs, could provide additional insights into marginal profitability.

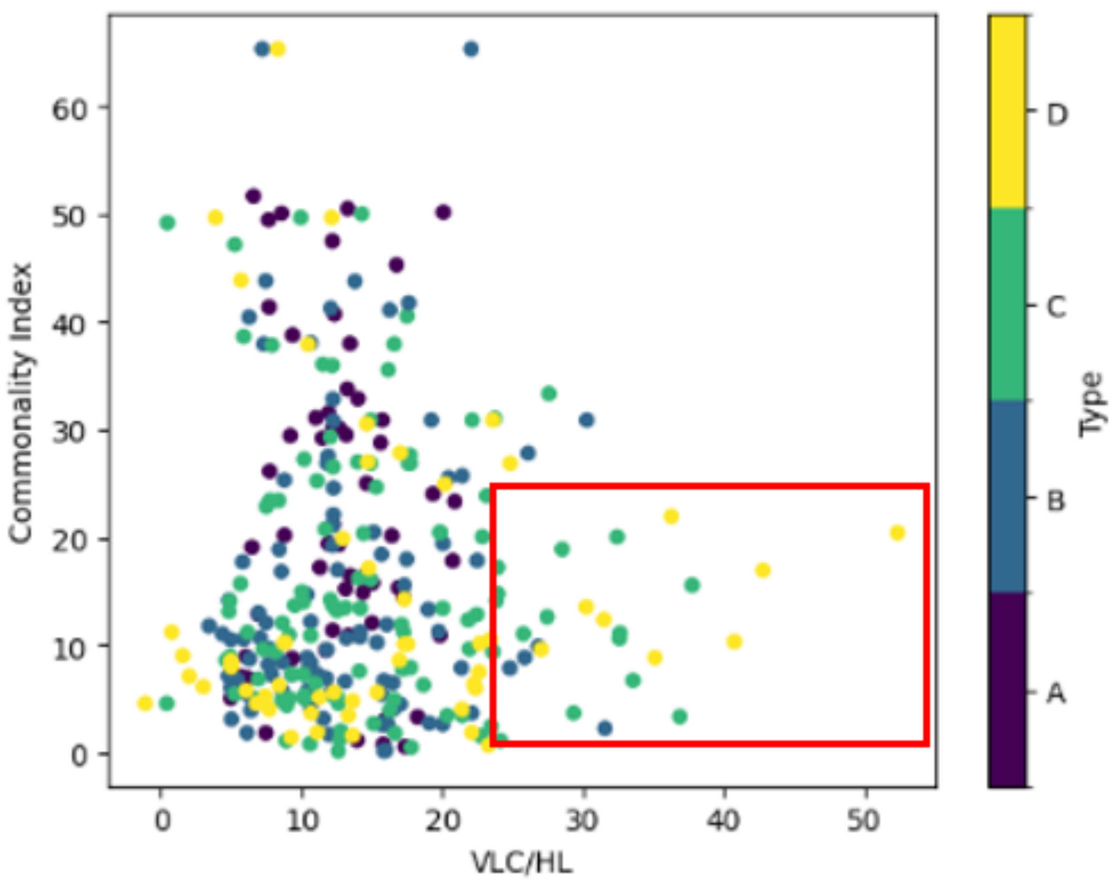
4.3.2.3.3. VLC/HL vs. Commonality Index

When plotting the variable logistic costs adjusted for volume (VLC/HL) against the commonality index and type, we observed type C and D SKUs with high VLC/HL and low commonality index scores. As mentioned previously, type B and type C SKUs are products with average profitability relative to the entire portfolio. Hence, the observation of type C products with high VLC/HL and low commonality is significant. This finding highlights the importance of including

Type C SKUs with unique materials in the decomplexity analysis, which were not initially considered by the initiative from the sponsor company (see Figure 18). If these type C products can maintain a significant margin despite their high VLC/HL and low commonality, they are likely to perform even better financially with a more common component. However, this outcome will be discussed in greater depth in the discussion chapter.

FIGURE 18

VLC/HL vs. Commonality Index

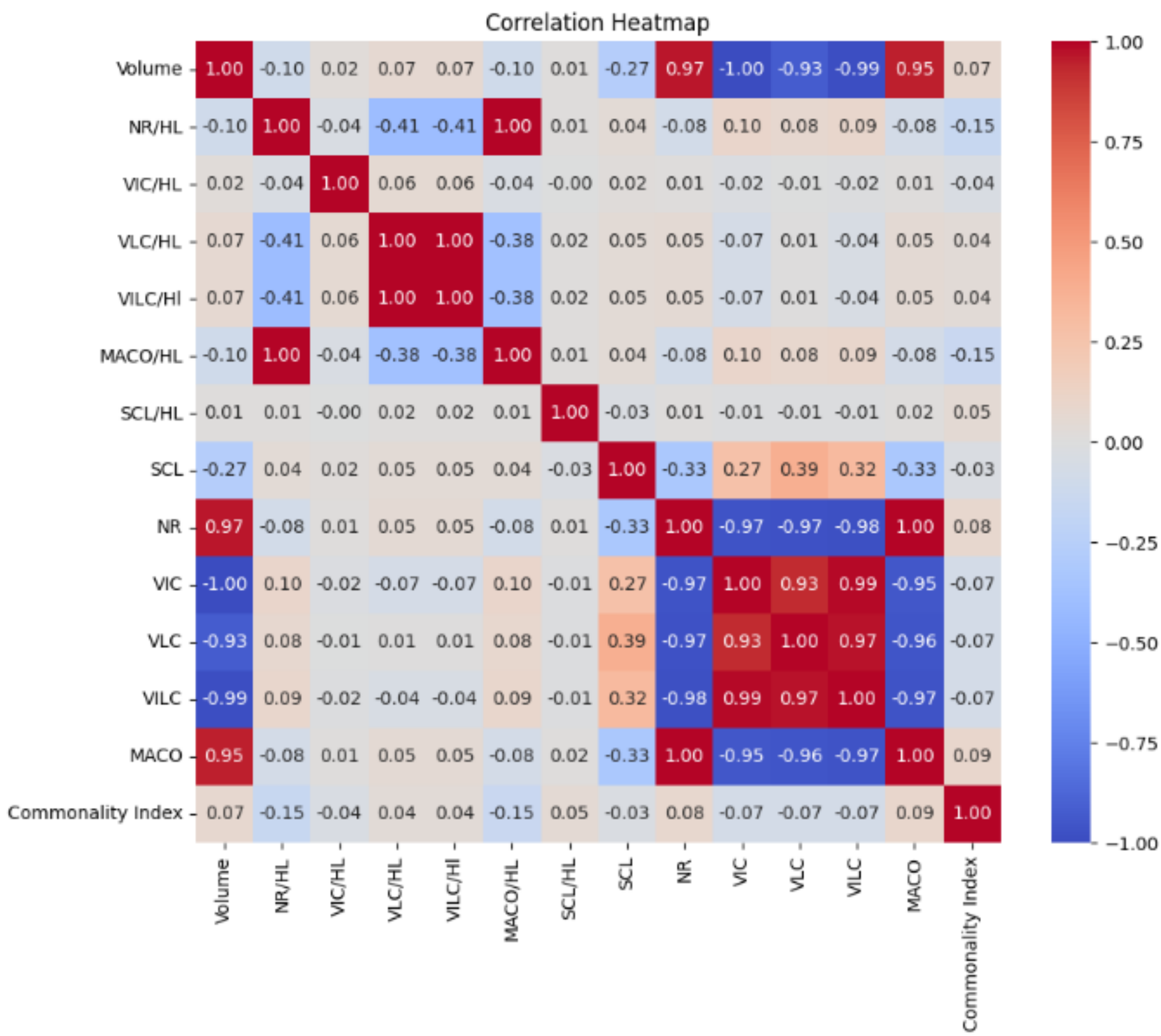


4.3.2.3.4. Commonality Index Correlations

We conducted a correlation analysis after plotting the metrics against the commonality index to determine if there was a significant relationship between them, indicated by a high correlation. However, no significant results were found. We expect a significant correlation between the commonality index and VIC/HL, since packaging costs are included in VIC. However, we will discuss the metric's data limitations in this report's discussion chapter. Again, the correlation between volume and aggregated cost metrics like VIC, VLC and MACO can be observed clearly (see Figure 19).

FIGURE 19

Commonality Index Correlations



4.4. Financial Analysis

The focus of financial analysis is to perform an in-depth analysis of transportation, warehousing, and production costs for a specific dataset. The goal is to then compare the differences between low and high commonality SKUs.

4.4.1. Data Selection

To gain insights into component configurations, cost allocations, and commonality scores, we collaborated with the company to select 10 high-profitability and 10 low-profitability SKUs (see Table 3). However, we excluded four SKUs from the analysis due to costing-related data limitations. These 16 SKUs serve as the basis for our remaining financial analysis.

TABLE 3

SKUs in Scope of Financial Analysis

High profitability

Assessment	Family brand	SKU	Operational SKU	Volume	Maco/Hl
Keep	A	AHNH010101112901	88115	135	$ 2,686
Keep	A	AHNH020101112901	83986	175	$ 2,453
Keep	D	AABS050203412401	3412	777	$ 2,292
Keep	TK	AAOS010101110504	61685	2,746	$ 785
Keep	H	AADQ090101111402	58458	431	$ 663
Keep	I	AABP020101110018	95227	1,545	$ 453
Keep	D	AABS060203412401	3404	517	$ 442
Keep	H	AADQ090101111406	58937	1,913	$ 420
Keep	K	AAJF010101110504	74456	241	$ 412
Keep	B	AABO030201110219	18715	1,353	$ 386

Low profitability

Assessment	Family brand	SKU	Operational SKU	Volume	Maco/Hl
Delist	CU	ACSF010101110506	76625	5,715	$ 120
Delist	C	AAHP180101110512	95869	837	$ 109
Delist	H	AAAB130101110212	63287	7,308	$ 108
Delist	L	AAAE010102311143	71012	867	$ 107
Delist	CU	ACSF020101110506	76642	1,161	$ 97
Delist	J	AACH030201110206	40099	1,044	$ 94
Delist	V	AHMO010201110504	77051	2,025	$ 91
Delist	L	AAAE3G0101110212	75236	4,128	$ 88
Delist	L	AAAE3J0201110519	62313	108	$ 54
Delist	K	AAJF030201110506	94604	139	-$ 62

4.4.2. Commonality Index and Costs

To aggregate costs by SKU, we divided the list of healthy and unhealthy SKUs into two categories: high and low commonality. We used the median CI value of 11.9 as a deterministic threshold to categorize each SKU as high or low. SKUs with CI scores greater than 11.9 were labeled as high, and SKUs with CI scores lower than 11.9 were labeled as low. We then calculated each category's average VIC and VLC, allowing financial comparisons across groups (see Table 4).

The analysis indicates that products with low CI exhibit a total average cost that is 40.8% higher than products with high CI. The key difference is attributed to VIC, with costs for overhead expenses being 400% greater and costs for packaging materials being 105% greater. Additionally, the cost of primary transportation was 83% greater for low commonality products than that of high commonality. These findings support the hypothesis that the inclusion of unique components contributes to increased costs and restricts the potential for profitability.

Products with high commonality index scores had greater costs for the primary warehousing category, however we find this to be negligible due to the absence of an in-depth cost-to-serve analysis.

TABLE 4

Commonality Index Financial Comparison

	Low CI	High CI
VIC	**$ 160.14**	**$ 113.58**
Raw materials	$ 5.99	$ 11.07
Packaging	$ 109.52	$ 53.25
Labour	$ 27.91	$ 45.95
OH	$ 16.73	$ 3.31
Primary Warehousing	**$ 2.62**	**$ 2.96**
Picking	$ 0.16	$ -
Brand distribution	$ 1.50	$ 2.17
Warehousing	$ 0.95	$ 0.79
Primary Transportation	**$ 5.82**	**$ 3.18**
Domestic	$ 2.69	$ 2.77
Exports	$ 3.13	$ 0.41
Total average cost	**$ 168.59**	**$ 119.72**

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5. DISCUSSION

In this chapter we present the insights and implications of our analysis as well as the limitations encountered.

5.1. Insights

MACO is a critical metric when deciding which products to keep and which to delist. It is highly correlated with company revenue and production volume. However, relying solely on MACO can be limiting given that it does not examine operational complexity associated with product components. Therefore, it is also essential to use other criteria. We propose that the commonality index and MACO/HL should be used in conjunction with MACO. We consider several possible scenarios (outlined in Figure 20):

In the case of low MACO and low MACO/HL, if there is a high commonality index, there is almost no room for action, and it may be best to delist those products if other processes and products are not tied to the SKU. The low profitability is likely driven by consumer behavior, not material costs. However, if there is a low commonality index score, it may be possible to interchange components. For example, utilizing a standard bottle or packaging material rather than unique components can facilitate greater margin growth.

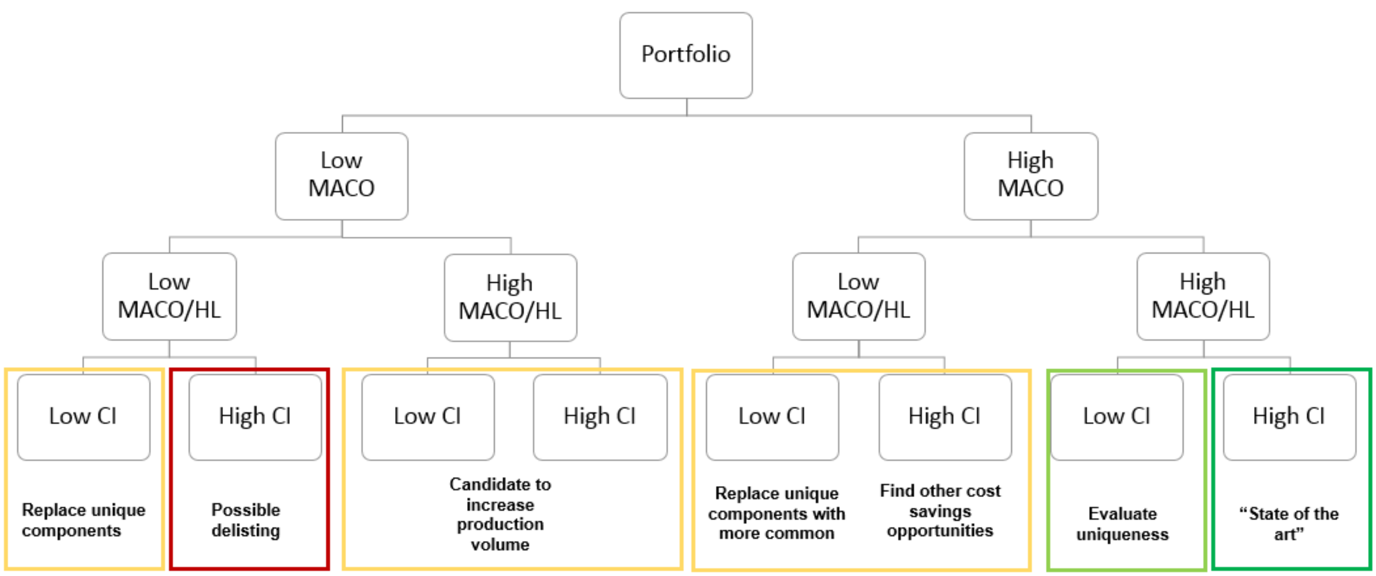
For products with a high MACO and low MACO/HL, there is a significant opportunity for improvement. These products are produced in high volume and may justify having unique components for specific SKUs. It can be even more beneficial if these products also have a high commonality index score. If there is still a low MACO/HL, it may be worth looking for other opportunities to reduce costs unrelated to packaging. Both of these first two scenarios are illustrated in Figure 3, adapted from Zhang et al. (2019), where it was shown that products that utilize common configurations observe greater margins and lower break-even points.

In the case of low MACO and high MACO/HL, the production volume of the product was likely so low that the product could not sufficiently cover its costs of goods sold and other logistic expenses. These SKUs should be the primary target for scaling production as MACO can increase by leveraging economies of scale and learning curve effects to decrease allocated production costs at the product level (Thyssen et al. 2005)

If both MACO and MACO/HL are high, this justifies keeping a unique component in the portfolio. This is likely indicative of a product consumers enjoy for its unique position in the market. A product with a high commonality index score and MACO and MACO/HL is considered the healthiest. This product performs well with consumers and utilizes standard low-cost components. This concept is also discussed by Zhang et al. (2019) where products with high distinctiveness, and low commonality, may be justified by their to grab consumer attention.

In summary, while MACO is an important metric, it should not be the only factor to decide which products to keep and which to delist. By incorporating a commonality index, companies can make more informed decisions about which SKUs are most valuable to their business.

FIGURE 20: MACO Scenarios



5.1.1. Recommended strategies

Based on the cases presented in section 5.1., we recommend the following actions to the sponsor company:

- Introduce a commonality index and a MACO/HL criterion in the bi-yearly assessment to address different aspects of complexity and profitability.
- Delist SKUs that have low MACO, low MACO/HL, and high commonality index.
- For SKUs that have a low commonality index, explore potential alternative components that could be used instead.

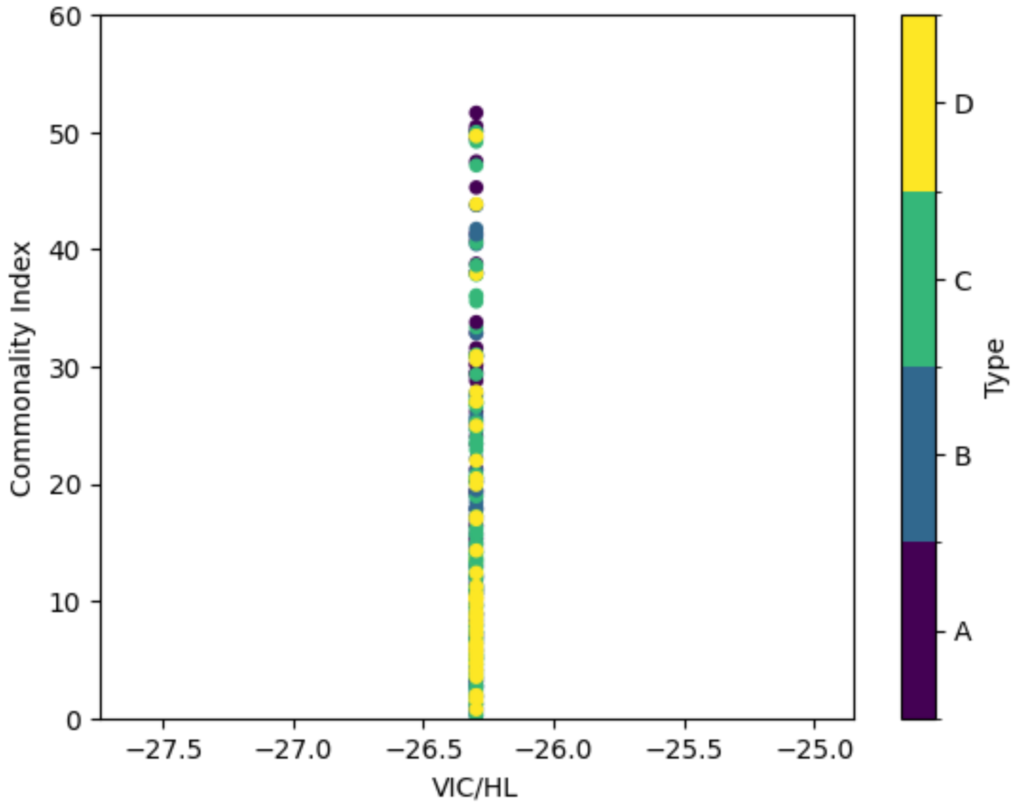
5.2. Limitations

Our study was constrained by time and data limitations, which prevented us from thoroughly analyzing the costs associated with the packaging of products. We could not obtain disaggregated data on commercial and operating expenses, which limited our ability to consider all cost factors. Additionally, our analysis was based on a small sample of SKUs, so the scalability of our findings to a larger population is uncertain.

Our analysis of variable industrial costs per hectoliter (VIC/HL) for the complete portfolio revealed that the company allocates VIC/HL costs based on volume rather than considering other exact VIC/HL costs per SKU (see Figure 21).

FIGURE 21

VIC/HL vs. Commonality Index



While this cost allocation method may be sufficient for evaluating costs based on volume, it does not help conduct a marginal analysis. A marginal analysis is necessary for comparing the commonality index of specific SKUs against production costs. This relationship is crucial because packaging costs are embedded in the quantification of VIC, and a standard allocation of costs does not allow for a VIC comparison across product SKUs or product types.

6. CONCLUSION AND FUTURE RESEARCH

We began this project by exploring the complexities of portfolio management within the consumer packaged goods (CPG) industry, driven by globalization and the demand for customized offerings. Through an extensive review of relevant literature and discussions with our sponsor company and advisor, we gained significant insights into the value of measuring operational and financial complexity when evaluating portfolio management decisions. To comprehend the specific challenges faced by our sponsor company, we thoroughly examined their current decomplexity activities and familiarized ourselves with their product portfolio performance metrics. Equipped with the necessary data, we set out to address the following research questions:

- *Question 1: How can the sponsor company measure complexity and manage its product portfolio?*
- *Question 2: What is the financial impact of delisting complex stock-keeping units (SKUs) from the core portfolio?*

By addressing these questions, we aim to provide an actionable methodology that will enable the sponsor company to streamline its product portfolio, reduce operational complexity, and improve financial performance.

The literary analysis of packaging complexity and its impact on product portfolio profitability underscores the importance of considering multiple factors when deciding which products to retain and which to discontinue. While the sponsor company currently utilizes margin after cost of operating (MACO) as the key metric for evaluating product profitability, it should not be relied upon in isolation. Our project proposes a methodology for quantifying a commonality index for components and SKUs in order to measure portfolio component uniqueness and compatibility. Our methodology also recommends paring commonality index scores with other metrics, such as MACO per hectoliter (MACO/HL) or variable industrial costs per hectoliter (VLC/HL) to obtain a more comprehensive view of a product's profitability on a unitary basis.

After developing a commonality index from the portfolio bill of materials (BOM), the sponsor company is able to leverage a complexity metric that explains which products rely on unique and common components across their product families. By aggregating variable industrial costs (VIC) and variable logistic costs (VLC), which is comprised of warehousing and logistics costs, we are able to realize the cost disparity between products with a low and high commonality index scores. At the total average cost perspective, products with low commonality index scores are 40.8% costlier than products with high commonality index scores. This finding enables our sponsor company to pair financial data with our operational complexity metric, or commonality index, to go beyond MACO and evaluate delisting decisions from both a total cost and supply chain impact perspective.

6.1. Future Research

The sponsor company can consider several avenues for future research. First, robust costing methods such as cost to serve that consider operational and commercial expenses could be employed. Cost to serve methods can evaluate more realistic cost and profitability metrics that consider the impact of complexity for unique and common materials. Moreover, a more representative sample of SKUs could be used for financial analysis to produce more stable and trustworthy results.

Next, a sensitivity analysis can be conducted to evaluate possible trade-offs between materials. This analysis can estimate the marginal savings on MACO/HL or cost to serve when a specific packaging component is changed. While conducting field research, several key metrics were identified that are directly impacted by packaging materials complexity but were not quantified in our datasets. These include changeover times in production lines, gross line yield (GLY), obsolescence, and cannibalization. Therefore, the cost to serve analysis should also include the costs related to these metrics.

Finally, using an optimization approach to improve the use of resources related to package complexity, such as changeover times, obsolescence, and cannibalization. These additional factors could also be studied to provide a complete view of the costs of packaging complexity. We could have also a combined technique such as K-prototypes if sufficient numerical data were provided. Lastly, we need to consider the strategic trade-offs involved in launching new products, allocating storage space for inventory, and the opportunity cost associated with using that space for alternative purposes such as leasing or reallocating it to other components from different stock-keeping units (SKUs).

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