Deep Integration of Intelligent Logistics and Supply Chain under Digital Transformation Empirical Evidence of Inventory Precision Control and Cost Optimization Supported by IoT Technology

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ABSTRACT Driven by the digital economy and industrial digital transformation, the deep integration of intelligent logistics and supply chains has become a key approach to improving operational efficiency and resilience. Wireless sensing and electromagnetic information transmission enabled by Internet of Things (IoT) technologies provide essential support for real-time perception and intelligent coordination in modern logistics systems. Traditional supply chains still suffer from inventory backlogs, demand forecasting deviations, high operational costs, and information asymmetry. To address these challenges, this study constructs a four-in-one analytical framework integrating IoT technology, inventory precision control, cost optimization, and supply chain integration. The proposed framework systematically investigates the internal mechanisms of intelligent logistics under digital transformation and emphasizes the application of IoT-enabled real-time data acquisition, information exchange, and intelligent decision-making for precise inventory management. The results demonstrate that the proposed approach provides an effective pathway for improving inventory control accuracy, reducing operational costs, and enhancing supply chain collaboration, offering valuable guidance for intelligent logistics systems supported by wireless communication and electromagnetic sensing technologies..

INDEX TERMS digital transformation, intelligent logistics, internet of things, wireless sensing, supply chain integration

I. INTRODUCTION

A. RESEARCH BACKGROUND

THE report of the 20th National Congress of the Communist Party of China clearly proposes to accelerate the construction of a modern economic system, focus on improving total factor productivity, and enhance the resilience and safety level of industrial and supply chains. As the core link connecting fiber production, textile manufacturing, and final consumption, the efficiency and resilience of the distribution network are directly related to the high-quality development of the weaving industry and the stability of the national economy. This seamless flow ensures that raw spinning materials and finished textile products are managed with the precision necessary to maintain industrial stability and economic growth [1-4]. Digital transformation provides the core driving force for supply chain upgrading, and intelligent logistics, as a key link in supply chain digitization, has become an inevitable choice to deeply integrate with the supply chain to solve the pain points of traditional supply chains. However, China's traditional supply chain still faces many challenges: extensive inventory management, coexistence of inventory backlog and shortage. According to the "2023 China Supply Chain Development Report", the average inventory turnover rate of industrial enterprises in China is only 6.8 times per year, far below the level of developed countries; The deviation in demand forecasting is large, with a prediction error rate generally exceeding 30%, resulting in inefficient resource allocation; Serious information silos and low collaboration efficiency in various links of the supply chain; The comprehensive logistics cost is still high, accounting for 14.6% of GDP, which is 5-8 percentage points higher than developed countries [5,6].

B. RESEARCH CONTENT AND TECHNICAL ROUTE

1) Research Content

The main research content of this article includes:

1. Theoretical basis and framework construction: By synthesizing theories of digital transformation, intelligent logistics, and IoT technology, this study constructs a four-in-one framework to reveal how real-time sensing supports inventory control and cost optimization within the textile manufacturing process. This framework demonstrates the inherent mechanism by which IoT-driven data flows synchronize raw fiber storage with high-speed weaving schedules to minimize waste and maximize operational efficiency in the textile industry.

2. Core features and IoT support mechanisms of intelligent logistics and supply chain integration: Analyze the core features of integration (data connectivity, intelligent decision-making, collaborative efficiency, and resilience enhancement), and explore the support mechanisms of IoT technology in data collection, information sharing, intelligent decision-making, and collaborative scheduling.

3. Design of inventory precision control system based on IoT technology: Design an inventory precision control system from four dimensions: data collection, demand forecasting, dynamic replenishment, and intelligent scheduling, and develop corresponding technical application modules and processes.

4. Optimization strategy proposal: Based on theoretical and empirical research, propose strategic suggestions for the deep integration of intelligent logistics and supply chain, precise inventory control, and cost optimization under digital transformation.

2) Technical Roadmap

The technical route of this article is as follows:

1. Literature research stage: Sort out the research results in related fields such as the integration of intelligent logistics and supply chain, the application of Internet of Things technology, inventory and cost optimization, and clarify the research status and shortcomings.

2. Theoretical construction stage: Integrate multidisciplinary theories, construct a four in one analysis framework, and reveal the technical support mechanism and integration mechanism.

3. System and Model Design Phase: Design an IoT based inventory precision control system and construct an inventory cost optimization model.

4. Empirical research stage: Select typical industry enterprises, collect data, conduct empirical analysis, and verify the effectiveness of the system and model.

5. Strategy proposal stage: Based on empirical results, propose targeted optimization strategies.

6. Conclusion and Prospect Stage: Summarize the research results, point out the research limitations and future research directions.

II. THEORETICAL BASIS AND ANALYTICAL FRAMEWORK

A. DEFINITION OF CORE CONCEPTS

Accurate inventory control refers to an inventory management model based on real-time data and intelligent algorithms, which achieves precise demand forecasting, dynamic inventory monitoring, timely replenishment optimization, and intelligent resource scheduling. The core goal is to minimize inventory levels and related costs while meeting demand.

Inventory cost optimization refers to the use of technology applications, process optimization, collaborative management, and other methods to reduce procurement costs, warehousing costs, stockout costs, and transportation costs related to inventory, in order to minimize the overall cost of the supply chain.

B. THEORETICAL BASIS

1) Supply Chain Collaboration Theory

The theory of supply chain collaboration emphasizes the collaborative effect of "1+1>2" among various nodes of the supply chain through information sharing, resource integration, and process collaboration. The core of the deep integration of intelligent logistics and supply chain is collaboration. The Internet of Things technology breaks down information silos, achieves collaborative decision-making and scheduling in various links, and improves supply chain efficiency.

2) Inventory Management Theory

Inventory management theory includes classic theories such as Economic Order Quantity (EOQ), Material Requirements Planning (MRP), Just in Time (JIT), Collaborative Planning, Forecasting and Replenishment (CPFR), etc. The Internet of Things technology provides technical support for the implementation of these theories, achieving dynamic and precise inventory management [7].

C. CONSTRUCTION OF FOUR IN ONE ANALYSIS FRAMEWORK

Constructing a four in one analysis framework of "Internet of Things technology - precise inventory control - cost optimization - supply chain integration", the core connotations and interrelationships of each dimension are as follows:

1) Dimensions of IoT Technology

The Internet of Things technology is the core support of the entire system, including the hardware layer (sensors, RFID, GPS, smart terminals) and the network layer (5G, WiFi, Bluetooth, etc.) LoRa), The platform layer (IoT cloud platform) and application layer (data collection, analysis, decision-making system) provide real-time data and technical support for inventory control and supply chain integration.

2) Dimensions of Accurate Inventory Control

Accurate inventory control is the core application link, based on the data support provided by IoT technology, to achieve demand forecasting, inventory monitoring, dynamic replenishment, intelligent scheduling, and solve the extensive problem of traditional inventory management.

3) Cost Optimization Dimensions

Cost optimization is one of the core goals, which aims to reduce inventory related costs such as procurement, warehousing, stockouts, and transportation through precise inventory control, and improve the economic efficiency of the supply chain.

The interrelationship between four dimensions: IoT technology provides technical and data support for precise inventory control; Accurate inventory control is the core path of cost optimization; Cost optimization is an important achievement of supply chain integration; Supply chain integration, in turn, provides a broader scenario and collaborative environment for the application of IoT technology and inventory control, forming a closed-loop logic of "technical support control optimization cost reduction integration deepening" [8,9]. The original "four-dimensional parallel framework" is optimized into a progressive framework:

IoT Technology: Underlying technical support (providing data and technical guarantees);

Precise Inventory Control: Core execution tool (key entry point and core application scenario for supply chain integration);

Cost Optimization: Direct goal orientation (phased achievement through core tools);

Supply Chain Integration: Final ecological implementation (achieving full-chain collaboration through inventory control breakthroughs).

D. THE INTRINSIC MECHANISM OF IOT TECHNOLOGY SUPPORTING THE INTEGRATION OF INTELLIGENT LOGISTICS AND SUPPLY CHAIN

The Internet of Things technology supports the deep integration of intelligent logistics and supply chain through four mechanisms: data collection, information sharing, intelligent decision-making, and collaborative scheduling. The specific mechanisms are as follows:

1) Data Collection Mechanism

The Internet of Things technology uses sensors, RFID, GPS and other devices to achieve real-time data collection at various links of the supply chain, including:

1. Inventory data: quantity, location, status, etc. of raw materials, work in progress, and finished products;
2. Environmental data: temperature, humidity, lighting, vibration, etc. during storage and transportation;
3. Demand data: terminal sales data, customer order data, market trend data;
4. Logistics data: transportation vehicle location, driving status, cargo transportation progress, etc. [10]. Real time data collection provides accurate basis for decision-making in various links of the supply chain, breaking the information asymmetry of traditional supply chains.

2) Information Sharing Mechanism

The Internet of Things platform serves as a data sharing carrier to achieve data interoperability among various nodes of the supply chain enterprises (suppliers, manufacturers, distributors, retailers, logistics providers), including:

1. Demand information sharing: Real time synchronization of terminal demand data to upstream enterprises to guide production and replenishment;
2. Inventory information sharing: The inventory status of each node is visible in real-time, avoiding duplicate inventory and stockouts;
3. Logistics information sharing: Real time synchronization of logistics progress and status to improve collaborative efficiency [11].

The information sharing mechanism eliminates information silos in various links of the supply chain, laying the foundation for collaborative decision-making.

3) Intelligent Decision-Making Mechanism

Based on the massive data collected by the Internet of Things, combined with big data and artificial intelligence algorithms, achieve intelligent decision-making in the supply chain, including:

1. Demand forecasting decision-making: Based on historical data, real-time data, and market data, accurately predict future demand;
2. Inventory optimization decision: dynamically adjust inventory levels, determine the optimal replenishment quantity and replenishment timing;
3. Logistics scheduling decisions: Optimize transportation routes, warehouse layout, vehicle scheduling, and improve logistics efficiency [12].

The intelligent decision-making mechanism enhances the scientificity and timeliness of supply chain decision-making, replacing the traditional experience driven decision-making model.

4) Collaborative Scheduling Mechanism

Under the support of IoT technology, collaborative scheduling is achieved in various links of the supply chain, including:

1. Production and sales synergy: Real time matching of production plans and sales demand to avoid overproduction and inventory backlog;
2. Supply and demand coordination: Suppliers and purchasers collaborate to adjust their supply plans, ensuring timely supply of raw materials;
3. Logistics collaboration: Logistics providers collaborate with both supply and demand sides to schedule logistics resources and improve transportation and warehousing efficiency.

The collaborative scheduling mechanism achieves efficient linkage among various links in the supply chain, enhancing the agility and resilience of the supply chain.

III. THE CORE CHARACTERISTICS OF THE INTEGRATION OF INTELLIGENT LOGISTICS AND SUPPLY CHAIN AND THE SUPPORT SYSTEM OF IOT TECHNOLOGY

A. CORE FEATURES OF DEEP INTEGRATION OF INTELLIGENT LOGISTICS AND SUPPLY CHAIN

1) Data Integration

Data connectivity is a fundamental feature of integration, which achieves full process connectivity of data in all links of the supply chain through IoT technology. From the demand side to the supply side, from the production side to the logistics side, data flows in real-time and is fully visible, ensuring that each node enterprise can obtain accurate and real-time decision-making basis [13].

2) Intelligent Decision Making

Intelligent decision-making is the core feature of integration. Based on the massive data collected by the Internet of Things, combined with big data analysis and artificial intelligence algorithms, it realizes the automation and intelligence of decision-making such as demand forecasting, inventory optimization, and logistics scheduling, replacing traditional empirical decision-making and improving decision-making efficiency and accuracy.

3) Collaborative Efficiency

Collaborative efficiency is a key feature of integration. Based on information sharing platforms, enterprises at various nodes in the supply chain achieve supply and demand collaboration, production and sales collab oration, and logistics collaboration, breaking down departmental barriers and enterprise boundaries, and improving the overall operational efficiency of the supply chain [14,15].

B. CONSTRUCTION OF IOT TECHNOLOGY SUPPORT SYSTEM

Build a four layer IoT technology support system of "hardware perception network transmission platform support application services" to provide comprehensive technical support for the deep integration of intel ligent logistics and supply chain:

1) Hardware Perception Layer

The hardware perception layer is the core of data collection, including various IoT terminal devices:

1. RFID equipment: including RFID tags and card readers, used for identity recognition, quantity statistics, and location tracking of inventory goods and logistics packages. The recognition distance can reach 1-10 meters, the recognition speed is $\leq$ 0.1 seconds, and it supports simultaneous recognition of multiple tags;

2. Sensor equipment: including temperature sensors, humidity sensors, pressure sensors, vibration sensors, etc., used to monitor storage and transportation environmental parameters, with measurement accuracy of $\pm$ 0.1 °C (temperature) and $\pm$ 2% RH (humidity) [16];

3. GPS/Beidou positioning equipment: used for real-time positioning of transportation vehicles and logistics packages, with a positioning accuracy of $\pm$ 5 meters and an update frequency of $\geq$ 1 time/minute;

4. Intelligent terminal devices: including intelligent forklifts, AGV robots, intelligent shelves, etc., used for automated execution of warehousing operations.

2) Network Transport Layer

The network transport layer is responsible for real-time data transmission and adopts a multi network fusion solution of "5G+WiFi+LoRa+Bluetooth":

1. 5G network: used for high-speed transmission of massive data and high-definition videos, with a transmission rate of $\geq$ 1Gbps and a latency of $\leq$ 10ms, supporting wide coverage and multi device connections;

2. WiFi network: used for data transmission in indoor scenarios such as warehouses and workshops, with a transmission rate of $\geq$ 300Mbps, supporting short distance high-speed transmission;

3. LoRa network: used for low-power, long-distance sensor data transmission, with a transmission distance of up to 3-5 kilometers, low power consumption, suitable for outdoor scenes;

4. Bluetooth network: used for data transmission between short-range devices, such as the connection between smart terminals and sensors.

5G Network: High-speed transmission for cross-regional logistics and large-scale warehouse clusters (e.g., real-time temperature/humidity/location data for fresh food cross-provincial cold chain transportation);

WiFi Network: Short-distance high-speed data exchange in indoor warehouses/workshops (e.g., real-time scheduling instructions for smart shelves and AGV robots);

LoRa Network: Low-power data collection for outdoor distributed warehouses and remote suppliers (e.g., inventory status and environmental monitoring of suburban raw material warehouses);

Bluetooth Network: Point-to-point communication between short-range devices (e.g., local data synchronization between RFID readers and smart terminals in warehouses).

3) Platform Support Layer

The platform support layer is the core of data processing and sharing, building an IoT cloud platform with the following functions:

1. Data storage and management: Adopting a distributed storage architecture, supporting the storage of massive structured and unstructured data, with a data storage capacity of $\geq$ 100TB and a data retention time of $\geq$ 3 years;

2. Information sharing and collaboration: Build a hierarchical information sharing platform that supports data queries and collaborative operations among various nodes of the supply chain enterprises;

3. Security protection: Adopting technologies such as data encryption, access control, and security auditing to ensure the security of data transmission and storage [17].

4) Application Service Layer

The application service layer is the core of technology implementation, providing specialized application services for various links in the supply chain

1. Inventory management services: including real-time inventory monitoring, demand forecasting, dynamic replenishment, inventory warning, and other functions [18];
2. Logistics tracking services: including functions such as cargo positioning, transportation status monitoring, and logistics trajectory inquiry;
3. Collaborative scheduling services: including production and sales collaboration, supply and demand collab oration, logistics collaboration, and other functions;
4. Decision support services: Based on data analysis, provide demand forecasting reports, inventory optimization suggestions, cost analysis reports, etc. [19].

IV. DESIGN OF INVENTORY PRECISE CONTROL SYSTEM BASED ON INTERNET OF THINGS TECHNOLOGY

A. OVERALL ARCHITECTURE OF THE SYSTEM

Design a precise inventory control system that integrates data collection, demand forecasting, dynamic replenishment, and intelligent scheduling. This system is supported by Internet of Things technology to achieve full process automation and intelligence of inventory management. The core goal is to improve inventory turnover, reduce demand forecasting errors, reduce inventory backlog and stockouts, and lay the foundation for cost optimization.

B. CORE MODULE DESIGN

1) Multi Source Data Acquisition Module

The multi-source data collection module integrates IoT hardware perception layer devices to achieve comprehensive and real-time collection of inventory related data, including:

1. Static inventory data: Basic information such as product name, specifications, model, initial inventory, safety stock, and inventory limit is collected through a combination of RFID tags and system input;
2. Inventory dynamic data: Real time data such as incoming and outgoing quantities of goods, remaining inventory, and changes in storage locations, automatically collected through RFID card readers and intel ligent shelves;
3. Environmental data: Temperature, humidity, lighting, vibration and other data of the storage environment are collected in real time through sensors, and automatic warnings are issued in case of abnormalities;
4. Demand data: Terminal sales data, customer order data, market promotion data, seasonal trend data, etc., synchronized in real time through sales terminals, e-commerce platforms, and IoT platforms;
5. Logistics data: raw material procurement and transportation data, finished product distribution data, in transit goods status data, etc., collected through GPS positioning devices and logistics systems [20]. The collection frequency of the data collection module is dynamically adjusted according to the data type: the collection frequency of inventory dynamic data and environmental data is ≥ 1 time/minute; The frequency of collecting demand data and logistics data is ≥ 1 time/hour; Static data is regularly updated.

The collection frequency of the data collection module is dynamically adjusted according to the data type:

Static inventory data (basic specifications, safety stock): Once per day (consistent with daily decision-making cycles); Dynamic data (in-transit goods status, fresh inventory temperature and humidity): $\geq$1 time/minute (high real-time requirements for abnormal warning);

Demand and logistics summary data: $\geq$1 time/hour (balancing real-time performance and data redundancy). A "data filtering module" is added to process high-frequency redundant data using the sliding average method, retaining only key fluctuation information (e.g., abnormal temperature changes, sudden inventory adjustments) to avoid noise interference in decision-making.

2) Intelligent Demand Forecasting Module

Based on multi-source data, build an intelligent demand forecasting model that integrates time series analysis and machine learning algorithms to achieve accurate demand forecasting:

1. Data preprocessing: Clean, normalize, and extract features from collected multi-source data to remove outliers and noisy data [21];
2. Model construction: Integrate ARIMA time series models, LSTM neural network models, and random forest models to build an integrated prediction model, fully utilizing the advantages of different models;
3. Prediction process: Input historical demand data, real-time sales data, and market environment data, and the model outputs demand prediction results for the next 1-3 months, including predicted demand volume and prediction error interval;
4. Dynamic correction: Based on real-time sales data and market changes, dynamically adjust forecast results to improve forecast accuracy.

The prediction error rate of the intelligent demand forecasting module is controlled within 15%, significantly lower than traditional forecasting methods (with an error rate of over 30%) [22].

Real-time terminal sales data obtained through IoT (e.g., sales fluctuations during promotional activities) provides a basis for dynamic model correction. The integrated model (ARIMA+LSTM+random forest) can quickly respond to market changes, rather than relying solely on historical data.

3) Dynamic Replenishment Optimization Module

Based on demand forecasting results and real-time inventory data, a dynamic replenishment optimization model is constructed to achieve precise optimization of replenishment quantity and timing

1. Inventory status assessment: Real time monitoring of current inventory levels, in transit inventory, and safety stock to evaluate the ability of inventory to meet demand;

2. Replenishment trigger mechanism: When the inventory level is below the critical value of safety stock+pre dicted demand, the replenishment process is automatically triggered;

3. Replenishment quantity calculation: Based on the improved EOQ model, combined with demand forecast ing, procurement costs, warehousing costs, and out of stock costs, calculate the optimal replenishment quantity;

4. Replenishment execution: Automatically generate replenishment orders, synchronize them with suppliers through an information sharing platform, and track replenishment progress in real-time [23]. The dynamic replenishment optimization module achieves automation and precision in replenishment, avoiding inventory backlog and stockouts.

4) Intelligent Scheduling Execution Module

The intelligent scheduling execution module is based on inventory data, logistics data, and demand data to achieve intelligent scheduling of warehousing and transportation:

1. Warehouse scheduling: Optimize warehouse location allocation, use ABC classification method to classify and store goods, and allocate high-frequency outbound goods to near outbound warehouse locations; Automated warehousing, outbound, and inventory operations are achieved through AGV robots and intelligent forklifts;

2. Transportation scheduling: Based on GPS positioning and path planning algorithms, optimize transportation routes, avoid congested sections, and shorten transportation time; Integrate transportation needs, achieve a reasonable combination of whole vehicle transportation and less than truckload transportation, and reduce transportation costs;

3. Emergency dispatch: In case of unexpected situations such as inventory abnormalities or logistics interruptions, an emergency dispatch plan will be automatically generated, such as emergency replenishment or alternative transportation route planning.

The intelligent scheduling execution module has improved the efficiency of warehousing and transportation, and reduced related costs [24].

C. SYSTEM OPERATION PROCESS

1. Data collection stage: Collecting multi-source data through IoT devices, transmitting it to the IoT platform for storage and preprocessing;

2. Demand forecasting stage: The intelligent demand forecasting model outputs demand forecasting results based on preprocessed data;

3. Replenishment Decision Stage: The dynamic replenishment optimization module generates and executes replenishment plans based on predicted results and real-time inventory;

4. Scheduling execution stage: The intelligent scheduling execution module optimizes the warehousing and transportation processes to ensure accurate inventory control and implementation;

5. Monitoring feedback stage: Real time monitoring of inventory status, logistics progress, and demand fulfillment, dynamically adjusting parameters of each module to form a closed-loop operation [25].

V. CONSTRUCTION OF INVENTORY COST OPTIMIZATION MODEL

A. COMPOSITION AND QUANTITATIVE INDICATORS OF INVENTORY COSTS

Inventory costs mainly include four categories: procurement costs, warehousing costs, out of stock costs, and transportation costs. The composition and quantitative indicators of each type of cost are as follows:

1) Procurement Cost

Procurement cost refers to the cost incurred by an enterprise to obtain raw materials and goods, including:

1. Purchase cost: The purchase price of a product is directly proportional to the quantity purchased;

2. Ordering cost: The order processing fees, negotiation fees, transportation fees, etc. incurred during the procurement process are directly proportional to the number of purchases made;

3. Inspection cost: The cost of inspection and testing before the goods are put into storage.

2) Storage Costs

Storage costs refer to the costs incurred during the storage of goods, including:

1. Storage facility costs: warehouse rent, equipment depreciation, maintenance expenses;

2. Inventory holding costs: interest on capital occupation, insurance premiums, taxes and fees;

3. Inventory loss cost: losses caused by product damage, deterioration, and expiration [26,27].

3) Shortage Cost

Shortage cost refers to the cost incurred due to insufficient inventory that cannot meet demand, including:

1. Order loss cost: The loss of sales revenue caused by the loss of customer orders;

2. Customer churn cost: Long term revenue loss caused by customers turning to competitors due to stockouts;

3. Emergency replenishment cost: The cost of emergency procurement and transportation incurred to make up for shortages.

4) Transportation Costs

Transportation cost refers to the cost incurred during the transportation of goods from suppliers to enterprises and from enterprises to customers, including:

1. Transportation costs: vehicle fuel costs, tolls, driver salaries, etc;

2. Packaging costs: Packaging and protection costs incurred during the transportation of goods;

3. Transportation loss cost: Losses caused by damage or deterioration of goods during transportation.

B. CONSTRUCTION OF INVENTORY COST OPTIMIZATION MODEL

Using genetic algorithm to solve the model, the steps are as follows:

1. Encoding: Encode decision variables such as purchase quantity Q, purchase frequency n, and transportation route L into chromosomes;

2. Initialize the population: Randomly generate a certain number of initial chromosomes to form the initial population;

3. Fitness function: The fitness function is based on minimizing the comprehensive inventory cost;

4. Selection, crossover, and mutation: Select excellent chromosomes through roulette wheel selection method, perform crossover and mutation operations, and generate a new generation population;

5. Iteration termination: When the number of iterations reaches the preset value or the fitness function converges, output the optimal solution.

Encoding: Real-number encoding is adopted. Decision variables Q (purchase quantity), n (purchase frequency), and L (transportation route) correspond to a chromosome length of 3, with encoding ranges [100, 5000], [1, 30], and [1, 20] (route number) respectively.

Fitness function:

$$F = \frac{1}{C_p + C_w + C_s + C_t},$$

where C_p = procurement cost, C_w = warehousing cost, C_s = stockout cost, and C_t = transportation cost. A larger function value indicates lower comprehensive cost.

Specific parameters for the empirical phase: Population size = 50, number of iterations = 100, crossover rate = 0.8, mutation rate = 0.05, selection strategy = tournament selection (selection pressure = 2), ensuring algorithm replicability.

Control variable method verifies parameter rationality: When the crossover rate is 0.8 and mutation rate is 0.05, the model converges fastest and the optimal solution stability is highest, avoiding subjectivity in parameter settings.

C. THE IMPACT PATH OF IOT TECHNOLOGY ON COST OPTIMIZATION

IoT technology optimizes various inventory costs through the following paths:

1) Procurement Cost Optimization Path

1. Accurate demand forecasting: reduce the risk of excessive or insufficient procurement, and minimize unnecessary procurement frequency;

2. Supplier collaboration: Through information sharing and collaborative procurement, obtain bulk purchase discounts and reduce purchase costs;

3. Inspection automation: Automated inspection of product quality through IoT devices to reduce inspection costs.

2) Warehouse Cost Optimization Path

1. Rationalization of inventory levels: dynamically adjust inventory, reduce inventory backlog, lower capital occupation costs and loss costs;

2. Automation of warehousing operations: By using AGV robots, intelligent shelves, and other equipment, the efficiency of warehousing operations can be improved and labor costs can be reduced;

3. Space utilization optimization: Intelligent warehouse allocation improves warehouse space utilization and reduces warehouse rental costs.

3) Optimization Path for Out of Stock Costs

1. Agile demand response: Real time monitoring of demand changes, timely replenishment, and reducing the frequency of stockouts;

2. Real time inventory monitoring: timely detection of inventory abnormalities, early warning, and avoidance of stock shortages;

3. Intelligent emergency dispatch: Quickly respond to out of stock crises and reduce out of stock losses.

4) Transportation Cost Optimization Path

1. Route planning optimization: Based on real-time traffic data, select the optimal transportation route to shorten the transportation distance;

2. Integration of transportation resources: Integrate transportation demand, improve vehicle loading rates, and reduce unit transportation costs;

3. Transportation status monitoring: Real time monitoring of the transportation process to reduce transportation losses.

VI. MULTI INDUSTRY EMPIRICAL RESEARCH

A. EMPIRICAL DESIGN

1) Selection of Research Subjects

Three typical industry enterprises, namely manufacturing (automotive parts enterprise A), retail (chain supermarket enterprise B), and fresh food (fresh e-commerce enterprise C), were selected as empirical research objects. All three types of enterprises have carried out intelligent logistics and supply chain integration practices and applied IoT technology for inventory management, which is representative. The basic information of the enterprise is shown in Table 1:

TABLE 1. Basic Information of Empirical Research Objects

Enterprise Type	Enterprise Name	Business Scope	IoT Technology Application Status	Supply Chain Scale
Manufacturing Industry	Enterprise A	Production and sales of auto parts	Deployed RFID devices, sensors, and IoT platforms to realize inventory monitoring of raw materials and finished products	Annual sales volume: 500 million yuan; 30 suppliers; 50 distributors
Retail Industry	Enterprise B	Chain supermarket operation, covering food, daily necessities, etc.	Deployed RFID tags, smart shelves, and sales terminal data collection systems to realize real-time commodity inventory monitoring	20 stores; annual sales volume: 800 million yuan; 100 suppliers
Fresh Food Industry	Enterprise C	Online sales of fresh products, covering fruits, vegetables, meat, seafood, etc.	Deployed cold chain sensors, GPS positioning, and IoT platforms to realize inventory and transportation monitoring of fresh products	Annual sales volume: 300 million yuan; 40 suppliers; distribution scope covering 2 provinces/cities

2) Data Collection and Processing

1. Data collection: Collect inventory data, cost data, and sales data from 2021 to 2023 through the internal system of the enterprise, including inventory turnover rate, inventory accuracy rate, demand forecasting error rate, various inventory costs, etc;

2. Data processing: Clean the collected data to remove outliers and missing values; Using 2021 as the baseline period (without fully applying IoT technology) and 2023 as the empirical period (with fully applying IoT technology and inventory control system), compare and analyze the changes in indicators.

3) Evaluation Indicator System

Constructing a three-dimensional evaluation index system of "inventory control effect cost optimization effect supply chain integration effect". The Empirical Evaluation Index System is shown in Table 2:

B. EMPIRICAL RESULTS AND ANALYSIS

1) Comparison of Inventory Control Effects

The Comparison of Inventory Control Effects is shown in Table 3:

According to Table 3, the application of IoT technology supported inventory precision control systems in three types of enterprises has significantly improved the effectiveness of inventory control:

1. The average inventory turnover rate increased by 43.0%, with manufacturing increasing by 44.2%, retail increasing by 42.5%, and fresh food increasing by 42.3%, indicating a significant improvement in inventory turnover efficiency;

2. The average accuracy of inventory has increased by 7.2%, reaching over 98.8%, indicating a significant improvement in the accuracy of inventory data and a reduction in inventory counting errors;

3. The average error rate of demand forecasting has decreased by 39.3%, from over 35% in the benchmark period to below 23% in the empirical period, indicating a significant improvement in the accuracy of demand forecasting.

Original: "simply through IoT implementation" → Revised: "with the support of IoT real-time data and optimization of the integrated prediction model"

2) Comparison of Cost Optimization Effects

The Comparison of Cost Optimization Effects is shown in Table 4:

According to Table 4, after applying the inventory cost optimization model to the three types of enterprises, the cost optimization effect is significant:

1. The average comprehensive cost was reduced by 24.1%, with the fresh food industry experiencing the largest reduction (26.2%), followed by the retail industry (24.0%), and the manufacturing industry having the lowest (22.1%), indicating that the model has significant optimization effects on different industries;

2. In terms of cost types, the reduction rate of out of stock costs is the highest (43.6%), followed by warehousing costs (32.7%). The reduction rates of transportation costs (24.5%) and procurement costs (18.9%) are relatively low, which is more directly related to the optimization effect of IoT technology on out of stock and warehousing links; The reduction rates of procurement costs, warehousing costs, and out of stock costs in the fresh food industry are higher than those of the other two types of enterprises, indicating that IoT technology has a more significant cost optimization effect on industries such as the fresh food industry that require high inventory freshness and timeliness.

3) Comparison of Supply Chain Integration Effects

The comparison of Supply Chain Integration Effects is shown in Table 5:

TABLE 2. Empirical Evaluation Index System

Primary Indicator	Secondary Indicator	Indicator Description	Calculation Method
Inventory Control Effect	Inventory Turnover Rate	Reflects inventory turnover efficiency	Cost of sales / Average inventory balance
	Inventory Accuracy Rate	Reflects the accuracy of inventory data	Actual inventory quantity / System-recorded inventory quantity × 100%
	Demand Forecasting Error Rate	Reflects the accuracy of demand forecasting	-
Cost Optimization Effect	Procurement Cost Reduction Rate	Reflects the optimization effect of procurement costs	(Procurement cost in benchmark period - Procurement cost in empirical period) / Procurement cost in benchmark period × 100%
	Warehousing Cost Reduction Rate	Reflects the optimization effect of warehousing costs	(Warehousing cost in benchmark period - Warehousing cost in empirical period) / Warehousing cost in benchmark period × 100%
	Stock-out Cost Reduction Rate	Reflects the optimization effect of stock-out costs	(Stock-out cost in benchmark period - Stock-out cost in empirical period) / Stock-out cost in benchmark period × 100%
	Transportation Cost Reduction Rate	Reflects the optimization effect of transportation costs	(Transportation cost in benchmark period - Transportation cost in empirical period) / Transportation cost in benchmark period × 100%
	Comprehensive Cost Reduction Rate	Reflects the overall cost optimization effect	(Comprehensive cost in benchmark period - Comprehensive cost in empirical period) / Comprehensive cost in benchmark period × 100%
Supply Chain Integration Effect	Supply Chain Response Speed	Reflects supply chain agility	Order processing cycle
	Collaboration Efficiency	Reflects supply chain collaboration	Timeliness rate of cross-enterprise data sharing
	Customer Satisfaction	Reflects supply chain service quality	Customer satisfaction survey score (5-point scale)

TABLE 3. Comparison of Inventory Control Effects

Enterprise Type	Indicator	Benchmark Period (2021)	Empirical Period (2023)	Change Range
Manufacturing Industry (Enterprise A)	Inventory Turnover Rate (Times/Year)	5.2	7.5	+44.2%
	Inventory Accuracy Rate (%)	92.3	99.5	+7.8%
	Demand Forecasting Error Rate (%)	35.6	21.5	-39.6%
Retail Industry (Enterprise B)	Inventory Turnover Rate (Times/Year)	8.7	12.4	+42.5%
	Inventory Accuracy Rate (%)	93.5	99.3	+6.2%
	Demand Forecasting Error Rate (%)	32.8	19.8	-39.6%
Fresh Food Industry (Enterprise C)	Inventory Turnover Rate (Times/Year)	12.3	17.5	+42.3%
	Inventory Accuracy Rate (%)	91.7	98.8	+7.7%
	Demand Forecasting Error Rate (%)	38.7	23.7	-38.8%
Average	Inventory Turnover Rate (Times/Year)	-	-	+43.0%
	Inventory Accuracy Rate (%)	-	-	+7.2%
	Demand Forecasting Error Rate (%)	-	-	-39.3%

TABLE 4. Comparison of Inventory Control Effects

Enterprise Type	Indicator	Benchmark Period (2021) (10,000 yuan)	Empirical Period (2023) (10,000 yuan)	Reduction Rate
Manufacturing Industry (Enterprise A)	Procurement Cost	8600	7150	16.9%
	Warehousing Cost	2300	1560	32.2%
	Stock-out Cost	980	560	42.9%
	Transportation Cost	1800	1380	23.3%
	Comprehensive Cost	13680	10650	22.1%
Retail Industry (Enterprise B)	Procurement Cost	12500	10150	18.8%
	Warehousing Cost	3800	2580	32.1%
	Stock-out Cost	1560	870	44.2%
	Transportation Cost	2600	1950	25.0%
	Comprehensive Cost	20460	15550	24.0%
Fresh Food Industry (Enterprise C)	Procurement Cost	6800	5380	20.9%
	Warehousing Cost	2100	1390	33.8%
	Stock-out Cost	1280	720	43.8%
	Transportation Cost	1900	1420	25.3%
	Comprehensive Cost	12080	8910	26.2%
Average	Procurement Cost Reduction Rate	-	-	18.9%
	Warehousing Cost Reduction Rate	-	-	32.7%
	Stock-out Cost Reduction Rate	-	-	43.6%
	Transportation Cost Reduction Rate	-	-	24.5%

TABLE 5. Comparison of Supply Chain Integration Effects

Enterprise Type	Indicator	Benchmark Period (2021)	Empirical Period (2023)	Change Range
Manufacturing Industry (Enterprise A)	Order Processing Cycle (Days)	7.8	4.2	-46.2%
	Data Sharing Timeliness Rate (%)	75.3	96.8	+28.5%
	Customer Satisfaction (Score)	3.8	4.6	+21.1%
Retail Industry (Enterprise B)	Order Processing Cycle (Days)	3.5	1.8	-48.6%
	Data Sharing Timeliness Rate (%)	82.5	97.5	+18.2%
	Customer Satisfaction (Score)	4.0	4.7	+17.5%
Fresh Food Industry (Enterprise C)	Order Processing Cycle (Days)	2.8	1.2	-57.1%
	Data Sharing Timeliness Rate (%)	78.6	96.2	+22.4%
	Customer Satisfaction (Score)	3.7	4.5	+21.6%
Average	Order Processing Cycle (Days)	-	-	-50.6%
	Data Sharing Timeliness Rate (%)	-	-	+23.0%

According to Table 5, the deep integration effect of intelligent logistics and supply chain in three types of enterprises is significant:

The average order processing cycle has been shortened by 50.6%, with the fresh food industry experiencing the largest reduction (57.1%), indicating a significant improvement in supply chain response speed;

2. The average timely rate of data sharing has increased by 23.0%, reaching over 96%, indicating a significant improvement in the efficiency of information sharing in various links of the supply chain;

3. The average customer satisfaction has increased by 19.7%, reaching 4.5 points or above, indicating a significant improvement in the quality of supply chain services.

4) Empirical Conclusion

The inventory precision control system and cost optimization model supported by IoT technology have signif icant effectiveness, and the inventory control effect, cost optimization effect, and supply chain integration effect of the three types of enterprises have been greatly improved, verifying the scientific and operable nature of the proposed system and model.

2. There are differences in the application effects among different industries: the fresh food industry has the most significant effect in improving inventory turnover, reducing out of stock costs, and shortening order processing cycles, which is related to the industry characteristics of high requirements for inventory timeliness and freshness in the fresh food industry; The manufacturing industry has the best effect in improving inventory accuracy, while the retail industry has shown outstanding performance in reducing procurement costs.

3. The deep integration of intelligent logistics and supply chain has achieved the synergistic improvement of inventory control and cost optimization through the mechanism of "data connectivity decision intelligence collaborative efficiency", proving that integrated development is the core path for high-quality development of supply chain.

4. Internet of Things technology is the core support for the integration of intelligent logistics and supply chain. Its application in data collection, information sharing, intelligent decision-making, and collaborative scheduling provides key guarantees for accurate inventory control and cost optimization.

VII. CONCLUSION

Based on the background of digital transformation, this article constructs a four-in-one analysis framework of "Internet of Things technology - precise inventory control - cost optimization - textile production integration" to synchronize raw fiber management with high-speed weaving schedules. This structure reveals how real-time data from spinning machinery and textile storage units drives the intelligent coordination of materials to achieve systematic efficiency throughout the manufacturing cycle. Through theoretical analysis, system design, model construction, and multi industry empirical research, the following core conclusions are drawn: The core features of the deep integration of intelligent logistics and supply chain include data connectivity, intelligent decision-making, efficient collaboration, and agile resilience. IoT technology provides comprehen sive technical support for the integration through four mechanisms: data collection, information sharing, intelligent decision-making, and collaborative scheduling.

2. The inventory precision control system based on IoT technology (data collection demand forecasting dynamic replenishment intelligent scheduling) can significantly improve the inventory control effect, increase the average inventory turnover rate of enterprises by 43.0%, achieve inventory accuracy of over 98.8%, and reduce the demand forecasting error rate by 39.3%, effectively solving the problem of extensive traditional inventory management.

3. The inventory cost optimization model achieves an average reduction of 24.1% in the comprehensive cost of the supply chain by quantifying four types of costs: procurement, warehousing, stockouts, and trans portation. Among them, the stockout cost reduction rate is the highest (43.6%), followed by warehousing cost (32.7%), verifying the cost optimization effect of the model.

4. Empirical evidence from multiple industries shows that IoT technology and the proposed system and model have significant effectiveness in manufacturing, retail, and fresh food industries. However, there are industry differences in their application effects. The fresh food industry has the most significant effects in improving inventory turnover, reducing out of stock costs, and shortening order processing cycles. Manufacturing has the best performance in improving inventory accuracy, while retail has outstanding performance in reducing procurement costs.

5. The deep integration of intelligent logistics and textile production cycles achieves the collaborative improvement of fiber inventory control and weaving cost optimization through a mechanism of "data connectivity-decision intelligence-collaborative efficiency." This synergy constitutes the core path for the high-quality development of textile manufacturing networks under digital transformation by ensuring real-time synchronization between raw spinning materials and automated loom outputs.

The demand forecasting error rate decreased from 35.6% to 21.5% (39.6% improvement), which is a synergistic effect of IoT real-time data support and integrated prediction model optimization, rather than a single effect of IoT hardware.

AUTHOR CONTRIBUTIONS

Conceptualization –Zongyao Sun, Yuqing Qin and Jie Liu; methodology – Zongyao Sun, Yuqing Qin and Jie Liu; investigation – Zongyao Sun, Yuqing Qin and Jie Liu; writing-original draft preparation – Zongyao Sun, Yuqing Qin and Jie Liu. All authors have read and agreed to the published version of the manuscript.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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REFERENCES

[1] S. Deepti, K. Bijendra, S. Samayveer, et al., “A Secure IoT-Based Mutual Authentication for Healthcare Applications in Wireless Sensor Networks Using ECC,” International Journal of Healthcare Information Systems and Informatics (IJHISI), vol. 16, no. 2, pp. 21-48, 2021, doi: 10.4018/IJHISI.20210401.OA2.

[2] H. John, T. Stephen, M. Subhas, et al., “A randomised control trial for measuring student engagement through the Internet of Things and serious games,” Internet of Things, vol. 13, Art. no. 100332, 2021, doi: 10.1016/j.iot.2020.100332.

[3] G. Martin, B. Joakim, P. Francesca, et al., “Evaluating the performance of the OSCORE security protocol in constrained IoT environments,” Internet of Things, vol. 13, Art. no. 100333, 2021, doi: 10.1016/j.iot.2020.100333.

[4] A. Ramsha, C. Yueyun, H. Bilal, et al., “CR-IoTNet: Machine learning based joint spectrum sensing and allocation for cog nitive radio enabled IoT cellular networks,” Ad Hoc Networks, vol. 112, Art. no. 102390, 2021, doi: 10.1016/j.adhoc.2020.102390.

[5] N. Sameena, “Detection of Phishing in Internet of Things Using Machine Learning Approach,” International Journal of Digital Crime and Forensics (IJDCF), vol. 13, no. 2, pp. 1-15, 2021, doi: 10.4018/IJDCF.2021030101.

[6] B.D, “D, Fadi A,” Lightweight authentication for IoT/Cloud-based forensics in intelligent data computing. Future Generation Computer Systems, vol. 116, pp. 406-425, 2021, doi: 10.1016/j.future.2020.11.010.

[7] R. Hasan M, R. Asifur M N A, A. Habiba U, et al., “IoT Botnet Detection Using Various One-Class Classifiers,” Vietnam Journal of Computer Science, pp. 8(2), 2021, doi: 10.1142/S2196888821500123.

[8] M.C, “R A, R,” B A, M. A P O, et al. Multifaceted infrastructure for self-adaptive IoT systems. Information and Software Technology, vol. 132, Art. no. 106505, 2021, doi: 10.1016/J.INFSOF.2020.106505.

[9] G. Mengmeng, S. Firdous N, F. Xiping, et al., “Towards a deep learning-driven intrusion detection approach for Internet of Things,” Computer Networks, pp. 186, 2021, doi: 10.1016/J.COMNET.2020.107784. 4606.

[10] I. Bakir, M. Aerts-Veenstra, J. Roodbergen K, et al., “Supply chain and logistics in digital transformation,” A Research Agenda for Digital Transformation, pp. 187-224, 2024, doi: 10.4337/9781035306435.00014.

[11] H. Timber, L. Minh T P, N. Nhan, et al., “Business model innovation through the application of the Internet-of-Things: A comparative analysis,” Journal of Business Research, vol. 126, pp. 126-136, 2021, doi: 10.1016/J.JBUSRES.2020.12.034.

[12] L. Qiang, S. Songlin, Y. Xueguang, et al., “Ambient backscatter communication-based smart 5G IoT network,” EURASIP Journal on Wireless Communications and Networking, Art. no. 2021(1), 2021, doi: 10.1186/S13638-021-01917-3.

[13] R. Khaled and C. Jieren, “Adaptive XACML access policies for heterogeneous distributed IoT environments,” Information Sciences, vol. 548, pp. 135-152, 2021, doi: 10.1016/j.ins.2020.09.051.

[14] P. Alejandro, C. Carlos, and P. Ernesto, “Modelling digital avatars: A tuple space approach,” Science of Computer Programming, pp. 203, 2021, doi: 10.1016/J.SCICO.2020.102583.

[15] N. Agafonova A, “Digital transformation of logistics,” Vestnik of Samara State University of Economics, vol. 9, no. 203, pp. 18-22, 2021, doi: 10.46554/1993-0453-2021-9-203-18-22.

[16] A. Nazir, S. Sholla, and A. Bashir, “An Ontology based Approach for Context-Aware Security in the Internet of Things (IoT),” International Journal of Wireless and Microwave Technologies(IJWMT), vol. 11, no. 1, pp. 28-46, 2021, doi: 10.5815/ IJWMT.2021.01.04.

[17] J. Mukhopadhyay, V. Singh K, S. Mukhopadhyay, et al., “A truthful budget feasible mechanism for IoT-based participa tory sensing with incremental arrival of budget,” Journal of Ambient Intelligence and Humanized Computing, 2021, doi: 10.1007/S12652-020-02844-9.

[18] A. Kerem and K. Ömer, “IoT based intelligence for proactive waste management in Quick Service Restaurants,” Journal of Cleaner Production, pp. 284, 2021, doi: 10.1016/J.JCLEPRO.2020.125401.

[19] R. Akpalu, “Digital Transformation in Logistics: Strategic Use of Mathematics for Supply Chain Optimization,” International Journal of Research and Innovation in Social Science, vol. IX, no. I, pp. 4155-4163, 2025, doi: 10.47772/ ijriss.2025.9010324.

[20] A. Toymentseva I, D. Chichkina V, and A. Shafieva M, “Digital Transformation of Transport Logistics Under Current Conditions,” Lecture Notes in Networks and Systems, pp. 355-362, 2022, doi: 10.1007/978-3-030-83175-2_45.

[21] R. Stasiak-Betlejewska and K. Czarczyk, “Digital Transformation of Logistics: How Modern Technologies Increase Supply Chain Safety,” System Safety: Human - Technical Facility - Environment, vol. 6, no. 1, pp. 410-420, 2024, doi: 10.2478/ czoto-2024-0042. 4607.

[22] J. Maecka, M. Grodecka, and A. Koliski, “Digital Transformation in Logistics: Adoption of Intelligent Technologies and Determinants in Supply Chain Enterprises,” Horizons of Politics / Horyzonty Polityki, pp. 16(57), 2025, doi: 10.35765/ HP.2919.

[23] A. Volkova, Y. Nikitin, and V. Plotnikov, “Digital transformation of procurement logistics,” Economics and Management, 2022, doi: 10.35854/1998-1627-2022-8-778-785.

[24] H. Tsikh and V. Suhoversha, “Logistics in the context of digital transformation,” Galician economic journal, vol. 91, no. 6, pp. 40-48, 2024, doi: 10.33108/galicianvisnyk_tntu2024.06.040.

[25] S. Pan, D. Trentesaux, D. McFarlane, B. Montreuil, E. Ballot, and Q. Huang G, “Digital interoperability and transforma tion in logistics and supply chain management: Editorial,” Computers in Industry, pp. 129(1), 2021, doi: 10.1016/ j.compind.2021.103462.

[26] T. Tran H, T. Pham Q T, and V. Nguyen P, “Digital transformation solution implementation risk in logistics and supply chain industry,” Discover Sustainability, pp. 7(1), 2026, doi: 10.1007/s43621-026-02603-4.

[27] E. Ali A A, Z. Xinli, M. Ul Hoque M, et al., “Impact of Digital Transformation of Logistics and Supply Chain in the Automotive Manufacturing Industry,” Journal of Business & Management Studies (2709-0876), pp. 7(10), 2025, doi: 10.32996/jbms.2025.7.10.3. 4608.