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# Effects of Consumer Demand, Product Lifetime, and Substitution Ratio on Perishable Inventory Management

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**Abstract:** With the intensification of global population, food security is a big concern. Food waste stems from inappropriate inventory management. Companies offer a wide range of products to capture more sales, yet this increases inventories and complicates inventory management. Management challenges are worsened by three factors: uncertain consumer demand, product lifetimes, and consumer substitution among the product range. This research aims to understand the effects of these factors on inventory performance. The analytic hierarchy process (AHP) method was used to weight the importance of each of the non-financial performance measures from the simulation results and data envelopment analysis (DEA) was used to rank and evaluate the scenarios. Then, the most favorable scenario or replenishment policy, which had the lowest DEA efficiency score, was chosen. The results show that when the substitution ratio is greater, its interaction with consumer demand and product lifetime has mostly a small- or medium-sized effect on retailers' performance, in contrast to relatively larger effects on the supplier. These findings show that suppliers' performance is affected largely by the existence of the bullwhip effect in the model. Recommendations are provided for managers who are facing uncertainties of consumer demand, substitution, and product lifetime.

## 1. Introduction

The global population is currently over seven billion, and in the next 30 years, it is expected to reach over nine billion [1]. Thus, there are concerns about finding ways to feed them all. The United Nations has set as one of its goals to achieve a sustainable world by 2030 by reducing food waste [1]. However, food security is still far from satisfactory because food quality deteriorates over time and demand is uncertain, as an example, around 15% of perishable products are lost by retailers due to spoilage and damage [2]. Moreover, while this is easier when managing only a few products, the situation becomes more complicated as companies choose to offer a range of products [3].

Knowledge of the effects of the characteristics of a problem and the interactions with others in system performance under different contexts helps to define a suitable replenishment policy to resolve the food waste issue. Understanding these characteristics and their interactions have been demonstrated as important by Kök and Fisher [4] who, in reference to a real-world apparel case, suggested that profits may be increased by up to 50% when taking the operational characteristics

of products into account during planning. In a similar finding, Musalem et al. [5] found that the financial costs associated with stock-outs can be sizeable, even accounting for the benefits accruing from substitution. Holding the right level of inventory at the right locations is not only profitable for firms, it also minimizes product wastage and improves the sustainability of their firm.

The purpose of this research is to address the question, given the most favorable replenishment policy, how do the characteristics of the inventory model influence the performance of a two-echelon inventory model for perishable and substitutable products? Thus, this research investigates the effects of these factors on inventory performance while considering a supplier, who defines replenishment policy for itself and two retailers in the context of three perishable and substitutable products. Understanding product characteristics can support managerial decisions that can have many outcomes such as reducing costs and product waste. We argue that managers must carefully consider the characteristics of the environment (e.g., substitutability and consumer behaviors) and the products (e.g., perishability) when developing a replenishment model. Considering their operational objectives (e.g., cost minimization or increased service level), the managers are then able to develop replenishment models that better achieve their desired outcomes.

This research relates to a rich literature stream regarding the perishable supply chain where Yang et al. [6] highlighted that it is a challenging task to manage a perishable supply chain due to uncertainty in product lifetime and customer demand. This research contributes to the literature on perishable supply chain by considering a two-echelon model with three perishable products. The findings contribute to the reduction of product waste and the improvement of customer service. These findings will have a significant impact on not only economic but also environmental aspects; e.g., saving costs of producing and distributing surplus products or greenhouse gas emission related to energy used in production. Thus, the research could serve as the basis for more advanced research or motivate further research in the sustainability domain.

This research is important because even though it is a modelling work, it demonstrates how an explicit focus on *waste* reduction (rather than costs) can be valuable as part of a decision-support system that can change behaviors and move companies towards more sustainable decisions. Sustainability concerns have become a crucial part of perishable supply chain management [7]. The sustainability of supply chains that manage materials, information flow, and cooperation among companies along the supply chain are measured by three dimensions, i.e., economic, social, and environment [8], which have been represented in dozens of metrics [9]. Of them, waste reduction is one of the most common efforts toward the sustainable development [10]. By reducing waste, companies can lower operational costs (e.g., materials or packaging costs) and higher awareness of environmental issues amongst stakeholders, suppliers, and consumers. As an example in the food industry, Kaipia et al. [7] stated that synchronizing information and material flow is essential to food waste reduction, which improves the sustainability of perishable supply chain.

The research has two primary contributions to the literature. First, the research uses non-financial measures that will be more meaningful to operations managers. These measures better capture multi-echelon effects, reflect the multi-dimensional nature of supply chain, support continuous improvement, improve overall company performance, are more comprehensible to managers and employees, avoid difficulties in cost estimation, and overcome the complexities of mathematical calculations [11–13]. Second, the research examines the interaction effects over multi-echelons with substitution and perishability. Through the numerical example, these interactions and their importance to managers, depending on their operational focus and supply chain position, are highlighted. Our results will be beneficial to managers and provide help to guide replenishment decisions, accounting for the circumstances they face.

The next section reviews literature focusing on the influence of problem characteristics (e.g., consumer demand, substitution, and product lifetime) on replenishment policies. The third section discusses the design of the simulation and research framework. Fourth, the numerical results are

presented and discussed. Finally, the limitations of the study design and potential future research opportunities are provided, before the concluding remarks are presented.

## 2. Literature Review

### 2.1. The Effects of Consumer Demand

The purpose of inventory management is to match supply and demand, and thus, to answer two questions—when to place a replenishment order and how much to order [14]. A replenishment policy is calculated based on information about consumer demand [15], which is also affected by the efforts of suppliers and retailers. The ability to meet consumer demand without excess waste improves the sustainability of the firm and ensures that harvested food goes further towards feeing the population. It aligns with the concept of sustainable nutrition, which is increasingly important due to scare resources of energy, water, or land [16].

The suppliers and retailers usually apply promotion programs (e.g., media advertisements, or loyal reward programs) that are expected to increase consumer awareness of brands and increase consumer demand [17]. Besides these benefits, these promotion programs increase the uncertainty of consumer demand and create complexities in inventory management. The demand uncertainty of perishable products results in a large quantity of unsalable products and high shortage level [18]. Therefore, it is beneficial to understand the effects of consumer demand on inventory management for suppliers and retailers [19]. Besides the economics benefits, this knowledge is crucial to the sustainability of the system as unsalable products cause significant environmental impacts [6].

Extant studies have investigated the effects of consumer demand on total cost or profit. It is shown that a failure to forecast demand increases inventory holding cost [20] and high demand uncertainty decreases the expected total profit [21]. Inventory management is an active and vital part of a company [22]. Thus, it is not suitable to focus on inventory management from only total cost or profit perspectives [23]; the effects of consumer demand should be measured by not only financial (e.g., total cost or profit) but also non-financial performance measures to motivate improvements [24]. Among non-financial measures, fill rate (FR) is the most common measure. FR increases as demand uncertainty decreases [25,26].

Despite these works, there are four issues relating to knowledge about the effects of consumer demand on perishable inventory management. First, there are not many works that study the effects of consumer demand on non-financial measures. The effects of consumer demand have been investigated mostly from FR perspectives. However, focusing on only FR may lead to inaccurate inventory decisions (e.g., managers keep high inventory levels to achieve high FR, but it may result in a high quantity of expired products). Thus, besides FR, it is necessary to investigate the effects of consumer demand on other non-financial measures. The non-financial measures provide a more comprehensive understanding of a company's ability in achieving long-term value and promoting sustainable development. According to a global survey by McKinsey in 2014 [27], 43% of 2900 survey executives stated that they align sustainability with business objectives including waste reduction, energy use reduction, and corporate reputation management. Non-financial reports that describe companies' policies, plans, and programs towards sustainability performance, have become a new instrument for stakeholders in making investment decisions.

Second, there is a lack of models that investigate the effects of consumer demand for a multi-echelon supply chain model. The effects of consumer demand have been investigated for a single-product single-echelon model [25], or for a two-echelon model but focused only on the manufacturer, not the supplier [26]. These two models support an investigation of the effects of consumer demand on an echelon of the supply chain. However, real businesses usually involve multiple products in collaboration with multiple parties. Thus, it is important to evaluate the performance of the whole supply chain as it provides guidelines for improvement [28]. Moreover, performance evaluation of the whole supply chain is necessary as in such multi-echelon models, the bullwhip effect exists [29] and

results in high cost and excessive inventory [30]. Optimizing only at a single point may lead to waste of inventory and loss of food (in food supply chains) at other points in the chain.

Third, there has been a lack of investigation into the effects of consumer demand for products having a random lifetime. Pauls-Worm et al. [25] studied a product with a fixed lifetime and Xue et al. [26] investigated a newsvendor product. However, products, especially grocery products, usually have a random lifetime. Moreover, research on single products with a fixed lifetime might reach a saturation point [31,32]. Thus, there have been calls for more research that considers the effects of consumer demand on supply chain performance when products have a random lifetime.

Fourth, there has been a lack of investigation into the interactive effects between consumer demand and other problem characteristics. In addition to consumer demand, a real business model involves many characteristics, e.g., product lifetime or substitution ratio. Extant studies have studied the main effects of consumer demand; for example, the effects of demand uncertainty on production capacity, safety stock, and diversifying suppliers [33]. However, the understanding of the interactive effects of different problem characteristics would enable proper benchmarking of the performance of a company [34]. Thus, an investigation of the interactive effects of consumer demand and other problem characteristics is also necessary.

*2.2. The Effects of Product Lifetime*

Product lifetime refers to the length of time that a product may be stored before quality deteriorates. The increasing demand of perishable products in modern life not only brings more profit but also creates more difficulties to manage due to large quantities and varieties. Because of the limited lifetime, all perishable products have to be sold before the expiry date or they have to be destroyed. When products are destroyed (e.g., food waste), the product itself and resources involved in production, transportation or disposal are wasted [35]. Moreover, Aschemann-Witzel et al. [35] stated that food waste leads to the impression of inequitable and unjust *luxury* on consumers and stakeholders. This causes negative environmental, economic and social effects on the sustainability the supply chain [36]. An efficient inventory management for perishable products has to not only increase profits but also reduce product wastages, which is one of critical actions for the sustainability [35]. Consequently, product lifetime, as one of the major factors that affect perishable inventory management systems [31], has received significant attention in the literature to develop a sustainable supply chain system [37,38]. However, most of the literature has studied the effects of product lifetime on total cost or profit only (e.g., Kouki et al. [39]). We believe there are three issues relating to understanding the effects of product lifetime on perishable inventory management.

First, there are not many studies on multiple products under multi-echelon models. A focus on multi-echelon models is a step towards the development of sustainability as the supply chain considers the entire sequence of steps from processing raw materials to deliver final products to the customer [36]. Merely reducing food waste at a single level would be an insufficient response and the multi-echelon approach improves the system-wide sustainability rather than pushing wastage to another point in the supply chain where a manager believes it could be ignored. While considering multiple products and multi-echelon settings helps to reduce the total cost of the whole supply chain, research of multi-echelon models with multiple products is still limited [40]. Products, especially food products, usually have random lifetimes; e.g., storage conditions can reduce or increase the lifetime of fresh fruits and research should pay more attention to these types of product lifetime [41].

Second, the extant literature has been based on financial measures to investigate the effects of product lifetime. Non-financial measures have the ability to provide information for continuous improvement and ease of communication between responsible departments or people, it is also interesting to investigate the effects of product lifetime on perishable inventory management from non-financial measures perspectives. Third, future research should consider the benefits of understanding the interactive effects of different problem characteristics [34] and investigate the interactive effects of product lifetime and other problem characteristics.

## 2.3. The Effects of Substitution

When dealing with multiple products under multi-echelon models, researchers (e.g., Ruiz-Benitez and Muriel [42]) have studied perishable inventory management without substitution. However, suppliers and retailers usually sell more than one product. These products are substitutable with each other. During a stock-out period, substitution is a common situation as customers may try an alternative product [43]. Moreover, in an attempt towards the sustainable development, companies draw upon sustainability strategies including product substitution [44]. This product substitution strategy is adopted not only for competitive reasons (i.e., providing more choices to customers to gain market share) but also environmental reasons (e.g., using organic raw materials). Thus, considering only one product limits the application of these studies.

Considering substitution in inventory management leads to a better inventory policy [32]. Although, substitution is common in practice, especially for perishable products (e.g., fruits or healthcare products), there are not many papers that study inventory management for perishable and substitutable products in a multi-echelon model. The complexity of mathematical problems might be a reason that limits the number of articles that include substitution in the model [13].

Table 1 summarizes four papers that considered perishable and substitutable products with single-period lifetime. All of these papers studied a two-echelon model and optimized the total profit function (Table 1). Gürler and Yılmaz [45] and Zhang et al. [46] observed lost sales through the service level; Zhang et al. [47] and Zhang et al. [48] did not study lost sales in the model, which limited the usefulness of the study. While papers that ignored substitution considered the total cost function, papers that included substitution considered total profit. The reason could be that substitution increases customer satisfaction and consumer demand that leads to higher sales, meaning it is more relevant to consider the total profit in models with substitution. These four papers developed mathematical functions and used numerical studies to derive inventory policies.

**Table 1.** Summary of papers in two-echelon models for single-period and substitutable products.

| Research | # of Item | Excess Demand |
| --- | --- | --- |
| Gürler and Yılmaz [39] | Two | Service level |
| Zhang et al. [40] | Two | Not considered |
| Zhang et al. [41] | Two * | Service level |
| Zhang et al. [42] | Two | Not considered |

(* Zhang et al. [41] generated three-item and four-item examples from a two-item problem).

In the context of a multi-period lifetime, Duan and Liao [49] is the only work that studied inventory management for perishable and substitutable products under a multi-echelon model. The reason for this limitation is that when a product has a multi-period lifetime, the inventory status (e.g., product age) remains for many periods. It results in a more complicated model, compared to a newsvendor problem, where the inventory status renews at the beginning of each period. Thus, it is more difficult to define the inventory policy when products have a multi-period lifetime.

Consequently, there is a lack of knowledge of the effects of substitution on perishable inventory management. This research identifies two issues relating to this gap. First, most research considers substitutable products with a fixed lifetime, not a random lifetime. For example, Duan and Liao [49] considered blood products with a fixed lifetime of three days. These types of products are not common in practice due to different storage conditions. Motivated by the social issue of food waste, this research studies inventory management for products that have a lifetime which follows an exponential distribution, which is a common assumption in the literature on perishable inventory management [41].

Second, there is a lack of research on the effects of substitution on the performance of inventory models from non-financial measure perspectives. As mentioned in Section 2.2, non-financial measures have many benefits for inventory management, especially under a multi-echelon model where the bullwhip effect exists [50]. Therefore, this research investigates the effects of substitution and its interactions with non-financial measures in the inventory model.

## 3. Research Methodology

### 3.1. Model Description

This paper considers an inventory management problem for perishable and substitutable products under the two-echelon model with one supplier and two retailers. The problem has other characteristics, including:

- Each of the three perishable products can substitute for the others
- The inventory follows the first in first out rule
- Excess demand is lost with a given probability
- The lead time is positive and fixed
- The product lifetime follows an exponential distribution
- Consumer demand follows a Poisson distribution
- It uses a finite horizon model with a periodic review inventory policy (*T, S*).

In contrast to extant research, this paper does not optimize a total financial function to define the most favorable replenishment policy for the model. This paper considers common cost factors in a perishable inventory management as they are used in recent works. The paper selects similar model characteristics to those in recent works (e.g., Kouki et al. and Smith and Agrawal [39,51]). This selection ensures that the results of this paper can be compared with other works. The cost factors include ordering cost, holding cost, outdated cost, and stock-out cost. These common costs are converted into three non-financial measures following the guidelines in Cannella et al. [50].

The AI is the average inventory during an inspection period (e.g., a month, a year). This measure has been used as representative of internal process efficiency to assess inventory investment of production and distribution systems. It provides information on inventory investment, probability of expiration, stock capacity utilization, and relates to holding and outdated cost.

The FR is the percentage of orders delivered on time and is representative of other customer satisfaction measures. This measure relates to the customer service level and stock-out cost.

The ORVR, defined as the ratio of the order variance at an echelon to the order variance of the consumer (or market demand), is the most common measure to identify the bullwhip effect. A value more than one means the bullwhip exists, while a value smaller than one means the orders are smoothed. This measure provides information on the cost of procurement and subcontracting.

The notations and formulas are formed and presented as follows:

| | |
|---|---|
| $i$ | The number of retailers $i = 0, 1, 2$ |
| | $i = 0$ means the supplier |
| $j$ | The number of products $j = 1, 2, 3$ |
| $t$ | The number of periods in model $t = 1 \ldots T$ |
| $\beta$ | The required customer service level |
| $S_j^i$ | The maximum inventory level of product $jth$ at $ith$ supplier and retailers |
| $I(t)_j^i$ | The inventory level of product $j$ at the retailer $i$ at the beginning of period $t$ |
| $D(t)_j^i$ | The demand of product $j$ at the retailer $i$ for the period $t$ |
| $p_{jj'}^i$ | The probability that a customer substitutes the product $j$ with the product $j'$ at the retailer $i$ if the product $j$ is out of stock at the retailer $i$ |
| $DE(t)_j^i$ | The demand of product $j$ at the retailer $i$ for the period $t$ |
| $DO(t)_j^i$ | The delivered quantity of product $j$ at the retailer $i$ for the period $t$ |
| $l$ | The lost sales probability |
| $\lambda$ | The rate of Poisson distribution of demand |
| $1/\delta$ | The rate of exponential distribution of lifetime |
| $L$ | Replenishment lead time |
| $T$ | Review period |

| $S$ | Order-up-to level or inventory target |
|---|---|
| $s^2_{Or(t)^i_j}$ | The order variance of product $j$ at the vendor and retailer $i$ |
| $s^2_{DE(t)^i_j}$ | The variance of demand of product $j$ at the vendor and retailer $i$ |

The replenishment lead time $L$, $L \leq T$ ensures there is at most one outstanding order at any time and to reduce the complexity of the model [39].

We defined the demand function for each product. This paper considers products that can be substituted each other. Thus, the demand for each product includes the original demand and the demand because of substitution from other products. The substitution demand is a fraction of the excess demand multiplied by the substitution ratio [49]. Hence, the demand function is defined as:

$$DE(t)^i_j = D(t)^i_j + \sum p^i_{j'j}\left(D(t)^i_{j'} - I(t)^i_{j'}\right)^+, x^+ = \max(x, 0) \tag{1}$$

In the demand function, the substitution ratio is calculated by the random substitution matrix method proposed by Smith and Agrawal [51].

The substitution ratio formula is:

$$p^i_{jj'} = \frac{1-l}{j-1} = \frac{1-l}{2} \tag{2}$$

The demand function is used to calculate the inventory level, outdated quantity, and shortage quantity. Kouki et al. [39] suggested that the inventory level is calculated from demand quantity, the target inventory level, outdated quantity, and shortage quantity:

$$I(t)^i_j = \left(S^i_j - DE(t)^i_j - O(t)^i_j + SE(t)^i_j\right)^+ \tag{3}$$

Where the shortage quantity of product $j$ at the supplier and retailer $i$, which includes the shortage because of substitution with other products, is

$$SE(t)^i_j = \left(DE(t)^i_j - I(t)^i_j\right)^+ \tag{4}$$

The outdated quantity of product $j$ at the supplier and retailer $i$ is

$$O(t)^i_j = \delta \times I(t)^i_j \tag{5}$$

The order quantity of product $j$ at the supplier and retailer $i$ is

$$Or(t)^i_j = S^i_j - I(t)^i_j \tag{6}$$

The performance measures for the inventory management model is calculated below using the formulas presented in Cannella et al. [52].

The ORVR at the supplier and retailer $i$ for product $j$ is

$$\text{ORVR}^i_j = \frac{s^2_{Or^i_j}}{s^2_{DE^i_j}} \tag{7}$$

The AI of the product $j$ at the supplier and retailer $i$ is

$$\text{AI}^i_j = E\left[I(t)^i_j\right] \tag{8}$$

The FR of the product *j* at the supplier and retailer *i* is

$$\text{FR}_j^i = \frac{DO(t)_j^i}{DE(t)_j^i} = \frac{I(t)_j^i - SE(t)_j^i}{DE(t)_j^i} \tag{9}$$

Since these non-financial measures conflict with each other, it is impossible to find a replenishment policy which optimizes all three measures simultaneously. Instead of that, this paper aims to find the most favorable replenishment policy that is the best trade-off between these three non-financial measures. This paper also examines the effects of the consumer demand, product lifetime, and substitution ratio on the inventory performance under the most favorable replenishment policy.

### 3.2. Research Framework

Given the complexity of the perishable and substitutable inventory model and a wide range of replenishment policies, this research uses simulation to evaluate the performance of each policy [53]. When each policy is measured by multiple conflicting criteria, AHP is usually employed to rank the performance of each policy [54]. However, the AHP method cannot rank a large number of policies [55], which therefore calls for the integration of DEA and AHP [56].

This paper proposes to integrate simulation, AHP, and DEA methods to define the most favorable replenishment policy. Each of these methods has advantages and disadvantages. An integration of these methods has the ability to manipulate the advantages [57] and to overcome the disadvantages of each method. The integration framework was developed based on the guidelines to develop a decision support system for complex systems, suggested by Bonney and Jaber [58]. The framework has three steps as presented in Figure 1.
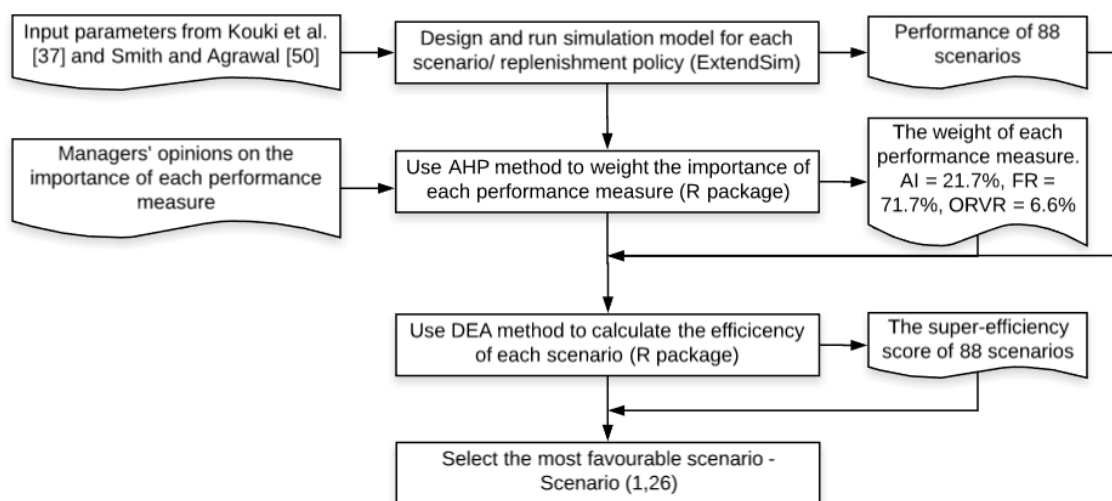


**Figure 1.** Integration framework of the model that combines simulation, the analytic hierarchy process (AHP), and data envelopment analysis (DEA).

First, a simulation model that replicated the studied inventory model was built and run for each scenario of the replenishment policy. The performance for each scenario is recorded by three non-financial measures and extracted from the simulation model. Second, the importance of each performance measure was weighted by the AHP method. Third, the performance of all scenarios or replenishment policies were evaluated and ranked by the DEA method. Then, the most favorable replenishment policy was selected as the policy that has the lowest DEA efficiency score.

This proposed integration framework is similar to that of Azadeh et al. [59], in which the authors developed a simulation model to verify and validate the alternatives of the railway system. The qualitative output criteria of each railway system scenario was weighted by the AHP method.

Then, the authors used the DEA method to rank and select the best railway system. In this example, the DEA model used performance measures obtained from simulation and AHP (e.g., travel time and unscheduled stop time) as input and reliability of the timetable as the output to score and rank all scenarios of railway system improvement. The integrated model of simulation, AHP, and DEA was used to consider multiple performance measures for selecting an optimum system.

The proposed framework is also adequate for the objective of sustainable development. The concept of sustainability still remains difficult to express in operational terms [60]. According to Labuschagne et al. [61], a system approach that considers sustainable development at a company level attempts to: cover social, economic, and environmental sustainability; convey the concept of sustainability; manage a step-by-step approach; advocate the continuous improvement; and show the relationship among various initiatives. However, the available tools do not support decision-makers in evaluating their company's performance [61]. This research proposes a framework that balances conflicting non-financial measures to define the most favorable replenishment policy. This framework can be used to balance social, economic, and environmental aspects; to advocate the continuous improvement; to provide the relationship among three sustainability aspects; and to manage easily. This framework, therefore, can be used to assess the sustainability of company.

## 4. Numerical Example

This section conducts a numerical example to show the use of the proposed framework in finding the most favorable replenishment policy. The numerical example studies a two-echelon model with a supplier who distributes milk products to two retailers who are selling points of the supplier. These products have a random lifetime and are substitutable. Similar to other dairy companies, the supplier defines the replenishment policy for retailers. The supplier identifies a replenishment policy that performs best simultaneously in three performance measures (i.e., AI, FR, and ORVR).

This paper proposes an alternative approach using non-financial measures for finding the replenishment policy, and we compare our results to similar research; namely Kouki et al. [39]. The consumer demand follows a Poisson distribution with a mean of 15 with lost sales probability at 0.9, the product lifetime follows an exponential distribution with a mean of 6, and the lead time is fixed at 1.

This milk product brand competes strongly with other brands. The supplier and retailers also realize that in a stock-out situation, there is a high probability that consumers will buy another milk brand. If the stock-out situation happens frequently, consumers may change their tastes, and eventually, the supplier loses customers. Therefore, both supplier and retailers aim at keeping a high customer service level and FR is the most important measure for them.

The supplier and retailers also want to reduce the quantity of expired products or reduce average inventory. The supplier and retailers keep inventory at a suitable level to reduce costs, to easily manage warehouses, and to increase investment in other business activities (e.g., marketing and research). As the supplier and retailers expect to have a higher market share, AI can be sacrificed to achieve a high FR level. Finally, the ordering and procurement costs are not problematic since the supplier and retailers are within a business area. Thus, the ORVR is not problematic in this example as the ordering and procurement costs relate to ORVR.

The above information is based on the authors' working experience in the supply chain field. It is used to create the comparison matrix presented in Table 2 and to perform pairwise comparisons for the AHP. The FR is the most important measure, followed by the AI and ORVR. It is reasonable to state that compared to AI, FR is moderately important for the supplier and retailers. Compared to ORVR, FR is extremely important for supplier and retailers. Finally, compared to ORVR, AI is moderately important for the supplier and retailers.

**Table 2.** The pairwise comparison results of three measures.

| Measures | Average Inventory | Fill Rate | Order Rate Variance Ratio |
|---|---|---|---|
| Average inventory | 1 | 1/4 | 4 |
| Fill rate | 4 | 1 | 9 |
| Order rate variance ratio | 1/4 | 1/9 | 1 |

### 4.1. The Most Favorable Replenishment Policy

This section presents the results received from the proposed integration framework. The simulation model was built on ExtendSim software (Imagine That Inc., San Jose, CA, USA). Events on the simulation model follow the sequence: (1) expired products are discarded; (2) a replenishment order arrives and is updated to inventory; (3) consumer demand is observed and satisfied; (4) the inventory level is reviewed if it is a review period;(5) a replenishment order is triggered if needed. Each replenishment policy was replicated 10 times, the length of each simulation was 200,000 units of time (i.e., days), and the first 5000 units of data were discarded from calculating the system's performance because of the warm-up period.

There are 88 possible replenishment policies with the range of $T$ and $S$ which are reused from Kouki et al. [39] as follows:

- 　$T \geq T_{min} = L = 1$
- 　$T \leq T_c = 4$, $T_c$: review period in case the product has an infinite lifetime
- 　$26 \leq S \leq 47$,

Each replenishment policy was evaluated by three non-financial measures: AI, FR, and ORVR. The importance of each measure might be different from the point of view of each decision-maker. Therefore, the AHP method was used to synthesize these opinions to determine the overall importance of the performance measures. The AHP method was conducted by using the R package 'pmr' [62].

The information in Table 2 was used to calculate the importance of each non-financial measure. Firstly, to assure the consistency and appropriateness of comparison information, the consistency ratio was calculated. From data in Table 2, the consistency ratio was 3.9%, less than the critical value 10%. Therefore, the comparison information is consistent [63], and can be used to calculate the importance of each measure. In case the consistency ratio is over 10%, the decision-makers are required to amend the comparison information [63]. The weighting results for AI, FR, and ORVR were $w1 = 21.7\%$, $w2 = 71.7\%$, and $w3 = 6.6\%$, respectively.

In this proposed framework, the DEA method helped to evaluate and rank the performance of replenishment policies. The DEA model in this research had two inputs (i.e., $T$, $S$), and 27 outputs (i.e., $w1/AI$, $w2 \times FR$, and $w3/ORVR$ for one supplier, two retailers, and three products). The principal assumption of selecting inputs and outputs is that inputs are better when smaller and outputs are better when larger. This research relies on the assumption that companies prefer a low order level to reduce the inventory level and low review period to quickly respond to the market. Thus, the review period T and order-up-to level S are better when smaller and selected as inputs of the DEA model. Regarding the outputs, the research aims to increase FR and decrease AI and ORVR. Thus, this research used multiplicative inverse transformation by using the reciprocal of the value of AI and ORVR so that all three outputs are better when larger.

There are 88 DMUs or replenishment policies which are combinations of the review period and order-up-to level. A rule of thumb for using the DEA model is that the number of DMUs is over three times the total number of inputs and outputs [64]. This research satisfies this rule (i.e., $88 > 3 \times (2 + 27)$ = 87). Thus, the data in this research is homogenous and allows the use of DEA model.

This research employed the super-efficiency procedure and output-oriented method developed by Cook et al. [64]. The results showed that replenishment policy (1, 26) had the lowest super-efficiency score at 0.45147. Therefore, policy (1, 26) was the most favorable replenishment policy. In the given

context of perishable inventory management for a two-echelon model and given a range of policies, this replenishment policy best balanced the three performance measures—AI, FR, and ORVR.

### 4.2. Sensitivity Analysis

This research applied the $2^k$ factor-level design technique to gain knowledge of the effects of input factors on the inventory performance. The $2^k$ factorial is simple and has the ability to analyze interactions between factors and their main effects, thus, it has been used frequently in operations management research [65]. Assume that there are k studied factors in the model, this technique requires that researchers choose two levels (i.e., low and high) for each factor and run the simulation model for each of the $2^k$ factor-level combinations. These low and high levels are far apart enough to observe the difference in outputs.

The low and high levels of input factors in this research were extracted from the work of Kouki et al. and Smith and Agrawal [39,51] and presented in Table 3. These low and high levels were combined to form eight experiments or the design points that are used to run the simulation, presented in Table 4.

**Table 3.** The high and low levels of input factors.

|  | **Mean of Demand** | **Mean of Lifetime** | **Lost Sales Probability** |
|---|---|---|---|
| High | 15 | 6 | 0.9 |
| Low | 5 | 2 | 0.1 |
| Source | Kouki et al. [34] | Kouki et al. [34] | Smith and Agrawal [45] |

**Table 4.** The combination of a $2^3$ factorial design.

| **Experiment** | **Mean of Demand** | **Mean of Lifetime** | **Lost Sales Probability** |
|---|---|---|---|
| 1 | 15 | 6 | 0.9 |
| 2 | 5 | 6 | 0.9 |
| 3 | 15 | 2 | 0.9 |
| 4 | 5 | 2 | 0.9 |
| 5 | 15 | 6 | 0.1 |
| 6 | 5 | 6 | 0.1 |
| 7 | 15 | 2 | 0.1 |
| 8 | 5 | 2 | 0.1 |

For each experiment, the selected replenishment policy was replicated 10 times; each time ran 200,000 units of time (i.e., days). Because of the warm-up period, the first 5000 data units were discarded from calculating the performance of the replenishment policy. The performance was measured by AI, FR, and ORVR. As this research assumes two retailers and three products have similar characteristics, without loss of generalization, the following section only discusses the performance at the supplier, retailer #1, and for product #1.

## 5. Analysis Results

We now turn to the examination of the effects of consumer demand, product lifetime, and lost sales probability on the performance of inventory models. Such knowledge helps decision-makers anticipate and respond better to the uncertainty. This section used two statistical techniques, namely univariate analysis of variance (ANOVA) and multivariate analysis of variance (MANOVA), to test the interactive effects of independent variables on dependent variables. While ANOVA is known as a univariate test and is used for one dependent variable (or output), MANOVA measures differences in two or more outputs and is known as a multivariate test [66].

The MANOVA technique was used to test the effects of three independent variables (i.e., consumer demand, product lifetime, and lost sales probability) on all 27 dependent variables (i.e., AI, FR, and ORVR measured for each of three products). There was one three-way interaction, three two-way

interactions, and three main effects were tested. The MANOVA result tables are presented in the Supplementary Material (Table S1–Table S10). As a common guideline from Field [56], a relationship between variables is significant if the Sig. value is less than 0.05. Moreover, the effect size of the relationship is defined by the "Partial ETA Squared", value cut-offs of 0.2 for small effects, 0.5 for medium effects, 0.8 for large effects. A value less than 0.2 indicates a negligible effect [66].

The MANOVA results showed that all independent variables had effects on the performance of the studied inventory model. These effects are summarized in Figure 2.

| Source of variation | Supplier side | | | | | | Retailer side | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | AI | | FR | | ORVR | | AI | | FR | | ORVR | |
| | Effect | Size | Effect | Size | Effect | Size | Effect | Size | Effect | Size | Effect | Size |
| DM | P | L | N | L | N | L | P | L | N | L | N | L |
| LF | P | L | P | L | P | L | P | L | P | L | N | L |
| LS | N | L | P | L | P | L | N | M | P | M | P | M & L |
| DM x LF | P | L | N | L | N | L | P | L | N | L | N | L |
| DM x LS | P | L | N | L | N | L | P | S & M | N | M & L | N | M |
| LF x LS | P | L | P | L | P | L | P | S | P | M | N | S & M |
| DM x LF x LS | | L | | S & N | | L | | S & N | | S & M | | S & N |

Note:   DM: Consumer demand; LF: Product lifetime; LS: Lost sales probability
P: Positive effect; N: Negative effect
S: Small effect size; N: Negligible effect size; M: Medium effect size; L: Large effect size

**Figure 2.** Summary of main and interaction effects on inventory performance.

First, the statistical tests showed that consumer demand had a significant effect on all 27 performance measures of the studied model. A system has high average inventory, low fill rate, and low order rate variance ratio when consumer demand is high. The reason is that because of high consumer demand, at the end of each day, the inventory level is low and triggers a high replenishment quantity. On the next day (note that this research considered replenishment policy (1, 26) and the lead time is 1), the inventory on hand at the beginning of each day is recorded after the replenishment quantity arrives. Thus, the inventory on hand is always high and results in a high average inventory. This result means that a company can apply sales and marketing programs to lead consumer demand to an acceptable level which benefits both fill rate and average inventory measures.

Second, the statistical tests showed that the product lifetime had a significant effect on all 27 performance measures of the studied model. High lifetime products result in high average inventory levels, high fill rates, and low order rate variance ratios. The reason is that a high lifetime increases the availability of a product and thus, increases fill rates. Consequently, a company might apply advantage technologies to extend product lifetime to increase fill rates and reduce order rate variance ratios.

Third, the statistical tests showed that lost sales probability has a significant effect on all 27 performance measures of the studied model. In the case that lost sales probability is high, customers do not want to substitute other products, and demand does not increase much. Thus, a high lost sales probability results in companies that experience low average inventory levels, high fill rates, and high order rate variance ratios. Consequently, a company should improve forecast accuracy and avoid sudden demand from substitution. Alternatively, a company could increase product differentiation to reduce the substitution ratio.

Fourth, the statistical tests showed that the interaction of consumer demand and product lifetime had a significant effect on all 27 performance measures of the studied model. This effect was stronger as consumer demand is low. There is no difference in the effect when the lost sales probability is high or low.

Fifth, the statistical tests showed that the interaction of consumer demand and lost sales probability had a significant effect on all 27 performance measures of the studied model. This effect was mostly medium for retailers and strong for suppliers. If a product has a low lifetime, the effect is larger.

Sixth, the statistical tests showed that the interaction of product lifetime and lost sales probability has a significant effect on all 27 performance measures of the studied model. For suppliers,

this interaction had a strong effect, and stronger if consumer demand is low. For retailers, this interaction had a small effect on the average inventory, a medium effect on the fill rate, and small or medium effects on the order rate variance ratio.

Seventh, the statistical tests showed that the interaction of consumer demand, product lifetime, and lost sales probability had a significant effect on all 27 performance measures of the studied model. For suppliers, this interaction had a strong effect on average inventory and order rate variance ratio, and negligible or small effects on fill rate. For retailers, this interaction had negligible or small effects on average inventory and order rate variance ratio, and small or medium effects on fill rate.

Eighth, the statistical tests showed that all three input factors and the interactions of the three input factors had large effects on three performance measures for suppliers. For suppliers, the interaction of consumer demand, lifetime, and lost sales probability had small or negligible effects on fill rate. The possible reason is that the supplier is easily impacted by the bullwhip effect phenomenon. In contrast, for retailers, only the interaction of consumer demand and product lifetime has a large effect on three performance measures.

## 6. Discussion and Conclusions

This research aims to understand the effects of a problem characteristic and its interactions with others on perishable and substitutable inventory management. Perishable and substitutable products are very common in practice. A suitable replenishment policy for these types of products results in high customer satisfaction level, low product waste, and is able to improve food security. Consequently, this policy supports in achieving both economic and environmental aspects and improves the sustainability of perishable supply chains.

In the context of perishable and substitutable products, this is the first known research that provides knowledge on the effects of consumer demand, product lifetime, and substitution ratio on non-financial performance measures, namely, AI, FR, and ORVR. This knowledge enables us to support superior inventory performance. This research shows that the supplier's performance is affected largely due to the existence of the bullwhip effect. In contrast, the retailers mostly experience medium or small effects. These effects and managerial implications are discussed as follows.

### 6.1. Effects of Consumer Demand

The research showed that under a low consumer demand situation, AI is low and FR and ORVR are high for both the suppliers and retailers, which suggests four implications. First, as the objectives are reducing AI and increasing FR, suppliers and retailers should improve forecast accuracy to reduce uncertainty in consumer demand. Reducing AI also reduces product waste and operational costs for suppliers and retailers. Second, when consumer demand uncertainty is high, suppliers and retailers could focus on demand-driven techniques (e.g., product differentiation strategy) to reduce substitution ratio, and thus, reduce AI and increase FR. Third, when the uncertainty of consumer demand is high, techniques to increase product lifetime and reduce uncertainty in product lifetime (e.g., storage condition, manufacturing technology) could be applied to increase FR. Fourth, activities to increase consumer demand (e.g., sales and marketing activities) could be used to reduce ORVR.

### 6.2. Effects of Product Lifetime

The research showed that under a low product lifetime situation, AI and FR are low for suppliers and retailers, and ORVR is low for suppliers and high for retailers, which suggests two implications as follows. First, if the objectives are reducing AI and ORVR, companies should apply technologies (information sharing, storage condition) to reduce uncertainty in product lifetime. Second, under a situation where the uncertainty of product lifetime is high, suppliers should also focus on strategies to reduce substitution ratio (e.g., forecast techniques and product differentiation strategy) to increase FR and reduce AI.

*6.3. Effects of Substitution*

The research showed that under a low substitution ratio situation, suppliers and retailers experience low AI, low FR, and high ORVR. Moreover, for retailers, the substitution ratio and its interaction with consumer demand and product lifetime has mostly a small or medium effect on performance. Whereas, for suppliers, all of these effects are large. These results suggest that when the substitution ratio is high, if the objectives are reducing AI and increasing FR for suppliers, suppliers should focus on technologies to reduce uncertainty in consumer demand or to increase product lifetime.

*6.4. Limitations and Future Research*

To our knowledge, this is the first study to explicitly investigate the effects of consumer demand, product lifetime, and substitution ratio on non-financial performance measures of the inventory model. Thus, there are four opportunities for future research from this research.

First, the research showed that techniques (e.g., forecasting and sharing information) could be applied to reduce the uncertainty in consumer demand and product lifetime, and consequently, improve performance for suppliers and retailers. Future research could explore how much these techniques improve performance. The results could be used as an analysis factor for adopting these possible techniques.

Second, the research showed that average inventory and fill rate performance can be improved, especially for suppliers, by reducing the substitution ratio for each product. Possible techniques such as product differentiation or increasing the number of products may reduce the substitution ratio for each product. However, increasing the number of products creates difficulties in managing inventory. Therefore, future research may investigate the trade-off decision and define how many products for each brand a company can offer.

Third, future research could consider other types of problem characteristics which were used in this research. For example, future research may consider other types of demand distribution (e.g., fuzzy theory) or product lifetimes distribution (e.g., Weibull distribution, constant rate), which covers more realistic situations. Alternatively, future research may consider other substitution scenarios besides the random substitution matrix in this research.

Fourth, sensitization is an important topic of food waste. Managers should visualize non-financial measures to improve the flow of communication along the perishable supply chain. For this reason, future research should identify and analyze possible communication structures to promote sensitization and thus, sustainability in the perishable supply chain.

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