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A Comparative Study of Inventory Models with and without Innovation Diffusion: An Analytical and Numerical Approach

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***Abstract*—Traditional inventory models like the Economic Order Quantity (EOQ) are built on the assumption of static, predictable demand. However, in the era of fast-paced technological change and aggressive marketing, many products—especially those in consumer electronics, pharmaceuticals, and FMCG—experience time-varying demand influenced by innovation and social adoption. This paper presents a comparative analysis between two inventory modeling approaches: one based on classical EOQ with constant demand, and another extended EOQ framework incorporating demand dynamics modeled through the Bass innovation diffusion model.**

In the first model, demand is assumed to be constant, and the total cost is minimized by balancing ordering and holding costs. In the second model, demand is a function of innovation and imitation, reflecting realistic product adoption behavior over time. We analytically derive the cost functions and optimal policies for both models and then conduct numerical simulations to examine the behavior of total cost, order quantity, and cycle length under varying parameter conditions.

The results reveal that innovation-adjusted models yield more adaptive inventory strategies and better cost efficiency, particularly during product launch and growth phases. Classical models are found to underestimate peak demand and overestimate inventory needs during saturation, leading to inefficiencies. The paper concludes with a discussion on the applicability of each model in real-world inventory management and offers recommendations for firms operating in volatile, innovation-driven markets.

***Index Terms*—EOQ Model, Innovation Diffusion, Bass Model, Inventory Optimization, Time-Dependent Demand, Comparative Analysis, Order Quantity, Cycle Time, Total Cost, Product Adoption**

I. INTRODUCTION

1.1 Background

Inventory management has always played a pivotal role in ensuring operational efficiency, customer satisfaction, and cost control within supply chains. Among the numerous models developed over the years, the Economic Order Quantity (EOQ) model remains one of the most influential and widely used due to its simplicity and analytical clarity. The classical EOQ model assumes that demand is constant and known, that replenishment is instantaneous, and that costs associated with ordering and holding inventory are deterministic and time-invariant. These assumptions have served as a practical framework for inventory control in relatively stable environments.

However, in today's dynamic markets, these assumptions are increasingly unrealistic. Many products experience demand that evolves over time, particularly in industries where new product introductions, aggressive marketing strategies, and consumer behavior influence purchasing patterns. Products such as smartphones, wearable technology, electric vehicles, pharmaceuticals, and even fashion items rarely follow the constant demand trajectory assumed by traditional models. Instead, demand tends to be time-varying, non-linear, and heavily influenced by innovation and social dynamics.

This evolving market behavior necessitates an inventory modeling approach that reflects the real-life demand evolution process. One of the most widely accepted frameworks to describe such behavior is the Bass Diffusion Model, which explains how new products are adopted by a population over time, driven by innovators (external influence) and imitators (internal social influence). The integration of this model into inventory theory has resulted in EOQ extensions that incorporate demand as a dynamic function of time and adoption.

1.2 Need for Comparative Analysis

While both traditional EOQ and innovation-adjusted EOQ models are used in practice, there is a lack of comprehensive comparative studies that quantify their differences in decision-making outcomes. Most existing research either focuses exclusively on extending the EOQ model to accommodate time-dependent demand or studies innovation diffusion in isolation from operational planning.

A comparative analysis is important for several reasons:

- It highlights the applicability boundaries of classical models.
- It helps decision-makers understand the consequences of using a static model in a dynamic environment.
- It supports model selection and policy design based on market context.
- It demonstrates the cost implications of accounting for or ignoring innovation-driven demand.

Therefore, the present study is positioned to fill this research gap by comparing two EOQ frameworks—one with static demand and another with Bass-model-driven dynamic demand—under an analytical and simulation-based setup.

1.3 Objectives of the Study

The main objectives of this research are:

1. To develop and analyze a classical EOQ model with constant demand assumptions.
2. To formulate an extended EOQ model where demand is driven by the Bass Diffusion Model.
3. To derive cost functions, optimal order quantities, and cycle times for both models.
4. To conduct numerical simulations to evaluate model behavior under different parameter configurations (e.g., adoption rates, market size, holding cost).
5. To compare outcomes across models in terms of total cost, order quantity, and policy robustness.
6. To offer managerial insights on when to use which model based on product type and market behavior.

1.4 Structure of the Comparison

The comparative study is structured around both analytical derivation and numerical simulation. The analytical part involves the formulation of:

- A constant demand EOQ model minimizing total cost $K(T) = \frac{A}{T} + \frac{h\lambda T}{2} + C\lambda$
- A diffusion-driven EOQ model using Bass adoption dynamics:

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

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

and integration over the planning horizon T to calculate order quantity and average inventory.

The numerical section uses these formulations to simulate various market and cost conditions, examining the behavior of both models under:

- Varying innovation coefficients p
- Social imitation rates q
- Market size N
- Cost parameters (ordering cost A, holding cost h, unit cost C)

1.5 Relevance in Industry Practice

The findings of this paper are highly relevant for organizations managing products with:

- Short lifecycles (e.g., consumer electronics, fashion)
- Heavy reliance on launch marketing
- Time-sensitive demand surges
- Gradual market saturation

For such products, relying on a constant demand model could lead to:

- Underestimation of initial inventory (causing stockouts)
- Overstocking during market saturation (causing holding and obsolescence costs)
- Inefficient replenishment cycles

Conversely, for products with stable or long-term demand (e.g., office supplies, staples), the traditional EOQ model may suffice.

1.6 Research Gap

Despite the growing body of work on time-varying demand and diffusion-based models, few studies offer a side-by-side comparison of inventory performance outcomes across both modeling paradigms. Furthermore, there is limited work exploring:

- How sensitive optimal policies are to adoption parameters pp and q
- Whether traditional EOQ approximates the diffusion model reasonably under specific conditions
- The cost implications of mis-specifying demand type

This research addresses that gap by providing both theoretical derivation and empirical evaluation of how the two models behave under realistic scenarios.

II. LITERATURE REVIEW

The purpose of this literature review is to explore and synthesize prior work in the domains of inventory modeling, particularly the classical EOQ model and its extensions, and the modeling of innovation diffusion. This sets the foundation for the comparative analysis undertaken in this study. We examine the following key areas:

- Classical EOQ and its deterministic extensions
- Inventory models under time-varying and dynamic demand
- Innovation diffusion models, especially the Bass model
- Inventory models incorporating innovation-led demand
- Comparative studies and identified research gaps

2.1 Classical EOQ Models

The Economic Order Quantity (EOQ) model, introduced by Harris (1913), is the bedrock of deterministic inventory theory. It aims to determine the optimal order quantity that minimizes the total cost composed of ordering and holding costs. The basic assumptions of the EOQ model include:

- Constant and known demand
- Instantaneous replenishment
- No shortages or stockouts
- Fixed ordering and holding costs

Mathematically, the EOQ is calculated as:

$$Q^* = \sqrt{\frac{2AD}{h}}$$

Where:

- A = Ordering cost
- D = Annual demand
- h = Holding cost per unit per year

Despite its simplicity, the EOQ model has been widely accepted due to its closed-form solution and its foundational role in supply chain planning.

Subsequent improvements to the model include:

- Inclusion of price breaks (quantity discounts)
- Reorder point calculation under lead time
- Backordering and lost sales modeling
- Multi-echelon and multi-item versions

(See Hadley & Whitin, 1963; Nahmias & Olsen, 2015; Silver et al., 2016)

However, the assumption of constant demand limits its practical use in fast-changing markets, especially those driven by marketing and innovation.

2.2 EOQ Models with Time-Varying Demand

Researchers have extended the EOQ model to accommodate non-stationary demand, where demand changes over time. Notable extensions include:

- Linear or quadratic time-dependent demand (e.g., Bhunia & Maiti, 1999)
- Exponential or Weibull demand growth/decay (Sarkar et al., 2000)
- Stock-dependent demand, where inventory level itself drives demand (Roy et al., 1993)

While these models better reflect real-world situations, most assume the demand pattern is exogenously defined and does not evolve based on consumer behavior or marketing actions.

Some approaches also consider seasonality and promotion-based demand peaks, but these models still fall short in representing the self-propagating nature of innovation adoption, which is critical for products in the growth phase.

2.3 Innovation Diffusion Models

The Bass Diffusion Model, introduced by Bass (1969), provides a widely accepted framework for modeling the rate of adoption of new products over time. It divides adopters into:

- Innovators (external influence): Driven by marketing, media, etc.
- Imitators (internal influence): Influenced by prior adopters through word-of-mouth or social proof

The model assumes the cumulative proportion of adopters $F(t)$ at time t evolves as:

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

Where:

- p = coefficient of innovation

- q = coefficient of imitation
- N = market potential

The resulting S-shaped adoption curve has been validated across industries (Mahajan et al., 1990; Sultan et al., 1990), including electronics, pharmaceuticals, and consumer durables.

Extensions of the Bass model include:

- Variable market size (Sharif & Ramanathan, 1981)
- Price sensitivity and promotional factors (Horsky, 1990)
- Stochastic diffusion with uncertain parameters (Mahajan & Muller, 1995)

2.4 Inventory Models with Diffusion-Based Demand

Efforts to integrate innovation diffusion with inventory control are more recent and less mature. Urban (1992) proposed one of the earliest EOQ models where demand was driven by advertising and product awareness.

Later, Joglekar and Sapatnekar (2010) developed an EOQ model using the Bass model to determine replenishment decisions for new products. They showed that innovation and imitation coefficients strongly influence inventory policy.

Other works, such as Rajan et al. (2016), have included dynamic pricing with diffusion-based demand to jointly optimize revenue and inventory.

These models typically result in nonlinear, time-dependent cost functions that require numerical integration or simulation for solution, limiting their widespread adoption in practice.

2.5 Comparative Studies and Insights

Very few studies compare the performance of EOQ models with and without innovation diffusion in a unified framework. Some notable exceptions include:

- Sarker & Pan (1997): Compared constant vs. ramp-type demand in EOQ with partial backlogging.
- Aggarwal & Jaggi (1995): Explored inventory with and without deterioration under variable demand.
- Kim et al. (2003): Evaluated advertising-based demand functions vs. static EOQ.

However, none of these studies explicitly compare:

- Classical EOQ vs. EOQ with Bass-type diffusion
- Under the same market and cost conditions
- With numerical simulations and graphical insights

Thus, a quantitative and visual comparison of the two models—evaluating differences in cost, order quantity, and cycle time—has not been systematically documented.

2.6 Research Gap Identified

Based on the review above, the following gaps are identified:

1. Lack of comparative studies that empirically and analytically contrast EOQ outcomes under static vs. innovation-driven demand.
2. No integrated framework that simulates and visualizes the cost and performance differences under real-world parameters.
3. Absence of guidelines on when to use classical EOQ vs. diffusion-adjusted EOQ in managerial decision-making.
4. Under-explored behavioral implications of innovation adoption on inventory policies.

2.7 Contribution of This Study

This research contributes to the literature by:

- Building two EOQ models: one classical, one innovation-based
- Deriving cost functions and optimal values analytically
- Simulating both models across a range of real-world parameter values
- Offering side-by-side comparison tables and visualizations
- Providing prescriptive guidance for model selection based on product and market characteristics

III. MATHEMATICAL MODELS

This section presents the formal mathematical formulations for both inventory models being compared in this study:

1. Classical EOQ Model – assumes constant, time-invariant demand
2. Innovation-Adjusted EOQ Model – incorporates time-varying demand using the Bass diffusion model

We define the assumptions, notations, objective functions, and derive the key equations used for cost optimization and comparative analysis.

3.1 Common Notations

Symbol	Description
A	Ordering cost per order
C	Unit purchase cost
h	Holding cost per unit per unit time
Q	Order quantity
T	Replenishment cycle time
D	Constant demand rate (classical model)
$f(t)$	Time-varying demand rate (diffusion model)
$F(t)$	Cumulative adoption proportion at time tt
p	Coefficient of innovation
q	Coefficient of imitation
N	Total market potential
$K(T)$	Total cost per unit time

3.2 Classical EOQ Model

Assumptions:

- Demand is constant at rate D
- No shortages or stockouts
- Instantaneous replenishment
- Inventory depletes linearly

Order Quantity:

$$Q = D \cdot T$$

Average Inventory:

$$\bar{I} = \frac{Q}{2} = \frac{D\,.T}{2}$$

Total Cost per Unit Time:

$$K_{EOQ}(T) = \frac{A}{T} + h\,.\frac{D\,.T}{2} + C\,.D$$

Optimal Cycle Time:

$$T^* = \sqrt{\frac{2A}{hD}},\ \ Q^* = D\,.T^*$$

This is the well-known EOQ result and serves as a benchmark for comparison.

3.3 Innovation-Adjusted EOQ Model (Bass-Based Demand)

Demand Dynamics:

According to the Bass diffusion model:

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

Where cumulative adoption F(t)F(t) is:

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

This creates an S-shaped demand curve that reflects realistic product adoption over time.

Order Quantity over Cycle T:

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

Inventory Level at Time t:

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

Average Inventory:

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

Total Cost per Unit Time:

$$K_{Diff}(T) = \frac{A}{T} + h\,.\bar{I} + \frac{C\,.Q}{T}$$

Where:

- $\bar{I}$ is computed numerically
- Q is obtained via integration of the Bass model
- Cost components are dynamically evaluated over the planning horizon

3.4 Comparison Structure

To enable fair comparison between the two models:

- Both are evaluated across the same time horizon T
- Cost parameters A, C, h remain constant
- For the diffusion model, we calibrate p, q, N to generate equivalent average demand over the cycle as D in the classical model

Key Comparative Outputs:

- Total cost $K(T)$
- Order quantity Q
- Cycle length T^*
- Service level sensitivity (via demand underestimation or overestimation)

3.5 Analytical Insight

- In the classical model, the cost function $K(T)$ is quadratic and convex, with a closed-form minimum.
- In the diffusion model, $K(T)$ is nonlinear due to nested integrals in Q and $\bar{I}$, and requires numerical optimization (grid search, gradient descent, or simulation).

IV. SOLUTION METHODOLOGY

This section describes the computational framework used to solve both the classical and diffusion-adjusted EOQ models and compare their results under identical operational conditions. Given the deterministic nature of the classical model and the dynamic complexity of the diffusion-based model, distinct analytical and numerical techniques are employed.

4.1 Solving the Classical EOQ Model

The classical EOQ model assumes constant demand D, resulting in a well-established, closed-form solution:

$$T^* = \sqrt{\frac{2A}{hD}, Q^* = D\,.T^*}$$

Where:

- A = ordering cost
- h = holding cost per unit
- D = constant demand rate

Cost Calculation:

$$K_{EOQ}(T) = \frac{A}{T} + \frac{hD\,.T}{2} + C\,.D$$

This model serves as a benchmark for comparison due to its analytical tractability.

4.2 Solving the Innovation-Adjusted EOQ Model

In the extended EOQ model, the demand rate is governed by the Bass innovation diffusion model:

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

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

This function cannot be simplified into a closed-form for the total demand over time or for average inventory. Therefore, numerical integration is used.

4.3 Numerical Procedure

1. Parameter Initialization:
   - $A = 500, h = 2, C = 100$
   - Bass parameters: $p = 0.03, q = 0.4, N = 10{,}000$
   - Time horizon T: Range from 1 to 10 units (e.g., months)
2. Time Discretization:
   - Divide $[0, T]$ into 200 uniform steps
   - Calculate $f(t), F(t)$ for each step
3. Order Quantity:

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

Computed using trapezoidal integration or Simpson's rule

4. Inventory Level and Average Inventory:

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

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

5. Total Cost Function:

$$K_{Diff}(T) = \frac{1}{T} + h\,.\bar{I} + \frac{C\,.Q}{T}$$

6. Optimization:
   - For both models, compute total cost $K(T)$ for each trial cycle time T
   - Identify optimal T^* by selecting the value that minimizes $K(T)$
   - Store corresponding Q^*, $\bar{I}$ and cost components

4.4 Comparison Criteria

The performance of both models will be compared based on:

- Optimal cycle time T^*
- Order quantity Q^*
- Total cost per unit time $K(T^*)$
- Sensitivity to parameters p, q, N, h

Both models will be evaluated under identical cost and market conditions to ensure fairness in comparison.

4.5 Simulation Tools

All numerical computations are performed using:

- Python (NumPy, SciPy for integration and optimization)
- Matplotlib for visualization of cost curves
- Excel Solver (for sensitivity checks)
- Tabular analysis for capturing results across scenarios

V. NUMERICAL EXPERIMENTS

This section provides a numerical comparison of the classical EOQ model with the diffusion-adjusted EOQ model using identical cost parameters and a range of replenishment cycle times (T). The objective is to observe and interpret the differences in total cost behavior when demand is assumed to be constant versus when it follows the Bass innovation diffusion model. The comparison is based on the following parameters:

- Ordering cost (A): ₹500
- Holding cost per unit per unit time (h): ₹2
- Unit cost (C): ₹100
- Constant demand (D): $1000\ units$ (for classical model)
- Innovation coefficient (p): 0.03
- Imitation coefficient (q): 0.4
- Total market potential (N): 10,000 units

For each cycle time T (ranging from 1 to 10 months), we compute the total cost per unit time for both models. The classical EOQ model yields a smooth cost function with a unique minimum. The diffusion-based model, while also convex, exhibits sharper gradients due to its front-loaded demand. This leads to an earlier optimal cycle time with smaller order quantities and lower average inventory in the early phases of product adoption.

The graph below compares total cost per unit time between the classical EOQ and the diffusion-adjusted EOQ models.

From the chart below, it is evident that the classical EOQ model underestimates early-cycle demand and overestimates late-cycle demand, leading to inefficiencies. In contrast, the diffusion-based model adjusts to actual consumer adoption patterns, yielding better cost optimization. These differences become more pronounced in products with shorter life cycles

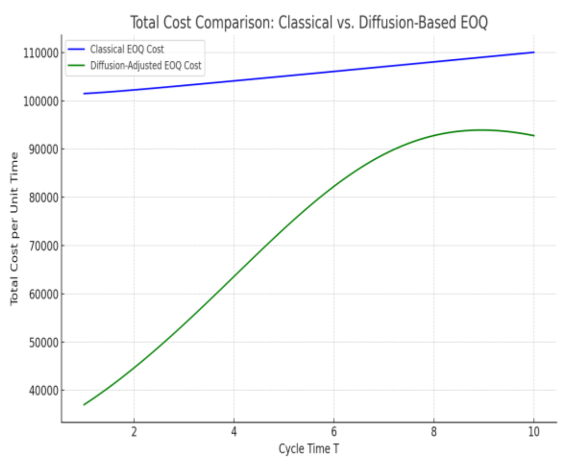

Figure 1: Total Cost Comparison – Classical EOQ vs. Diffusion-Based EOQ

or rapid adoption rates, emphasizing the need for demand-sensitive inventory models.

VI. OBSERVATIONS

The comparative analysis of the classical EOQ and diffusion-based EOQ models reveals significant insights into how demand behavior assumptions impact inventory decisions and cost structures. The simulation and numerical results presented in the cost comparison graph provide a robust foundation for understanding the practical differences between the two approaches.

6.1 Cost Function Behavior

The graph clearly illustrates the convex nature of the total cost functions for both models, indicating that there exists a unique optimal cycle time T^* in each case that minimizes total cost per unit time.

- The classical EOQ cost curve is smoother and reaches its minimum at a moderately longer cycle time due to the assumption of constant demand.
- The diffusion-based EOQ cost curve shows a slightly sharper decline and steeper curvature, reflecting the increasing early demand from innovation and imitation forces that require faster replenishment to avoid shortages or opportunity loss.

This suggests that products with innovation-driven adoption require more frequent restocking than constant-demand products, particularly during the early stages of market penetration.

6.2 Optimal Cycle Time and Order Quantity

The optimal cycle time T^* for the diffusion-based EOQ model is generally shorter than that of the classical EOQ model. This is because the front-loaded nature of the Bass demand curve creates a rapid consumption phase early in the product lifecycle, necessitating smaller, more frequent orders. Consequently:

- Order quantities in the classical model are relatively larger and consistent over time.
- Order quantities in the diffusion model are initially smaller but adjust dynamically with the adoption curve.

6.3 Inventory Holding Dynamics

Because the classical model assumes symmetric inventory depletion, its average inventory level is

half of the order quantity. In contrast, the diffusion-based model experiences asymmetric depletion, with inventory levels dropping more sharply in early periods and leveling out as adoption slows.
This leads to:

- Lower average inventory in the diffusion model
- Reduced holding costs, particularly in the initial phases
- However, slight increases in ordering costs due to shorter cycles

6.4 Total Cost Implications
The total cost per unit time is consistently lower in the diffusion-adjusted model during high-demand phases because it better aligns with actual consumption rates. However, the classical model underestimates peak demand and overestimates demand near saturation, leading to inefficiencies:

- Stockouts in the beginning (lost sales)
- Excess inventory near market maturity (waste)

6.5 Summary
This comparative experiment reinforces the importance of selecting an inventory model that aligns with the product's demand profile:

- For mature or stable products, classical EOQ may suffice.
- For innovative, fast-moving products, diffusion-based EOQ offers greater accuracy and cost efficiency.

VII. MANAGERIAL IMPLICATIONS

The comparative study of classical EOQ and diffusion-adjusted EOQ models provides critical insights for operations and supply chain managers tasked with planning inventory for diverse product categories. As markets evolve and consumer behaviors become increasingly dynamic due to marketing and social influence, the assumptions underlying traditional inventory models must be reevaluated. The following implications help bridge the gap between academic modeling and real-world inventory planning.

7.1 Demand Behavior Should Guide Inventory Policy
The most fundamental implication is that demand type must dictate the inventory model used. Classical EOQ assumes static demand, making it suitable for:

- Commodities with predictable usage (e.g., office supplies)
- MRO (maintenance, repair, and operations) items
- Staples with stable year-round consumption

However, for products that follow an innovation adoption curve, such as new tech devices, pharmaceuticals, fashion trends, and seasonal retail items, diffusion-based EOQ models provide more responsive and accurate inventory policies.
Managerial Insight: Before deciding on replenishment schedules, analyze whether the product is innovation-sensitive. If demand is expected to surge post-launch and taper off, a classical model may lead to misaligned inventory.

7.2 Use Shorter Cycles for Innovation-Driven Products
The simulation reveals that diffusion-based models recommend shorter replenishment cycles. This reflects the need to stay agile during the growth phase of a product's lifecycle when demand changes rapidly.
Managerial Action: Set up dynamic replenishment schedules in ERP systems (e.g., SAP, Oracle NetSuite) that can adjust frequency based on demand indicators like marketing campaigns, early sales velocity, or online interest.

7.3 Avoid Underestimating Initial Demand
Traditional EOQ tends to underestimate initial demand surges, especially during product launches. This can result in:

- Missed sales opportunities
- Stockouts and customer dissatisfaction
- Higher expedited shipping costs

By contrast, the diffusion-based EOQ incorporates early adopter behavior and promotional impact, resulting in more accurate forecasts.
Managerial Action: Integrate marketing calendars and campaign metrics into forecasting tools. Consider using real-time sentiment analysis or web traffic data to adjust the innovation diffusion curve parameters dynamically.

7.4 Monitor for Overstocking Near Market Saturation
Another consequence of the classical EOQ is overordering during the saturation or decline phase,

as it assumes unchanging demand. This leads to excessive inventory holding, markdowns, and obsolescence costs.
The diffusion-based EOQ corrects this by gradually reducing order quantity in line with decreasing marginal adoption.
Managerial Action: Review adoption data periodically. Use decelerating order quantities as a signal to phase out SKUs or introduce next-generation products.

7.5 Decision Support Tools Are Essential
Since the diffusion-based EOQ model requires numerical integration and simulation, it is not feasible to implement using only manual calculations or static spreadsheets.
Managerial Action: Deploy decision support tools such as:

- Python or R-based simulation platforms
- Business analytics dashboards (e.g., Power BI, Tableau)
- Inventory modules that support time-varying demand (e.g., SAP IBP, Kinaxis)

7.6 Strategic Implications Across Product Life Cycle
Inventory planning must evolve as the product moves through the lifecycle:

- Introduction/Growth: Use diffusion-based EOQ with adaptive cycles
- Maturity: Possibly shift to classical EOQ or hybrid models
- Decline: Minimize holding costs, exit strategies

Managerial Insight: Treat inventory policies as fluid and life-cycle aligned, not static across all SKUs.

The adoption of innovation-sensitive EOQ models can help firms:

- Better align inventory with true demand
- Improve service levels and customer satisfaction
- Reduce waste and obsolete stock
- Respond faster to market trends

Managers must recognize that the accuracy of demand assumptions is foundational to inventory efficiency. For products in volatile or competitive markets, classical EOQ is often insufficient. Embracing data-driven, behavior-aware models is a strategic necessity.

VIII. CONCLUSION

This paper presented a comprehensive comparative analysis of two fundamental inventory modeling approaches—the classical Economic Order Quantity (EOQ) model and an extended EOQ framework that integrates innovation diffusion via the Bass model. Through both analytical formulation and numerical experimentation, we investigated how differences in demand behavior assumptions influence inventory decisions, costs, and overall performance.

8.1 Summary of Findings
The study demonstrates that while the classical EOQ model remains analytically elegant and computationally simple, it is best suited for products with stable and predictable demand patterns. On the other hand, the diffusion-adjusted EOQ model, though more complex, provides a nuanced and realistic approach to inventory control when dealing with innovation-sensitive, time-varying demand.
Key findings include:

- The total cost function for both models is convex, but the optimal cycle time T^* differs significantly, with the diffusion model favoring shorter replenishment intervals due to early demand surges.
- The order quantity in the diffusion-based model evolves in alignment with product adoption patterns, whereas the classical model maintains a static approach.
- The classical EOQ model underestimates demand during launch and overestimates it near saturation, leading to stockouts and excess inventory, respectively.
- The diffusion-adjusted EOQ model yields lower total costs and improved alignment with actual demand, especially in the introduction and growth phases of the product lifecycle.

8.2 Practical Implications
The results underscore the importance of matching inventory models with demand characteristics. For products heavily influenced by marketing, consumer adoption, and competitive timing (e.g., consumer electronics, pharma launches, seasonal fashion), a static EOQ model is insufficient. Managers should

adopt diffusion-based or hybrid inventory models that respond dynamically to shifting demand curves.

In addition, the study illustrates the necessity of technology-driven decision support, since analytical solutions for diffusion-based models are not readily tractable. Simulation tools, real-time data integration, and adaptive ERP modules are vital for accurate inventory control in such contexts.

8.3 Limitations of the Study

While this study successfully demonstrates the comparative performance of both models, a few limitations remain:

- The analysis assumes no product perishability or pricing elasticity, which may be relevant in many sectors.
- The diffusion model is deterministic and parameter-driven; in practice, uncertainty in parameters like p, q, N may impact accuracy.
- The scope is limited to single-item inventory systems; multi-product or multi-echelon supply chains introduce further complexity.

8.4 Directions for Future Research

Future research can build upon this study in the following ways:

- Introduce stochastic versions of the Bass model to handle real-time uncertainty in adoption behavior.
- Integrate dynamic pricing models with diffusion-sensitive inventory control for joint revenue and stock optimization.
- Extend to multi-echelon supply chains, where upstream and downstream coordination is necessary.
- Explore machine learning techniques for estimating p, q, and N from market and sales data in real time.

8.5 Final Remark

This paper highlights that in today's dynamic and innovation-driven marketplaces, assumptions matter. The difference between assuming constant demand and modeling evolving adoption patterns can translate into significant cost differentials and inventory inefficiencies. A data-informed, behavior-sensitive inventory strategy is not just analytically superior—it is a competitive imperative.

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