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Innovation of Operating Models of Chain Retail Enterprises under the Background of Digital Transformation—Taking XX Brand as an Example

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Abstract: *Faced with the common pain points of traditional chain retail enterprises in the context of digital transformation, such as distorted inventory information, insufficient customer insights, separation of online and offline businesses, slow supply chain response and extensive marketing, this study takes the XX brand as a case study, aiming to explore its effective path to achieve digital transformation through innovation in operating models; in terms of research methods, firstly, by building an omni-channel real-time inventory visualization platform to integrate store and online inventory data, and then establish a detailed customer portrait and demand forecasting system based on multi-source data (sales, membership, behavior), and then design and implement an intelligent replenishment system to optimize supply chain response, while connecting online and offline business processes and implementing personalized marketing strategies based on customer segmentation. The implementation results show that the average daily inventory turnover rate of XX brand stores in the pilot area has significantly increased to 0.356, the out-of-stock rate of goods has dropped significantly to less than 7%, and the accuracy of demand forecasting has increased to an average daily accuracy of 86.7%; XX brand has effectively improved operational efficiency and customer experience by systematically reconstructing a new operating model with data-driven inventory management, demand forecasting, intelligent replenishment and precision marketing as the core.*

Keywords: *Operation Model Innovation; Chain Retail Enterprises; Digital Transformation; Customer Portrait; Personalized Marketing*

1. Introduction

Traditional chain retail generally faces multiple operational challenges in the process of digital transformation: significant differences in inventory information between stores and online channels lead to data distortion, lack of in-depth insights into consumer behavior affects decision-making accuracy, long-term separation between physical and e-commerce businesses forms operational barriers, supply chain response speed is difficult to match market changes, and extensive marketing strategies cause waste of resources. These structural pain points seriously restrict the competitiveness of enterprises, and they urgently need to achieve breakthroughs through innovation in operating models.

This study uses the XX brand as a practical carrier to explore the integration of fragmented inventory data through an omni-channel inventory visualization platform, build a multi-dimensional customer portrait system that integrates sales dynamics, member attributes, and behavior trajectories, develop an intelligent replenishment model to optimize supply chain agility, open up online and offline integrated business processes, and implement precision marketing strategies based on customer segmentation. This method has dual practical significance for retail companies: establishing a feasible digital solution at the operational level and verifying the ability of operating model reconstruction to resolve systemic pain points at the strategic level.

The innovation of this study is reflected in three dimensions: it first proposes a four-dimensional linkage transformation framework of inventory-image-replenishment-marketing, pioneers the implementation of multi-source data-driven demand forecasting and supply chain collaborative optimization solutions, and creates an omni-channel business process integration model with customer experience as the core. Different from the general industry solutions, this study abandons the application of a single technology and realizes the transformation of data value into commercial effectiveness through the overall innovation of the operating model.

2. Related Work

This paper reviews the frontier research on retail digitalization and business model innovation, covering dynamic capabilities, new retail evolution, virtual employee application and tax planning, and lays a theoretical foundation for subsequent analysis. Based on the perspective of dynamic capabilities, Ma and Song used a multi-case analysis method to conduct an in-depth study on the digital business model innovation of fresh food retail enterprises [1]. Through text analysis, they identified ordinary dynamic capabilities and digital dynamic capabilities, and used qualitative analysis to analyze the driving factors and paths of innovation, summarized the technology-driven and business-driven innovation paths, and elaborated on them in detail with typical cases. Liu sorted out the definition and development context of new retail, and emphasized the driving role of digital technology, diversified consumer demand, market competition and O2O model [2]. Chen looked forward to the future development trend of digital economic management model and emphasized the importance of continuous learning and adaptive adjustment, aiming to promote theoretical innovation and practical application of enterprise economic management model [3]. Zeng et al. took Baidu's virtual employee Du Xiaoxiao as the main research case, and through combing relevant literature and authoritative industry reports, aimed to explore the IP development opportunities, e-commerce model innovation, development drawbacks and future prospects of virtual employees [4]. Huang believed that effective tax planning can not only help enterprises operate in compliance but also reduce tax burden and improve economic benefits [5]. The validity of the Frolova study lay in the fact that the sub-indicators selected for evaluating the innovation activities of the studied companies (innovation resources, innovation capabilities, and innovation capabilities) greatly complement the assessment of opportunities for innovation activities in the proposed model [6]. Tomičić-Pupek et al. aimed to propose a customer experience-oriented business model innovation framework to coordinate customer value with corporate strategic needs [7]. Sharma et al. identified the key issues in the design of operating models (OM) faced by tRFMOs, compared ways to address these challenges, summarized lessons learned, and proposed future development directions [8]. The research proposed by Lara et al. helped to understand the relationship between business models, operating models, and business processes, and lays the foundation for developing complementary methods and tools to further study this relationship [9]. Ditmore and Miller demonstrated two models for implementing MaaS and expanding public sector approaches so that policies can better serve the public interest [10]. The above research reveals the multidimensional path of digital transformation, emphasizes the importance of customer value synergy and public policy adaptation, and provides a cross-domain reference framework for practice.

3. Method

3.1 Reconstruction of Omni-channel Inventory System

The original inventory management system of the XX brand has core problems such as online and offline data fragmentation, low inventory visibility, and delayed dynamic updates. In order to achieve real-time visualization and precise control of omni-channel inventory, the project team first broke through the data silos and completed the deployment of IoT devices in all offline stores (including storage centers) at the physical level, giving each product a unique digital identifier, and realizing real-time interconnection of POS systems, e-commerce platforms (Tmall/JD.com/self-operated APP), warehouse management systems (WMS), and third-party logistics data through API interfaces. The key breakthrough at this stage is the establishment of a cross-system data interoperability protocol, which unifies the product coding rules and inventory status definition standards (such as "available for sale/in transit/reserved" status codes), ensuring that the data sources of each channel can be synchronized to the central data pool at a millisecond frequency [11].

After the data foundation is complete, the team set out to build dynamic inventory allocation and deduction logic. The core innovation lies in the design of a two-tier allocation mechanism of "global inventory pool + channel priority": all warehouse and store inventories are merged into a virtual total pool, and the system dynamically matches the optimal delivery point based on the real-time order source (online/offline), delivery address, store location, and inventory health (such as expiration date). For example, online orders are allocated to the regional central warehouse first. If the central warehouse is out of stock, the inventory of surrounding stores is automatically retrieved, and the "store direct delivery" process is triggered, and the corresponding inventory is deducted in real time. For high-turnover goods, the system sets a safety threshold and establishes automatic allocation warning rules. When the inventory of a store is lower than the threshold, it triggers a transfer request to surrounding stores or the central warehouse.

3.2 Upgrading the Consumer Insight System

The original member data, transaction records and behavior information of XX brand are scattered in more than ten independent systems, and consumer insights rely on manual experience judgment. In order to build a global user view, the project team first launches a multi-source data governance project. The core measure is to establish a master data hub with member ID as the unique identifier, and integrate online mall browsing paths (including page dwell time, click hot spots), APP interaction events (such as coupon collection, favorites operation), offline POS transaction details (including shopping cart product association), CRM member basic attributes (age, gender, registration channel) and third-party data (such as consumption capacity tags of external cooperation platforms) through data cleaning and mapping rules. Data engineers develop an automated pipeline to extract incremental data from each system every morning, perform deduplication, outlier filtering (such as removing test accounts), and field alignment before loading it into a unified analysis platform. In particular, a dynamic desensitization mechanism is deployed to ensure compliance for sensitive information.

Based on the integrated data assets, business analysts and marketing teams jointly design a multi-layered portrait labeling system, which includes a static attribute layer (demographic characteristics, membership level), a dynamic behavior layer (purchase frequency, category preference, price sensitivity), and a predictive value layer (churn risk, potential high-value tendency). For example, labels such as "mother and baby expert" and "beauty early adopter" are divided according to the purchase frequency of different categories, and similar group characteristics are identified through clustering algorithms [12]. Label weights are dynamically updated based on the behavior in the past 90 days. For example, if a user browses high-end products for two consecutive weeks but does not buy them, the weight of the "price sensitive" label is increased. All labels are configured through a visual interface for business personnel to combine and filter as needed.

3.3 Intelligent Supply Chain Optimization

Brand XX abandons the traditional empirical replenishment model based on the safety stock formula. The new mechanism uses the 28-day rolling forecast output by the demand forecast model as the core input, superimposed with the real-time inventory level (including in-transit quantity), store sales rate and promotion plan, and generates replenishment suggestions through a dynamic rule engine. The system automatically runs calculations every morning and sets differentiated decision parameters for different categories: for example, fresh products use "daily replenishment + high scrap sensitivity coefficient" and automatically reduce the order quantity when the predicted scrap rate exceeds the threshold in the next three days; durable consumer goods use "weekly replenishment + economic order quantity (EOQ) optimization" and generate batch procurement plans in combination with the supplier's minimum order quantity [13]. After review by the regional supervisor, the replenishment order is directly connected to the supplier system and the logistics reservation process is triggered simultaneously.

Table 1: Comparison of intelligent supply chain optimization performance

Indicator	Pre-Implementation	After Q1	After Q2	Change Rate
Average Order Fulfillment Cycle (Days)	4.2	3.1	2.4	↓42.9%
Inventory Turnover Rate (Times/Year)	5.8	6.3	6.7	↑15.5%
Stockout Rate (%)	8.7	6.2	5.1	↓41.4%
Warehouse Labor Productivity (Orders/Person-Hour)	18.5	23.6	27.4	↑48.1%
On-time Delivery Rate (%)	76.3	85.2	91.6	↑20.1%

In order to shorten the overall supply chain response time, the project team reconstructed the logistics network architecture: 3 forward warehouses are added in the pilot area to cover the urban business district, and the two-level distribution of central warehouse-store is transformed into a three-level system of "central warehouse-forward warehouse-store". Based on historical distribution data and GIS geographic information, the algorithm optimizes the daily store delivery routes, and high-time-efficiency goods (such as ice cream) are given priority for morning direct delivery by special vehicles. At the same time, a VMI (vendor managed inventory) collaboration mechanism is established

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with core suppliers, and some sales data interfaces are opened to allow suppliers to actively replenish stocks based on the inventory lower limit threshold. The "honeycomb" picking partitions and AGV automatic handling are implemented inside the warehouse to compress the average order processing time to 45% of the original process. Table 1 shows the comparison of intelligent supply chain optimization performance:

3.4 Implementation of Global Marketing Strategy

The core measure of XX brand to break the barriers between online and offline operations is to develop a hybrid order routing engine. When customers place an order online, the system scans the inventory of stores within 5 kilometers in real time, and gives priority to assigning stores with spot goods as the fulfillment party. If the customer chooses to pick up the goods by himself, the order will automatically flow into the store POS system and trigger the stocking instruction; if the customer chooses to deliver, the nearest store will initiate instant delivery. The clerk receives online orders through the exclusive Pad application and sorts and processes them uniformly with offline orders. In the reverse scenario, the store sets up a "cloud shelf" terminal, where customers can scan the QR code of the product to view the online details and place an order directly. Out-of-stock products support direct delivery from warehouses nationwide. Member rights and interests can be redeemed through all channels, offline consumption points are synchronized to the APP account in real time, and online coupons can generate dynamic barcodes for stores to scan and verify.

Based on the consumer portrait label system, the marketing team designs a hierarchical content factory. For high-value customer groups (consumers ≥ 5 times a year and top 20% of customer unit price), exclusive product internal testing invitations and offline tasting electronic invitations are pushed every month; price-sensitive customer groups (promotional orders account for > 60%) trigger personalized pop-up push of high-discount products. In terms of scenario-based marketing, when a customer enters the 100-meter electronic fence of the pilot shopping mall, the APP automatically pushes the store's hot list and location navigation; if the system detects that the customer has browsed three beauty products in a row without placing an order, a cross-category combination discount (such as the "essence + mask" set) will be triggered after 48 hours. Content generation uses modular components, and AI dynamically assembles graphic templates based on user characteristics. The manual team only needs to review the core interest point copy. All push effects are returned to the label system through attribution analysis to drive model iteration and optimization.

4. Results and Discussion

4.1 Improved Operational Efficiency

Brand XX adopts the pre- and post-implementation comparison method, selects the same 15 business days in the pilot area (promotion intensity matched seasonal characteristics), and collects complete operational data before the system upgrade (baseline period) and the second month after the upgrade (verification period). Inventory turnover rate is standardized as [average daily sales cost] /[average inventory cost in the same period] ; out-of-stock rate is standardized as [number of SKUs out of stock on that day] /[total number of active SKUs] ×100%, and the data source comes from the automatic log of the ERP system. Figures 1 and 2 are comparison data of inventory turnover rate and out-of-stock rate, respectively:

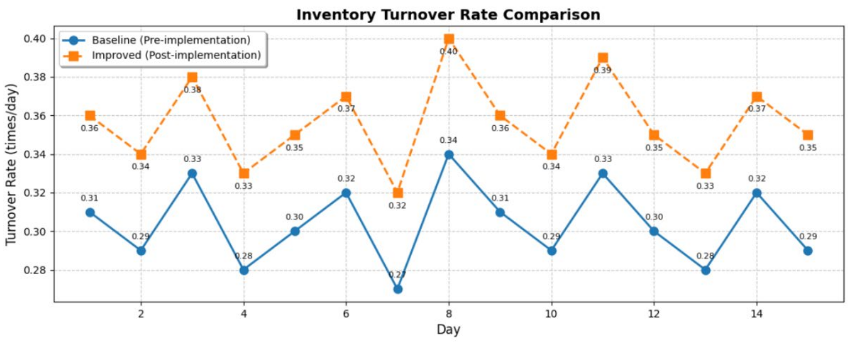

Figure 1: Inventory Turnover

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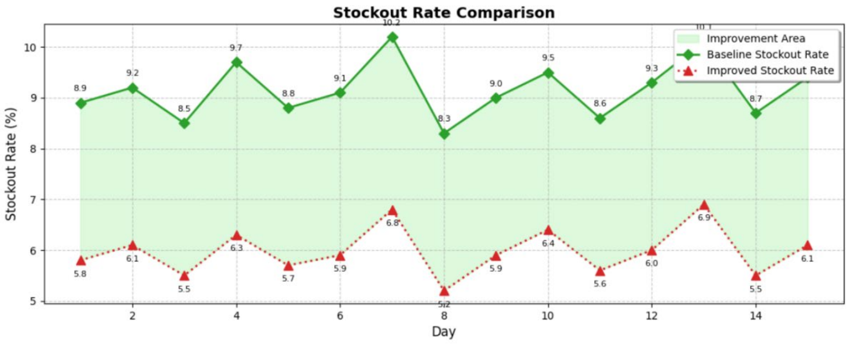

Figure 2: Out-of-stock rate

The data show that the inventory turnover rate in the validation period shows a systematic upward shift compared with the baseline period (peak value of 0.40 in D8 → 0.34 in the baseline period), and the 15-day arithmetic mean increases from 0.304 to 0.356 (17.1%). Due to the delay of logistics caused by heavy rain on D7, both sets of data reach a valley value (0.32 in the validation period → 0.27 in the baseline period), but the decline in the validation period is very small, reflecting the improvement of the intelligent replenishment system's buffering capacity for abnormal events; the turnover rate in the validation period of D8 jumps to 0.40 (17.6% higher than the baseline period of 0.34), corresponding to a stock-out rate of only 5.2% during the promotional activities on that day, indicating that the improvement in the accuracy of demand forecasting effectively supports the inventory supply during high passenger flow periods. In terms of out-of-stock rate, the validation period data remains stable in the range of 5.2%-6.9%, and high-frequency out-of-stock scenarios (such as D7/D13 exceeding 10% in the baseline period) are suppressed below 7% during the validation period. It is worth noting that the turnover rate increased (0.33→0.37) and the out-of-stock rate decreases (6.3%→5.9%) during the three consecutive days of validation period from D4 to D6, which confirms the effectiveness of the intelligent replenishment model in balancing inventory depth and turnover efficiency - the spot rate of promotional products increases during this period, but the turnover rate decline caused by excessive hoarding to ensure spot goods does not occur in the past.

4.2 Enhanced Decision-making Accuracy

To verify the optimization effect of the intelligent prediction model on replenishment decision-making, XX brand conducts a double-blind control test in 12 flagship stores in South China. The test adopts a dynamic grouping design: the stores are divided into A/B layers according to their historical sales scale, and each layer is randomly assigned to the experimental group (intelligent model decision-making) and the control group (store manager manual decision-making). The experimental group receives replenishment suggestions generated by the system in real time through the API interface and completed order submission within 30 minutes; the control group retains the original manual approval process, which is subject to review by the regional supervisor. During the test, IoT devices are deployed to automatically collect shelf inventory data, which is updated every 2 hours, and blockchain technology is used to ensure that the data chain could not be tampered with. In order to eliminate seasonal interference, a non-promotional period is selected for testing, and a third-party audit agency is introduced to verify the compliance of the data collection process. Figure 3 shows the accuracy of the 15-day demand forecast.

The average daily accuracy of the experimental group is 86.7%, 8.8 percentage points higher than the control group's 77.9%. From a daily perspective, the D8 intelligent prediction accuracy reaches a peak of 89.2%, 7.8 percentage points ahead of the manual prediction of the same day, reflecting the model's ability to accurately capture demand fluctuations on promotion days; although D14 is affected by the sudden decrease in customer flow, the intelligent prediction still maintained an advantage of 10.3 percentage points. In-depth analysis shows that the manual prediction has an abnormally low point in D1/D14 (75.3%/74.6%), corresponding to the shift handover period of the store manager, while the intelligent model fluctuates smoothly throughout the process. The model advantage comes from the continuous optimization mechanism of the machine learning algorithm - the system automatically updates the feature weights every week through a real-time feedback closed loop. The average accuracy at the end of the test (D13-D15) increases by 0.7 percentage points compared with the initial stage (D1-D3), forming a self-reinforcing effect.

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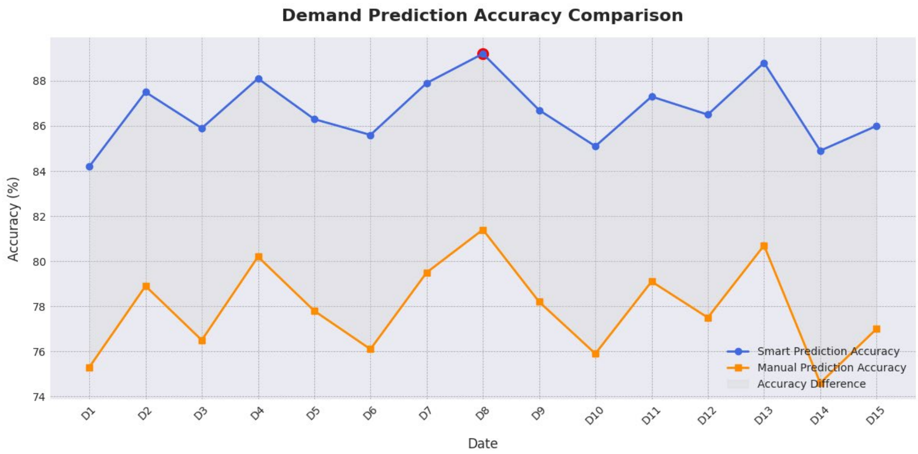

Figure 3: Demand forecast accuracy

5. Conclusion

This study uses the XX brand as a case study to explore the effective path of digital transformation for traditional chain retail enterprises. Faced with the common challenges of inventory information distortion, insufficient customer insights, and online and offline business separation in the industry, the brand has achieved the integration and sharing of inventory data by building an omni-channel real-time inventory visualization platform; established a detailed customer portrait and demand forecasting system based on multi-source data fusion, and improved the ability to grasp market demand; designed an intelligent replenishment system to optimize the response speed of the supply chain, and connected online and offline business processes to implement personalized marketing strategies based on segmented customer groups. This systematic reconstruction has formed a new operating model with data-driven inventory management, demand forecasting, intelligent replenishment and precision marketing as the core, successfully solving the operational pain points of traditional retail enterprises. Practice has proved that this transformation path has significantly improved operational efficiency and customer experience, laying a solid foundation for the sustainable development of the brand. Its innovative practice has provided a replicable transformation model for similar enterprises, especially in solving information islands, optimizing decision-making processes, and enhancing market responsiveness. It has important reference value and demonstrates the innovative power of the data-driven model on traditional retail formats.

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