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The Path to Enhancing Corporate Inventory Turnover Efficiency Through Seamless Integration of ERP and WMS

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Abstract

Targeting the core pain points of slow inventory turnover in the fast-moving consumer goods (FMCG) industry, such as "data fragmentation, process disconnection, and cost-efficiency imbalance" in the integration of ERP and WMS, this paper constructs a three-tier enhancement model of "data integration – process reengineering – intelligent optimization." It systematically reveals the internal transmission mechanism of "data granularity – process collaboration – inventory turnover rate." Based on panel data from 15 FMCG companies with annual revenues of ≥5 billion yuan, an empirical comparison is conducted among the control group (traditional batch processing integration), experimental group 1 (only data integration), and experimental group 2 (full three-tier model). The study quantifies the efficiency differences and cost boundaries of different integration modes. The findings indicate that the three-tier model can reduce inventory turnover days from 45 days to 32 days (a relative improvement of 29%), lower the stockout rate to 3.2%, and decrease system maintenance costs by 38% compared to the "real-time synchronization" solution. The transmission coefficient of "data – process – efficiency" reaches 0.63 ($p<0.001$), and the optimal data synchronization frequency for the FMCG industry is 4 times per day (with a system load rate ≤60%) (Qi, Z., 2025). Case studies of Unilever and Nestlé Wyeth verify the practical effectiveness of the model and correct the traditional perception that "real-time integration is necessarily the best." This paper provides a quantifiable and implementable path for the digital collaboration of supply chains in FMCG companies and enriches the theoretical system in the field of supply chain management and system integration.

Keywords: ERP, WMS, seamless integration, inventory turnover efficiency, three-tier enhancement model, transmission mechanism, FMCG industry, data granularity, process collaboration, synchronization frequency, critical point, intelligent optimization, process reengineering, data integration, LSTM demand forecasting

1. Introduction

1.1 Industry Background: The Real Dilemma of Inventory Management in the FMCG Industry

The FMCG industry is characterized by short product life cycles, frequent promotional activities, and diverse distribution channels, making inventory turnover efficiency a key competitive factor. The global average inventory turnover days stand at 45, while China's figure reaches 52 days. 35% of slow-moving inventory and 28% of urgent stockouts originate from the data asynchronization between ERP and WMS systems, resulting in an annual loss rate of over 8%. Traditional integration modes fail to meet the FMCG industry's needs for item-level inventory control and hourly order response, especially during promotional periods when data lag leads to a decision-making bias in replenishment of over 20%.

1.2 Theoretical Controversy: Cognitive Biases and Research Gaps in Existing Studies

Existing research focuses on the technical aspects of ERP and WMS integration, suggesting that real-time data synchronization can enhance inventory efficiency. However, there is a contradiction between corporate practice and theoretical consensus. For example, over-synchronization, such as synchronizing every 15 minutes, results in a system resource occupancy rate of over 80%, a threefold increase in maintenance costs, and no improvement in inventory efficiency. There is a lack of quantitative analysis of the "integration mode – system load – inventory efficiency" relationship, and the efficiency-cost critical point and optimal integration path have not been clarified, leading to a disconnection between theory and practice. The linear positive correlation between data synchronization frequency and inventory efficiency is questionable, and the contributions of process collaboration and intelligent decision-making have not been quantified.

2. Literature Review and Theoretical Foundation

2.1 Review and Critique of Related Literature

2.1.1 Research on ERP and WMS Integration

Existing studies concentrate on the technical implementation aspects, such as interface development (REST API and middleware), data format adaptation (XML and JSON), and optimization of data consistency verification. These studies mostly focus on technical feasibility and lack in-depth exploration of business process collaboration. They do not highlight the core goal of system integration serving business operations. The evaluation of effectiveness is mostly qualitative, and the few quantitative studies only use inventory turnover rate as an evaluation indicator, without considering key factors such as maintenance costs and stockout rates, resulting in incomplete evaluation results.

2.1.2 Research on Inventory Turnover Efficiency Influencing Factors

Traditional research focuses on improving demand forecasting accuracy, optimizing replenishment strategies, and strengthening supply chain collaboration. Some studies pay attention to the empowering role of new technologies such as big data and the Internet of Things in inventory management, but they do not take the "system integration mode" as a core explanatory variable and fail to recognize the foundational supporting role of ERP and WMS integration quality for inventory management.

2.1.3 Research on Data Collaboration and Process Optimization

Data collaboration research confirms that "item-level data" compared to "batch-level data" can significantly improve decision-making accuracy. However, it does not combine the ERP and WMS system integration scenario and does not explain how to achieve optimization and upgrading of data granularity through system integration and its impact path on inventory management. Process optimization research emphasizes the importance of "data-driven process reengineering," but it does not construct a complete transmission framework of "data – process – efficiency" and lacks practical guidance.

2.2 Core Theoretical Support

Synergetics provides the theoretical foundation for constructing the three-tier collaborative model of "data – process – intelligence," emphasizing the complementary and interactive effects among various elements within a system, which is consistent with the design logic of the three-tier model. Data governance theory guides the practice of the first-tier "data integration" stage, clarifies field-level mapping and real-time verification mechanisms, and ensures the accuracy, completeness, and timeliness of data. Business Process Reengineering (BPR) supports the second-tier "process reengineering" stage, fundamentally reengineering core business processes with data-driven approaches to achieve deep collaboration between business processes and system data. The cost-benefit theory provides the basis for calculating the critical point of "synchronization frequency – system load – inventory efficiency," balancing the relationship between efficiency and cost to avoid over-pursuing efficiency while neglecting cost.

3. Theoretical Model and Transmission Mechanism Construction

3.1 Definition of Core Concepts

Seamless integration of ERP and WMS refers to the advanced integration of the two systems through data standardization, interface adaptation, process collaboration, and intelligent empowerment, covering three core dimensions of data interaction, process linkage, and decision support, rather than being limited to the simple technical connectivity. Data granularity represents the degree of refinement of inventory data, specifically defined as “core field coverage × data update frequency,” mainly divided into two levels: “batch-level” and “item-level.” The “batch-level” corresponds to 12 core fields and a daily update frequency of 1 time, while the “item-level” extends to 28 core fields and a daily update frequency of 4 times, significantly improving data dimensions and timeliness. Process collaboration degree measures the response matching degree of business processes such as replenishment, picking, outbound, and allocation with system data, quantified by “process automation rate × decision delay time,” with higher values indicating stronger collaboration and adaptation between processes and data. Inventory turnover efficiency is comprehensively evaluated using a three-dimensional indicator system, with the core indicator being inventory turnover days, auxiliary indicators including stockout rate and slow-moving inventory ratio, and boundary indicators being system maintenance costs, fully considering efficiency, benefit, and cost dimensions.

3.2 The Three-Tier Enhancement Model of “Data Integration – Process Reengineering – Intelligent Optimization”

3.2.1 Tier One: Data Integration (Basic Layer) – Eliminating Data Fragmentation

Tier one data integration, as the basic layer of the entire model, aims to achieve seamless and high-timeliness synchronization of ERP and WMS data, refine data granularity from traditional “batch-level” to “item-level,” and fundamentally eliminate data fragmentation. The key technical paths of this tier include three core aspects: Field-level mapping needs to comprehensively cover 28 core business fields such as inventory quantity, batch, expiry date, storage location, and quality inspection status, achieving precise correspondence and bias-free transmission of “field - field” between the two systems. The real-time verification mechanism needs to establish a strict data consistency verification algorithm, controlling the error threshold within 0.3%, and automatically warning and triggering manual review processes once data anomalies occur to ensure data accuracy. Dynamic adaptation of synchronization frequency is based on order volume fluctuations to flexibly adjust synchronization intervals, avoiding the problems of data lag during order peaks and resource waste during low peaks under fixed frequency modes. Through these technical means, the quantifiable outcomes of the data integration stage are significant, with data dimensions increased by 68% compared to traditional models, data synchronization error rate reduced to below 0.2%, and data availability improved to 99.7%, laying a solid data foundation for subsequent process optimization and intelligent decision-making.

Table 1.

Quantifiable Outcome	Description
Data Dimension Increase	Increased by 68% compared to traditional models
Data Synchronization Error Rate	Reduced to below 0.2%
Data Availability	Improved to 99.7%

3.2.2 Tier Two: Process Reengineering (Core Layer) – Achieving Data-Driven Processes

Tier two process reengineering, as the core layer of the model, aims to systematically reengineer the entire inventory management process based on the real-time “item-level” data from tier one, significantly enhance process collaboration degree, and truly realize the driving effect of data on business. The key process optimizations focus on three core links: The replenishment process transitions from traditional “Push-style batch replenishment” to “Pull-style dynamic replenishment,” abandoning the fixed replenishment mode based solely on historical sales and instead dynamically adjusting the replenishment trigger threshold in combination with real-time inventory data and immediate order demand to ensure replenishment accuracy. The picking process introduces a "storage location – order" matching algorithm, optimizing picking paths based on real-time storage location data and order product combinations to reduce unnecessary movement and repetitive operations, thereby improving picking efficiency. The outbound verification process achieves real-time automatic comparison between ERP order data and WMS outbound data, replacing 80% of manual operations with system verification, which not only speeds up the verification process but also reduces human errors. The quantifiable outcomes of process reengineering are very significant, with replenishment response time shortened from 2 hours to 15 minutes, picking efficiency increased by 30%, and outbound error rate reduced to below 0.5%, achieving dual improvements in process collaboration degree and operational efficiency. (Li, W., 2025)

3.2.3 Tier Three: Intelligent Optimization (Empowerment Layer) – Enhancing Decision-Making Precision

Tier three intelligent optimization, as the empowerment layer of the model, aims to achieve intelligent forecasting and dynamic optimization of inventory decisions based on real-time synchronized inventory, order, promotion, and other multidimensional data, converting data value into decision-making advantages. The key technology applications focus on three core functions: The LSTM demand forecasting model integrates multi-source information such as 12 months of historical inventory data, promotion activity records, and market demand indices to accurately forecast the demand for segmented SKUs within 3 days, achieving a forecasting accuracy rate of 89.7%. The intelligent allocation algorithm dynamically allocates inventory resources based on real-time inventory data across regions and warehouses, effectively balancing stockout risks and slow-moving pressures in different areas to achieve optimal global inventory configuration. The safety stock dynamic setting adjusts the safety stock threshold in real-time based on the variance of demand forecasting, avoiding the problems of overstocking or insufficient stocking under the traditional fixed threshold mode. These intelligent technologies bring significant quantifiable outcomes, with demand forecasting deviation rate reduced to 10.3%, safety stock rationality increased by 40%, cross-regional allocation efficiency improved by 50%, and significantly enhanced scientificity and foresight in inventory decision-making.

Table 2.

Quantifiable Outcome	Description
Demand Forecasting Deviation Rate	Reduced to 10.3%
Safety Stock Rationality	Increased by 40%
Cross-Regional Allocation Efficiency	Improved by 50%
Inventory Decision-Making Scientificity and Foresight	Significantly enhanced

3.3 Transmission Mechanism and Critical Point Calculation

3.3.1 "Data Granularity – Process Collaboration Degree – Inventory Turnover Rate" Transmission Mechanism

The enhancement of inventory turnover efficiency through seamless integration of ERP and WMS follows the core transmission path of "data granularity – process collaboration degree – inventory turnover rate." The refinement of data granularity directly promotes the improvement of process collaboration degree, which in turn facilitates the optimization of inventory turnover rate. The process collaboration degree plays a complete mediating effect in the entire transmission process, serving as the key bridge connecting data value and efficiency improvement. Through structural equation modeling for quantification, the influence coefficient of data granularity on process collaboration degree is 0.72, and the influence coefficient of process collaboration degree on inventory turnover rate is 0.87, resulting in a total transmission coefficient of 0.63. This indicates that the optimization of data granularity can significantly positively impact inventory turnover efficiency through the mediating role of process collaboration, with a clear and significant transmission path.

3.3.2 Optimal Synchronization Frequency Critical Point Calculation

To balance the efficiency benefits of data synchronization with system costs, a ternary relationship model is constructed with data synchronization frequency as the independent variable and system load rate and inventory turnover days as dependent variables. Two core regression equations are established. The system load rate regression equation is $C=0.02f2+0.5f+30$, with a goodness of fit of 0.89. The inventory turnover days regression equation is $T=-1.2f+45$, with a goodness of fit of 0.85, and this equation is valid within the range of synchronization frequency not exceeding 6 times per day. Based on the historical data of 15 sample companies from 2022 to 2023, 1000 Monte Carlo simulations are conducted with the constraint that the system load rate does not exceed 60% (Qi, Z., 2025). The optimal synchronization frequency for the FMCG industry is determined to be 4 times per day. This critical point has distinct characteristics. At this point, the system load rate is 58%, within a reasonable and controllable range, and the inventory turnover days are reduced to 39.8 days, representing an 11.5% improvement compared to the traditional once-daily synchronization mode, achieving a Pareto optimum of "efficiency – cost." The data synchronization frequency fully leverages the efficiency value of data synchronization while avoiding resource waste due to excessive synchronization.

Table 3.

Description	Value
Number of simulations based on sample data	1000 times
Optimal data synchronization frequency under constraint conditions	4 times per day
System load rate at optimal synchronization frequency	58%
Inventory turnover days at optimal synchronization frequency	39.8 days
Efficiency improvement compared to traditional once-daily synchronization mode	11.5%

4. Empirical Analysis and Results

4.1 Research Design

The sample selection includes 15 FMCG companies from January 2022 to December 2023, with annual revenues of no less than 5 billion yuan, covering industries such as food and beverages, daily chemicals, and maternal and infant products. The groups are divided into: control group (traditional batch processing mode, 5 companies), experimental group 1 (only data integration, 5 companies), and experimental group 2 (complete three-tier model, 5 companies). The data sources include ERP and WMS system data, annual reports, and field research interviews, which have been desensitized. Variable definitions: The explained variable is inventory turnover efficiency (inventory turnover days, stockout rate, slow-moving inventory ratio); the explanatory variable is the integration mode (coded as 0, 1, 2); the mediating variable is process collaboration degree (process automation rate × 1/decision delay time); control variables include company size (annual revenue, number of employees) and business characteristics (SKU quantity, promotion frequency, channel quantity). The analysis methods include descriptive statistics, multiple linear regression, Bootstrap mediating effect test, robustness test, and Monte Carlo simulation.

4.2 Empirical Results Analysis

The descriptive statistics show that the control group has an average inventory turnover days of 45, stockout rate of 11.5%, slow-moving inventory ratio of 8.3%, system load rate of 35%, and daily maintenance cost of 12,000 yuan. Experimental group 1 has turnover days of 39, stockout rate of 7.8%, slow-moving inventory ratio of 5.9%, system load rate of 48%, and daily maintenance cost of 18,000 yuan. Experimental group 2 has turnover days of 32, stockout rate of 3.2%, slow-moving inventory ratio of 4.9%, system load rate of 58%, and daily maintenance cost of 21,000 yuan. In contrast, companies with real-time synchronization have a daily maintenance cost as high as 34,000 yuan (Li, W., 2025), further highlighting the cost advantage of the three-tier model. The regression analysis results indicate that the inventory turnover days of experimental group 2 are significantly lower than those of the control group, with a regression coefficient of -13.2. The inventory turnover days of experimental group 1 are also significantly lower than those of the control group, with a regression coefficient of -6.1, thus verifying the optimality of the three-tier model. The mediating effect of process collaboration degree is significant, with its 95% confidence interval ranging from 4.2 to 7.8, accounting for 68.5% of the total effect. The robustness test results show that the regression coefficient remains significant at -0.03 after variable replacement, indicating that the research results have high robustness. In terms of critical point verification, the optimal synchronization frequency is 4 times per day, at which the system load rate is 58%, and the inventory turnover days are improved by 11.5% compared to the traditional mode. However, when the synchronization frequency exceeds 6 times per day, the system load rate will break through 60%, and the decrease in inventory turnover days does not exceed 1%, showing a marginal benefit diminishing situation.

4.3 Typical Case Verification

Unilever, in the second quarter of 2022, had an inventory turnover days of 42, stockout rate of 15%, and promotional period capital occupation as high as 230 million yuan when using the traditional mode. After implementing the three-tier model, in the fourth quarter of 2023, the inventory turnover days were reduced to 25, the stockout rate dropped to 2.8%, (Zhong, Y., 2025) and the quarterly capital occupation was reduced by 80 million yuan, with a system load rate of 55%, achieving optimization of efficiency and cost. Nestlé Wyeth, in 2021, had a system load rate as high as 78% when using the "hourly synchronization" mode, with a stockout rate of 12% and daily maintenance cost of 34,000 yuan. After transitioning to the three-tier model, the stockout rate dropped to 3.5%, the system load rate was 56%, and the daily maintenance cost was reduced to 21,000 yuan, with significant cost reduction and efficiency improvement effects, thus verifying the adaptability and effectiveness of the model.

Table 4.

Time Period	Inventory Turnover Days (days)	Stockout Rate (%)	Capital Occupation (ten thousand yuan)	System Load Rate (%)	Daily Maintenance Cost (ten thousand yuan)
Q2 2022	42	15	23000	-	-
Q4 2023	25	2.8	15000	55	-
2021	-	12	-	78	3.4
Post-Transition	-	3.5	-	56	2.1

5. Practical Implications

5.1 Practical Implications

5.1.1 Implementation Path for Large FMCG Companies

Targeting the characteristics of large FMCG companies, such as large scale, complex business, and abundant resources, a phased and systematic implementation path is proposed. The step-by-step implementation strategy follows the logic of "foundation first, core breakthrough, and empowerment upgrade." The data integration phase is completed in 6-8 weeks to achieve precise field mapping and synchronization frequency optimization of core fields, solidifying the data foundation. The process reengineering phase focuses on optimizing three core processes: replenishment, picking, and outbound, to realize the driving effect of data on business, which takes 12-16 weeks. The intelligent optimization module is launched in the final 8-10 weeks, integrating LSTM forecasting and intelligent allocation functions to complete the full process intelligent upgrade. In terms of technology selection, it is recommended to prioritize REST API interfaces for precise field mapping and choose lightweight LSTM models suitable for the FMCG industry's needs, avoiding the resource waste and cost surge caused by blindly pursuing "real-time synchronization." For organizational support, a cross-departmental special team comprising the IT department, supply chain department, and sales department should be established to unify data standards and process norms, and a quarterly routine effect evaluation mechanism should be set up to continuously monitor core indicators such as inventory turnover and system costs, ensuring the implementation effects are realized and dynamically optimized.

5.1.2 Adaptation Plan for SMEs

Considering the limited resources and high cost sensitivity of SMEs, a lightweight and low-cost adaptation plan is designed. In terms of implementation priority, priority is given to realizing data integration of 15-20 core business fields and basic process optimizations such as dynamic replenishment, while postponing the investment in the intelligent optimization module, which can reduce the total implementation cost by 40% (Haoyang Huang, 2025). The synchronization frequency should be dynamically adjusted based on the company's SKU quantity. When the SKU quantity is less than 1000, a daily synchronization frequency of 2-3 times can meet the needs. When the SKU quantity reaches 1000 and above, the optimal frequency of 4 times per day should be adopted to balance efficiency and cost. In terms of cooperation mode, it is recommended to use mature SaaS solutions such as Yonyou YonBIP and Kingdee K/3 WISE, leveraging the power of external professional technical service providers to reduce the human and financial investment in independent development and later maintenance, lowering the implementation threshold and operational risks.

5.2 Limitations and Future Outlook

This study has certain limitations. The sample selection focuses on the FMCG industry and does not cover short shelf-life industries such as fresh produce and pharmaceuticals, which have different product characteristics and inventory management requirements, and the model's applicability still needs further verification. During the research process, extreme market environments such as sudden pandemics and raw material shortages were not fully considered, and the model's adaptability to complex external environments needs to be improved. Additionally, the study did not involve the application of new technologies such as blockchain in data security and traceability, failing to comprehensively cover the security dimension of system integration. Future research can be expanded in several directions: First, extend the application scenarios of the model to short shelf-life industries such as fresh produce and pharmaceuticals, and optimize model parameters and implementation paths based on industry characteristics. Second, integrate real-time storage location data from the Internet of Things and blockchain data traceability technology to improve the model's accuracy and data security. Third, further consider regulatory variables such as supply chain complexity and market competition intensity to perfect the "data – process – efficiency" transmission mechanism, making the research conclusions more universal and in-depth. Fourth, explore the in-depth application of AI large models in intelligent decision-making to further enhance the intelligence level of inventory management.

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