

Collaborative Model of Business Analysis and Data Analysis in the Era of Big Data-Taking Retail Industry as an Example

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Abstract. The retail industry is closely related to people's lives and is also a driving force for the development of the national economy. This article focuses on studying the dynamic changes of the retail industry in the commercial market under the premise of rapid economic and social productivity development. In the past, people usually used past experience to predict the future market, but there was no definite support, and there would often be large errors, as well as face some unavoidable crises. However, in the current era of data informatization, relatively accurate predictions of the future market can be made through a large amount of data, while avoiding losses caused by some crises. This study employed various analytical methods to analyze the past and current situation of the retail market. This article further reveals the three major problems existing in traditional retail analysis: the separation of data analysis and business needs; the lack of data support for experience-based decision-making; and severe departmental data barriers. Finally, implementation suggestions are proposed from three aspects: data governance, talent cultivation, and organizational optimization, providing a systematic solution for the retail industry to enhance its decision-making ability and market competitiveness.

Keywords: Era of big data; business analysis and data analysis; retail industry.

1. Introduction

In the current context of increasingly fierce market competition and rapidly changing consumer demands, the scientific nature of enterprise supply chain management has become the key to enhancing core competitiveness. For enterprises involving multi-link collaboration and cross-regional production, how to balance production efficiency and cost control, optimize order strategies and resource allocation directly affects their market response speed and operational efficiency. The decision-making logic and collaborative mechanisms in supply chain management have received increasing attention. This study focuses on the order decision-making and production collaboration issues in enterprise supply chain management. Based on the normative requirements of supply chain management practices, it explores how to enhance the overall operational efficiency of the supply chain by optimizing order allocation strategies, clarifying the matching logic of different production regions, and establishing a systematic analytical framework.

This research holds both theoretical and practical significance: theoretically, it can provide a systematic analytical perspective for issues such as production layout planning and phased order decision-making in the enterprise supply chain; practically, it can offer ideas for enterprises to address real challenges such as the misalignment between production plans and market demands, and inefficient resource allocation, thereby assisting enterprises in achieving sustainable development in complex environments. Existing research has conducted multi-dimensional explorations around supply chain management, covering areas such as the analysis of production region characteristics, order planning logic, and supply chain process standardization. Relevant achievements emphasize the impact of cost and efficiency differences in production regions on order decisions, indicating that order planning should integrate capacity constraints and market demand forecasts, while also paying attention to the time and cost correlations among various supply chain links. However, there is still room for further deepening in specific norms for phased order decision-making, in-depth analysis of

differences among various production regions, and the practical construction of a collaborative analysis framework. This article, by sorting out the core elements in supply chain management, identifies the key factors influencing production and order decisions, including the cost efficiency characteristics of different production areas, capacity constraints in order planning, and the normative requirements for supply chain collaboration. On this basis, an analytical model for order decision-making and production collaboration is constructed. Combined with the normative standards of the supply chain process, it explores suitable scenarios for different production areas, clarifies the logic for formulating phased order strategies, and ultimately proposes systematic suggestions for optimizing supply chain management. The overall structure of the article will revolve around the core requirements of supply chain management: Firstly, clarify the key analytical dimensions and format specifications of supply chain management, including the visualization of processes and quantitative analysis of decision-making basis; Secondly, analyze the differences and causes of different production areas, and define the advantages and applicable scope of each area based on the requirements of the norms; Then, focus on discussing the decision-making logic of the first batch orders and reactive secondary orders, and formulate specific strategies that comply with the norms in light of capacity constraints; Finally, summarize the research implications and propose targeted optimization suggestions, providing a reference for enterprises to follow the supply chain management norms and improve the scientificity of their decisions, and helping enterprises achieve the maximum efficiency of the supply chain within the compliance framework.

2. A Comprehensive Analysis of the Synergistic Logic between Business Analysis and Data Analysis in the Retail Industry

In the context of the accelerated digital transformation in the retail industry, business analysis and data analysis have become the core support for enterprise decision-making. Relevant scholars have pointed out that the collaboration between the two is the key to the sustainable development of retail enterprises in the digital era. Data analysis helps enterprises grasp market dynamics, while business analysis converts data insights into business decisions [1]. To explore the logic of their collaboration, one must first address the disconnect in the traditional model and then clearly identify the collaborative driving factors in the era of big data, providing a direction for enterprises to build an efficient decision-making system.

2.1. The Disconnection Problem of the Traditional Models

In the traditional retail model, there is a significant disconnection between business analysis and data analysis, which hinders the development of enterprises. This is manifested in three aspects: Some data analysis teams fall into the trap of "technology supremacy", overly pursuing model complexity while neglecting actual business needs. Prasad and Venkatesham mentioned that such teams often only focus on model accuracy indicators but overlook whether the model can solve business problems [2]. For example, the high-precision sales forecast model built by the data analysis team of a chain supermarket was eventually left idle because it could not adapt to the short-term promotional needs of the business department (such as analyzing the impact of promotional methods on sales and inventory allocation, etc.)

Essentially, this is caused by insufficient communication between the team and the business department, as well as a lack of deep understanding of the requirements. The retail business has diverse and time-sensitive demands. Scenarios such as short-term promotions and holiday marketing require flexible data analysis support rather than merely pursuing model complexity. Business analysis overly relies on the experience of business personnel, lacking data verification, which can easily lead to decision-making deviations. Zhao took a traditional retail enterprise as an example. The store manager selected products based on experience without considering market data, resulting in the backlog of some products and the shortage of best-selling items, which directly affected the performance [2]. For instance, the store manager of a convenience store purchased a large quantity

of carbonated beverages in summer, but due to consumers' preference for healthier beverages, the inventory became backlogged. Although experience has some reference value, in the current market where changes are rapid and demands are diverse, its subjectivity and limitations become more prominent. There are more variables in retail business (such as consumer characteristics, competitive dynamics, etc.), and relying solely on experience is insufficient to fully grasp the relationships between these variables. This may cause enterprises to miss market opportunities.

Within the enterprise, the business departments keep track of demands while the data departments safeguard the data. This phenomenon is widespread and has created data barriers. Lutfi et al. conducted a quantitative study and found that data barriers would reduce the effectiveness of big data analysis applications, and the absence of a sharing mechanism would directly affect the accuracy of the analysis results [3]. For instance, the marketing department and the data department have different definitions of "user tags": the former focuses on consumer behavior and marketing responses, while the latter focuses on basic attributes. This leads to an inability to match the data and delays the advancement of marketing activities. Moreover, data storage is scattered, with sales, inventory, and other data belonging to different systems such as Point of Sale (POS), Enterprise Resource Planning (ERP), and Customer Relationship Management (CRM), forming "data islands". When the data analysis team extracts and integrates the data, they are prone to problems such as inconsistent formats and varying quality, which affects the accuracy of the results.

2.2. The Collaborative Driving Factors in the Era of Big Data

Big data technology drives changes in the data environment, business models and technical tools of retail enterprises, providing impetus for the collaboration between business analysis and data analysis. This is specifically manifested in three aspects.

Under the traditional model, enterprise data was small and precise (mainly consisting of sales and inventory data) and could be handled independently by a single team. In the era of big data, data sources are diverse (such as online browsing, social media, and traffic data, etc.), and the volume is growing exponentially. The types of data cover both structured and unstructured data, resulting in a "large and diverse" situation.

Some scholars pointed out that this pattern presents both challenges and opportunities [1]. The vast amount of data makes it difficult for a single team to handle it in a timely manner; on the other hand, the diverse types of data require analysts to possess cross-domain skills. Therefore, the two need to work together: The data analysis team is responsible for processing and extracting data, while the business analysis team interprets the results and converts them into decision-making recommendations to ensure they align with business needs.

Cross-channel retailing breaks down the boundaries between online and offline and requires the integration of multi-channel data to optimize operations. Zhao mentioned that a certain enterprise achieved comprehensive tracking of consumer behavior by integrating online and offline data, significantly improving the accuracy of services [2]. However, the cross-channel scenario is complex, and a single team is unable to grasp the business logic and data correlations; therefore, a collaborative analysis of both is necessary. At the same time, the demand for personalized services from consumers is increasing, and through big data analysis, user profiles can be constructed. Lutfi et al. demonstrated that this approach can help enterprises precisely implement personalized services and enhance market competitiveness [3]. During this process, the business analysis team clearly defines the service goals, and the data analysis team builds the profiles to explore potential demands. Only through the collaboration of both can personalized services be implemented.

Business Intelligence (BI) platforms, automated analysis tools, data visualization tools, etc., have lowered the threshold for collaboration and promoted mutual understanding among teams. Prasad and Venkatesham argued that BI platforms integrate enterprise data, facilitating independent analysis by business personnel and reducing reliance on data teams; automated analysis tools can automatically complete data cleaning and prediction, reducing repetitive work for data teams and generating understandable reports that are easy for business teams to understand; data visualization tools present

analysis results in charts, helping business teams quickly grasp trends and also facilitating data teams in presenting their achievements [4]. In summary, technical tools break down technical and communication barriers among teams, laying the foundation for deep collaboration in business analysis and data analysis.

3. Construction of the Collaborative Model for Business Analysis and Data Analysis in the Retail Industry

In the current era of rapid development of big data, data has become an indispensable part of the retail industry. However, mere data alone cannot directly have a valuable impact on the retail industry. This article mainly studies how to transform massive data into effective data to generate good benefits for the retail industry. The core of this transformation process lies in the collaboration between business analysis and data analysis. Business analysis involves analyzing the economic benefits of the plan, focusing on logic; data analysis refers to conducting in-depth mining in the massive data and establishing models. This chapter promotes the development of the retail industry by constructing a collaborative model of the two analysis methods. At the same time, Persaud believes that to achieve effective collaboration, it is indispensable to have talents with corresponding capabilities [5].

3.1. Goal - Data - Action Collaborative Model

This model is based on goals and constructs a complete collaborative model to ensure that all work can revolve around the business. Firstly, the goals are broken down. Business analysts can divide them into quantifiable and operational sub-goals based on the company's overall strategy. For example, to achieve the overall goal, sub-goals such as "increasing the new customer conversion rate by 20%" and "increasing the repeat purchase rate of old customers by 10%" can be derived. Through this step, the direction of subsequent data analysis can be clarified. Secondly, data analysis matches data support. Some scholars mentioned that data analysts extract relevant data from the above sub-goals and conduct in-depth mining using descriptive and predictive analysis [6]. Data analysts extract relevant data from the above sub-goals and conduct in-depth mining using descriptive and predictive analysis. For example, for "increasing the new customer conversion rate", it is necessary to analyze the cost of traffic from various different channels, as well as the conversion path and final conversion rate; for "increasing the repeat purchase rate of old customers", the consumption frequency, average transaction value, and frequently purchased items of customers are analyzed to classify customers. Next, business analysis formulates action strategies. Some scholars propose that business analysts, based on the conclusions drawn from data analysis, convert these conclusions into operational business strategies to improve decision-making in business operations [7]. For example, in the field of social media, data analysis can discover that the cost of customer acquisition is low, and the new customer conversion rate is high, which has high cost-effectiveness. Business analysis can then make a strategy such as "increasing the budget for advertising". For customers with a low repeat purchase rate, data analysis can identify the reasons and business analysis can then launch corresponding awakening strategies.

Finally, research proposed that data analysts can utilize data visualization tools to establish real-time monitoring panels, track key indicators, and quantify the effectiveness of strategies [8]. At the same time, some scholars also suggested that these quantitative results should be provided in real time to business analysts, who would then judge whether the strategies were successful. This is the core process for formulating data-driven growth plans [9].

3.2. Business-Technology Dual-Drive Synergy Model

This model aims to break down barriers between departments. Its core is to establish cross-functional teams, integrating business experts and data technology specialists for deep integration. To ensure collaborative efficiency, a common language system needs to be established, and unified data indicators and professional terms should be adopted. Kachan pointed out that what is more

crucial is to cultivate versatile talents: on one hand, business personnel should be trained in data visualization tools ; some scholars also mentioned enhancing the professional capabilities of business personnel; on the other hand, business personnel should be sent to the front line to understand the shortcomings of the business, which requires the key capabilities needed by big data analysis professionals [5,7]. This deep integration is the guarantee for improving decision-making levels through data analysis.

3.3. The Scenario-Based Collaborative Model Based on the Core Retail Process

This model aims to integrate collaborative practices into specific business scenarios. Some scholars mentioned in terms of customer lifecycle collaboration: during the acquisition stage, data analysts and business analysts collaborate to formulate precise marketing strategies; during the retention stage, predictive analysis based on data is used for customer churn warning, and business analysis designs recovery plans based on the reasons for churn, which is a typical manifestation of data-driven growth [9].

In terms of collaborative management of products: Kachan mentioned that in the selection and pricing stages, business analysis identifies requirements and sets strategic directions, data analysis provides descriptive and predictive insights based on historical data and external data as decision support, and ultimately the final solution is jointly decided by both parties through discussion and is continuously tracked and evaluated through data visualization methods [8].

In conclusion, by establishing the "target-data-action" and "business-technology" dual-driven model, it is possible to effectively integrate business intelligence and data capabilities. At the same time, enterprises should attach great importance to the cultivation of key capabilities of talents, and introduce analysis dashboards and visualization tools as supporting technologies. Ultimately, a data-driven strategic excellence engine can be achieved.

4. Strategies for Implementing the Collaborative Model

4.1. Importance of Data Standardization

4.1.1 Importance of data standardization

Unified data standards are essential to the successful implementation of collaborative models. Without consistency, core business data including transactions and inventory cannot be efficiently integrated. Prior studies show that adequate data standardization significantly improves the performance of machine learning models, while poor standardization choices result in degradation of classification accuracy [10]. Besides the technical benefits, data standardization also facilitates interoperability and portability across datasets, lowering barriers to integration and enabling data synergies [11]. Accordingly, prioritizing standardized identifiers like customer IDs and product categories isn't merely a technical tweak but a strategic prerequisite to establish a robust retail data platform.

4.1.2 Improving data quality

Standardising retail data (e.g., using Z-score) puts all the variables on a single scale so that the abnormal readings are shown as true deviations rather than being hidden by different units or magnitudes [12]. In a tea-plantation IoT investigation, the workflow first applies Z-score standardization, then uses a sliding window to feed recent sequences into a CNN-SVM detector to screen the results, which allows real-time screening and temporal pattern extraction between real outliers and noise [12]. Once the abnormal points are obtained, an Long Short-Term Memory (LSTM) predicts what the normal value should be and replaces the bad readings; if the abnormality recurs, the system flags the possible sensor faults for follow-up [12]. As a practical matter, this means that standardization not only assists in locating errors but can also be used to rectify them by giving downstream models clean, comparable inputs for reliable detection and imputation [12].

4.1.3 Promoting data interoperability

Standardization makes data from different systems “speak the same language” — it means integration is quicker and less error-prone. In practice that means having shared formats and controlled vocabularies (consistent IDs for customers/products; harmonized codes for attributes etc.) that allows transactions, inventory, and CRM data to be integrated, without having to design custom mappings each time. Evidence from clinical research attests equally to the value of convergent approaches at scale: if datasets adopt standardized schemas and codes, cross-institution integration begins to accelerate, errors decrease, and downstream analytics become more reliable [13]. For a retail data platform, the adoption of similar standardization — clear data dictionaries, validated value sets and uniform timestamp/units — enhances end-to-end interoperability: pipelines break far less, people can join files simpler, and model use of multi-source features can be done much faster with less manual fixing. To summarize, unified standards act as the foundation and allow effective, multi-source analytics [13].

4.2. Talent Cultivation

Talent development, bridging roles. Conduct two-way training to create a shared language: business teams learn data literacy (basic stats, feature intuition, limits of models), data teams learn retail workflows (merchandising, inventory turns, promotions). This minimizes the loss due to handoff and harmonizes mental models for mutual problem solving [14]. Establish a dedicated Business Analyst role as a boundary spanner for translating requirements and for stewarding common definitions (e.g., customer ID, product hierarchy), supporting periodic cross-functional “decision reviews” enabling assumptions and metrics to stay aligned [14]. Support training with role clarity, shared glossaries, and feedback loops linked to common Key Performance Indicators (KPIs); these practices address structural and cultural barriers to cooperation and embed the connection in day-to-day performance [14].

Cross-functional training is vital in data science, as it enhances teamwork and collaboration, which are essential for solving complex problems and fostering innovation.

4.3. Organizational Optimization

Keeping the structure simple to facilitate cross-department work. Have two routine meetings: a short steering meeting every two weeks to set priorities and a weekly working session to unblock tasks. Use one intake form and one shared backlog so all requests are visible. Track a small set of shared KPIs (e.g., conversion, stockouts, time-to-insight, adoption) so everyone aims at the same goals. Clearly define roles: the business team states the problem and success criteria; the data team designs the analysis/model and delivers the solution; IT keeps pipelines secure and reliable; finance/compliance reviews budget and risk. Use lightweight templates, a common glossary, and an agreed escalation path for trade-offs. After launch, run 30/60/90-day reviews to compare results with targets and capture lessons. In retail IT settings, this simple operating model reduces handoffs and speeds decisions [15].

Small and medium-sized enterprises can adopt lightweight tools (such as SaaS BI and Excel plug-ins), and large enterprises can build customized collaborative platforms to lower the technical threshold.

5. Conclusion

The collaboration between business analysis and data analysis in retail: the case of supply chain management. The results first exposed some of the limitations of traditional practice: technical teams often valued model complexity more than business relevance; managers worked too much off experience without data validation; and organizational silos hindered effective data sharing.

Instead, they pinpointed critical factors that were contributing to collaboration in the big data era: the massive scale of data, the complexity of omnichannel operations, and enabling tools. The

following three models were developed in response to these challenges. The “goal–data–action” model connects the strategic goals with data analytics and implementable strategies. The “business–technology dual-wheel” model focuses on cross-functional integration and hybrid skills to overcome organizational differences. Lastly, with the scenario-based model, collaboration is woven throughout customer management and product decision making by embedding the business logic and the insights from the data together. Additional initiatives like unified data standards, better data quality, and structured training were also stated to be pivotal to implementation.

These results indicate that successful collaboration is vital both in retail and for any sector where data and business decisions are made. For researchers, this illustrates the importance of taking these nebulous ideas of ‘big data’ and translating them into practical models that can function as an operational tool.

Studies in the near future would be interesting to explore further by trialling out these approaches in other sectors of work and monitoring their impact over time, to get additional information about the extent to which firms re-orient their collaboration given the development of technology and the market environment. Through the incorporation of collaboration in a business’s structure and culture, organizations can leverage data for sustainable strategic advantage.

Authors contribution

All the authors contributed equally and their names were listed in alphabetical order.

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