

Research on Dynamic Pricing and High-Frequency Replenishment-Based Intervention Strategies for Supermarket Near-Expiry Food Waste

Yunuo Li, Xuning Xu

Borong Ten Thousand Miles Silver Beach School, Huizhou 516347, Guangdong, China

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Abstract: Perishables with three or fewer days of shelf life, such as fresh-cut fruit, salads, bakery items, and fresh milk, suffer from substantial waste in supermarkets in Hong Kong. In the past, inventory orders were made every morning based on sales the day before. This method often resulted in inadequate inventory levels and waste. This study proposes an actual intervention through dynamic pricing and high-frequency replenishment. The proposal includes the following: the store replenishes its perishables three times per day; the pricing structure will be based on a “price decreases as the day goes on with purchasing limits” discount rule; a safety stock of 1.05 in place; and the use of electronic shelf labels for ensuring automatic pricing changes. The proposal is divided into a four-week pilot project plan. Each step will provide information on how to gather data from the perspectives of customers, employees, and the community. This paper includes assumptions, future plans, ethical issues, as well as innovations of importance. The primary innovation is the use of behavioral economics in everyday operations in the supermarket to create a “laboratory.”

Keywords: Near-expiry food; Dynamic pricing; High-frequency replenishment; Food waste; Newsvendor model; Behavioral economics

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1. Literature review: Existing evidence supports structured intervention

Food waste associated with near-expiry dates in supermarkets in Hong Kong mostly happens with products such as fresh-cut fruits, ready-to-eat salads, baked goods stored under refrigeration, and fresh milk. These products have a life expectancy of less than three days and are subject to the vicissitudes of demand that cannot be predicted. The current system used by supermarkets is called “next-day static orders.” Every morning, retailers place orders for the next day’s inventory for direct shipment based on the sales from the preceding day’s inventory. There is no provision for the adjustment of the demand levels that are realized every day, and this leads the retailers to stock too much safety inventory in order to avoid shortages, resulting in the loss of unsold stock and waste. According to the 2024 report of the Hong Kong Environmental Protection Department,

the daily food waste from the municipal authorities of Hong Kong amounts to approximately 3,287 tons, with over 1,000 tons resulting from the commercial and industrial sectors, as well as the supermarkets' supplies. In the USA, an estimated 119 billion pounds of food are wasted in supermarkets annually, resulting in 35 percent of all food provision lost ^[1]. In Europe alone, over \$65 billion is lost annually ^[1]. Therefore, addressing the challenge of food wastage in supermarket stores is an important environmental and economic problem.

Both theory and practice point to the same solution: dynamic pricing and high-frequency replenishment. The principle is simple: fluctuations in demand cannot be predicted completely and therefore, ordering too much product at once creates waste ^[2,3]. Logistics managers expect food waste to decrease, as well as a reduction in the level of spoilage in the supermarket's stores. The experience of Sanders is one of the best examples confirming the effectiveness of using a dynamic pricing strategy ^[4]. For instance, through the use of dynamic pricing, self-selection takes place whereby customers with different needs will purchase products at different prices. For example, people demanding caution will buy goods when the prices are normal, while wise people will wait.

Based on the above research, this paper proposes four interrelated parameter designs:

- (1) Three times a day replenishment (10:00, 14:00, and 18:00; focused on the three sources of demand and controlling safety stock build-up).
- (2) A dynamic discount mechanism of "cheaper as the day goes by and limits to purchases." The dynamic discount will gradually decrease based on the time left before the expiration date and establish a limit to purchases per person to avoid resale. This directly relates to the time sorting method in Sanders's framework ^[4].
- (3) Using a safety stock coefficient of 1.05 means that the target inventory shall equal 105% of the average consumption levels, covering 95% of the variations in demand. In traditional retailing of fresh fruits and vegetables, the safety stock coefficient ranges between 1.2 and 1.5, but this lowered figure is justified due to the dynamic pricing and high-frequency replenishment providing better visibility into demand, thereby allowing for waste reduction while not substantially increasing stock-out risks.
- (4) Electronic shelf labels will help reduce labor costs associated with manual price tags, thereby ensuring automatic price updates.

This proposal is based on the basic premise of the newsvendor model from behavioral economics. The newsvendor model establishes an optimal order quantity by calculating the costs related to stockout and overstock for a single period of time. The proposal divided the single period into several periods and considered high-frequency replenishment, which allows for dynamic pricing and thus positively affects the cost of overstock, reducing waste without affecting profit margins. According to Sanders, dynamic pricing has a large impact on waste when the marginal costs are low, and consumers respond differently to prices of goods and their degree of freshness ^[4].

There are five indicators to measure the efficiency of the model, namely spoilage rate (the share of expired or damaged losses) ^[5], forecast accuracy (the degree of match between actual and forecasted sales), inventory turnover rate ^[6], sell-through rate (the percentage of sales made before expiration) ^[7], and stockout occurrences (the number of times when customers aim to buy a product but found it out of stock) ^[8,9]. However, while the first four measurements should increase, it is essential to ensure that the stockout reference does not rise.

In the literature review, it was proven that there is a highly accurate possibility to forecast dynamic pricing using gradient boosting methods (MAE = 0.113, $R^2 = 0.828$) by Abdullah *et al.*; dynamic pricing and

static pricing were compared by the European Environmental Policy Institute where they proposed the idea of dynamic shelf life; and benchmarks for perishable inventory practices improvement were established by Minner and Transchel and Haijema, demonstrating that the potential for the improvement may be between 4% and 25%^[10,11]. The present proposal provides a combination of the influence of consumer behavior in the area of dynamic pricing and supply chain activities of high-frequency replenishment, which creates a necessary intervention strategy based on theoretical foundations, empirical evidence, and tangible results.

2. Practical implementation plan

2.1. Preparation (Week 1)

- (1) Identify high-loss SKUs: Pull from POS data the daily sales for fresh produce SKUs, spoilage quantities, and discount percentages over the last 30 days. Filter for only those items with an average of at least 20 units a day sold as well as at least 15% spoilage.
- (2) Set up electronic label reminders: Use existing electronic shelf labels to add a “Fresh Today” label as well as a “Recommended purchase” (i.e., “Good for one or two individuals for dinner”) on the stock of the pilot program.
- (3) Train Staff: Teach cashiers and shelf stockers to check on the inventory of the products in the pilot program at a minimum of three times during the day (9:30, 1:30, and 5:30), with the appropriate reminders in the automatic system.

2.2. Dynamic ordering rules (starting Week 2)

Cancel the original “order next day’s goods each morning” model and replace it with three same-day replenishments, see **Table 1**.

Table 1. Dynamic ordering rules

Replenishment time	Data basis	Order quantity calculation	Delivery deadline
10:00 AM	Previous day’s actual sales + real-time sales velocity from store opening to 9:30 AM	Predicted remaining daily sales $\times 1.05$ – current inventory	Before 12:00 PM
2:00 PM	Sales velocity from 10:00 AM to 1:59 PM	Predicted sales from 3:00 PM to closing $\times 1.05$ – current inventory	Before 4:00 PM
6:00 PM	Sales velocity from 2:00 PM to 5:59 PM	Predicted evening sales (6:00 PM to closing) $\times 1.05$ – current inventory	Before 7:30 PM

Parameter notes as previously described.

2.3. Supporting discount strategy adjustments

To complement dynamic replenishment, the discount structure is changed to “cheaper as the day goes on, but with purchase limits”:

- (1) Before 10:00 AM: Full price
- (2) 10:00 AM to 2:00 PM: >24 hours remaining shelf life = 20% off; ≤ 24 hours = 40% off (limit 2 per person)
- (3) 2:00 PM to 6:00 PM: >24 hours remaining = 30% off; ≤ 24 hours = 60% off (limit 2 per person)
- (4) 6:00 PM to closing: >24 hours remaining = 50% off; ≤ 24 hours = 80% off (limit 1 per person)

Electronic shelf labels automatically update prices; no manual price tag changes needed.

2.4. Data recording and performance assessment

After closing each day, the system automatically generates the following indicators and sends them to the store manager:

- (1) Ordering accuracy = $1 - (\text{actual sales} - \text{predicted sales}) / \text{actual sales}$
- (2) Near-expiry discard rate = $\text{daily spoilage quantity} / \text{daily total received quantity}$
- (3) Inventory turnover = $\text{daily sales} / \text{average inventory}$

After the pilot concludes, compare Week 1 (baseline) and Week 4 data to calculate the improvement margin.

3. Research outcomes in practice and social beneficiary validation

The practical purpose of this initiative is to convert the use of the traditional model of operation, the “next-day static ordering” model, into the use of a “same-day three-time dynamic replenishment” operational model. The aim of this conversion is to successfully implement the initiation of a four-week pilot project. In order to reach this goal, the following activities will be completed: the analysis of a historical POS data to determine the specific SKUs experiencing the highest losses; the use of electronic tags to identify “Fresh Today” goods and determine the quantity of required products; training of all employees to check the availability of products during no less than three time slots (9:30 AM, 1:30 PM, and 5:30 PM).

Regarding dynamic ordering rules, they will consist of calculating replenishment amounts by multiplying sales velocity for two hours by the number of operational hours left for the day, and multiplying it by the coefficient of 1.05 to determine the quantity for replenishment (at 10:00 AM, 2:00 PM, and 6:00 PM), with the transition to three deliveries a day at the cost of HK\$20. While implementing these changes, companies will still be able to reduce spoilage costs and bear the additional delivery costs. A new discounting policy includes changes from the fixed price to the four-tiered discount system, where prices will be reduced consistently during the entire day but with some restrictions for the customers. Finally, the last component of the plan is an analysis of the correctness of orders placed for the day, costs related to waste approaching the expiration date, and the speed of the renewal of inventory on a daily basis.

3.1. Formula

Formula 1: Pilot SKU Selection (Identifying "Problematic High-Volume" Items)

$$\bar{s} = \frac{1}{30} \sum_{d=1}^{30} s_d > 20 \quad \text{and} \quad \frac{\sum_{d=1}^{30} w_d}{\sum_{d=1}^{30} (s_d + w_d)} > 15\%$$

Objective: From all fresh items, select SKUs with high sales but significant waste as pilot candidates (high sales make optimization worthwhile; high waste indicates room for improvement).

Numerator ($\sum w_d$): Total write-off (discard) volume over the past 30 days.

Denominator ($\sum (s_d + w_d)$): Total received volume over the past 30 days (received = sold + wasted).

Threshold logic: Average daily sales > 20 portions means the item has high traffic; waste ratio > 15% indicates the current replenishment approach is too coarse and urgently needs dynamic adjustment.

Formula 2: Unified Replenishment Quantity (applies to all three order cycles)

$$Q = \max(0, \lceil \alpha \times v_{\text{period}} \times (T_{\text{close}} - T_{\text{delivery}}) - I_{\text{current}} \rceil)$$

where $\alpha = 1.05$

Objective: Calculate "how much to order this time" — enough to avoid stockouts and overstock.

$\alpha = 1.05$ (**safety factor**): After predicting future sales, order 5% more to handle unexpected rushes (e.g., weather changes bringing more customers).

v_{period} (**sales rate**): Number of portions sold per hour in the previous period. For example, for a 2 PM replenishment, reference the rate from 10 AM to 2 PM (4 hours).

$(T_{\text{close}} - T_{\text{delivery}})$ (**remaining selling time**): Hours left until closing. Multiply by the rate to get "how many more portions will be sold by close".

Subtract I_{current} : Deduct current on-hand inventory to avoid duplicate ordering.

$\lceil \rceil$: Ceiling (quantities must be integer portions).

$\max(0, \dots)$: If the result is negative (overstock), order 0 — never force a replenishment.

Formula 3: Dynamic Pricing Coefficient β (real-time price adjustment)

$$\beta(H, t) = \begin{cases} 1.0 & t \in [\text{open}, 10 : 00) \\ 0.8 (H > 24) \text{ or } 0.6 (H \leq 24) & t \in [10 : 00, 14 : 00) \\ 0.7 (H > 24) \text{ or } 0.4 (H \leq 24) & t \in [14 : 00, 18 : 00) \\ 0.5 (H > 24) \text{ or } 0.2 (H \leq 24) & t \in [18 : 00, \text{close}] \end{cases}$$

Real-time selling price = base price $\times \beta$

Objective: The closer to closing time and the nearer the expiry, the steeper the discount, stimulating customers to buy and reducing waste.

H (**remaining shelf life in hours**): e.g., 48 hours remaining upon morning delivery, dropping to ~20 hours by afternoon.

Time dimension (vertical): Full price in the morning; discounts start after 10 AM; steeper discounts later in the day (as low as 20% off).

Shelf-life dimension (horizontal): Remaining shelf life > 24 hours is still "fresh" — light discount; ≤ 24 hours is "short-dated" — deep discount to clear.

Combined logic: For example, at 3 PM with 20 hours remaining, the coefficient is 0.4, i.e., 40% of the base price.

Formula 4: Purchase Limit Constraint (to prevent hoarding)

$$C_{\max}(t) = \begin{cases} 2 & t \in [10 : 00, 18 : 00) \\ 1 & t \in [18 : 00, \text{close}] \end{cases}$$

Objective: The deeper the discount, the tighter the per-customer limit, preventing one person from buying all discounted items (hurting other customers' experience) and deterring bulk resellers.

Logic: From 10 AM to 6 PM (4–8折 / 40–80% price), each customer can buy at most 2 portions per transaction; after 6 PM (2–5折 / 20–50% price clearance), limit to 1 portion to ensure broader customer coverage.

Formula 5: Three Core KPIs at End of Day

① Order Accuracy (how accurate is the forecast?)

$$A = \left(1 - \frac{|S - F|}{S}\right) \times 100\%, \quad \text{if } S = 0 \text{ then } A = 100\%$$

S (actual sales): Portions actually sold today.

F (forecasted sales): Sum of all three replenishment forecasts made today.

Logic: Smaller deviation means higher accuracy. If actual sales = 100 and forecast = 90, deviation is 10%, accuracy = 90%. If actual sales = 0 (no business), the formula would divide by zero, so accuracy is set to 100% (no meaningful assessment).

② Spoilage Rate (how much is wasted?)

$$R = \frac{W}{P} \times 100\%$$

W (today's write-off): Portions expired or discarded today.

P (total received today): Sum of all three replenishment quantities ($P = Q_1 + Q_2 + Q_3$).

Logic: If 100 portions arrived and 5 were wasted, the spoilage rate is 5%. The lower this number, the more successful the dynamic pricing strategy.

③ Inventory Turnover (how fast does capital cycle?)

$$T = \frac{S}{\bar{I}}$$

$\bar{I}$ (average inventory): $\frac{\text{opening inventory} + \text{closing inventory}}{2}$, representing the average amount of stock sitting on shelves today.

Logic: If 100 portions were sold and average inventory was 20 portions, turnover is 5 (meaning the shelf was "refreshed" 5 times in one day). Higher turnover means more precise replenishment, less cold-storage space occupied, and less capital tied up.

Formula 6: Comprehensive Improvement Index (Week 4 vs. Week 1 — pilot success indicator)

$$\Phi = (\bar{A}_4 - \bar{A}_1) + (\bar{R}_1 - \bar{R}_4) + 0.5 \times \frac{\bar{T}_4 - \bar{T}_1}{\bar{T}_1}$$

Objective: Combine the three KPIs into a single composite score to decisively judge whether the new model is effective.

Term 1 ($\bar{A}_4 - \bar{A}_1$): Week 4 average accuracy minus Week 1 average. Positive means forecasting is improving (bonus).

Term 2 ($\bar{R}_1 - \bar{R}_4$): Week 1 average spoilage rate minus Week 4 average. Since spoilage is a "bad" metric, a decrease makes this term positive (bonus).

Term 3 (turnover lift): $\frac{\bar{T}_4 - \bar{T}_1}{\bar{T}_1}$ is the relative growth rate of turnover (e.g., from 1 to 2 is 100% growth). Multiplied by 0.5 because turnover can fluctuate significantly; this dampens its weight so it doesn't overwhelm the first two terms.

Decision rule: If $\Phi > 0.2$, the composite metric shows clear improvement, and the pilot can be rolled out store-wide.

3.2. Limitations and future research directions

This proposal is based on three assumptions. If any of these assumptions does not hold, the effectiveness of this proposal will be compromised. The first assumption concerns supplier management. If the density of the supplier network is insufficient or if bargaining power is unequal, then supplier costs may increase significantly from “+HK\$20 per order” to a level that jeopardizes profitability or creates complete disruption of supply. This is due to the fact that three deliveries every day violate the current practice of one delivery a day. The second assumption relates to employee employment stability. As the turnover rate in retailing is 30-40% annually, investments in training might turn into wasted money, since dynamic replenishment needs employees to check inventory formally three times a day. Moreover, an unlimited personal approach by a new store manager to the “1.05 safety coefficient” will not necessarily yield positive effects, as this person may make wrong decisions and either order too much stock or too little. The third issue is about the rationality of consumers. Although the idea behind “cheaper as the day passes” is to encourage consumers to buy more products faster, it may lead to actual destruction of sales for the products sold at full price. Restrictions concerning initial setup and operational costs related to electronic shelf labels will impede proper functioning of this technique in small and medium outlets, thus exacerbating digital inequality.

The applicable technological change taking place is the progression from “man-assisted systems” to “autonomous decision-making systems,” which will happen within the short term (1–2 years). Accordingly, in the short term, demand-sensing artificial intelligence will be implemented, thereby taking the prediction period from “2 hours into the future” to “72 hours, based on multi-factor analysis” (without using any human inputs or intervention). There will be subsequent advancement on the use of new technologies such as blockchain and smart contracts being used for automatic replenishment of inventory as well as instantaneous payment systems (without any manual reconciliation); finally, in the long-term case (5–10 years), a strategy for the sale of “fresh goods without any stock” will be implemented through decentralized storage, group purchasing, and price variability without perishability. As it pertains to the company structure, the company will advance to the point of becoming a “capability export platform,” which means the application of specialized reasoning and mental capabilities of specialists will be programmed into respective expert systems (for third-party use).

The concept of “time discrimination” in the discount strategy carries a number of fairness risks, as the low-income population (e.g., retired people) has flexible hours that allow them to shop at bargain prices during the late evening, while the office workers only have the opportunity to buy twice at full price; thus, the potential “price-income” inversion would take place. Although economically sound, some may see it as an “exploitation of the time-poor.” At the data level, sales velocity tracking includes profiling of consumers; therefore, if coupled with membership techniques, it could become “algorithm manipulation,” requiring precise data usage and the right to opt out. In terms of employee monitoring practices, checking inventory three times per day may create a “panoptic” effect, putting extensive pressure on workers who will avoid making mistakes but become afraid to innovate; thus, the system must provide for the use of “error allowances” and anonymous appeal procedures. In terms of the environmental narrative, the ESG halo about “decreasing food waste” should be verified by independent audits in order to avoid accusations of “greenwashing” (e.g., sale of goods about to expire that are eventually discarded instead of reducing food waste).

Disclosure statement

The authors declare no conflict of interest.

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