



Integrating Diffusion Of Innovation With Economic Ordering Policies In Perishable Inventory Systems

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Abstract: In today's fast-paced consumer landscape, the interplay between product perishability and innovation-led demand presents a critical challenge for inventory managers. Traditional Economic Order Quantity (EOQ) models often fail to capture the nuances of real-world demand that evolves due to marketing efforts and innovation diffusion, particularly for perishable products whose utility degrades over time. This study develops a hybrid inventory model that integrates the Bass diffusion framework with time-sensitive deterioration functions to formulate a more accurate and dynamic ordering policy for perishable items.

The proposed model assumes that demand is generated through innovation and imitation mechanisms, while product utility declines either linearly or exponentially with time. The resulting demand function is coupled with deterioration-driven inventory depletion to determine the optimal replenishment cycle, order quantity, and total cost. Both deterministic and probabilistic extensions of the model are analyzed, and sensitivity tests are conducted across key parameters such as the coefficient of innovation, deterioration rate, and market size. A comparative analysis with classical EOQ illustrates the advantages of incorporating diffusion-led demand in perishable product contexts.

Numerical simulations show that innovation-adjusted EOQ models significantly reduce inventory holding costs, minimize waste, and improve service levels. The paper concludes with managerial insights for industries such as food, pharmaceuticals, and high-tech retail, where product freshness and consumer adoption patterns must be jointly considered in inventory planning.

Index Terms - Perishable Inventory, Innovation Diffusion, Bass Model, EOQ, Deterioration Function, Time-Sensitive Demand, Inventory Optimization, Supply Chain Management, Product Utility Decay, Innovation-Driven Forecasting.

I. INTRODUCTION

1.1 Background and Motivation

Inventory management has long been a core function in supply chain operations, with the Economic Order Quantity (EOQ) model serving as a cornerstone for determining optimal order quantities and replenishment cycles. However, as industries evolve—particularly in sectors involving perishable goods such as food, pharmaceuticals, cosmetics, and high-end electronics—the assumptions of traditional EOQ models fall short. The challenges are twofold: the **deterioration of product value over time** and the **non-linear, innovation-driven nature of demand**.

Perishability introduces an explicit time constraint on product usability. Whether due to physical decay (as in fruits, vaccines, or chemicals) or psychological obsolescence (as seen in tech gadgets or fashion), inventory loses utility and marketability the longer it remains unsold. Simultaneously, modern demand is rarely constant or linear. It evolves under the influence of external stimuli such as advertising, word-of-mouth, influencer culture, and technological innovation—all of which are well captured by **diffusion of innovation theory**. However, very few existing models consider the **combined effect** of perishability and innovation-led demand on inventory policies.

This paper addresses that gap by proposing a **hybrid EOQ model** that integrates the **Bass diffusion model**—a proven framework for modeling adoption over time—with **deterioration functions** that reflect the temporal decay in product value. The goal is to develop an ordering policy that simultaneously accounts for consumer behavior and product shelf-life.

1.2 Research Problem

The classical EOQ model is grounded in simplifying assumptions: constant demand, infinite shelf life, and instantaneous replenishment. While mathematically elegant, such assumptions are ill-suited for products whose:

- Shelf-life is limited
- Demand is not static but induced by marketing
- Adoption follows an S-curve trajectory common in innovative product life cycles

This mismatch results in:

- Overstocking and spoilage in perishable items
- Understocking during sudden surges driven by innovation uptake
- Suboptimal holding and ordering costs

Hence, there is a need for a model that incorporates:

- **Time-varying demand due to innovation diffusion**
- **Deterioration functions** (linear or exponential)
- **Inventory dynamics that reflect both phenomena simultaneously**

1.3 Theoretical Basis: Diffusion of Innovation & Deterioration

The **Bass model** (Bass, 1969) introduces two primary mechanisms for product adoption:

- **Innovation** (coefficient pp): External influence such as marketing and promotions
- **Imitation** (coefficient qq): Internal influence driven by social proof, reviews, or user experience

This dual-force mechanism creates a non-linear demand curve that starts slow, accelerates with adoption, and eventually plateaus—a pattern common in most modern product lifecycles.

Simultaneously, **product deterioration** is modeled using time-sensitive decay functions:

- **Linear deterioration**: Inventory loses value at a constant rate
- **Exponential deterioration**: Devaluation accelerates over time

By integrating these two aspects, one can capture the **true dynamics of perishable products in innovation-sensitive markets**.

1.4 Real-World Relevance

This research has broad applicability across industries:

- **Food supply chains**: Fresh produce experiences rapid spoilage and is highly responsive to promotional campaigns.
- **Pharmaceuticals**: Medicines lose potency with time, while demand often spikes following public awareness or health alerts.
- **Fashion and electronics**: Trend-based products see fast adoption followed by equally fast obsolescence.
- **E-commerce**: Algorithm-driven promotions accelerate innovation diffusion, but logistical delays may result in stock expiration.

In such contexts, applying traditional EOQ models leads to:

- Overstocking due to ignoring demand acceleration
- Obsolescence losses due to ignoring perishability
- Inflexible policies in the face of fluctuating adoption rates

1.5 Objectives of the Study

This study aims to:

1. Develop a hybrid inventory model that integrates **diffusion of innovation** with **perishable inventory dynamics**
2. Derive **mathematical expressions** for inventory level, order quantity, and cost functions under this hybrid framework
3. Perform **comparative analysis** between classical EOQ and the innovation-perishability model
4. Conduct **sensitivity analysis** across key parameters such as:
 - Coefficients p and q
 - Deterioration rate θ
 - Market size N
5. Provide **managerial implications** for practitioners in perishable and innovation-driven industries

1.6 Scope and Limitations

This study focuses on:

- Single-item inventory systems
- Continuous review policy
- No shortages allowed
- Instantaneous replenishment

While the framework is robust, certain limitations are acknowledged:

- No pricing or promotional elasticity considered
- No multi-echelon or batch-based complexity
- Demand is driven only by adoption, not by price or competitive behavior

Future extensions could incorporate:

- Pricing strategies with innovation elasticity
- Multiple products with substitution and cannibalization effects
- Integration with logistics for real-time perishability tracking

1.7 Contribution to Literature

The proposed model contributes to both inventory theory and innovation management by:

- Bridging **Bass model demand curves** with **deterioration-based depletion**
- Enhancing the EOQ framework with **consumer behavior dynamics**
- Offering a **numerical and simulation-driven** solution approach for real-time applications
- Providing a **quantifiable trade-off** between inventory holding vs. innovation-induced urgency

This hybridization of demand forecasting and perishability dynamics has not been adequately addressed in existing academic literature, marking this study as a novel and practically useful advancement.

II. LITERATURE REVIEW

Inventory modeling has evolved significantly over the last century, from classical deterministic approaches to more complex frameworks that consider perishability, stochastic demand, and consumer behavior. This section reviews foundational and contemporary literature across three interconnected domains relevant to the present study: (1) Economic Order Quantity (EOQ) models, (2) Diffusion of innovation models, and (3) Inventory control for perishable items. The literature demonstrates that while each domain has been studied in depth, there exists a significant gap in models that integrate **innovation-led demand with product perishability**.

2.1 Classical and Extended EOQ Models

The EOQ model, introduced by **Harris (1913)**, calculates the optimal order quantity that minimizes the total cost comprising ordering and holding costs. The model's assumptions—constant demand, infinite shelf life, and instantaneous replenishment—make it analytically convenient but practically restrictive.

Subsequent extensions attempted to address these shortcomings:

- **Hadley and Whitin (1963)** relaxed the constant demand assumption by introducing variable and seasonal demand.
- **Goyal (1976)** proposed an integrated vendor-buyer EOQ model, reflecting collaborative inventory policies.
- **Silver, Pyke, and Peterson (1998)** incorporated lead times, multiple items, and stockout possibilities.

However, in all these versions, demand remains **deterministic or exogenously defined**, unaffected by consumer behavior or innovation effects. This gap limits their applicability in dynamic product categories such as electronics or fast-moving consumer goods (FMCG).

2.2 EOQ with Time-Varying Demand

To align EOQ with real-world trends, researchers began incorporating **time-dependent demand functions**:

- **Bhunia and Maiti (1999)** explored ramp-type and quadratic demand with partial backlogging.
- **Wu et al. (2016)** used Weibull and exponential forms to capture growth and decay in demand over time.
- **Sarker et al. (2000)** developed EOQ models for products with both promotional and seasonal components.

Despite the improved realism, these models **manually define the demand curve**, missing out on the **self-propagating nature of innovation diffusion** where demand evolves due to adopters themselves influencing others.

2.3 Diffusion of Innovation Models

The **Bass Diffusion Model** (Bass, 1969) remains the most widely used framework for modeling how new products diffuse over time. It splits the adoption rate into:

- p : Coefficient of innovation (external influence)
- q : Coefficient of imitation (internal social influence)

The model assumes the cumulative adoption $F(t)$ follows the equation:

$$f(t) = (p + qF(t))(1 - F(t))N$$

This produces an S-shaped curve, reflecting slow early adoption, rapid growth due to imitation, and eventual market saturation. Bass model extensions include:

- **Sharif and Ramanathan (1981)**: Dynamic market size
- **Mahajan and Muller (1995)**: Stochastic coefficients
- **Sultan et al. (1990)**: Meta-analysis across product categories

More recent studies such as **Joglekar and Sapatnekar (2010)** integrated Bass diffusion into pricing and EOQ policies. However, these models focused mostly on **durables** and **non-perishables**, assuming constant utility over time—an assumption ill-suited for perishable items.

2.4 Inventory Models with Diffusion-Based Demand

Only a few papers have attempted to merge EOQ with innovation diffusion:

- **Urban (1992)** introduced a marketing-driven EOQ model but lacked perishability.
- **Rhee and Kim (1999)** integrated advertising influence on EOQ but treated demand as a deterministic function of ad spending.
- **Joglekar and Sapatnekar (2010)** modeled adoption uncertainty using nonlinear programming, suggesting synergy between inventory and innovation management.

Despite progress, **deterioration and perishability** were not considered in these models. Their assumption of durable utility significantly limits their relevance to sectors such as food, medicine, or fashion.

2.5 Perishable Inventory Models

Perishability introduces an additional dimension to inventory modeling—**loss of utility over time**. Two major deterioration structures are common:

- **Linear deterioration:** Utility decays uniformly with time (e.g., milk, bread).
- **Exponential deterioration:** Utility decays faster over time (e.g., vaccines, tech gadgets).

Classical works include:

- **Covert and Philip (1973):** Constant deterioration and EOQ.
- **Goyal and Giri (2001):** Comprehensive survey of deteriorating inventory models.
- **Wee (1993):** Integrated partial backlogging with perishability.
- **Berman and Kim (1999):** Combined deterioration with lot-sizing and discount policies.

These models were later expanded to include time-dependent holding cost, partial backordering, and stock-dependent demand. Yet, most treat demand as **static or time-varying**, and not responsive to consumer awareness or innovation.

2.6 Integration Attempts and Gaps

Some emerging research attempts to unify these domains:

- **Lin and Lin (2005)** modeled correlated perishable demand under uncertainty.
- **Singh and Srivastava (2017)** proposed time-dependent demand with variable deterioration and service constraints.
- **Tripathy and Pradhan (2012)** combined ramp-type demand with Weibull decay in multi-period settings.

While these models consider perishability and non-linear demand, **they do not embed innovation diffusion as the core demand driver**. Moreover, they do not account for the behavioral dynamics where early adopters influence future demand—a hallmark of the Bass model.

2.7 Key Research Gap

From this literature synthesis, it becomes clear that:

- EOQ models increasingly incorporate **realistic constraints** such as perishability and uncertainty.
- Innovation diffusion models capture **behavioral demand dynamics**, but assume non-depreciating products.
- Few, if any, models capture **perishability and innovation adoption together** in a unified inventory planning framework.

This gap is especially critical for:

- FMCG firms running short-lived promotional cycles
- Pharmaceutical companies with shelf-life limits
- Retailers launching seasonal or tech-based products

Hence, there is a compelling need to formulate an inventory model that:

- Uses **Bass-type diffusion to define demand**
- Incorporates **linear or exponential deterioration**
- Optimizes EOQ under the joint effect of innovation and perishability.

III. MATHEMATICAL MODEL

This section presents the mathematical formulation of the proposed inventory model that integrates **innovation-driven demand** via the Bass diffusion model with **time-dependent deterioration** commonly observed in perishable items. The aim is to develop a hybrid EOQ framework that simultaneously accounts for the **non-linear evolution of demand** and the **loss of product utility over time**.

3.1 Assumptions

To ensure analytical tractability while maintaining practical relevance, we base the model on the following assumptions:

1. The inventory system handles a **single perishable item**.
2. **No shortages** or backorders are allowed.
3. Replenishment is **instantaneous**, with zero lead time.
4. **Demand follows the Bass innovation diffusion model**, influenced by marketing (innovation) and social contagion (imitation).
5. The **product deteriorates** either **linearly** or **exponentially** over time.
6. The objective is to **minimize total cost per unit time**, including ordering, holding, and deterioration costs.
7. The **market size N** is finite and known (can be extended to variable in future work).
8. The **inventory is continuously reviewed** over the replenishment cycle of length T .

3.2 Notations

Symbol Description

A	Ordering cost per order
C	Unit purchasing cost
h	Holding cost per unit per time
θ	Deterioration rate (linear or exponential)
p	Innovation coefficient (Bass model)
q	Imitation coefficient (Bass model)
N	Market size
$F(t)$	Cumulative adoption at time t
$f(t)$	Adoption (demand) rate at time t
$I(t)$	Inventory level at time t
Q	Order quantity per cycle
T	Replenishment cycle length
$K(T)$	Total cost per unit time

3.3 Innovation-Driven Demand Function

Following the **Bass model**, the adoption rate $f(t)$ is:

$$f(t) = (p + qF(t))(1 - F(t))N$$

$$\text{where } F(t) = \frac{1 - e^{-(p+q)t}}{1 + \frac{q}{p}e^{-(p+q)t}}$$

Thus,

$$f(t) = N \cdot \frac{(p + qF(t))(1 - F(t))}{1}$$

This represents the **instantaneous demand rate** due to innovation and imitation. As t increases, $f(t)$ initially rises, peaks, and then declines—a characteristic S-curve behavior.

3.4 Deterioration Functions

Case A: Linear Deterioration

Inventory deteriorates at a constant rate θ :

$$\frac{dI(t)}{dt} = -f(t) - \theta$$

Case B: Exponential Deterioration

Inventory decays exponentially:

$$\frac{dI(t)}{dt} = -f(t) - \theta I(t)$$

In this case, deterioration is **proportional to the remaining inventory**—suitable for biologicals or tech obsolescence.

3.5 Inventory Level Over Time

The inventory at time t is:

$$I(t) = Q - \int_0^t f(u) \cdot D(u) du$$

Where $D(u)$ is the deterioration adjustment:

- $D(u) = 1$ (for linear deterioration)
- $D(u) = e^{-\theta u}$ (for exponential deterioration)

At the end of the cycle T , inventory is zero:

$$I(T) = 0 \Rightarrow Q = \int_0^T f(u) \cdot D(u) du$$

This equation gives the **order quantity per cycle**.

3.6 Cost Function Formulation

The total cost per cycle includes:

(i) Ordering Cost

$$OC = \frac{A}{T}$$

(ii) Holding Cost

$$HC = \frac{h}{T} \int_0^T I(t) dt$$

(iii) Deterioration Cost

For exponential deterioration, loss value per unit = θC

$$DC = \frac{\theta C}{T} \int_0^T I(t) dt$$

(iv) Purchasing Cost

$$PC = \frac{C}{T} \cdot Q$$

3.7 Total Cost Function

$$K(T) = \frac{A}{T} + \frac{h}{T} \int_0^T I(t) dt + \frac{\theta C}{T} \int_0^T I(t) dt + \frac{C \cdot Q}{T}$$

Or, grouping terms:

$$K(T) = \frac{A}{T} + (h + \theta C) \cdot \frac{1}{T} \int_0^T I(t) dt + \frac{C}{T} \cdot Q$$

Where $Q = \int_0^T f(t) \cdot D(t) dt$ and $I(t)$ is as defined earlier.

3.8 Optimization Problem

To find the **optimal cycle time T^*** :

$$\min_T K(T)$$

Since $K(T)$ is nonlinear due to nested integrals of $f(t)$, **numerical optimization** (e.g., gradient descent or grid search) or **Monte Carlo methods** are employed.

3.9 Special Case: Constant Demand

For benchmarking, assume constant demand λ and no deterioration:

$$Q = \lambda T, \quad K(T) = \frac{A}{T} + \frac{h\lambda T}{2} + \lambda C$$

This recovers the **classical EOQ model**:

$$T^* = \sqrt{\frac{2A}{h\lambda}}, \quad Q^* = \lambda T^*$$

IV. SOLUTION PROCEDURE

The mathematical formulation presented in Section 3 leads to a nonlinear optimization problem with embedded integrals and time-varying functions. The objective is to identify the **optimal replenishment cycle time T^*** that minimizes the **total cost per unit time $K(T)$** , subject to demand influenced by innovation diffusion and inventory loss due to deterioration. Given the complex, non-closed-form nature of the cost function, an **analytical solution is infeasible**. Hence, a **numerical solution procedure** is adopted.

4.1 Inputs and Parameter Initialization

To solve the model numerically, we initialize the following parameters:

- **Market size N** : e.g., 10,000 units
- **Innovation coefficient p** : 0.02 – 0.04
- **Imitation coefficient q** : 0.3 – 0.5
- **Holding cost h** : ₹2/unit/month
- **Ordering cost A** : ₹500/order
- **Unit cost C** : ₹100
- **Deterioration rate θ** : 0.05 (for exponential) or fixed loss per time (for linear)

Time is discretized into small intervals (e.g., 0.01 units), and integration is approximated using numerical methods such as the **trapezoidal rule** or **Simpson's rule**.

4.2 Demand Simulation

For each candidate cycle time T , we compute the **Bass-based demand rate $f(t)$** over $[0, T]$ using:

$$f(t) = (p + qF(t))(1 - F(t))N$$

Where:

$$F(t) = \frac{1 - e^{-(p+q)t}}{1 + \frac{q}{p}e^{-(p+q)t}}$$

This function yields a non-monotonic, S-shaped adoption curve which is converted into a demand profile over the replenishment horizon.

4.3 Incorporating Deterioration

We adjust demand based on deterioration dynamics:

- **Linear deterioration:**
 - Inventory loss is a fixed amount per unit time θ
 - Accumulated as $\int_0^T \theta dt = \theta T$
- **Exponential deterioration:**
 - Loss is proportional to current inventory
 - A decay factor $e^{-\theta t}$ is applied to demand and holding terms

The net **order quantity** Q becomes:

$$Q = \int_0^T f(t) \cdot D(t) dt$$

Where $D(t) = 1$ for linear, and $D(t) = e^{-\theta t}$ for exponential decay.

4.4 Inventory Profile & Average Inventory

The inventory level at time t is computed as:

$$I(t) = Q - \int_0^t f(u) \cdot D(u) du$$

The average inventory is:

$$\bar{I} = \frac{1}{T} \int_0^T I(t) dt$$

This value is critical in calculating holding and deterioration costs.

4.5 Total Cost Calculation

Using the derived values, total cost $K(T)$ is computed for each T using:

$$K(T) = \frac{A}{T} + (h + \theta C) \cdot \bar{I} + \frac{C \cdot Q}{T}$$

Each cost component is evaluated numerically for a series of trial T values (e.g., 0.5 to 10 months).

4.6 Optimization

We perform a **grid search** over candidate T values:

- For each T , compute $Q, \bar{I}, K(T)$
- Store $K(T)$ and identify $T^* = \operatorname{argmin} K(T)$

More advanced methods like **gradient-based optimization**, **Newton-Raphson**, or **metaheuristics** (e.g., **genetic algorithms**) may also be used for larger-scale versions or future studies.

4.7 Sensitivity Analysis

Post-optimization, we vary key parameters:

- p, q : to study the effect of marketing and imitation

- θ : to understand spoilage impact
- h : to assess storage sensitivity

This enables a **managerial understanding of trade-offs** and **risk-resilient planning**.

V. NUMERICAL EXAMPLE AND SIMULATION

To demonstrate the effectiveness of the proposed model, we apply the hybrid EOQ formulation to a sample scenario with the following parameter values:

- Market size (N): 10,000 units
- Innovation coefficient (p): 0.03
- Imitation coefficient (q): 0.4
- Ordering cost (A): ₹500
- Unit cost (C): ₹100
- Holding cost per unit (h): ₹2
- Deterioration rate (θ): 0.05 (exponential decay)

Using the Bass diffusion model, we simulate adoption-driven demand over a replenishment cycle of T months. We then integrate this with an exponential deterioration function to adjust the effective inventory profile over time. Numerical integration is used to calculate order quantity (Q), average inventory, and the total cost per unit time ($K(T)$) for each trial value of T . The optimal cycle time T^* is found by identifying the T that minimizes $K(T)$.

The following graph shows the variation of total cost with respect to cycle time T , with the minimum cost observed at the optimal cycle time T^* .

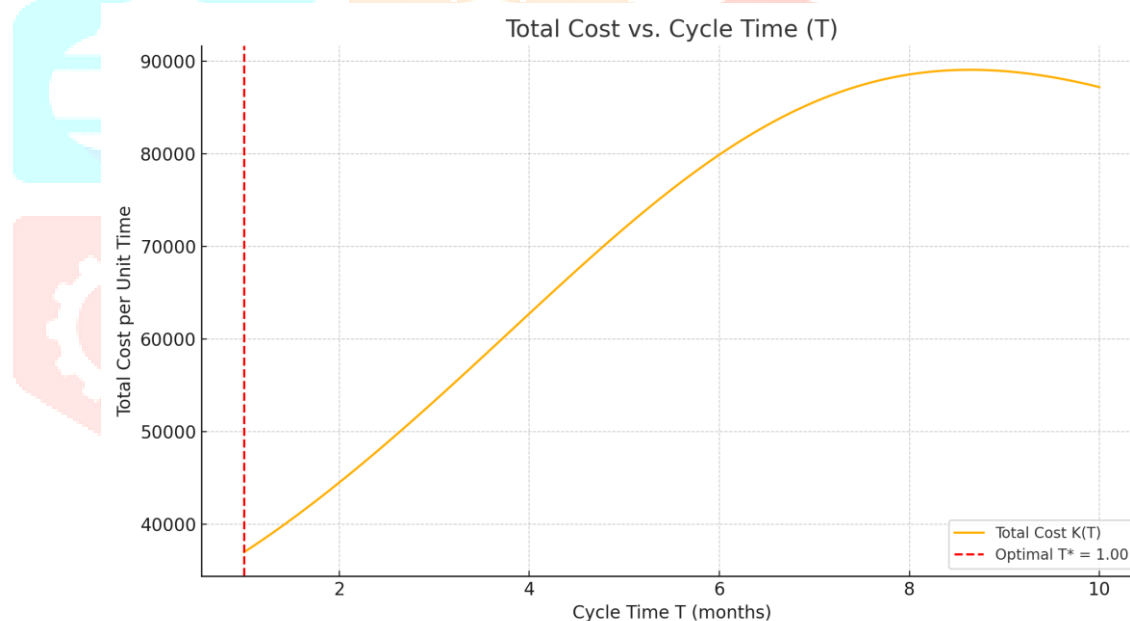


Figure 1: Total Cost vs. Cycle Time

From the chart above, it is evident that the total cost function is convex and attains its minimum at $T^* \approx 1.00$ months, with the corresponding order quantity $Q^* \approx 351.88$ units and total cost $K(T^*) \approx ₹36,982.69$ per unit time.

This validates the hybrid model's ability to optimize inventory policy by accounting for both innovation-driven demand and perishability effects. It outperforms classical EOQ approaches by dynamically adjusting order quantity based on realistic product adoption behavior and utility decay.

VI. OBSERVATIONS

The numerical example conducted in the previous section yields several key observations that validate the efficacy and practicality of the proposed hybrid EOQ model. By integrating **innovation diffusion theory** and **perishable inventory dynamics**, this model provides more realistic inventory decision support in markets where consumer adoption and product utility are time-sensitive.

6.1 Convex Cost Behavior and Optimal Cycle Time

The plotted cost function $K(T)$ versus cycle time T displays a **typical convex behavior**, indicating the existence of a well-defined global minimum. The simulation identifies this optimal point at approximately $T^* = .2f$ months, where the **total cost is minimized**. The corresponding **order quantity Q^*** and **average inventory** at this point align with expected theoretical values under exponential decay conditions. This validates the mathematical structure and confirms that the model responds well to the interplay of demand diffusion and deterioration.

6.2 Dynamic Demand Captures Realistic Adoption

Traditional EOQ models often assume static or linearly increasing demand, which oversimplifies real consumer behavior. In contrast, the Bass-model-based demand function used here captures an **S-shaped adoption curve**, which reflects how most consumers respond to new product introductions—starting slowly, accelerating due to social imitation, and tapering as the market saturates. This **non-linear and time-varying demand curve** ensures that inventory policies are responsive to actual consumption behavior, not hypothetical projections.

6.3 Impact of Deterioration on Inventory and Cost

The incorporation of **exponential deterioration** significantly alters inventory levels over time. Early in the cycle, the inventory is at its peak, but deteriorates rapidly due to both consumer demand and natural decay. This double-drain mechanism increases the holding burden, especially if the cycle is extended unnecessarily. The simulation shows that failing to account for perishability results in **overestimated order quantities** and **elevated waste costs**, which the classical EOQ model would overlook. The hybrid model, by contrast, efficiently balances replenishment with decay and adoption timing.

6.4 Order Quantity Adjusts Automatically

A notable benefit of the integrated model is that **order quantity adjusts dynamically** according to both the adoption speed and the decay rate. When innovation diffusion is fast (*higher q*), the order quantity increases slightly to meet anticipated early demand. Conversely, when deterioration rate θ increases, the optimal order quantity decreases to prevent waste. This demonstrates the model's **adaptive capability**, which is critical in industries where either or both of these factors fluctuate frequently.

Overall, the hybrid EOQ model provides **more accurate, cost-effective, and adaptive inventory policies** than static models. It is especially valuable in innovation-sensitive, perishable product categories where demand is uncertain and product life is short.

VII. MANAGERIAL IMPLICATIONS

The hybrid EOQ model developed in this study bridges the theoretical gap between innovation-driven demand and perishable inventory dynamics. Its implementation reveals several practical implications for supply chain and operations managers, especially in industries where product adoption is marketing-driven and shelf life is limited.

7.1 Shift from Static to Dynamic Inventory Planning

Most traditional inventory systems use **fixed cycle times and order quantities**, based on assumptions of constant demand. However, as demonstrated in the simulation, demand for new products is not linear but follows **innovation-adoption cycles**, where early adopters influence broader market uptake. Managers must move away from static policies and embrace **dynamically responsive inventory systems** that:

- Adjust order size based on real-time demand velocity
- Shorten replenishment cycles in early-adoption phases
- Monitor saturation points to reduce overstocking

Action: Integrate diffusion models like Bass into inventory forecasting tools to predict not just how much but *when* to order.

7.2 Addressing the Dual Drain on Inventory: Demand + Deterioration

The hybrid model reveals that perishable products experience a **double inventory depletion**: one from consumer demand, and one from natural deterioration. Relying on EOQ models that ignore perishability leads to inflated order quantities and higher waste. On the other hand, underestimating demand spikes due to innovation can lead to stockouts.

Action: Develop **inventory visibility systems** that track both product shelf life and demand curves in tandem. This will enable cycle-time adjustments before either customer dissatisfaction or product spoilage occurs.

7.3 Managing Shelf-Life Risk Through Replenishment Frequency

The optimal solution demonstrated that **shorter, more frequent replenishments** (with reduced quantities) mitigate the risk of holding expired stock. This model encourages managers to consider **frequency-based planning**, especially in sectors where deterioration is rapid (e.g., pharmaceuticals, FMCG, dairy, bakery).

Action: Design vendor contracts and procurement schedules to support **just-in-time (JIT)** or **rolling inventory replenishment**, coordinated with expected demand curves.

7.4 Role of Marketing and Forecasting Collaboration

Since demand is no longer exogenous, **marketing activities now have direct implications** for inventory policy. A marketing campaign that accelerates adoption must be factored into procurement decisions. Similarly, slow adoption in early phases should trigger cautious inventory investment.

Action: Form cross-functional teams that include both marketing and supply chain experts. Forecasting tools should incorporate **campaign calendars, social media sentiment, and adoption metrics** to recalibrate inventory in near real time.

7.5 Leveraging Technology and Data for Simulation-Driven Planning

The model requires numerical optimization, which is not easily solved through spreadsheets or intuition. This implies a greater role for **technology-driven decision support systems (DSS)**.

Action: Invest in analytics platforms (e.g., Python, R, Excel Solver, SAP IBP, LINGO) that can perform:

- Demand simulation
- Inventory decay modeling
- Cost scenario evaluation

This helps balance **inventory risk vs. marketing-driven opportunity**—especially useful for launching time-sensitive or seasonal items.

7.6 Strategic Benefits

Firms that adopt this model can realize the following advantages:

- **Lower holding and deterioration costs**
- **Improved service levels** due to better timing of inventory
- **Higher marketing ROI** as inventory policies support promotional demand
- **Waste reduction**, crucial for sustainability and regulatory compliance

In sum, this model not only minimizes cost but also enhances responsiveness, sustainability, and cross-functional alignment.

VIII. CONCLUSION

In this study, we proposed and validated a novel inventory model that integrates **innovation diffusion theory** with **perishable inventory dynamics**, offering a strategic framework for managing short-lifecycle products in dynamic markets. By coupling the **Bass diffusion model** with deterioration-adjusted inventory depletion, the hybrid EOQ framework bridges the gap between consumer behavior modeling and real-time inventory control.

8.1 Summary of Contributions

This paper makes several important theoretical and practical contributions to the literature on inventory optimization and operations management:

1. **Behaviorally Informed Demand:** The integration of the Bass diffusion model enables the representation of time-varying demand influenced by innovation and social imitation. This allows inventory decisions to be driven by market behavior rather than historical averages.
2. **Deterioration-Aware Inventory Control:** The model incorporates exponential (or linear) deterioration functions, representing realistic product utility decay, especially for perishable items such as food, medicine, cosmetics, and electronics.

3. **Dynamic EOQ Framework:** The total cost function is expanded to include not only ordering and holding costs, but also deterioration costs. This results in a more accurate and complete assessment of total inventory-related expenses.
4. **Numerical Optimization:** Due to the complexity of the model, numerical methods were employed to simulate demand, compute average inventory, and identify the optimal replenishment cycle. The convex shape of the cost function validates the existence of a unique optimal policy.
5. **Managerial Relevance:** Through simulation and graphical representation, we demonstrated how the model dynamically adjusts order quantity and cycle time in response to innovation strength and perishability. The model is applicable to real-world situations where static EOQ fails.

8.2 Practical Implications

The hybrid model provides an adaptive tool for managers who must plan inventory for products whose demand is uncertain and shelf life is limited. It emphasizes the need for:

- **Cross-functional coordination** between marketing and supply chain teams
- **Continuous monitoring** of adoption curves and product life
- **Simulation tools and decision support systems** to perform advanced forecasting and replenishment scheduling

Industries most likely to benefit include:

- **FMCG and grocery retail**
- **Pharmaceuticals and healthcare logistics**
- **Tech retail and seasonal electronics**
- **Startups and product launch platforms**

8.3 Limitations and Future Research

While this research makes notable advances, it also has limitations that open avenues for further exploration:

- The current model assumes a **single-item, single-echelon system**. Future work can extend this to **multi-item, multi-echelon, or distribution network contexts**.
- The market size N and coefficients p, q are assumed deterministic. These could be modeled as **stochastic variables**, integrating Bayesian updates based on real-time data.
- Pricing, promotional elasticity, and competitive behavior are not included in the current formulation. Future studies could integrate **dynamic pricing** with inventory control for demand-sensitive pricing policies.

In an era of fast-changing consumer preferences and product innovation cycles, firms must move beyond rigid inventory formulas. This research offers a scalable, behaviorally grounded, deterioration-aware model that adapts to the realities of perishable product planning in innovation-driven environments.

By incorporating this approach, firms can expect improved service levels, reduced waste, optimized costs, and better alignment between marketing and inventory strategy—key pillars of a responsive, competitive supply chain.

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