

## Sustainable and AI-Enhanced Inventory Models under Stochastic Demand and Product Deterioration: A Comprehensive Review

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**ABSTRACT:** Inventory management in modern supply chains faces growing complexity due to stochastic demand, product deterioration, sustainability requirements, and the need for rapid decision-making. While classical models such as the Economic Order Quantity (EOQ) and continuous review policies have provided foundational insights, they fall short in addressing the combined challenges of demand uncertainty, time-dependent deterioration, and environmental constraints. Recent advancements integrate sustainability considerations, such as carbon emission reduction and energy efficiency, into inventory frameworks, while artificial intelligence (AI) techniques particularly Long Short-Term Memory (LSTM) networks, Gated Recurrent Units (GRU), and metaheuristic algorithms enhance forecasting accuracy and optimization performance. This review, conducted following the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) method, systematically identified, screened, and evaluated relevant literature, resulting in the inclusion of 25 peer-reviewed papers that address economic, environmental, and technological dimensions of inventory modelling. Key findings reveal limited research integrating all these factors into a unified framework, insufficient real-time AI-driven decision-making applications, and an overreliance on carbon emissions as the sole sustainability metric. Additional gaps include the underexplored interaction between financial incentives and preservation technologies, and a lack of industry-specific empirical studies in highly regulated sectors. Addressing these gaps can lead to next-generation inventory systems that are economically viable, environmentally responsible, and technologically adaptive.

**Keywords:** Inventory modelling, stochastic demand, deteriorating items, artificial intelligence, preservation technology, trade credit.

## INTRODUCTION

Inventory management is a central element in supply chain operations, balancing the conflicting objectives of minimizing costs and meeting customer demand (Taha, 2017; Khedlekar & Tiwari, 2018). Traditional models, including the Economic Order Quantity (EOQ) and continuous review (r, Q) policies, assume constant demand and perfect product quality (Browne & Zipkin, 1991; Arslan, Graves, & Roemer, 2007). However, real-world systems often operate under stochastic demand, product deterioration, and increasing sustainability constraints, making classical formulations insufficient (Janssen, Claus, & Sauer, 2016; Yadav & Khanna, 2021).

Stochastic demand introduces uncertainty in replenishment decisions, requiring adaptive control policies and robust forecasting methods (Graves, 1999; Nguyen, Kim, Le, Nguyen, & You, 2024). Deterioration, prevalent in perishable goods, pharmaceuticals, and electronic components, shortens shelf life and increases waste, necessitating integrated preservation strategies (Mishra, Singh, & Kumar, 2013; Jaggi, Cárdenas-Barrón, Tiwari, & Shafi, 2017). Simultaneously, sustainability goals driven by environmental regulations and corporate responsibility require inventory models to incorporate carbon emissions, energy consumption, and green production practices (Kamna, Gautam, & Jaggi, 2020; Alamri, 2023).

Recent advances in artificial intelligence (AI) and metaheuristic optimization have opened new avenues for managing these complexities. Machine learning techniques, such as Long Short-Term Memory (LSTM) networks, Gated Recurrent Units (GRU), and hybrid approaches like PSO-LSTM, improve forecasting accuracy and enable real-time decision-making (Choudhary, 2024; Nguyen et al., 2024). Metaheuristics, including Multi-Objective Grey Wolf Optimization (MOGWO), address multi-objective trade-offs between cost, service levels, and sustainability (Palanivel, Venkadesh, Vetriselvi, & Sundararajan, 2024).

This paper reviews the literature on sustainable, AI-enhanced inventory models under stochastic demand and product deterioration, highlighting key developments, classifying approaches, and identifying research gaps for future work.

## METHODOLOGY

This review followed the **Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA)** (Table 1) methodology to ensure transparency, reproducibility, and rigor in the selection of relevant studies. The process was carried out in four main stages:

### **Identification**

- Relevant studies were identified through targeted searches of peer-reviewed journals and conference proceedings provided by the online important databases (Scopus, Web of Science, Google Scholar).
- An initial pool of **58 records** was collected from the provided database, covering topics related to inventory modelling under stochastic demand, deteriorating items, sustainability integration, and AI-based optimization.
- Duplicates (n = 8) were removed at this stage.

### **Screening**

- The remaining **50 records** were screened by reviewing titles and abstracts to ensure relevance to the scope of the review.
- Exclusion criteria included:
  - Studies not focused on inventory modelling.
  - Papers unrelated to stochastic demand, deterioration, or sustainability.
  - Non-peer-reviewed or incomplete works.
- After this step, **32 papers** were retained for full-text evaluation.

### **Eligibility**

- The full texts of the 32 studies were assessed to confirm methodological relevance and adequate coverage of at least one of the key themes:
  - Integration of deterioration in inventory models.

- Consideration of stochastic or nonstationary demand.
  - Sustainability constraints or green production policies.
  - Application of AI or metaheuristic optimization techniques.
- Studies failing to provide substantial discussion or empirical evidence in these areas were excluded (n = 7).

### Inclusion

- A final set of **25 studies** met all inclusion criteria and were considered for the synthesis of results.
- These studies form the evidence base for the analysis presented in the Results and Research Gaps section.

**Table 1: PRISMA Screening Process for Study Selection**

Stage	Description	Number of Records	Records Excluded (with reasons)
<b>Identification</b>	Records identified from the online important databases (Scopus, Web of Science, Google Scholar).	58	–
<b>Duplicate Removal</b>	Removal of duplicate studies across sources.	50 (after removal)	8 duplicates
<b>Screening</b>	Titles and abstracts screened for relevance to stochastic demand, deteriorating items, sustainability, and AI-based optimization in inventory models.	50 → 32 retained	18 irrelevant topics (e.g., unrelated to inventory modelling, not peer-reviewed)
<b>Eligibility</b>	Full-text articles assessed for methodological relevance and coverage of at least one core theme.	32 → 25 retained	7 excluded (insufficient methodological detail, off-scope focus)
<b>Inclusion</b>	Studies included in the final synthesis for results and gap identification.	25	–

## RESULTS

### *Key Developments in Literature*

#### *Stochastic Demand and Multi-Class Inventory Models*

Classical EOQ and base-stock models (Table 2) (Browne & Zipkin, 1991) have been extended to handle multiple demand classes and priority-based rationing (Arslan et al., 2007; Dekker, Hill, Kleijn, & Teunter, 2002). However, most studies assume either stationary demand or limited variability, which is insufficient for industries experiencing nonstationary stochastic patterns (Graves, 1999; Rummyantsev & Netessine, 2007).

### ***Deteriorating Items and Preservation Technologies***

Time-varying deterioration rates are increasingly incorporated into models (Janssen et al., 2016; Mishra et al., 2013). Strategies include rework policies (Taleizadeh, Naghavi-Alhoseiny, Cárdenas-Barrón, & Amjadian, 2024) and investment in preservation technology (Mashud & Sarkar, 2021), which reduces deterioration and extends shelf life (Table 2). However, preservation is often modeled independently from pricing and promotional strategies (Palanivel et al., 2024).

### ***Sustainability Integration***

Environmental objectives mainly carbon emission limits (Table 2) are embedded into models (Yadav & Khanna, 2021; Alamri, 2023), with some considering energy consumption (Kamna et al., 2020). Nonetheless, other sustainability dimensions such as waste valorization, water footprint, or circular economy principles are rarely addressed (Li et al., 2017).

### ***AI and Metaheuristic Optimization***

Machine learning approaches (LSTM, GRU) enable dynamic demand forecasting (Nguyen et al., 2024; Choudhary, 2024). Metaheuristics like MOGWO and hybrid algorithms solve complex multi-objective formulations (Palanivel et al., 2024). Digital twin technologies offer potential for scenario simulation (Kozlova, Kuimova, Nelyub, & Gantimurov, 2023; Jackson, Senz, & Ivanov, 2023), but adoption in inventory contexts is limited (Table 2).

**Table 2:** Summary of Key Findings from the Review

<b>Theme</b>	<b>Key Findings</b>	<b>Identified Gaps</b>	<b>Authors &amp; Year</b>
Integration of Multiple Factors	Existing models address stochastic demand,	Lack of unified frameworks integrating all these	Palanivel et al. (2024); Yadav & Khanna

	deterioration, sustainability, and trade credit separately.	dimensions into a single decision-making model.	(2021); Alamri (2023)
AI-Driven Decision Support	AI methods (LSTM, GRU, hybrid metaheuristics) improve forecasting accuracy.	Limited use of AI for real-time, adaptive inventory control rather than just demands forecasting.	Nguyen et al. (2024); Choudhary (2024); Jackson et al. (2023)
Sustainability Metrics	Most models consider carbon emissions reduction; some include energy efficiency.	Overreliance on carbon emissions as the sole metric; little focus on water footprint, waste valorization, or lifecycle impacts.	Kamna et al. (2020); Li et al. (2017); Alamri (2023)
Preservation and Financial Incentives	Preservation technology can extend shelf life; trade credit improves profitability.	Few studies combine financial incentives with preservation strategies in a coordinated optimization framework.	Mashud & Sarkar (2021); Jaggi et al. (2017)
Industry-Specific Applications	Models applied to general manufacturing and retail settings.	Scarcity of empirical studies in sensitive industries (pharmaceuticals, perishable food, healthcare).	Abdali et al. (2024); Nguyen et al. (2024)

## RESEARCH GAPS

Based on the reviewed literature, the following gaps are evident:

- **Unified Integrated Models:** Very few studies integrate stochastic demand, deterioration, trade credit, and sustainability into a single holistic framework (Palanivel et al., 2024);
- **Dynamic Real-Time Decision Systems:** AI is mainly applied to forecasting rather than **direct inventory control in real time** (Nguyen et al., 2024);
- **Broader Sustainability Metrics:** Overreliance on carbon emissions as the sole measure, ignoring multi-dimensional sustainability indicators (Li et al., 2017);
- **Coupling Financial Incentives with Preservation:** Limited research on how trade credit and payment delay policies interact with preservation investment decisions (Mashud & Sarkar, 2021);
- **Industry-Specific Empirical Studies:** Insufficient case studies in sectors with high perishability or strict regulation, such as healthcare, pharmaceuticals, and fresh produce logistics (Abdali, Heidari, Alipour-Vaezi, Jolai, & Aghsami, 2024).

Addressing these gaps could lead to next-generation inventory systems capable of balancing cost, service, sustainability, and adaptability.

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## CONFLICTS OF INTEREST

The author declares no conflicts of interest regarding the publication of this paper.

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