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Calculating the Encouragement and Hesitation Coefficients of Customers When Increasing Discounts for Perishable Products

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ABSTRACT

Human beings have various needs, including the essential, daily need for food. Edible goods, such as many other products, reach customers through supply chains. However, due to the nature of food items, quality deterioration is unavoidable for this group of products throughout the supply chain. This decline in quality can result from factors such as time and environmental conditions. In any case, this quality deterioration affects customers' willingness to purchase the product. The resulting decrease in demand increases product accumulation, leading to increased product spoilage. Some sellers use increasing discounts to stimulate demand and prevent product spoilage. The extent of encouragement and hesitation created can aid the organization in making better decisions. The present study aims to examine the impact of discounts on changing the level of customer encouragement and hesitation. An integrated decision-making method for calculating the changes in these coefficients is proposed and solved using Microsoft Excel 2016 software. The research results indicate that increasing discounts simultaneously increases customers' encouragement and hesitation toward purchasing the product. However, it sustains customers' willingness to purchase the goods at approximately 48%, in stark contrast to the nearly negligible willingness observed in the no-discount scenario.

1. Introduction

Humans are constantly faced with various needs and strive to meet them. Some of these needs are of great necessity and individuals deal with them on a daily basis. One of these fundamental and highly important needs is food. Food materials and products are used daily, playing a crucial role in maintaining health and the proper functioning of the body. Therefore, humans

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strive to consume high-quality and healthy products whenever possible. Food products, such as many other products, today reach end customers through supply chains. A supply chain is a set of facilities, individuals, activities, and resources that directly or indirectly play a role in getting goods to end customers (Cooper et al., 1997).

Food products have a unique characteristic that makes planning for them throughout the supply chain extremely difficult. This important characteristic is the perishability of these products, which has led to the establishment and utilization of a different type of supply chain, known as the supply chain for perishable goods (Esteso et al., 2021). Although efforts are continuously made in this type of supply chain to reduce the spoilage of products, in many cases, the volume of spoilage is quite significant. Various reasons lead to the spoilage of food products. Time is the main factor in the deterioration of various products. As time passes from the production of a product, its quality decreases, ultimately leading to spoilage (Dagne et al., 2020). Alongside the time factor, environmental conditions are also considered as factors that contribute to spoilage in perishable products. Each item, depending on its characteristics, provides specific conditions for storage. If these conditions are not adhered to, the item quickly loses its quality and, eventually, perishes. Therefore, the type of product affects its storage conditions throughout the supply chain (Grillo et al., 2017). In addition to all these factors, the issue of demand is also relevant. Fluctuations in demand affect order volumes and inventories, and with the accumulation of goods in warehouses and their lack of sales, a significant amount of spoiled products ultimately remains for suppliers and retailers (Shrivastava et al., 2017).

Given the diversity of spoilage factors, the methods used to prevent product deterioration throughout the supply chain and reduce its extent are highly varied. Researchers pursue different objectives when designing supply chains for perishable products. However, their ultimate goal is to reduce the costs imposed on various levels of the supply chain due to product spoilage. Some researchers address issues of timing and product spoilage in the supply chain by altering the network, redesigning the supply chain, and changing transportation systems. Wu et al. (2018) attempted to reduce the delivery time of food trains by redesigning the supply chain network, thereby reducing the spoilage of products in the supply chain (Wu et al. 2018). Manouchehri et al. (2020) aimed to reduce the final delivery time of goods in their research. They designed a model based on determining delivery priorities. As a result, the final route taken was shortened, thereby reducing product spoilage in the supply chain. It is noteworthy that, in addition to the issue of delivery time, Manouchehri et al. (2020) placed significant emphasis on product storage conditions and temperature controls. They even determined the optimal temperature for product storage in their study.

Other studies have focused solely on examining environmental factors and addressing these issues. For instance, Hassoun et al. (2023) emphasized that continuous control of environmental factors, such as temperature and humidity, using the Internet of Things can reduce product spoilage. Although this method is very costly, it highlights the significant impact of environmental conditions on the volume of spoiled products. Zhang et al. (2017) concluded in their research, emphasizing the importance of environmental conditions and the necessity of storing products under suitable conditions, that it is better to establish storage and distribution centers alongside producers, and consequently, stores in close proximity so that products can quickly reach the sales stage after production and dispatch from the factory. This approach can help reduce spoilage.

As evident, most of these methods are quite expensive. Implementing many of them, even on a trial basis, imposes significant costs on organizations. A highly effective scientific method for minimizing product spoilage is the implementation of dynamic pricing within the supply chain of perishable goods (wami & Shah, 2013). This method allows for the evaluation and control of product demand, thereby altering the inventory levels in warehouses and stores and preventing spoilage and waste of products throughout the supply chain. Despite its effectiveness, the planning, implementation, and management of this method are low-cost, which is why it is often utilized even by local retailers (generally without adopting specific rules).

Despite numerous studies in this area, the foundation of dynamic pricing systems dates back to 1996 when Elon and Malaya introduced demand systems as price-dependent systems (Elionand & Mallaya, 1996). With the emergence of such concepts among researchers and over time, the relationship between demand, quality, and price was discussed by various researchers, ultimately leading to the use of dynamic pricing systems by different researchers (Huang et al., 2018). Zhao and Zheng (2000) were among the first to utilize such a system. They demonstrated in their research that customers of products determine the final price of goods based on product quality. Consequently, a fixed price cannot be applied to a perishable product. Their model was based on statistical models. The results of their research indicated that using dynamic pricing models can effectively manage revenue and demand. Tisao and Sheen (2008) proposed the use of dynamic pricing as a solution to reduce the extent of product spoilage. He et al. (2020) presented a dynamic pricing model to control inventory levels. They showed that such a system can effectively stimulate demand and prevent product spoilage in the supply chain. Wee (1997), one of the pioneers in designing dynamic pricing models, demonstrated that by obtaining the spoilage rate function of products through existing statistical methods, prices can be adjusted over different time intervals, thereby reducing the extent of product spoilage.

Similar studies also exist in the literature; however, all these studies face a fundamental problem: a strong dependence on sales records and statistical functions. This is because a specific analysis of customer behavior during discounts cannot be performed. For example, Dehghan-Nayeri et al. (2020) used sales records of products during discounts to analyze and evaluate customer behavior during discounts. In another case, Yang et al. (2017) utilized statistical records to identify the extent of product quality degradation to achieve a better analysis of demand changes. Although these methods are scientifically accepted and effective, their practical application is fraught with difficulties and complexities. This is because, in many cases, discounts may be applied for the first time, resulting in the absence of records in this regard. Furthermore, analyzing product spoilage to obtain a statistical function is challenging and imprecise. Spoilage and degradation of products may occur due to various conditions, including storage methods and practices, and not solely due to time.

2. Problem Statement

Based on the existing research background, calculating product demand for pricing decisions is of utmost importance. However, demand calculation is highly challenging due to its unpredictable nature. Although existing statistical methods for calculating spoilage rate functions and making pricing decisions are quite helpful, their use is difficult and requires extensive statistical information. Additionally, forecasting demand using sales records is not very effective since, in many cases, discounts may be applied for the first time on a product, resulting in no available records for calculation. Therefore, there is a pressing need for a scientific solution to calculate the incentive and hesitation created by the application of discounts.

This research seeks to develop a solution for quantifying the incentives and hesitations experienced by customers. The study focuses on facilitating demand forecasting based on discounts applied to products, employing a scientific approach that incorporates mathematical calculations. The coefficients derived from these calculations can be utilized directly or serve as support in the development of mechanisms within demand forecasting models.

3. Proposed Solution and Mathematical Modeling

To calculate the incentive and hesitation coefficients, it is first necessary to explain the rationale behind calculating these coefficients mathematically. For this purpose, familiarity with demand calculation models is crucial. Demand is a function of price and quality. This function is usually represented as an exponential function, and there is often a constant coefficient indicating the purchase of the product under any conditions. For example, relation (1) shows a demand function where a is a constant ampunt, b is the price elasticity of demand, P_t is the price of the product on day t, and $\frac{1}{\sqrt{t}}$ is the coefficient of demand reduction as the product approaches spoilage (Dehghan-Nayeri et al., 2020).

Demand= $P_t^b \frac{1}{\sqrt{t}}$

In this relation, calculating a and b is somewhat challenging. Typically, these values, especially regarding a, are obtained empirically using sales records. Even when such records exist, in many cases, the resulting values are associated with a high degree of error due to their dependence on the distribution function, which reduces the accuracy of the final solution. Moreover, increasing the amount of discount, in addition to encouraging customers to buy, creates hesitation among some regarding the product's quality. This issue leads to a discrepancy between the final output of the existing model and the actual market conditions. Consequently, a negative coefficient c is required in conjunction with b to ensure that the aforementioned relationship accurately reflects the challenges encountered in the real world.

To calculate the values of the incentive and hesitation coefficients, decision-making methods can be effective. However, it should be noted that the use of methods providing probabilistic and uncertain answers is appropriate since the nature of the incentive and hesitation coefficients is inherently probabilistic and heavily dependent on customer behavior. In this research, a combined grey hierarchical analysis and grey TOPSIS method is used to calculate the incentive and hesitation coefficients of customers. This decision-making method has a probabilistic nature, making it suitable for calculating such values. The symbols and parameters used in this method are presented in Table 1 (Faraji & Maralani, 2009).

Table 1. Parameters and Explanation of Symbols for the Combined Grey TOPSIS and Grey AHP Method

Description	Parameter	Description	Parameter
Row i and Column j of Pairwise Comparison Matrix	a_{ij}	Number of Criteria or Experts	n
Pairwise Comparison Matrix after Normalization	r_{ij}	Number of Comparable Options	m
Weight of Option (or Criterion)	W_i	Consistency Rate	CI
Positive Ideal Value	V_i^+	Randomness Index	RI
Negative Ideal Value	V_i^-	Consistency Ratio	CR
Average Distance of Each Option from Positive Ideal Options	d_i^+	Maximum Values of Consistency Matrix	λ
Average Distance of Each Option from Negative Ideal Options	d_i^-	Numerical Value of Expert Opinion in Comparison i with j	q_{tij}
Similarity Index	CC_i	Average Geometric Value of Expert Opinion t	Q_{tij}
Grey Possibility Degree (Probability)	$P(A_i \leq A^{max})$		

3.1. Methodology

The AHP method fundamentally operates based on the opinions of experts and weights the elements and evaluation options through pairwise comparisons between decision elements (Amiri et al., 2016). Since this method relies on expert opinions, experts may not be able to express their views clearly. The Grey-AHP method is similar to the AHP method, where, to account for the uncertainty present in qualitative parameters, the scores of decision elements are expressed in intervals using grey numbers (Wang & Liu, 2007; Zhu et al., 2015). Here, there are two options: one for encouragement and the other for hesitation. In practice, these two options are not compared against one another; rather, the extent of changes and setbacks of one is calculated based on the progress of the other. The experts' opinions are collected with qualitative degrees and are equivalently represented, as shown in Table 2 (Ince et al., 2017; Kadkhodaei et al., 2021).

Table 2. Corresponding Grey Numbers to Precise Numbers

Descriptive Value	**Corresponding Value for Each Description**	**Precise Value**	**Corresponding Grey Value**
Very Low Importance	1	1	[1.5 - 1]
Low Importance	3	2, 3	[1.5 - 3.5]
Medium Importance	5	4, 5	[3.5 - 5.5]
High Importance	7	6, 7	[5.5 - 7.5]
Very High Importance	9	8, 9	[7.5 - 9]
Intermediate State Between Two Descriptions	2, 4, 6, 8		

To maintain the accuracy of opinions, a consistency ratio is used to evaluate the collected opinions. Relations (2) and (3) are employed for this purpose (Kadkhodaei et al., 2021).

$$CR = \frac{CI}{RI} \tag{2}$$

$$CI = \frac{\lambda_{max} - n}{n - 1} \tag{3}$$

The values for RI are taken from the values in Table 3.

Table 3. Numerical Value of Random Index RI Based on the Number of Criteria

n	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
RI	0	0	0.58	0.9	1.12	1.24	1.32	1.41	1.45	1.49

If the CR value is less than 0.1, then the expert's opinion in the pairwise comparison matrix is accepted; otherwise, it is rejected and needs to be reviewed and revised (Zebardast, 2001). After the experts' opinions have been expressed as fuzzy numbers, it is necessary to merge these opinions. This is because these opinions now possess uncertainty and their validity has been evaluated and confirmed. One method for merging opinions is the geometric mean method. This approach has the advantage of being sensitive to varying numerical values. In other words, infrequent values that exhibit significant differences can impact the results nearly as much as frequently occurring values. Using the geometric mean method, opinions are merged according to relation (4) (Amiri et al, 2016).

$$Q_{T_{ij}} = (\prod_{t=1}^{n} q_{t_{ij}})^{\frac{1}{n}} \quad (4)$$

By substituting grey numbers for precise numbers, the weight of each criterion or option is calculated. Before calculating the weights, it is necessary to normalize the pairwise comparison matrices. For this purpose, relation (5) is used (Amiri et al, 2016).

$$r_{ij} = \frac{a_{ij}}{\sum_{i=1}^{n} a_{ij}} \quad (5)$$

Then, using relation (6), the weight of each option and criterion is calculated (Amiri et al, 2016).

$$W_i = \frac{\sum_{j=1}^{n} r_{ij}}{n} \quad (6)$$

The TOPSIS method is a technique for evaluating an m×n matrix, including m options and n criteria. To use the TOPSIS method, qualitative indicators must first be converted into quantitative values and these quantitative data must be dimensionless. After calculating the weights of the criteria and options, these weights are multiplied together, and the resulting matrix, known as the weighted matrix, is examined and evaluated. Given that in the current model, the desired weights have been calculated using the hierarchical analysis method, these values are dimensionless and do not require re-normalization. The positive ideal values (V_i^{+})[5] and negative ideal values (V_i^{-})[6] for each positive criterion are, respectively, the maximum and minimum scores of the evaluated options in that criterion. After extracting these values, the evaluated options are ranked based on minimizing the distance from the positive ideal value and maximizing the distance from the negative ideal value. The average distance of each option from the positive ideal options (d_i^{+}) and negative ideal options (d_i^{-}) across different criteria is obtained using relations (7) and (8) (Amiri et al, 2016).

$$d_i^{+} = \sqrt{\sum_{j=1}^{n} \left[\left(V_{ij} - V_j^{+}\right)^2\right]} \quad (7)$$

$$d_i^{-} = \sqrt{\sum_{j=1}^{n} [(V_{ij} - V_j^{-})^2]} \quad (8)$$

Then, the similarity index parameters are determined and calculated for each criterion using relation (9). The value of this index ranges between zero and one, and the closer it is to one, the more desirable the option is. Therefore, by calculating the similarity index for all available options, prioritization is done from larger to smaller values (Amiri et al, 2016).

$$CC_i = \frac{d_i^{-}}{d_i^{-} + d_i^{+}} \quad (9)$$

An important point is that since grey numbers are used in this research, for calculating the weighted matrix, which is the product of the weights of the criteria and the weights of the options, it is necessary to follow the rules of grey numbers. Accordingly, for multiplying two grey numbers in a bounded manner, relation (10) is used.

$$\left(\underline{V}_{ij},\overline{V}_{ij}\right) = (\underline{a}_{ij} \times \underline{W}_{j},\overline{a}_{ij} \times \overline{W}_{j}) \tag{10}$$

After forming the weighted evaluation matrix in the grey TOPSIS method, the ideal reference grey value is determined, and based on that, the grey possibility degree for each option relative to the ideal reference value in each criterion can be calculated using relation (11) (Amiri et al, 2016).

$$P\left(V_{ij} \leq V_j^{max}\right) = \frac{Max\left(0, L^* - Max\left(0, \overline{V}_{ij} - \underline{V}_j^{max}\right)\right)}{L^*}$$

Where

$$L^* = L\left(V_{ij}\right) + L\left(V_j^{max}\right) \tag{11}$$

$$L\left(V_{ij}\right) = \overline{V}_{ij} - \underline{V}_{ij}$$

By calculating the average grey possibility degree for each option across various criteria, we determine the probability of that option being less than the superior options. Any option with a lower probability of being inferior to others will have a smaller distance from the superior option and will therefore rank higher. The numerical value of the average grey possibility degree is derived from relation (14) (Amiri et al, 2016).

$$P(A_i \leq A^{max}) = \frac{1}{n}\sum_{j=1}^{n} P(V_{ij} \leq V_j^{max}) \tag{12}$$

In this research, however, calculating the probability of one option being smaller has a different meaning. In this research, two options are compared across five marketing criteria. In this comparison, due to the occurrence of probabilistic distances, the probability of one option occurring is heavily dependent on the movement of the other. In fact, this research is not focused on desirability; rather, the degree of achieving the incentivizing goal is what can be calculated using this method.

4. Computational Results

For the computations in this research, a real case study was used. Three experts in marketing, management, and customer relations were selected, and their opinions were collected. Five criteria were chosen to calculate the degree of encouragement and hesitation. These criteria resulted from the experts' opinions and multiple meetings with them, and they include product stability (expiration), price, quality, past purchase experience, and brand. The results are as follows. The order of the criteria in the matrices include quality, price, expiration, past purchase experience, and brand:

$$\text{Matrix of Average Criteria}=\begin{bmatrix} [1,1] & [4\text{-}73, 6\text{-}76] & [2\text{-}64, 4\text{-}73] & [4\text{-}73, 6\text{-}76] & [6\text{-}76, 8\text{-}47] \\ [0\text{-}15, 0\text{-}21] & [1,1] & [2\text{-}64, 4\text{-}73] & [2\text{-}64, 4\text{-}73] & [3\text{-}57, 5\text{-}82] \\ [0\text{-}21, 0\text{-}38] & [0\text{-}21, 0\text{-}38] & [1,1] & [1\text{-}5, 3\text{-}5] & [1\text{-}5, 3\text{-}5] \\ [0\text{-}15, 0\text{-}21] & [0\text{-}21, 6\text{-}76] & [0\text{-}29, 0\text{-}38] & [1,1] & [1\text{-}5, 3\text{-}5] \\ [0\text{-}12, 0\text{-}15] & [0\text{-}17, 0\text{-}28] & [0\text{-}29, 0\text{-}67] & [0\text{-}29, 0\text{-}67] & [1,1] \end{bmatrix}$$

Weights of Criteria=[[0-44, 0-59] [0-18, 0-29] [0-09, 0-16] [0-06, 0-10] [0-04, 0-06]]

The results obtained from calculations in Microsoft Excel 2016 indicate that 98% of customers feel encouraged and 50% exhibit hesitation. Subtracting these two values results in a willingness to purchase products nearing expiration due to increased discounts that amounts to 48%. This means that with increased discounts customers are significantly inclined to purchase the desired product. However, due to the nature of the goods, a certain level of hesitation arises among customers. This is primarily because customers become doubtful about the quality of the goods and perceive excessive discounts as a sign of potential spoilage or deterioration of the products.

5. Conclusion and Recommendations for Future Research

This research was conducted with the aim of examining the degree of hesitation and willingness of customers during increased discounts on food products. Since food items fall under the category of perishable goods, they gradually experience a decline in quality over time throughout the supply chain, complicating their sales process, leading to a portion of these products being spoiled and discarded. Therefore, employing various strategies to prevent the wastage of these products is essential. One of the most important strategies is to stimulate demand and increase buyer willingness through offering greater discounts.

In most studies, researchers use statistical methods to estimate demand and suggest discounts. However, less attention has been paid to the issue of customer hesitation or the lack of precise sales information, a factor that makes calculations complex, error-prone, and in some cases, unusable. Therefore, this research aimed to assess the degree of encouragement and hesitation created in customers through a scientific approach based on expert opinions. In this context, a combined decision-making method with a probabilistic nature was utilized. The grey TOPSIS and grey hierarchical analysis methods were selected and examined for this purpose.

Given the characteristics of perishable goods, increasing discounts can not only encourage customers but may also raise their level of hesitation. The results of the research confirmed this hypothesis. As the amount of discount increased, customer encouragement rose to approximately 98%, but simultaneously, their hesitation also grew significantly, reaching 50%. Ultimately, the net effect of discounts on increasing customer encouragement was estimated at around 48%. These values can serve as valuable data for modeling and forecasting demand in equations.

As a suggestion for future research, the results of this study could be compared and validated with data obtained from field surveys at the community level. Additionally, examining and aligning the results with actual sales data in various stores could provide clearer insights for future research. Furthermore, developing this method by employing other decision-making techniques or defining direct relationships to calculate incentive and hesitation coefficients based on experimental data could provide a solid foundation for future research endeavors.

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