

AI-Based Forecasting Models for Critical Inventory: A Systematic Review

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Abstract— Inventory management in industrial settings is shaped by high variability in consumption and replenishment lead times, which hinders planning. Given the dispersion of predictive approaches reported in the literature, a systematic review helps consolidate comparable evidence. Accordingly, this study conducts a systematic literature review (SLR) aimed at characterizing recurrent models and variables used for forecasting critical supplies, with a focus on the dairy industry and AI. The review followed Fink's methodology; from 780 initial records, 39 eligible studies were selected. Results show that the most recurrent variables are concentrated in the temporal and operational components of demand, highlighting historical consumption and seasonality, complemented by lead time and, when traceability exists, available stock. In terms of approaches, neural networks/deep learning predominate—especially recurrent architectures (LSTM/GRU/RNN)—while traditional machine learning methods are used as comparative baselines. For evaluation, error metrics (MAE, RMSE, MSE, MAPE) prevail; however, for intermittent consumption a dual framework is proposed that separates occurrence (Macro-F1) and magnitude (MAE). These findings guide the design and evaluation of predictive models applicable to real-world scenarios with limited data availability.

Keywords— Inventory Forecasting, Artificial Intelligence; Predictive Models; Systematic literature review; Dairy Industry

I. INTRODUCTION

The dairy industry is a strategic sector within the agri-food economy, with sustained demand driven by changes in consumption and market expansion [1]. In Ecuador, the dairy industry continues to represent an economic and social pillar. According to the Dairy Panorama 2025, the sector contributes approximately 0.52% of national Gross Domestic Product and records a per capita consumption of 108 liters/year, with cumulative sales of USD 1.414 billion through August 2025 [2].

Despite its relevance, the sector faces structural challenges that limit its competitiveness. Among them, inefficiency in inventory management and replenishment planning is central, as it directly affects production, distribution, and market stability [3]. In particular, many companies lack formal procedures to determine the optimal quantity and timing for replenishing supplies, which leads to stockouts, unnecessary accumulation of inputs, economic losses, and production downtime [4], [5].

In this context, tools based on machine learning and, particularly, artificial neural networks (ANNs) offer a promising alternative to traditional forecasting methods by

capturing nonlinear relationships and complex temporal patterns present in input consumption. These techniques enable adaptive learning, self-organization, and fault tolerance, making them suitable for addressing complex problems without relying on rigid algorithmic models [6].

Previous studies have demonstrated their effectiveness in the dairy sector, where neural networks have been applied to improve the accuracy of demand forecasting. For example, Abaddi (2025) used a feedforward artificial neural network to estimate weekly sales in a dairy company, achieving lower prediction error compared to classical techniques such as exponential smoothing and moving average methods. This highlights the ability of ANNs to model nonlinear patterns and support planning and inventory decisions for perishable products [7].

Similarly, in an industrial time-series prediction study (electricity generation and gas consumption), the authors emphasize that ANNs can capture complex interrelationships without requiring detailed prior knowledge of the phenomenon, achieving low average percentage errors, which demonstrates their usefulness for more accurate forecasting in real-world contexts [8].

In industrial environments, the combination of volatility and supply chain disruptions has increased the complexity of planning purchases and production; in particular, forecasting becomes critical because traditional methods may be insufficient when consumption patterns change markedly. Along these lines, recent supply chain literature emphasizes that volatility makes forecasting “more crucial than ever” and that Artificial Intelligence/ Machine Learning (AI/ML) emerges as an alternative to improve forecasting adaptability to market fluctuations and behavioral changes [9].

From an inventory perspective, this challenge manifests as a persistent trade-off between preventing stockouts and reducing excess inventory (overstock), which calls for more responsive, data-driven systems; therefore, ML approaches have been investigated both to improve forecasting and to integrate directly into optimization and dynamic policies (including reinforcement learning) [10].

In addition, many critical inputs exhibit zero-inflated and irregular series (intermittent demand), where classical models face difficulties and ML is proposed as an alternative to capture nonlinear relationships and adapt to complex data [11].

Therefore, this paper presents a systematic literature review (SLR) aimed at synthesizing (i) the most commonly used predictive models, (ii) the most recurrent input and output variables, and (iii) the predominant evaluation metrics employed in forecasting applications for critical supply inventories. This synthesis seeks to provide a structured and integrated understanding of current research trends, methodological approaches, and practical considerations that support the design and implementation of data-driven forecasting models in industrial contexts.

Although the literature already includes systematic reviews that synthesize the use of machine learning in inventory control and optimization—covering both forecasting-oriented approaches and dynamic replenishment policy models—there is still limited evidence that explicitly integrates models, variables, and metrics together with criteria for operational applicability in real industries [12].

Likewise, systematic review protocols have been proposed to compare ML-based predictive approaches against traditional models by incorporating performance criteria and methodological reporting standards; however, these frameworks are not specifically focused on industrial input inventories or the dairy sector [13].

Consequently, the distinctive contribution of this review is to connect the technical synthesis (models–variables–metrics) with decision-making in order to select viable predictive modeling alternatives for critical input inventories in industrial contexts, with an emphasis on the dairy environment.

II. METHODOLOGY

The systematic literature review conducted in this study follows the methodology proposed by Fink [14], which consists of seven steps: (1) definition of the research questions:

- 1) What input and output variables are prioritized most frequently in forecasting applications for critical supplies inventory in industrial settings?
- 2) Which predictive models and architectures are most frequently used for forecasting supplies in industrial settings?
- 3) Which evaluation metrics are most frequently used to assess forecasting models applied to critical supplies inventory?

(2) Selection of information sources: Scopus, IEEE Xplore, Google Scholar, Dialnet, and SciELO; additionally, MDPI was considered as an editorial repository to identify relevant articles; (3) construction of search strings using Boolean operators; (4) first screening by applying inclusion and exclusion criteria (year, subject areas, document type, and language); (5) second analytical screening by reading titles and abstracts to retain studies focused on forecasting supplies/inventory with a quantitative/predictive approach; (6) full-text review of eligible studies; and (7) synthesis of results. Fig. 1 summarizes the search and article selection process. A

total of 780 articles were identified, of which 39 specifically addressed the target topic.

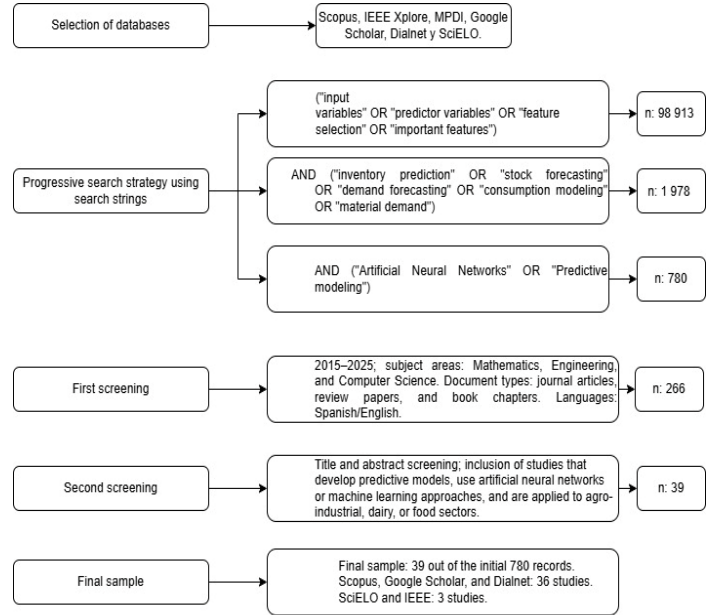


Fig. 1. Summary flow diagram of the applied methodology

III. RESULTS AND DISCUSSION

Based on the 39 selected studies, the results are presented in two sections:

A. Descriptive quantitative analysis

Scopus and Google Scholar accounted for nearly 90% of the included articles. The remaining studies came from IEEE Xplore, Dialnet, and SciELO; MDPI did not contribute eligible studies after applying the inclusion criteria.

The annual distribution of publications shows limited output prior to 2019. From 2019 onward, a sustained increase is observed, with a peak around 2022, indicating growing academic and industrial interest in predictive models applied to inventory management. In 2023–2025, some variation with a slight decline is observed, possibly associated with full-text access restrictions and the temporal cutoff of the search (see Fig. 2).

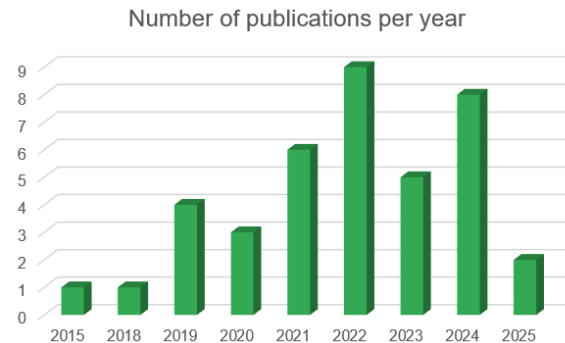


Fig. 2 Number of publications per year in the selected studies

Scientific output is primarily concentrated in Asia and Europe. India leads with seven publications, followed by the United Kingdom (6) and China (5). A second tier includes the United States and Switzerland (4 each), while Indonesia contributes two studies. The remaining countries identified contribute one publication each, indicating limited dispersion beyond the main research hubs (see Fig. 3).

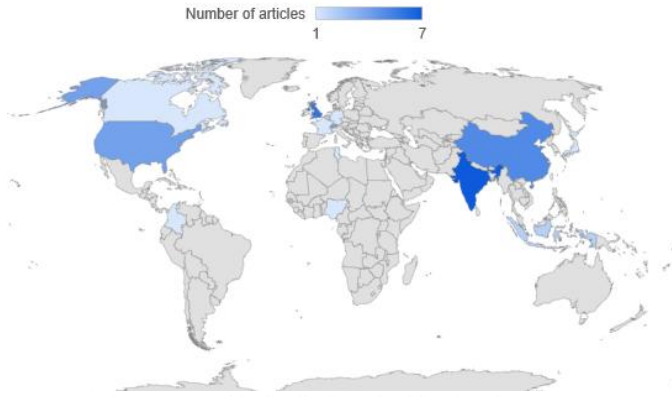


Fig. 3 Geographic distribution of publications by country

B. Thematic and content analysis

Based on the research questions, the descriptive analysis of the included studies is organized into three parts: (1) standardization and classification of variables used in the models; (2) forecasting models and architectures; and (3) evaluation metrics reported in the literature. Each part is detailed below:

1. From the selected studies, the reported variables were extracted and standardized, and then classified as input variables and output variables according to their role in the predictive models. The systematization was conducted in RStudio through data cleaning and term consolidation, followed by a frequency count. To prioritize variables, three complementary approaches were applied: (1) frequency and ranking analysis, (2) co-occurrence analysis to identify variables that appear jointly, and (3) a weighted decision matrix to assess relevance and implementation feasibility.

The ranking results show that *historical_consumption* is the most recurrent variable (34 occurrences), followed by *seasonality* (24), *price* (18), and *lead_time* (16). Internal variables such as *product* and *available_stock* also show high recurrence (15 each), whereas variables such as *location* and *replenishment_frequency* appear less frequently (6), and *safety_stock* and *stockout* are only marginally reported (Table I).

The co-occurrence analysis confirms that *historical_consumption*, *seasonality*, *price*, *lead_time*, *available_stock*, and *product* form a central core, frequently appearing together across studies (see Fig. 4).

TABLE I
MOST FREQUENTLY USED VARIABLES

Variable	Frequency
Historical_consumption	34
Seasonality	24
Price	18
Lead_time	16
Product	15
Available_stock	15
Location	6
Replenishment_frequency	6
Safety_stock	4
Stockout	3

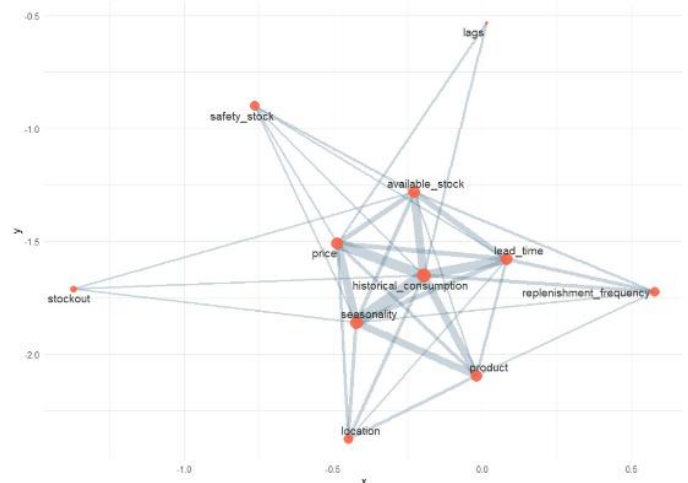


Fig. 4 Co-occurrence network among the identified variables

The results confirm that item-level forecasting relies primarily on temporal and operational variables. In particular, *historical_consumption* and *seasonality* exhibit the highest recurrence and also appear as central nodes in the co-occurrence network, suggesting that they provide a cross-cutting informational basis across different sectors and modeling approaches. In contrast, variables such as *safety_stock* and *stockout* show lower frequency, which does not necessarily imply low relevance; rather, it is often associated with data recording and standardization challenges in real settings, where these indicators are calculated heterogeneously or are not available as comparable historical data. Consequently, the final variable selection should balance recurrence in the literature with data capture feasibility within the company.

2. In order to identify methodological trends in forecasting applied to inventory management, the selected studies were classified by predictive approach family (Table II). The results show a predominance of neural networks/deep learning (43.6%), followed by traditional machine learning methods (17.9%) and review articles without implementation (25.6%). To a lesser extent, statistical/econometric models (7.7%) and heuristic/optimization approaches (5.1%) were identified. Overall, this distribution suggests that recent literature favors approaches capable of capturing nonlinearities and temporal dependencies in demand and inventory problems, especially in highly variable contexts.

TABLE II
CLASSIFICATION BY SPECIFIC TECHNIQUE/ARCHITECTURE

Predictive model type	Number of articles	Percentage	Authors
Neural networks	17	43.6%	[15], [16], [17], [18], [19], [20], [21], [22], [23], [24], [25], [26], [27], [28], [29], [30], [31]
Machine learning models	7	17.9%	[32], [33], [34], [35], [36], [37], [38]
Statistical / Econometric models	3	7.7%	[39], [40], [41]
Heuristic / Optimization approaches	2	5.1%	[42], [43]
Review (models without implementation)	10	25.6%	[44], [45], [46], [47], [48], [49], [50], [51], [52], [53]
TOTAL	39	100%	

To refine the analysis, the studies were disaggregated by specific technique or architecture (Table III). Within neural networks, time-series-oriented approaches stand out, including Long Short-Term Memory (LSTM) (5 studies) and other recurrent variants—Recurrent Neural Network (RNN) / Gated Recurrent Unit (GRU) (2 studies)—as well as feedforward architectures such as Multilayer Perceptron (MLP), Backpropagation Artificial Neural Network (BP-ANN), and Extreme Learning Machine (ELM) (4 studies). In addition, reinforcement learning approaches were identified, mainly Deep Reinforcement Learning (DRL) (4 studies) and, to a lesser extent, Q-learning (1 study), which are oriented toward learning replenishment policies rather than direct forecasting. Traditional machine learning methods—Random Forest (RF), Extreme Gradient Boosting (XGBoost), Support Vector Regression (SVR), Logistic Regression (LR), among others—also show a relevant presence (7 studies), typically used as baseline models or for comparison in applied studies.

TABLE III
CLASSIFICATION OF PREDICTIVE MODELS

Classification by predictive model type	Number of articles
LSTM (Long short-term memory)	5
RNN / GRU / recurrent variants	2
Feedforward neural networks (MLP / BP-ANN / ELM)	4
Non-recurrent deep learning (CNN / DNN / Transformer)	1
Traditional machine learning (RF, XGBoost, SVR, LR, etc.)	7
Statistical / econometric methods (ARIMA, GARCH, etc.)	3
Heuristics / optimization	2
Deep reinforcement learning (DRL)	4
Tabular reinforcement learning (Q-learning)	1
Review (method taxonomy: LSTM/MLP/RF/XGBoost/ARIMA...)	10
TOTAL	39

Methodologically, the results indicate that recurrent architectures (LSTM/GRU/RNN) account for a substantial share of the implemented studies, which is consistent with the sequential nature of consumption and its seasonality. However, the significant presence of traditional models (e.g., RF, SVR, or linear regression) supports their use as baselines due to their lower complexity and greater interpretability, especially when data availability is limited. Finally, reinforcement learning approaches (DRL/Q-learning) should be interpreted as a complementary trend focused on learning replenishment policies rather than replacing forecasting.

3. To standardize performance comparisons across approaches, the evaluation metrics reported in the selected studies were analyzed. In general, forecasting-oriented works use error-based metrics such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Mean Squared Error (MSE), and Mean Absolute Percentage Error (MAPE), whereas decision/control-oriented approaches (e.g., reinforcement learning) prioritize operational and cost indicators (service level, stockouts, and inventory costs). Table IV summarizes the most frequently reported metrics by predictive approach family.

TABLE IV
EVALUATION METRICS

Approach / model	Most frequently reported metrics
Recurrent models (LSTM, Bi-LSTM, CNN-LSTM, RNN) and GRU	RMSE, MAE, MAPE, MSE (most frequent); R ² is also reported in several studies. RMSLE occasionally appears in comparative analyses.
Feedforward models (MLP, BP-ANN, ELM)	MSE, RMSE, MAE, MAPE, R ² . In classification settings, Accuracy is reported and occasionally F1-score.
Non-recurrent deep learning (CNN/DNN/Transformer and variants)	RMSE, MAE, MAPE, and MSE; in some cases, additional uncertainty-related metrics are included, although forecast error metrics predominate.
Deep reinforcement learning (DRL: DQN/DDPG/PPO/MARL, etc.)	Operational/cost KPIs: total cost, holding cost, stockouts, service level (OTIF/fill rate), cumulative reward, or other performance measures.

In line with the literature, error-based metrics (MAE/RMSE/MAPE/MSE) are suitable for evaluating continuous forecasting; however, in inventories of critical supplies it is common to observe intermittent consumption (multiple days with zero consumption), which can distort evaluation if a single global metric is used. Therefore, a dual framework consistent with the nature of the problem is adopted: (i) for consumption occurrence (day with consumption vs. no consumption), Macro-F1 is used due to its robustness under class imbalance; and (ii) for consumption magnitude, MAE is employed, defined as the MAE computed only on days with positive real consumption ($y > 0$), preventing an abundance of zeros from artificially reducing the error. This scheme enables more consistent model comparisons in scenarios of sporadic demand and high operational variability.

This systematic literature review provides a useful foundation for future research because it organizes, in a reproducible manner, the available evidence on predictive models applied to inventories of critical supplies. In particular, the synthesis of the most used architectures, recurrent variables, and evaluation metrics helps guide the methodological design of new models—from selecting input variables to defining a forecasting model and a validation scheme. Moreover, by identifying trends and research gaps, this SLR facilitates the formulation of future work such as: (i) the development of hybrid models and robust approaches for intermittent demand, (ii) integrating forecasting with replenishment policies, and (iii) adapting and evaluating these models in food sectors, especially in the dairy industry, where operational and data constraints require predictive solutions that are applicable and scalable.

IV. CONCLUSION

This systematic review, guided by Fink's methodology, consolidated evidence from 39 studies related to forecasting and inventory management using artificial intelligence approaches. The results confirm that the most frequently used variables focus on the historical and temporal structure of demand, where historical consumption and seasonality dominate as predictors, while logistical variables (lead time) and state variables (available stock) are incorporated in a complementary way when sufficient traceability exists.

Likewise, the literature shows a preference for models capable of capturing temporal dependencies and nonlinear relationships, highlighting LSTM and MLP architectures, alongside a relevant use of traditional machine learning methods as comparative baselines.

In terms of evaluation, regression error metrics prevail; however, in intermittent consumption contexts, comparisons may be biased by the presence of zeros, which supports the use of a dual framework based on Macro-F1 (occurrence) and MAE (magnitude).

As a limitation, the results depend on the scope of the consulted sources and the availability of full-text access, which may influence the observed temporal distribution. As future work, it is proposed to validate the minimum set of variables and the selected architectures in a real industrial case on a per-critical-item basis, incorporating sensitivity analysis under partial variable availability and comparisons against baseline models.

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