Decision Analytics Journal 2 (2022) 100019

Contents lists available at ScienceDirect

Decision Analytics Journal

journal homepage: www.elsevier.com/locate/dajour

# A DEA-based decision analytics framework for product deletion in the luxury goods and fashion industry

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ARTICLE INFO

*Keywords:*
Product deletion (discontinuation)
Supply chain
Data envelopment analysis
Decision analysis
Marketing analytics

ABSTRACT

Traditionally, product deletion is a reactive decision driven by low sales volume and profit margin. However, the complexities involved in product management and consumer behavior volatilities make it necessary to account for a broad range of financial and non-financial factors. Besides, proactive product deletion may be required for a company to reduce the risk of draining resources, adjust to the market changes, and stay competitive. This study develops an analytics-based product deletion decision framework that considers multidimensional measurements, from finance to supply chain and competitive considerations. For this purpose, an innovative application of Data Envelopment Analysis (DEA) is explored within a novel framework. Input from a luxury goods company is used to evaluate the applicability of the tool. In the case study, the developed framework identified 41 out of 74 products for deletion consideration from which, two received a higher priority for possible deletion. The results provide insights into a deeper analysis of product deletion decisions showing that short-term financial perspectives should not stall managers. The study also provides recommendations for further research on modeling and implementation of product deletion decisions in practice. The developed method can be further validated and tested in other industries to contribute to this understudied topic.

*"... But while deletion is an uninspiring and depressing process, in a changing market it is almost as vital as the addition of new products."*
– Alexander [1]

## 1. Introduction

Supply chains are formed around the products; adjusting the company's portfolio helps maintain the supply chains' performance at the desired norm. Timely adaption to shifting needs and commercial opportunities is a prerequisite to maintaining competitive advantage [2]. In the sectors with a large product variety and short product lifecycle, well-informed and timely decisions on which products should be eliminated are of high importance to avoid the risk of draining resources and make room for new products. Procter & Gamble is a good example of the regular adjustment of the products portfolio by deleting poor-performing products [3].

As a major tool in product portfolio management [4], product deletion decision goes beyond and above the mere elimination of outdated or mature goods [5]. Product deletion is as important as new product launches [6,7] and may fail if not practiced cautiously [8,9]. Traditionally, financial perspectives like dropped customer demand, increased costs of raw materials, and shrunken profit margin are considered as the main drivers for eliminating a product from the company's portfolio [10–14]. However, the complexities and uncertainties involved in product deletion influence a company's overall product policy and management [15]. Upstream and downstream supply chain operations such as sourcing, manufacturing, delivering, marketing, and service [5,16–18] and competitive factors [16] are all impacted by product deletion decisions, hence, should be considered in strategic product deletion decisions.

The strategic product deletion is underdeveloped with the early studies being mostly conceptual with limited practicality [19,20]. The empirical analysis by [21,22] was one of the first studies that disclosed the influence of market and supply chain complexities on product deletion decisions. [5] conceptually showed that product deletion decisions have implications for environmental management and natural resources. [23]'s Rough Set Theory-based method analyzed the impact of discontinuing green products. Product deletion decision modeling is limited to a few studies. [5] developed an integrated analytical hierarchy process to study a general supply chain situation and used the benefits, opportunities, cost, and risks analysis to investigate lean and sustainability factors. [3] was the first to use the industrial experts'

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https://doi.org/10.1016/j.dajour.2021.100019
Received 10 September 2021; Received in revised form 23 November 2021; Accepted 8 December 2021
Available online 13 December 2021

opinion to model the product deletion decisions; they developed a Fuzzy Inference System to model product deletion decisions based on a set of if-then rules and qualitative judgments using inputs from the fast-moving consumer goods industry. [16] developed a qualitative approach for the analysis of the interrelationship between product deletion factors and introduced the so-called sequential effect. Most recently, [24] applied an improved Analytic Network Process method to model product deletion decisions for adjusting food supply chains' strategy based on the expert's opinion. Despite the relative development in the product deletion literature, there still is a lack of data-driven decision analysis approaches for evaluating product deletion candidates [25]; such an approach is required to replace the simplistic categorization of Stock Keeping Units (SKUs) in the real-world product deletion practice where the current approach only considers profit margin and sales volume to determine the high-risk products for possible deletion decisions.

The contributions of the present paper are twofold; we first develop an analytics-based product deletion decision framework (dashboard) for the periodic assessment of a large set of products; this will help to both identify the inefficient products and the candidate(s) for eventual deletion. For this purpose, an innovative application of the Data Envelopment Analysis (DEA) is investigated by developing a novel framework. Second, a case study from the luxury goods and fashion industry is conducted to evaluate the applicability of the method; on this basis, a set of quantifiable factors from the financial, market, supply chain, and competitive aspects are identified for product deletion decisions in luxury goods and fashion industries.

The remainder of this paper is structured in four sections. Section 2 provides the conceptual background on product deletion and discusses the measurements used in developing the product deletion decision framework. The proposed method is described in Section 3. Section 4 is dedicated to the case study, the presentation of major findings, and practical implications. The study is concluded in Section 5 by discussing the theoretical contributions and outlining limitations and areas for future research.

## 2. Background and decision factors

The luxury goods and fashion industries are among the fastest-growing sectors worldwide. According to [26], the top 100 luxury goods companies generated a total value of 281 billion USD in 2019, up more than ten percent from 2018. The luxury goods and fashion industry is characterized by high product variety, large transport distances, long manufacturing and delivery periods, short product sales times, and demand unpredictability [27]; these characteristics together with the growing demand in the emerging economies highlight that rivalry among major corporations is mostly over the competitiveness of their supply chains. Product management decisions have a direct influence on supply chain competitiveness [3].

As an essential product management decision, product deletion (removal, discontinuation) refers to the process of stopping the production, marketing, or sale of a particular product [10]. Early product management literature recognized that products are deleted when they reach the end of their life cycle [1]. The grounds for product deletion are often set when there is a decrease in customer demand, increase in operational cost, and low marginal profit [13]; this outlook of product deletion decision is regarded as a reactive approach [15]. Considering the need for multifaceted evaluation for a company's overall performance and competitiveness [28], a transformation into proactive, strategic product deletion is necessary [29].

Recent studies suggested that a wider variety of tangible and intangible factors should be taken into consideration for strategic product deletion [3,16,18]. In addition to the financial and market aspects, measurements reflecting the supply chain operational and competitive factors are necessary to ensure well-informed product deletion decisions. Inspired by the factors introduced by [3,16], the following measurements are considered for developing the analytics-based product deletion decision framework in the present study.

**Total profit ($\mathbf{F_1}$)** is a seminal financial ratio that represents the net profit of the goods sold after accounting for the production costs. The effect of a product on the company's profitability and financial structure is the main factor to be considered when a product portfolio is assessed [1]. Increased costs and a drop in product pricing as a result of rivalry in the market may result in a low total profit. General Motors' deletion of two low-profit vehicle lines in 2000 is a prime example of the role of total profit in product deletion.

**Customer feedback ($\mathbf{F_2}$)** is integral to firms' decision-making in every operation and product management aspect including product deletion [14]. Customer feedback measures the satisfaction level of the clients and provides insights into the responsiveness of the company and operational excellence. Considering the intense rivalry in the luxury goods and fashion industries and the market characteristics, notably high elasticity in price, using customer feedback for quality improvement is necessary [30]. Customers' negative feedback impacts the reputation and image of the company and has a sequential effect on the financial performance, particularly in industries where the customers are less price sensitive.

**Product growth rate ($\mathbf{F_3}$)** is an indicator to estimate whether a product is going to succeed or fail in the future. The position of a product on a growth curve is deemed to be an essential decision factor for product deletion decisions [10]. Sales growth of a product concern the long-term market prospects and the company's strategy. A product with a downward trend over a period can signal the product's decline stage. Products with a decline in growth rate should be watched carefully particularly if they are subject to high monetary value, which may result in excess inventory and loss.

**Sales volume percentage ($\mathbf{F_4}$)** of a product represents its relative performance in comparison with other products in the company's portfolio. A product with low sales volume may not necessarily fall into a low-profit category [24], but it may have a sequential effect on the sales performance in the long-term considering the type of the product and market conditions [16]. For example, a luxury goods market with increasing supply and demand may pressure the company to reduce the price and compensate for the marginal loss with an increase in the sales volume. Otherwise, deletion may be inevitable if lowering the price contradicts the company's competitive strategy.

**Logistics expense ($\mathbf{F_5}$)** is the biggest contributor to the profitability of the company in the manufacturing sector [31]. Logistics expenses are incurred throughout the product value chain from the procurement of raw materials to last-mile delivery and return services. This cost is particularly considerable in the supply chain of luxury goods because the supply and demand points are geographically scattered, and products are of relatively high monetary value. Substantial product diversity, short product life cycles, and low demand predictability are the major causes of high logistics expenses [27].

**Average time in the supply chain ($\mathbf{F_6}$).** Time is one of the main metrics for evaluating supply chains performance [31]. Given volatilities in customer demand, long lead times, and short sales periods of luxury and fashion products, and the high monetary value of the products, time is of even higher significance in the luxury goods and apparel industries. Time has a direct influence on logistics expenses; a sudden increase in the average time a product spends in the supply chain will show itself in logistics cost after a certain period. Despite the recent advances in real-time tracking of products, it is still not widely used and it may be hard to obtain exact data on $F_6$. Therefore, the average time in the supply chain is estimated based on the inventory turnover rate, i.e., the cycle time a firm requires to sell its inventory. In so doing, a high inventory turnover implies that the good is supplied and sold relatively fast and spends a short time in the system.

**Inventory stock level ($F_7$)** indicates the size of each SKU kept throughout the supply chain; it plays a significant role in deciding whether or not to delete a product from the company's portfolio [10]. The high level of stock inventory level is clear-cut evidence signifying the high risk of an SKU becoming obsolete inventory and increasing the cost of carrying inventory [18]. This is particularly the case for short-shelf-life products such as luxury goods and fashion items, where a low inventory stock level help avoid excess inventory. Inventory stock level differs from average time in the supply chain as the former refers to the batch size of a particular SKU remaining in stock, whereas the latter concerns the flow of cash in terms of time.

**Defects and returns rate ($F_8$)** is one of the indicators for assessing product quality. Given quality as a supply chain competency metric [31], a product that is deemed to be of poor quality or defective should be carefully examined for revitalization or deletion to avoid additional costs along with brand image damages [32]. Besides, removing products with high defects and return rates will improve the resource efficiency of the supply chain. Considering the direct influence of $F_8$ on product management decisions [33], it should be considered in product deletion decisions.

**Bargaining power over suppliers ($F_9$)** is one of the Competitive Forces introduced by [34]. In industries where suppliers have a large impact on the company's performance and profitability, particularly in terms of sourcing price and quality, the power of suppliers should be taken into consideration in strategic managerial decisions [3]. In other words, the company can reduce the cost of raw material and services or enhance quality if it has good leverage over the suppliers; otherwise, it may be hard to revitalize a poor-performing product. Payment term, as one of the conditions that show the negotiating leverage of the company over its supplier, is considered to estimate this factor. For this purpose, the average payment period for production materials is considered. A longer average payment period indicates that the firm has rather good power over the supplier [35].

## 3. Proposed method

### 3.1. Background

Introduced by [36], DEA is a non-parametric frontier analysis approach for evaluating the efficiency of a collection of comparable Decision-Making Units (DMU). The DEA method is originally developed for the evaluation and benchmarking of DMUs based on their performance [37]. DEA has also been applied for several other use cases and contexts (see [38]), such as preference voting and project selection [37], ranking and optimization of the branches of a bank [39], supplier selection [38], supply chain performance evaluation [40,41] and network optimization [42], and forecasting the performance of manufacturing companies [43].

The DEA method considers the maximization of the ratio between the weighted sum of outputs and inputs to identify DMUs with an efficiency score of 1 as the efficient units, which form the efficient frontier. DMUs with an efficiency score less than 1, the inefficient units, will be enveloped by the efficient frontier. In this approach, the efficiency score represents the distance of an inefficient DMU from the respective efficient DMU on the frontier. Inspired by this concept, we investigate a novel application of DEA in the product deletion context. The developed framework is based on the Inverted Data Envelopment Analysis (IDEA) and Super-Efficiency Method which are extensions to the CCR model.

IDEA was introduced by [44] to evaluate DMUs in a pessimistic manner, where the distance of DMUs from the inefficient frontier is the basis of computations. IDEA maximizes the ratio of inputs and outputs, hence, DMUs with an inefficiency score of 1 are defined as inefficient units and form the inefficient frontier. In this definition, the DMU that is farthest away from the inefficient frontier is the most efficient unit. The Supper-Efficiency Method, developed by [45], measures the overall efficiency of the system; it excludes the evaluated DMU from the constraints and measures the distance between the remaining DMUs and the new efficiency frontier after updating the DMU list.

### 3.2. Developed framework

The product deletion (elimination) process consists of (1) screening products against decision factors for the identification of candidates for deletion and taking remedial actions to revitalize the products; (2) evaluating the impact of a possible product deletion on the supply chain as a whole; (3) eventual selection for product deletion implementation [46]. In this context, the main purpose of the developed framework is to screen a large set of SKUs, identify the inefficient ones, and investigate the performance of the portfolio after removing poor SKUs from the system. Fig. 1 presents the developed framework followed by a step-by-step elaboration on the computational procedure.

*Step 1. Categorize factors into inputs and outputs.* After obtaining and processing raw data, they should be categorized into positive and negative factors. A larger value is preferred for the positive factors while negative factors are desirable when they accept a smaller value [42]. Positive factors are considered as outputs ($y_s$) and negative factors are referred to as input and are indicated by $x_m$. In this definition, $s$ and $m$ indices represent the number of output and input factors, respectively.

*Step 2. Calculate the inefficiency score of the DMUs.* Considering the inefficient frontier as the basis of the calculations, the IDEA model determines the inefficiency score of every DMU using the following optimization problem [44].

$$Max\theta = v_1 x_{1k} + v_2 x_{2k} + \cdots + v_m x_{mk} \tag{1}$$

Subject to:

$$u_1 y_{1k} + u_2 y_{2k} + \cdots + u_s y_{sk} = 1 \tag{2}$$

$$v_1 x_{1k} + v_2 x_{2k} + \cdots + v_m x_{mk} - u_1 y_{1k} + u_2 y_{2k} + \cdots + u_s y_{sk} \le 0 (k = 1, \ldots, n) \tag{3}$$

$$v_1, v_2, \ldots, v_m \ge 0 \tag{4}$$

$$u_1, u_2, \ldots, u_s \ge 0 \tag{5}$$

Assuming that there are $k$ DMUs in the system, the objective function in Eq. (1) maximizes the weighted sum of input variables where $v_m$ represents the weight values. In Eq. (2), the weighted sum of output values is assumed to be equal to one with $u_s$ forming the weight vector. Eq. (3) is defined to ensure that inputs are less than the outputs, which is in contrast with the original DEA. Equations (4)–(5) indicate that the weight variables cannot accept negative values.

*Step 3. Evaluate the extent of improvement after excluding inefficient unit separately.* Given the set of DMUs with an inefficiency score of 1, i.e., the inefficient frontier, remove one DMU at a time and calculate the inefficiency score of other DMUs. In this approach, eliminating an inefficient unit from the system shifts the inefficient frontier closer to the best DMUs, hence, improves the overall efficiency. An optimization problem inspired by the Super-Efficiency concept is used to measure the distance of other DMUs with a new inefficient frontier after excluding an inefficient unit. This problem is different from the IDEA model in the following points [47]: (I) the selected inefficient DMU is no longer included in the objective function, as shown in Eq. (6). (II) Inequality (7) replaces Constraint (3) to exclude the respective DMU from the calculations.

$$Max\theta = v_1 x_{1k} + v_2 x_{2k} + \cdots + v_m x_{mk} (k \ne j) \tag{6}$$

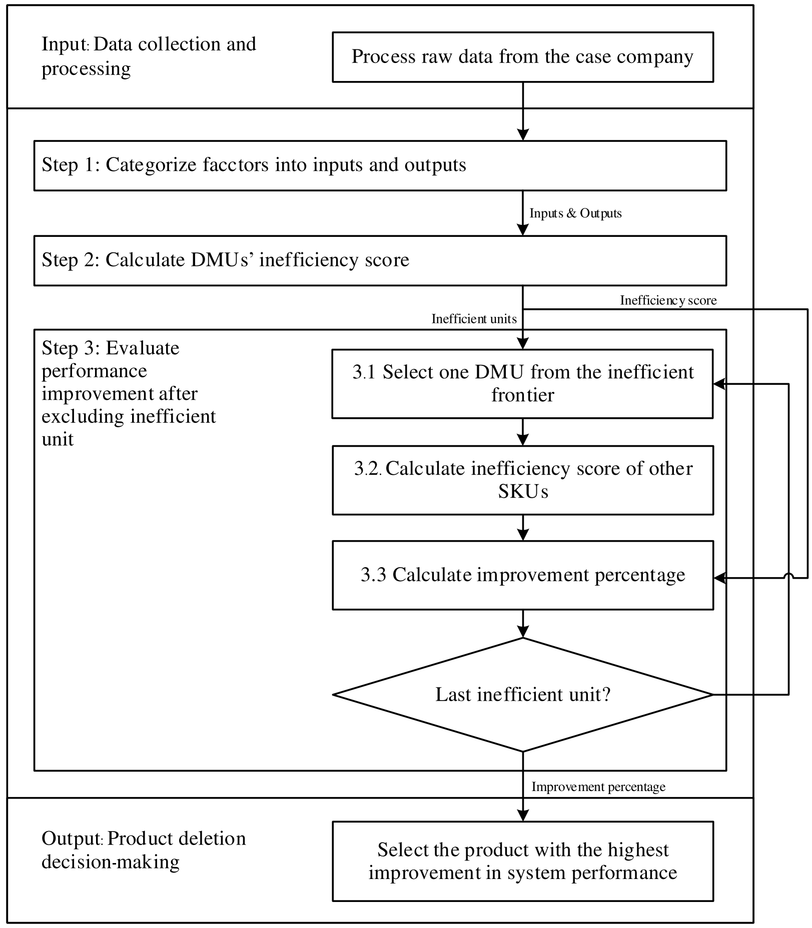


**Fig. 1.** The computational procedure of the product deletion decision framework.

$$v_1x_{1k}+v_2x_{2k}+\cdots+v_mx_{mk}-u_1y_{1k}+u_2y_{2k}+\cdots+u_sy_{sk}\leq 0(k=1,\ldots,n\&k\neq j) \quad (7)$$

After repeating this procedure for all the inefficient units, results should be compared considering the improvement percentage. For this purpose, the percent improvement (deviation) of the Should-be scenarios is compared with that of the baseline, i.e. As-is situation. In so doing, the deletion scenario that results in a higher deviation from the baseline situation indicates the best product deletion decision.

## 4. Case study

### 4.1. Data collection

The luxury goods market is one of the fastest-growing [48]; the demand for luxury goods has not been significantly impacted by the global financial crisis [49]. In this situation, luxury goods companies are trying to expand their customer base by offering a wider variety of products [50,51]. The variety of products and high logistics costs in the luxury goods industry make the strategic product deletion imperative. Our study acquired data from an America-based international corporation, which is one of the largest upscale luxury goods and jewelry retailers worldwide, to provide insights into this understudied operations management topic. The company manufactures and sells products through over 300 retail store subsidiaries and boutiques, its website, corporate merchandising, and catalogs. The company-owned and managed retail stores are in the Americas, Asia-Pacific, Japan, Europe, and the United Arab Emirates. The company offers a wide range of luxury goods collections such as jewelry, dishware, silverware, stationery, fragrances, and fashion items like watches, leather goods, and personal accessories. Given the wide width of the products portfolio and the variety in color and size, a significant number of Stock-Keeping Units (SKU) should be managed by the company. In this situation, the retailers can maintain a limited number of each SKU to respond to forecasted demand. These characteristics together make the product deletion decisions inevitable.

Given nine quantifiable decision factors identified from the literature, a set of measurements listed in Table 1 are confirmed by the product manager to appraise the performance of the products. Besides, a total of 74 SKUs suggested by the store managers are considered in our analysis; the respective data is presented in Appendix. The products that cannot be discontinued due to strategic reasons are not included in the analysis.

### 4.2. Results analysis

Given a total of nine factors, Logistics Expenses, Defects & Return Rate, Stock Level, and Average Time in the Supply Chain are categorized as inputs to the IDEA model. The rest of the factors, i.e., Total Profit, Customer Feedback, Bargaining Power over Suppliers, Market Growth Rate, and Sales Volume Percentage are defined as model outputs. The selection of poor-performing candidates is first completed considering their position on the IDEA frontiers. From 74 SKUs, a total of 41 SKUs show an inefficiency score of 1 (see Table 2), positioned on the inefficient frontier. It implies that these DMUs are performing poorly and their deletion from the system may result in an improvement in the overall performance of the portfolio. Next, the

**Table 1**
Summary of product deletion decision factors.

| Factor | Explanation | Measure |
|---|---|---|
| Total Profit ($F_1$) | Monetary loss from total profit may lead to different risks, additional costs of goods sold (COGS), and a reduction in the price of the product. Low-profit products may be candidates for elimination. | Total Profit $= \frac{Total\ Revenue - COGS}{Total\ Revenue} \times 100$ |
| Customer Feedback ($F_2$) | Negative customer feedback represents customers' dissatisfaction, which negatively impacts the company's reputation and brand image, especially in the luxury goods industry. | Net Promoter Score: an index ranging from 0 to 100 |
| Product Growth Rate ($F_3$) | Sales growth is concerned with the long-term market prospects; an SKU with declines in sales growth may be an alternative for deletion. | Product Growth Rate $= \frac{Market\ Value\ Yn}{Market\ value\ Yn-1} - 1 \times 100$ |
| Sales Volume Percentage ($F_4$) | Decreases in sales volumes lead to decreases in profit, hence, has an impact on product deletion decisions. | Sales Volume Percentage $= \frac{Product A's\ Sales\ Volume}{Total\ Sales\ Volume} \times 100$ |
| Logistics Expenses ($F_5$) | High logistics expenses trigger a decrease in profit. | Logistics Expenses $= \frac{Logistic\ expenses}{Total\ Profit} \times 100$ |
| Average Time in the Supply Chain ($F_6$) | Long average time in the supply chain and a slow inventory turnover (IVTR) may be a warning sign of weak sales performance, which also increases obsolete inventory and incompetence of inventory management. | Days Sales in Inventory $= \frac{Average\ IVTR}{COGS} \times 365$ |
| Inventory Stock Level ($F_7$) | The high stock level of an SKU increases the risks of high operational costs and may be a sign of a product reaching the decline stage of its lifecycle. | Ending IVTR $= (Beginning\ IVTR + Purchase) - COGS$ |
| Defects & Returns Rate ($F_8$) | A high rate of defects and returned items may threaten brand image and company reputation, especially in luxury goods industries. | Defects & Returns Rate $= \frac{No.\ of\ Items\ Returned\ \&\ Defected}{No. of\ ItemsSold} \times 100$ |
| Bargaining Power over Suppliers ($F_9$) | A shorter payment period implies the company's weak bargaining power over the supplier, which may influence product quality and cost. | Avg Payment Period for Production Materials $= \frac{Material\ Payable}{Total\ Cost\ of\ Material} \times Days\ in\ Period$ |

**Table 2**
Inefficiency score of each SKU (inefficient SKUs in **bold**).

| SKU | Score | SKU | Score | SKU | Score | SKU | Score |
|---|---|---|---|---|---|---|---|
| 1 | **1.0000000** | 21 | **1.0000000** | 41 | **1.0000000** | 61 | **1.0000000** |
| 2 | **1.0000000** | 22 | 0.9998884 | 42 | **1.0000000** | 62 | **1.0000000** |
| 3 | **1.0000000** | 23 | 0.9998188 | 43 | **1.0000000** | 63 | 0.9999998 |
| 4 | 0.9999783 | 24 | **1.0000000** | 44 | **1.0000000** | 64 | 0.9999979 |
| 5 | **1.0000000** | 25 | 0.9998907 | 45 | 0.9999939 | 65 | **1.0000000** |
| 6 | **1.0000000** | 26 | 0.9998801 | 46 | **1.0000000** | 66 | **1.0000000** |
| 7 | 0.9998462 | 27 | 0.9996991 | 47 | **1.0000000** | 67 | **1.0000000** |
| 8 | **1.0000000** | 28 | **1.0000000** | 48 | **1.0000000** | 68 | **1.0000000** |
| 9 | 0.9999239 | 29 | **1.0000000** | 49 | 0.9999893 | 69 | **1.0000000** |
| 10 | 0.9995062 | 30 | 0.9999697 | 50 | **1.0000000** | 70 | 0.7582315 |
| 11 | 0.9999225 | 31 | 0.9999675 | 51 | **1.0000000** | 71 | **1.0000000** |
| 12 | 0.9999560 | 32 | 0.9999988 | 52 | **1.0000000** | 72 | **1.0000000** |
| 13 | **1.0000000** | 33 | 0.9999926 | 53 | **1.0000000** | 73 | 0.9999894 |
| 14 | **1.0000000** | 34 | 0.9999991 | 54 | 0.9999679 | 74 | **1.0000000** |
| 15 | 0.9999829 | 35 | 0.9999895 | 55 | **1.0000000** | | |
| 16 | **1.0000000** | 36 | 0.9999758 | 56 | 0.9999389 | | |
| 17 | **1.0000000** | 37 | 0.9999726 | 57 | 0.9999762 | | |
| 18 | **1.0000000** | 38 | **1.0000000** | 58 | **1.0000000** | | |
| 19 | 0.9996687 | 39 | 0.9999908 | 59 | 0.9999373 | | |
| 20 | **1.0000000** | 40 | **1.0000000** | 60 | 0.9999535 | | |

**Table 3**
Performance improvement over the deletion scenarios (largest in **bold**).

| Scenario | Improvement (*$10^6$) | Ranking | Scenario | Improvement (*$10^6$) | Ranking |
|---|---|---|---|---|---|
| 1 | 0.00 | 38 | 44 | 0.00 | 28 |
| 2 | 40.61 | 10 | 46 | 40.13 | 11 |
| 3 | 12.90 | 16 | 47 | 34.92 | 13 |
| 5 | 0.00 | 27 | 48 | 2.12 | 23 |
| 6 | 0.00 | 28 | 50 | 35.43 | 12 |
| 8 | 33.24 | 14 | 51 | 0.00 | 41 |
| 13 | 89.65 | 6 | 52 | ***5132.99*** | 2 |
| 14 | 24.27 | 15 | 53 | 0.00 | 40 |
| 16 | 190.29 | 4 | 55 | 11.00 | 17 |
| 17 | ***338.25*** | 3 | 58 | 0.00 | 28 |
| 18 | 0.00 | 39 | 61 | 3.16 | 22 |
| 20 | 69.54 | 7 | 62 | 0.00 | 28 |
| 21 | 96.98 | 5 | 65 | 41.48 | 9 |
| 24 | 0.57 | 24 | 66 | ***21760.10*** | 1 |
| 28 | 54.45 | 8 | 67 | 0.00 | 28 |
| 29 | 0.00 | 28 | 68 | 6.55 | 19 |
| 38 | 4.14 | 21 | 69 | 0.00 | 28 |
| 40 | 0.00 | 28 | 71 | 0.00 | 25 |
| 41 | 0.00 | 28 | 72 | 7.08 | 18 |
| 42 | 0.00 | 26 | 74 | 0.00 | 28 |
| 43 | 6.38 | 20 | | | |

inefficiency scores are used as the reference to estimate the overall percentage improvement in forms of product deletion scenarios.

To evaluate the deletion scenarios, inefficient items are excluded once at a time to explore the extent of changes in the score of the rest of the SKUs in the system. Given a total of 41 possible deletion scenarios, the deviation of inefficiency score in the Should-be compared to the As-is situation is considered. The average deviation from the original state when eliminating potential candidates, i.e., the improvement percentage, is presented in Table 3.

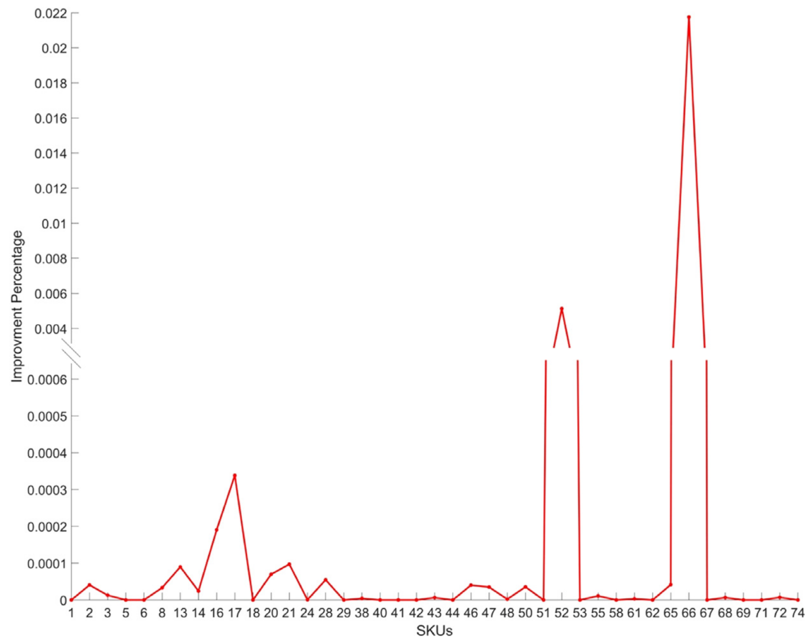


**Fig. 2.** Results analysis for the final selection of the alternative SKU(s) for deletion.

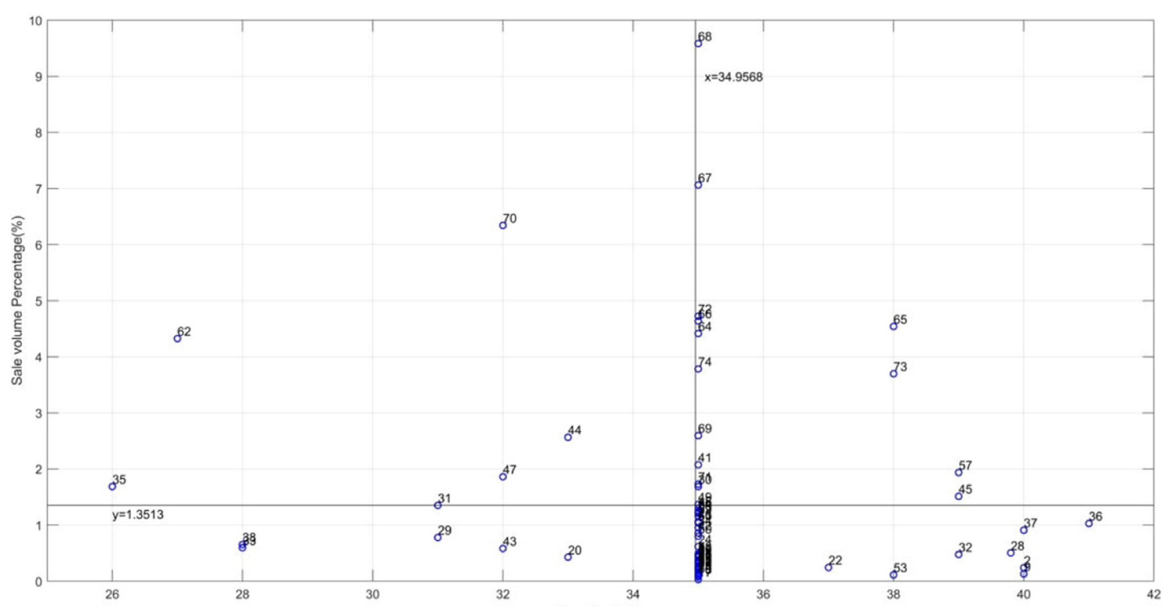


**Fig. 3.** Product deletion outcome in the as-is situation.

A higher deviation between the two situations indicates a more significant improvement in the overall performance. Fig. 2 visually compares the extent of improvement over 41 deletion scenarios. Deleting SKU 66, as one of the inefficient units, has resulted in a meaningfully larger deviation, hence, it should be considered as the candidate with the highest priority. SKUs 52 and 17 are the next alternatives if more than one product is meant to be deleted from the portfolio.

The as-is product deletion decisions in the case company and the vast majority of other companies are made considering the margin and sales volume of the SKUs as the main gauges for measuring profitability. On this basis, the items falling below both thresholds, i.e., the mean margin and sales volume values in this example, are categorized as high-risk and are considered as the alternatives for immediate deletions or fade-out (see Fig. 3). The major findings are now discussed to shed light on the shortcoming of the existing simplistic approach.

From the category of high-risk products in the case company, SKU-33 and SKU-38 are recommended by the traditional approach for deletion. According to Figs. 2–3, SKU-38 is regarded as the priority candidate for deletion in both approaches. However, and despite its presence among the 41 candidates selected after the initial evaluations, SKU-38 is far behind the top-priority deletion candidates. On the other hand, SKU-33 is not even recognized as a candidate for the final product deletion assessment. This difference is due to considering their relative efficiency compared to other SKUs in the portfolio. That is, SKU-33 and SKU-35 with the most stagnant sales and margin may have been selected for eventual deletion if only myopic financial aspects were considered.

Considering the outcomes presented in Table 3, the candidate PD priorities have changed. We have noticed some of the SKUs are prone to sequential degradation in the financial factors, which make them

**Table A.1**
Input data used in the product deletion decision framework.

| SKU | Logistics expenses | Defects & Return rate (%) | Stock level (Units) | Average time in the supply chain (Days) | Total profit | Customer's feedback (Points) | Bargaining power over suppliers (Days) | Market growth rate (%) | Sales volume percentage |
|---|---|---|---|---|---|---|---|---|---|
| 1 | 264 | 9.6774 | 3315 | 247.2581 | 35 | 79 | 6.3400 | −24.3902 | 0.4747 |
| 2 | 133 | 7.1429 | 7125 | 1160.1786 | 40 | 36 | 15.2083 | −41.6667 | 0.2396 |
| 3 | 208 | 3.8462 | 2080 | 533.4615 | 35 | 67 | 7.5592 | −33.3333 | 0.3747 |
| 4 | 263 | 0.0000 | 1706 | 245.0714 | 35 | 90 | 5.6154 | −20.4545 | 0.4729 |
| 5 | 238 | 8.0000 | 7101 | 562.1000 | 35 | 64 | 7.8615 | −28.5714 | 0.4279 |
| 6 | 171 | 0.0000 | 6484 | 800.9722 | 35 | 46 | 10.9188 | −35.7143 | 0.3081 |
| 7 | 238 | 0.0000 | 4323 | 365.0000 | 35 | 64 | 7.8615 | 13.6364 | 0.4279 |
| 8 | 55 | 18.1818 | 2438 | 945.6818 | 35 | 28 | 17.8671 | −21.4286 | 0.0991 |
| 9 | 72 | 0.0000 | 3135 | 912.5000 | 40 | 33 | 16.3782 | 30.0000 | 0.1288 |
| 10 | 48 | 0.0000 | 0 | 365.0000 | 35 | 15 | 32.7564 | −33.3333 | 0.0865 |
| 11 | 128 | 0.0000 | 5801 | 888.1667 | 35 | 38 | 13.1026 | −16.6667 | 0.2297 |
| 12 | 124 | 10.5263 | 3803 | 691.5789 | 35 | 49 | 10.3441 | 26.6667 | 0.2225 |
| 13 | 154 | 0.0000 | 3185 | 464.5455 | 35 | 56 | 8.9336 | 22.2222 | 0.2774 |
| 14 | 70 | 0.0000 | 4875 | 1225.3571 | 35 | 36 | 14.0385 | 40.0000 | 0.1261 |
| 15 | 200 | 0.0000 | 6484 | 773.4524 | 35 | 54 | 9.3590 | 50.0000 | 0.3594 |
| 16 | 194 | 2.9412 | 2779 | 413.3088 | 35 | 87 | 5.7805 | 13.3333 | 0.3491 |
| 17 | 17 | 0.0000 | 4111 | 4197.5000 | 35 | 8 | 65.5128 | −57.1429 | 0.0297 |
| 18 | 44 | 0.0000 | 4111 | 1802.1875 | 35 | 21 | 24.5673 | 100.0000 | 0.0793 |
| 19 | 87 | 0.0000 | 0 | 283.8889 | 35 | 23 | 21.8376 | 80.0000 | 0.1573 |
| 20 | 238 | 24.0000 | 5729 | 642.4000 | 33 | 64 | 7.6269 | 38.8889 | 0.4279 |
| 21 | 88 | 0.0000 | 4862 | 1076.7500 | 35 | 26 | 19.6538 | 233.3333 | 0.1585 |
| 22 | 135 | 0.0000 | 1890 | 547.5000 | 37 | 46 | 11.2654 | 125.0000 | 0.2432 |
| 23 | 180 | 0.0000 | 3315 | 285.9167 | 35 | 77 | 6.5513 | 30.4348 | 0.3243 |
| 24 | 342 | 0.0000 | 1755 | 67.2368 | 35 | 97 | 5.1721 | 31.0345 | 0.6161 |
| 25 | 207 | 7.1429 | 0 | 0.0000 | 35 | 72 | 7.0192 | 33.3333 | 0.3733 |
| 26 | 190 | 0.0000 | 1625 | 259.3421 | 35 | 97 | 5.1721 | 22.5806 | 0.3423 |
| 27 | 110 | 0.0000 | 0 | 365.0000 | 35 | 56 | 8.9336 | 69.2308 | 0.1982 |
| 28 | 280 | 0.0000 | 3010 | 560.5357 | 40 | 36 | 15.1578 | −30.0000 | 0.5044 |
| 29 | 432 | 5.5556 | 12420 | 354.8611 | 31 | 46 | 10.2858 | −45.4545 | 0.7783 |
| 30 | 936 | 0.0000 | 5460 | 42.1154 | 35 | 100 | 5.0394 | −13.3333 | 1.6863 |
| 31 | 750 | 0.0000 | 1035 | 65.7000 | 31 | 64 | 7.4058 | −19.3548 | 1.3512 |
| 32 | 264 | 0.0000 | 11407 | 958.1250 | 39 | 31 | 17.4522 | −40.0000 | 0.4756 |
| 33 | 330 | 0.0000 | 9504 | 511.0000 | 28 | 38 | 11.8287 | 36.3636 | 0.5945 |
| 34 | 528 | 0.0000 | 0 | 365.0000 | 35 | 62 | 8.1891 | 4.3478 | 0.9512 |
| 35 | 936 | 12.5000 | 1443 | 53.2292 | 26 | 62 | 7.1931 | 50.0000 | 1.6863 |
| 36 | 570 | 0.0000 | 13452 | 778.6667 | 41 | 38 | 14.4350 | 114.2857 | 1.0269 |
| 37 | 504 | 4.7619 | 13680 | 252.0238 | 40 | 54 | 10.1389 | 10.5263 | 0.9080 |
| 38 | 363 | 9.0909 | 27324 | 1211.1364 | 28 | 28 | 16.1301 | 57.1429 | 0.6540 |
| 39 | 644 | 0.0000 | 13455 | 260.7143 | 35 | 72 | 7.0192 | −12.5000 | 1.1602 |
| 40 | 185 | 0.0000 | 13991 | 1277.5000 | 35 | 23 | 21.8376 | −57.1429 | 0.3324 |
| 41 | 1152 | 0.0000 | 1170 | 313.6719 | 35 | 82 | 6.1418 | −28.8889 | 2.0754 |
| 42 | 477 | 0.0000 | 20670 | 547.5000 | 35 | 46 | 10.9188 | −50.0000 | 0.8594 |
| 43 | 324 | 11.1111 | 12240 | 932.7778 | 32 | 23 | 20.8742 | −57.1429 | 0.5837 |
| 44 | 1424 | 5.1282 | 0 | 18.7179 | 33 | 100 | 4.8890 | −17.0213 | 2.5646 |
| 45 | 840 | 0.0000 | 2928 | 41.7143 | 39 | 90 | 5.9836 | −10.2564 | 1.5133 |
| 46 | 588 | 0.0000 | 13650 | 586.6071 | 35 | 72 | 7.0192 | −12.5000 | 1.0593 |
| 47 | 1033 | 0.0000 | 8024 | 166.8571 | 32 | 90 | 5.3676 | −20.4545 | 1.8601 |
| 48 | 722 | 36.8421 | 2470 | 96.0526 | 35 | 49 | 10.3441 | −42.4242 | 1.3008 |
| 49 | 760 | 0.0000 | 0 | 292.0000 | 35 | 26 | 19.6538 | −28.5714 | 1.3692 |
| 50 | 444 | 0.0000 | 38480 | 1825.0000 | 35 | 15 | 32.7564 | −50.0000 | 0.7999 |
| 51 | 100 | 0.0000 | 0 | 0.0000 | 35 | 3 | 196.5385 | −95.8333 | 0.2126 |
| 52 | 200 | 0.0000 | 42900 | 3193.7500 | 35 | 5 | 98.2692 | −93.3333 | 0.4324 |
| 53 | 63 | 20.0000 | 5038 | 1788.5000 | 38 | 13 | 41.2097 | −79.1667 | 0.1126 |
| 54 | 690 | 0.0000 | 12675 | 103.1522 | 35 | 59 | 8.5452 | 1050.0000 | 1.2431 |
| 55 | 137 | 0.0000 | 2324 | 582.2619 | 35 | 54 | 9.3590 | −52.2727 | 0.2459 |
| 56 | 250 | 8.0000 | 4875 | 240.9000 | 35 | 64 | 7.8615 | 177.7778 | 0.4504 |
| 57 | 1075 | 0.0000 | 3642 | 168.9815 | 39 | 69 | 7.7565 | 145.4545 | 1.9360 |
| 58 | 270 | 0.0000 | 10530 | 803.0000 | 35 | 38 | 13.1026 | 66.6667 | 0.4864 |
| 59 | 677 | 0.0000 | 15522 | 171.7647 | 35 | 44 | 11.5611 | 183.3333 | 1.2190 |
| 60 | 672 | 0.0000 | 20020 | 593.1250 | 35 | 31 | 16.3782 | 1100.0000 | 1.2107 |
| 61 | 184 | 0.0000 | 9773 | 701.1842 | 35 | 49 | 10.3441 | 137.5000 | 0.3320 |
| 62 | 1200 | 0.0000 | 0 | 136.8750 | 27 | 21 | 21.8750 | −52.9412 | 4.3238 |
| 63 | 576 | 0.0000 | 6240 | 60.8333 | 35 | 15 | 32.7564 | 200.0000 | 1.0377 |
| 64 | 2450 | 0.0000 | 9555 | 328.5000 | 35 | 64 | 7.8615 | 78.5714 | 4.4139 |
| 65 | 2520 | 9.5238 | 55800 | 338.9286 | 38 | 54 | 9.8118 | 110.0000 | 4.5400 |
| 66 | 2574 | 0.0000 | 19305 | 154.4231 | 35 | 33 | 15.1183 | −45.8333 | 4.6373 |
| 67 | 3920 | 0.0000 | 6370 | 155.1250 | 35 | 51 | 9.8269 | 122.2222 | 7.0623 |
| 68 | 5320 | 7.8947 | 36400 | 57.6316 | 35 | 97 | 5.1721 | 40.7407 | 9.5845 |
| 69 | 1440 | 0.0000 | 44200 | 517.0833 | 35 | 46 | 10.9188 | 157.1429 | 2.5943 |
| 70 | 1650 | 0.0000 | 0 | 199.0909 | 32 | 28 | 17.0789 | 450.0000 | 6.3416 |
| 71 | 450 | 0.0000 | 104000 | 1581.6667 | 35 | 8 | 65.5128 | −25.0000 | 1.7295 |
| 72 | 2622 | 30.4348 | 44460 | 126.9565 | 35 | 59 | 8.5452 | 91.6667 | 4.7238 |
| 73 | 2052 | 0.0000 | 23436 | 566.7105 | 38 | 49 | 10.8447 | 137.5000 | 3.6969 |
| 74 | 1050 | 0.0000 | 0 | 0.0000 | 35 | 18 | 28.0769 | −63.1579 | 3.7834 |

candidates for phase-out even though they are currently performing fine in terms of sales volume and margin. On the other hand, the dashboard has recognized SKU-66, SKU-52, SKU-17, SKU-16, and SKU-21 as the candidates with the highest deletion priority. In particular, SKU-66 is by far the worst-performing SKU, whereas it attained a moderate level of sales volume and profit margin. This result is in contrast with the traditional product deletion consideration of the company, where SKU-66 would remain in the company's portfolio owing to its moderate profitability and despite its burdensome nature.

## 5. Concluding remarks

Product deletion goes above and beyond reacting to short-term financial downturns. Supply chain and competitive considerations should be considered for well-informed product deletion decisions, particularly if applied as a proactive and operational strategic tool. This research introduced an analytics-based product deletion decision framework considering multidimensional measures. For this purpose, an innovative application of the DEA is introduced for screening a large set of SKUs and identifying the eventual deletion candidate(s). The developed framework integrates the IDEA method and Super-Efficiency concept to estimate the inefficiency level of SKUs and the overall performance of the portfolio before and after removing an SKU. A case study from the luxury goods industry was conducted to show the applicability of the developed approach.

The product portfolio's performance was measured with respect to financial, market, supply chain, and competitive force considerations integrated into a unique overall score. On this basis, the dashboard identifies the SKU with the highest deletion priority. Outcomes appeared to be different from that of the traditional product deletion practice. The current practice in the case company consists of evaluating products based on the sales volume and the profit margin. Results from our proposed approach showed that SKUs with higher inventory stock levels, the longer average time in the supply chain, and the negative market growth rate may receive a higher deletion priority. In other words, an inefficient product – which is burdensome to the supply chain – is likely to be discontinued even if it has a moderate sales volume. The outcomes of this study were verified by the managers of the case company and the developed product deletion decision framework may be considered for adoption. We think that such an approach is necessary for the periodic evaluation of products regardless of their life cycle stage; this has implications for the companies that cannot further optimize their production and supply chain operations. As a prime example, including measures pertinent to the Emissions Trading Scheme may reveal that deleting certain products is more cost-effective in the long term than spending in carbon markets.

This study is limited in that it uses a limited set of product deletion decision factors since some of them are hard to quantify. The first suggestion for future research is to address the mentioned limitation by extending the DEA to address less tangible qualitative measures, i.e., through Fuzzy quantification methods. The second limitation comes from the evaluation scope. Ideally, the products should be benchmarked against those of rivals in the market in addition to the company's own products. To address this limitation, future research may consider extending our method, for example by using Network DEA [52] for the simultaneous evaluation of the products within and outside of a company's portfolio. As the third direction for future research, one should validate the applicability of the developed framework across contexts and sectors considering different and/or additional factors. The fourth suggestion comes from integrating the time variable into the product deletion decision framework to allow fade-out and immediate product deletion decisions. Finally, sustainability factors like carbon footprint, waste generation, pollutions, and energy consumption should be considered to account for the environmental degradation caused by a product. Considering law (political) and technological factors may also be relevant in other contexts.

*"Just as a crust of barnacles on the hold of a ship retards the vessel's movement, so do a number of worn-out items in a company's product mix affect the company's progress". – [1]*

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Appendix

See Table A.1

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