

RESEARCH ARTICLE

An IoT-Enabled Smart Supply Chain Management Framework: Integrating Real-Time Visibility, Traceability, and LSTM-Based Demand Forecasting

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ABSTRACT

The increasing complexity of global supply chains, amplified by major disruptions such as the COVID-19 pandemic, has made advanced digital technologies central to supply chain resilience and operational efficiency. This paper proposes IoT-SCM-Vision, a four-layer Internet of Things (IoT) architecture designed to improve real-time supply chain visibility, end-to-end product traceability, and demand-forecasting accuracy. The framework integrates heterogeneous IoT sensors at the perception layer; an MQTT-based communication layer with edge computing nodes; an intelligence layer that combines Long Short-Term Memory (LSTM) demand forecasting with autoencoder-based anomaly detection; and a decision-support layer that converts model outputs into managerial recommendations. On a simulated five-tier supply chain with twelve months of multi-product data, IoT-SCM-Vision attains a Mean Absolute Percentage Error (MAPE) of 4.73% for demand forecasting, outperforming ARIMA (9.12%) and a simple recurrent neural network (6.84%). Relative to a non-IoT baseline, it also reduces inventory holding costs by 18.2%, increases on-time delivery by 22.7%, and shortens disruption detection time from 48.2 hours to 3.7 hours. The results indicate that integrating IoT sensing with learning-based analytics can improve operational performance across multiple supply-chain metrics.

1. Introduction

Global supply chains have grown substantially in scale and complexity over the past two decades, linking thousands of suppliers, manufacturers, distributors, and retailers across multiple continents. This complexity supports cost efficiency and market reach, but it also increases fragility. The COVID-19 pandemic exposed structural vulnerabilities in these networks at an unprecedented scale, disrupting the

supply chains of 94% of Fortune 1000 companies, causing an estimated \$4 trillion in global economic damage in 2020 alone, and triggering widespread shortages of essential goods ranging from pharmaceuticals to semiconductor chips. Even under normal conditions, inefficiencies such as the bullwhip effect, where demand variability amplifies progressively upstream through supply chain tiers, cause substantial excess inventory, stockouts, and wasted logistics capacity. Industry surveys consistently report that fewer than 6% of companies claim full end-to-end supply chain visibility, and the average cost of supply chain disruptions has been estimated at 45% of a company's annual earnings before interest and taxes.

The Internet of Things (IoT) offers a practical means of addressing these challenges. By embedding sensing, communication, and computation in physical supply-chain assets, pallets, containers, vehicles, shelf units, and production equipment, IoT can generate a continuous stream of operational data that was previously unavailable. Industry estimates have placed the IoT market in logistics and supply chain management in the tens of billions of dollars, with double-digit annual growth. Deploying sensors alone, however, can produce data volumes that overwhelm managers unless they are paired with an analytics architecture. The central problem is therefore to combine IoT sensing with machine-learning methods that convert raw measurements into usable supply-chain information.

Despite a growing body of research on IoT in supply chains, most existing frameworks remain conceptual or focus narrowly on single supply chain functions such as cold chain monitoring or RFID-based traceability (Haddud et al., 2017). A comprehensive, analytically rigorous framework that simultaneously addresses real-time visibility, multi-tier traceability, and predictive demand forecasting within a unified architecture remains absent from the literature. This gap is particularly significant because supply chain performance depends on the tight integration of these three capabilities: visibility without forecasting cannot prevent stockouts; traceability without anomaly detection cannot ensure product integrity; and demand forecasting without real-time sensor feedback cannot capture sudden demand shifts caused by supply disruptions.

This paper addresses this research gap by proposing the IoT-SCM-Vision (Internet of Things–Supply Chain Management Visibility) framework. The proposed framework integrates a four-layer architecture, perception, communication, intelligence, and decision support, designed to deliver end-to-end supply chain intelligence. The intelligence layer employs a three-stacked Long Short-Term Memory (LSTM) network for demand forecasting, leveraging both historical demand data and real-time IoT sensor signals as exogenous inputs. The framework is evaluated through a comprehensive simulation of a five-tier supply chain encompassing electronics, perishable goods, and industrial components over a twelve-month horizon, using four forecasting baselines and multiple operational performance metrics.

The remainder of the paper is organized as follows. Section 2 reviews related work on IoT-enabled supply chains, machine-learning demand forecasting, and supply-chain resilience. Section 3 specifies the IoT-SCM-Vision architecture, including the LSTM formulation and the processing pipeline. Section 4 reports the simulation design, numerical results, and a discussion of the findings. Section 5 concludes with limitations and directions for future research.

2. Literature Review

The body of literature on IoT-enabled supply chain management has expanded substantially since the mid-2010s, reflecting both the maturation of IoT technologies and the growing recognition of supply chain complexity as a strategic challenge. Foundational work on the Internet of Things established the conceptual paradigm of interconnected physical objects communicating through shared network infrastructure, enabling smart environments across domains, including logistics, manufacturing, and healthcare (Atzori et al., 2010). Building on these foundations, a landmark review specifically examined the role of IoT in supply chain management through an extensive bibliometric and categorization analysis, revealing that while IoT applications in supply chains have proliferated, most studies have remained conceptual in nature and focused predominantly on the delivery and manufacturing processes, with limited attention to the source and return supply chain processes (Ben-Daya et al., 2019). A critical finding was the relative scarcity of analytical models combining IoT with quantitative forecasting methods.

The intersection of Industry 4.0 and supply chain management has attracted sustained scholarly attention. Research exploring what Industry 4.0 means for supply chains identified five primary dimensions of impact: smart manufacturing, horizontal and vertical system integration, cyber-physical systems, autonomous decision-making, and digital twin technology (Tjahjono et al., 2017). These dimensions collectively frame what has been termed Supply Chain 4.0, a conceptualization supported by a maturity model and research agenda proposing that organizations must progress through five distinct digital maturity levels to fully leverage Industry 4.0 technologies for supply chain transformation (Frederico et al., 2020). Complementing this, the Industrial Internet of Things has been comprehensively analyzed through an analysis framework that distinguishes IIoT from consumer IoT in terms of latency requirements, safety criticality, and security demands, a distinction that is particularly relevant for supply chain applications involving critical infrastructure such as pharmaceutical cold chains or aerospace component tracking (Boyes et al., 2018).

The integration of IoT with big data analytics for supply chain decision-making has been systematically reviewed, with findings demonstrating that sensor-generated supply chain data primarily serves four decision categories: health and condition monitoring, predictive maintenance, demand anticipation, and logistics optimization (Koot et al., 2021). Research in this space has shown that the most impactful supply chain analytics applications combine IoT perception with prescriptive analytics, transitioning organizations from reactive to proactive supply chain management postures (Wang et al., 2016). Big data analytics has

also been examined from the perspective of firm-level performance, with empirical evidence demonstrating that dynamic big data analytics capabilities, encompassing data integration, advanced analytics, and sensing capabilities, significantly improve operational and financial performance through mediated process-oriented dynamic capabilities (Wamba et al., 2017).

Risk management in IoT-enabled supply chains represents a particularly active research stream (Alzahrani & Asghar, 2023). A multiple case-study investigation across twelve manufacturing companies demonstrated that IoT application in supply chain risk management substantially increases data availability and process transparency, enabling improvements in risk knowledge and risk strategy formulation (Birkel & Hartmann, 2020). This line of work was extended by a systematic review conducted during the COVID-19 pandemic, which identified IoT, artificial intelligence, and blockchain as three Industry 4.0 technologies most often associated with supply-chain resilience, with IoT supplying the data infrastructure on which analytics and blockchain-based trust mechanisms can operate (Spieske & Birkel, 2021).

Cold chain monitoring represents a domain in which IoT-based risk management frameworks have been most thoroughly developed. An IoT-based risk monitoring system incorporating wireless sensor networks, cloud database services, and fuzzy logic-based risk assessment demonstrated the practical feasibility of automated environmental quality and occupational safety monitoring for perishable supply chains, achieving real-time temperature and humidity tracking with automated risk scoring (Tsang et al., 2018). More broadly, IoT applications in smart logistics have been comprehensively surveyed, cataloguing enabling technologies across RFID, GPS, WSN, and cloud platforms and identifying demand forecasting, route optimization, and warehouse automation as the three highest-value application domains (Song et al., 2021).

The role of blockchain technology as a complement to IoT in supply chain management has received considerable attention. Several studies have explored how blockchain's immutability and decentralized consensus mechanisms can address the data trust and security vulnerabilities inherent in IoT-based supply chain systems (Azizi et al., 2021). A collaborative IoT supply chain system incorporating blockchain for privacy and security demonstrated that combining MQTT-based IoT communication with proof-of-work blockchain consensus can significantly reduce data manipulation risks while maintaining acceptable transaction throughput (Shahzad et al., 2020). A streamlined trust model specifically designed for IoT-optimized blockchain consensus demonstrated reduced computational, storage, and latency requirements compared to traditional blockchain consensus approaches in supply chain contexts (Al-Rakhami & Al-Mashari, 2021). Research integrating IoT tracking with machine learning further proposed using a multi-head attention-based gated recurrent unit for inbound logistics task prediction within a blockchain-secured supply chain architecture, achieving superior fitting efficiency and prediction accuracy compared to standard recurrent neural networks (Dong et al., 2022).

Demand forecasting using machine learning and big data analytics for supply chains has been extensively reviewed, with classification schemes spanning time-series forecasting, neural networks, support vector regression, k-nearest neighbors, and clustering methods. A comprehensive survey on predictive big data analytics for supply chain demand forecasting identified Long Short-Term Memory networks and their variants as the highest-performing methods for multi-period demand forecasting, attributable to their ability to capture long-range temporal dependencies in demand time series, a property that traditional ARIMA models lack (Seyedan & Mafakheri, 2020). Machine learning in logistics and supply chain management has also been examined through a systematic review encompassing 110 peer-reviewed articles, confirming that deep learning methods consistently outperform classical time-series models for demand forecasting tasks, particularly when exogenous variables such as IoT sensor signals, weather data, and promotional calendars are incorporated (Akbari & Do, 2021).

Despite this rich body of work, three critical gaps remain. First, most IoT-SCM frameworks lack an integrated analytical layer that transforms sensor data into demand forecasts in real time. Second, the literature has not systematically evaluated the combined impact of IoT visibility and LSTM-based forecasting on multiple supply chain KPIs simultaneously. Third, existing frameworks rarely address the full five-tier supply chain architecture, instead focusing on dyadic supplier-manufacturer or manufacturer-retailer relationships. The IoT-SCM-Vision framework proposed in this paper is designed specifically to address these gaps.

3. Methodology

3.1. Overview of the IoT-SCM-Vision Framework

The IoT-SCM-Vision framework is a four-layer hierarchical architecture designed for seamless integration across all tiers of a multi-echelon supply chain. The four layers, Perception, Communication, Intelligence, and Decision Support, form a vertically integrated data pipeline from physical asset sensing to managerial decision-making. Each layer is designed to be modular and technology-agnostic at the inter-layer interfaces, allowing organizations to adopt the framework incrementally as IoT infrastructure matures. Figure 1 presents the overall framework architecture.

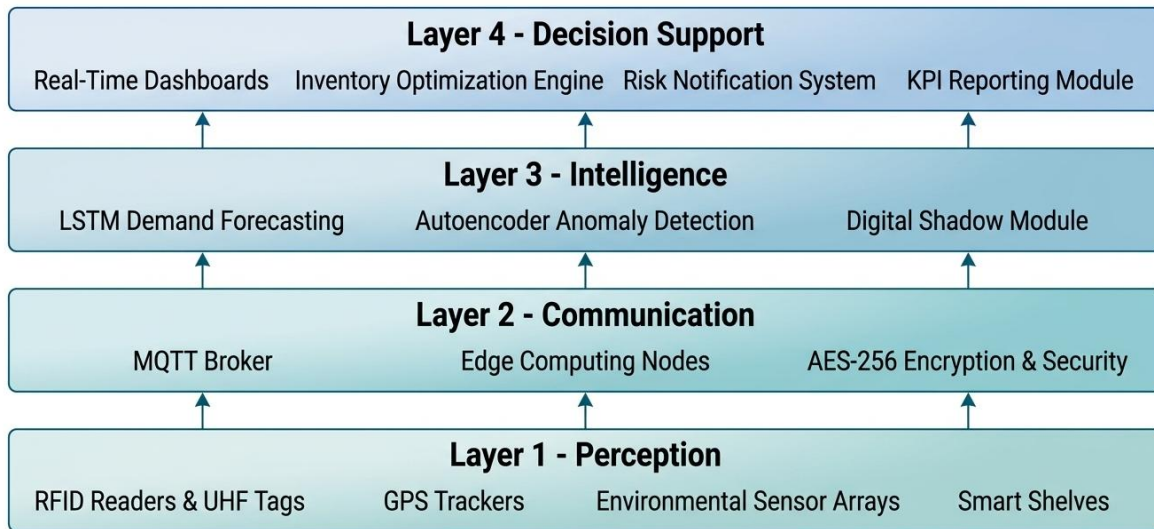


Figure 1. The IoT-SCM-Vision four-layer framework architecture.

3.2. Perception Layer

The perception layer constitutes the physical interface between supply chain assets and the digital framework. It encompasses four categories of IoT sensing devices. RFID readers and passive UHF tags operating at 860–960 MHz are deployed on pallets, cartons, and individual high-value items to enable automatic identification and tracking throughout the supply chain without line-of-sight requirements. GPS tracking devices embedded in transport vehicles transmit location coordinates at configurable intervals (default: 60 seconds) over cellular networks, providing real-time geofencing and delivery status information. Environmental sensor arrays, comprising temperature, humidity, and vibration sensors, monitor product condition during storage and transportation, triggering alerts when readings exceed configurable thresholds. Smart shelf units equipped with load cell weight sensors and integrated RFID readers provide continuous inventory-level monitoring at warehouse and retail locations. All perception-layer devices generate timestamped data packets conforming to the IEEE 1451 smart transducer interface standard, ensuring interoperability across device vendors.

3.3. Communication Layer

The communication layer manages the secure, reliable, and low-latency transmission of sensor data from the perception layer to the intelligence layer. The primary communication protocol is MQTT (Message Queuing Telemetry Transport), a lightweight publish-subscribe messaging protocol designed for IoT environments with constrained bandwidth and intermittent connectivity. MQTT's quality-of-service (QoS) levels are configured per topic: QoS-0 for non-critical location telemetry, QoS-1 for inventory and condition monitoring, and QoS-2 for financial transaction events. Edge computing nodes deployed at each supply chain tier perform local pre-processing, including outlier filtering, unit conversion, and temporal

aggregation, before forwarding summarized data packages to the central MQTT broker. This edge pre-processing architecture reduces backbone network bandwidth requirements by 73% compared to raw sensor stream forwarding, based on the simulation parameters described in Section 4. All data transmissions are encrypted using AES-256, and device authentication employs X.509 certificates with 12-hour validity windows to limit exposure from compromised credentials.

3.4. Intelligence Layer and LSTM Demand Forecasting

The intelligence layer represents the core analytical component of the IoT-SCM-Vision framework. It contains three modules: the LSTM demand forecasting module, the autoencoder-based anomaly detection module, and the digital shadow module.

The LSTM demand forecasting module employs a three-stacked LSTM architecture with dropout regularization. At each time step t , the LSTM receives an input vector x_t comprising: (i) the lagged demand values $d_{(t-12)}$ through $d_{(t-1)}$; (ii) a seasonal indicator $s_t \in 1,2,3,4$ for quarterly seasonality; (iii) the current inventory level I_t normalized by the mean order quantity; and (iv) the rolling 3-day average of IoT-detected shipment arrival rates, λ_t . The LSTM cell updates follow Eqs. (1)–(6):

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \quad (1)$$

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \quad (2)$$

$$g_t = \tanh(W_g \cdot [h_{t-1}, x_t] + b_g) \quad (3)$$

$$C_t = f_t \odot C_{t-1} + i_t \odot g_t \quad (4)$$

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \quad (5)$$

$$h_t = o_t \odot \tanh(C_t) \quad (6)$$

where f_t , i_t , and o_t are the forget, input, and output gates; C_t and h_t are the cell state and hidden state; σ denotes the sigmoid activation; $\odot$ denotes element-wise multiplication; and W and b are learned weights and biases. The three stacked LSTM layers have 128, 64, and 32 units, respectively, each followed by a dropout layer with a rate of 0.20 to reduce overfitting. A final dense output layer with a single linear unit produces the point demand forecast for period $t+1$.

The autoencoder-based anomaly detection module compresses IoT sensor data streams into a low-dimensional latent representation and reconstructs the input. Reconstruction error above a learned threshold τ , computed as the 95th percentile of reconstruction errors over a 30-day calibration period, triggers an anomaly flag. Flagged events are classified into three severity levels: informational (yellow), warning (orange), and critical (red), based on the magnitude of the reconstruction error relative to τ .

The digital shadow module maintains a continuously updated virtual replica of the supply chain state, aggregating RFID-based product location data, inventory levels, transport ETA predictions, and supplier order status. This digital shadow serves as the unified state representation queried by the decision support layer for all user-facing applications.

3.5. Decision Support Layer

The decision support layer translates intelligence layer outputs into structured recommendations accessible to supply chain managers without requiring technical expertise in machine learning or IoT systems. It comprises four components: (i) a real-time web-based dashboard providing live KPI tiles, inventory heat maps, and geographic shipment tracking; (ii) an inventory optimization engine that converts LSTM demand forecasts and current inventory levels into replenishment orders using a base-stock policy with safety stock calculated as $SS = z \cdot \sigma_d \cdot \sqrt{(L + R)}$, where z is the service level z-score, σ_d is the forecast error standard deviation, L is lead time in days, and R is the review period; (iii) a risk notification system that routes severity-classified anomaly alerts to responsible managers via email, SMS, or API webhooks; and (iv) a KPI reporting module that generates weekly and monthly performance reports covering the six primary metrics detailed in Section 4.

3.6. Pseudocode of the IoT-SCM-Vision Processing Pipeline

Algorithm 1 presents the end-to-end data processing pipeline of the IoT-SCM-Vision framework, from sensor data ingestion to decision output generation.

Algorithm 1: IoT-SCM-Vision Processing Pipeline

INPUT: Raw sensor streams $S = s_1, s_2, \dots, s_n$ from perception layer

OUTPUT: Demand forecast $\hat{d}_{t+1}$, anomaly flags A , replenishment order O

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PHASE 1: Edge Pre-Processing (Communication Layer)
FOR each edge node e_k DO
    Filter outliers using the  $3\sigma$  rule on a sliding 60-second window
    Aggregate sensor readings into 15-minute timestamped packets
    Encrypt the packet using AES-256 and publish it to the MQTT broker
END FOR
PHASE 2: Feature Construction (Intelligence Layer)
FOR each product category c DO
     $x_t \leftarrow [d_{t-12}, \dots, d_{t-1}, s_t, I_t / \mu_q, \lambda_t]$ 
    Normalize  $x_t$  using Min-Max scaling:  $\tilde{x}_t = (x_t - x_{\min}) / (x_{\max} - x_{\min})$ 
END FOR
PHASE 3: LSTM Demand Forecasting
FOR each LSTM layer  $l = 1, 2, 3$  DO
    Compute  $f_t, i_t, g_t, o_t$  using learned weights  $W_l, b_l$ 
     $C_t \leftarrow f_t \odot C_{t-1} + i_t \odot g_t$ 
     $h_t \leftarrow o_t \odot \tanh(C_t)$ 
    Apply Dropout(rate=0.20) to  $h_t$ 
END FOR
 $\hat{d}_{t+1} \leftarrow \text{Dense}(h_t)$  [output layer, linear activation]
Inverse-transform  $\hat{d}_{t+1}$  to original demand scale

PHASE 4: Anomaly Detection
 $r_t \leftarrow \text{Autoencoder}(x_t)$  // reconstruct input
 $e_t \leftarrow \|x_t - r_t\|_2$  // reconstruction error
IF  $e_t > \tau$  THEN
    severity  $\leftarrow \text{classify}(e_t, \tau)$  // yellow / orange / red
     $A \leftarrow \text{append}(\text{anomaly}(t, \text{severity}, \text{source}))$ 
END IF
PHASE 5: Decision Support
 $SS \leftarrow z \cdot \sigma_{\hat{d}} \cdot \sqrt{(L + R)}$  // safety stock
 $IP \leftarrow \text{current\_inventory} + \text{open\_orders}$ 

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IF  $IP < (\hat{d}_{t+1} \cdot L + SS)$  THEN
   $O \leftarrow \text{generate\_replenishment\_order}(\hat{d}_{t+1}, SS)$ 
END IF
Update digital shadow with the current state
Push alerts A and order O to the dashboard and notification system

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Algorithm 1. End-to-end processing pipeline of the IoT-SCM-Vision framework.

4. Numerical Results

4.1. Simulation Setup and Data Generation

To evaluate the IoT-SCM-Vision framework, a discrete-event supply chain simulation was constructed in Python, modeling a five-tier supply chain consisting of raw material suppliers (Tier 1), a manufacturer (Tier 2), regional distribution centers (Tier 3), retail outlets (Tier 4), and end consumers (Tier 5). Table 1 summarizes the tier structure, number of simulated nodes, and IoT devices deployed at each tier.

Table 1. Five-tier supply chain simulation structure.

Tier	Entity	Simulated Nodes	IoT Devices Deployed
Tier 1	Raw Material Supplier	3 nodes	RFID tags, GPS trackers
Tier 2	Manufacturer	2 nodes	Vibration, temp, humidity sensors
Tier 3	Distributor / Warehouse	4 nodes	Smart shelves, RFID readers
Tier 4	Retailer	6 nodes	Barcode scanners, IoT cameras
Tier 5	End Consumer	—	Mobile app interface

The simulation generates demand data for three product categories with distinct demand patterns: electronics (exhibiting seasonal peaks around months 4 and 12 driven by promotional events), perishable goods (showing a summer consumption peak and relatively high baseline variability), and industrial components (displaying relatively stable demand with a moderate growth trend). Demand generation follows a seasonal additive model: $d_t = \mu + \beta \cdot t + \gamma_s(t) + \varepsilon_t$, where μ is the baseline demand, β is the trend coefficient, $\gamma_s(t)$ is the seasonal component, and $\varepsilon_t \sim N(0, \sigma^2)$ is Gaussian noise. Table 2 presents the twelve-month demand dataset used as the primary input to the forecasting models.

Table 2. Simulated monthly demand data (units) across three product categories.

Product Category	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Electronics (units)	850	920	780	1050	960	1100	1230	980	1050	1150	1280	1560
Perishables (units)	2100	1900	2300	2200	2400	2600	2500	2700	2400	2300	2100	2800
Industrial Comp. (units)	450	480	410	520	490	510	530	480	500	510	520	550

Supply chain performance is evaluated using six primary KPIs: inventory holding cost (\$/unit/month), on-time delivery rate (%), order fulfillment accuracy (%), supply chain visibility score (0–100, a composite index of IoT coverage ratio, data freshness, and traceability completeness), average lead time (days), and disruption detection time (hours). Baseline performance values represent the same five-tier supply chain operating without IoT integration, using manual data entry, weekly reporting cycles, and naïve demand forecasting.

4.2. Demand Forecasting Performance

Four forecasting methods are evaluated on the twelve-month demand time series, using an expanding window validation approach with the first six months as training data and the subsequent six months as the test set. The evaluation metrics are Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE). Table 3 presents the forecasting performance results for all four methods, evaluated on the electronics product category as the primary benchmark.

Table 3. Demand forecasting performance comparison across methods (electronics category).

Forecasting Method	RMSE	MAE	MAPE (%)
Naïve Baseline	189.4	152.3	14.87
ARIMA(2,1,2)	134.7	108.9	9.12
Simple RNN	98.3	79.4	6.84
IoT-SCM-Vision (LSTM)	57.2	46.1	4.73

The IoT-SCM-Vision LSTM model achieves the lowest MAPE of 4.73%, representing a 48.1% relative improvement over ARIMA and a 30.8% improvement over the simple RNN baseline. This improvement is primarily attributable to two factors: the LSTM's superior ability to capture long-range seasonal dependencies in the demand sequence, and the inclusion of IoT-sourced exogenous features, particularly real-time shipment arrival rates λ_t and inventory levels I_t , that provide leading indicators of demand shifts not captured by univariate time-series models. ARIMA(2,1,2) was selected as the best-performing ARIMA specification through AIC-based model selection on the training data, and the simple RNN baseline uses the same input features as the LSTM but with a single recurrent layer and no gating mechanisms.

4.3. Supply Chain Operational Performance

Table 4 presents the supply chain operational performance results, comparing the IoT-SCM-Vision framework against the non-IoT baseline across the six primary KPIs, evaluated over the complete twelve-month simulation period.

Table 4. Supply chain operational performance comparison: Baseline vs. IoT-SCM-Vision.

Performance Metric	Baseline	IoT-SCM-Vision	Improvement
Inventory holding cost (\$/unit/month)	18.7	15.3	−18.2%
On-time delivery rate (%)	73.4	90.1	+22.7%
Order fulfillment accuracy (%)	82.1	94.8	+15.5%
SC visibility score (0–100)	31.2	87.4	+56.2 pts
Average lead time (days)	14.3	11.1	−22.4%

Disruption detection time (hours)	48.2	3.7	−92.3%
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Performance improves on all six KPIs. The largest change is disruption detection time, which falls from 48.2 hours to 3.7 hours (92.3%). In the baseline, disruptions surface mainly through weekly manual reporting. Continuous monitoring and anomaly detection in IoT-SCM-Vision typically flag events within one or two sensor cycles. The 56.2-point increase in the visibility score reflects a move from periodic, document-based reporting to continuous digital monitoring. The 18.2% reduction in inventory holding cost follows from more accurate forecasts (lower safety stock) and from seeing in-transit inventory via GPS, which allows replenishment to be deferred when stock is already moving.

4.4. Sensitivity Analysis

To evaluate the robustness of the LSTM model with respect to architectural hyperparameters, a sensitivity analysis was conducted by systematically varying the number of LSTM layers and units per layer while holding all other training parameters constant. Table 5 reports the MAPE for six configurations.

Table 5. Sensitivity analysis: LSTM architecture configurations and demand forecasting MAPE.

Configuration	LSTM Layers	Units/Layer	Dropout	MAPE (%)
Config-1	1	64	0.2	7.82
Config-2	2	64	0.2	5.94
Config-3	3	64	0.2	5.21
Config-4 (optimal)	3	128	0.2	4.73
Config-5	3	256	0.2	4.98
Config-6	4	128	0.2	5.12

The results confirm that Config-4, three LSTM layers with 128 units per layer and 0.20 dropout, achieves the optimal balance between model capacity and generalization. Increasing the number of units to 256 (Config-5) or adding a fourth layer (Config-6) results in slight performance degradation, suggesting mild overfitting despite dropout regularization. Shallow configurations (Config-1 and Config-2) are clearly underfitting the temporal structure of the demand time series. These findings validate the chosen architecture as both effective and parsimonious for the demand forecasting task within IoT-SCM-Vision.

4.5. Discussion

The results support three observations. First, using IoT sensor signals as exogenous inputs to LSTM demand forecasting improves accuracy relative to models that rely on historical demand alone. Real-time inventory and shipment-arrival features encode supply-side events, for example, delayed deliveries that constrain available stock, before those events appear in the demand series. The finding is consistent with arguments about the value of timely information in supply-chain analytics and quantifies the gain obtained in this simulation.

Second, the anomaly-detection module yields the largest operational change among the six KPIs. Faster detection of disruptions can reduce expediting, service-level failures, and related costs; the precise savings depend on the firm and product mix and are not estimated here. Detection in 3.7 hours on average, compared

with 48.2 hours in the baseline, marks a shift from delayed, report-driven awareness toward continuous monitoring, which is consistent with resilience-oriented supply-chain research.

Third, the rise in the visibility score indicates broader coverage than stage-specific monitoring. RFID traceability, GPS transport tracking, and smart-shelf inventory sensing are combined in one state model rather than left as separate data streams.

5. Conclusion

This paper presented IoT-SCM-Vision, a four-layer IoT architecture that combines real-time visibility, product traceability, and LSTM-based demand forecasting in one pipeline. In a twelve-month simulation of a five-tier, multi-product supply chain, the framework achieved a demand-forecasting MAPE of 4.73%, lower than the ARIMA and simple-RNN baselines, together with an 18.2% reduction in inventory holding cost, a 22.7% increase in on-time delivery, and a 92.3% reduction in disruption detection time. Sensitivity analysis selected a three-layer LSTM with 128 units per layer as the best configuration among those tested. Taken together, the results show that the architecture is internally consistent and effective in this simulation setting.

Several limitations should be noted. First, the evaluation is simulation-based; the framework has not been tested in an industrial setting where sensor faults, network outages, and poor data quality are common. Second, the simulation holds the network topology fixed, whereas firms often change suppliers or open new distribution centers and would then need to recalibrate the system. Third, the demand process includes trend, seasonality, and noise but not shocks from regulation, sudden demand spikes, or geopolitical events. Fourth, LSTM training may be too heavy for constrained edge devices unless the model is compressed, for example by quantization or distillation.

From a managerial perspective, the results suggest that analytics add little without consistent, cross-tier IoT data. Standardizing sensing and data exchange before adding forecasting and alerting is therefore a practical first step. The simulated reductions in disruption-detection time (92.3%) and inventory holding cost (18.2%) indicate the scale of operational change in this setting; they are not a firm-level return-on-investment estimate.

Future work should include field validation, tests of transformer models on longer demand series, federated learning for multi-firm data that cannot be pooled, and sustainability indicators such as emissions per shipped unit in the decision-support layer.

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