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Enterprise Data Analytics Frameworks and the Improvement of Operational Decision Response Efficiency

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Abstract

Enterprise operational decisions are being influenced by fluctuations in orders, supply chain delays, inventory usage, customer response pressure, and cross-departmental collaboration costs. Traditional reporting-based analysis often relies on periodic summaries and manual verification. When anomalies propagate from the front-line nodes to the management level, they have already shown significant delays, making it difficult to support rapid response and resource reallocation. By building an enterprise data analysis framework around data governance, real-time collection, scenario modeling, hierarchical response, and feedback calibration, it is possible to integrate scattered data from ERP, CRM, WMS, MES, and external logistics platforms into a unified analysis chain. This enables continuous closed-loop processes for anomaly identification, cause location, solution generation, execution tracking, and result review. Anonymous samples of enterprise order fulfillment and inventory scheduling show that this framework demonstrates improvement trends in indicators such as anomaly detection time, cause location time, closed-loop completion time, warning accuracy, and manual verification frequency, providing a feasible technical path for enterprises to shorten operational decision response cycles, enhance resource scheduling accuracy, and stabilize cross-departmental collaboration.

Keywords

Enterprise data analysis framework; operational decision; response efficiency; real-time analysis

Slow decision-making in enterprise operations is not usually due to managers lacking judgment experience, but rather because the path for data to reach the decision-making position is too long. Orders, inventory, logistics, customer service, procurement, and financial information are scattered across different systems. Initially, anomalies are only status changes at a certain node, and after being manually summarized, departmental confirmation, and hierarchical reporting, they gradually evolve into management issues that can be discussed. The value of the data analysis framework lies in reshaping this chain, enabling operational signals to be captured, classified, interpreted, and pushed to responsible positions at the initial stage, thereby shifting decision response from "waiting for complete information" to "continuous adjustment based on real-time evidence".

1. The Framework Basis for the Efficiency of Enterprise Operation Decision-making Response

1.1 Anchoring Response Indicators in Business Scenarios

The starting point of the enterprise data analysis framework should be in the high-frequency operational scenarios

[1]. First, break down matters such as order fulfillment, inventory scheduling, supply chain delivery, and customer service into measurable response nodes, and then set indicators such as abnormal detection time, cause location time, solution confirmation time, and execution loop time accordingly. Taking order fulfillment as an example, the delay judgment should not only consider whether the order is overdue, but also simultaneously read the inventory lock status, warehouse operation load, logistics first scan node, customer level, and commitment delivery time limit, so that the system can shift from a single state indication to a multi-field joint judgment. After the indicator design is completed, each indicator should be bound to the responsible position, data source, and trigger conditions to avoid operational analysis remaining at the level of report display [2].

1.2 Data Governance Supports the Credibility of Analysis

Data governance determines the accuracy of the analysis framework. If there are deviations in customer codes, product codes, order status, warehouse fields, and timestamp standards, the subsequent model output will generate errors in the identification process. Enterprises should first establish a unified ID for the core objects in ERP, CRM, WMS, MES, after-sales systems, and external logistics platforms, and complete field cleaning, format conversion, duplicate record elimination, and missing value marking before data enters the lake. For key events such as order creation, inventory locking, outbound handover, and logistics update, it is also necessary to retain the collection time, system source, and modification traces, so that the abnormal traceability has a complete evidence chain, providing a stable foundation for subsequent real-time analysis and model diagnosis [3].

2. The Technical Mechanism for Accelerating Response through an Enterprise Data Analysis Framework

2.1 Real-time Collection to Shorten the Identification Cycle

The core task of real-time collection is to move operational anomalies from periodic reports to the scene where the business event occurs. Enterprises can incorporate nodes such as order creation, inventory locking, picking completion, outbound handover, first scan of logistics, customer complaints, etc. into the event stream. Each record is simultaneously written with a timestamp, status code, responsible position, and system source [4]. If an order fails to enter the picking state 30 minutes after the promised delivery time, the system triggers a yellow alert; if there is no first scan of logistics after 60 minutes, it is upgraded to a red alert and automatically pushed to the warehouse, customer service, and logistics positions to compress the time for manual inspection and hierarchical reporting [5].

2.2 Scenario Model to Compress the Judgment Chain

The scenario model is responsible for the rapid hierarchical diagnosis of abnormal causes, with the focus being on converting multiple system fields into sortable handling clues. Taking order fulfillment delay as an example, the model synchronously reads inventory availability, warehouse operation load, carrier nodes, historical delay frequency, and customer level, and sets initial weights according to inventory gap 0.35, warehouse load 0.25, logistics delay 0.25, and address anomaly 0.15. After the system outputs the probability of the cause, operation personnel first verify the high-weight items and then enter the allocation, scheduling, reassignment, or customer communication process, reducing the time loss caused by item-by-item investigation [6].

2.3 Grading Rules to Enhance Handling Efficiency

After the analysis results enter the handling process, they need to be bound to the permission boundaries, response time limits, and position actions, as shown in Figure 1. General anomalies are closed by front-line positions within 4 hours, and the handling actions include adjusting picking sequence, supplementing logistics notes, and updating customer notifications; priority anomalies are confirmed by department managers within 1 hour, involving cross-warehouse allocation, carrier switching, or service upgrades; major anomalies are completed by cross-department teams within 30 minutes through joint signature, focusing on joint handling of key customer order interruptions, core material shortages, and regional distribution delays. This rule enables the warning signals to directly enter the execution chain, reducing the response lag caused by repeated confirmation and waiting for approval [7].

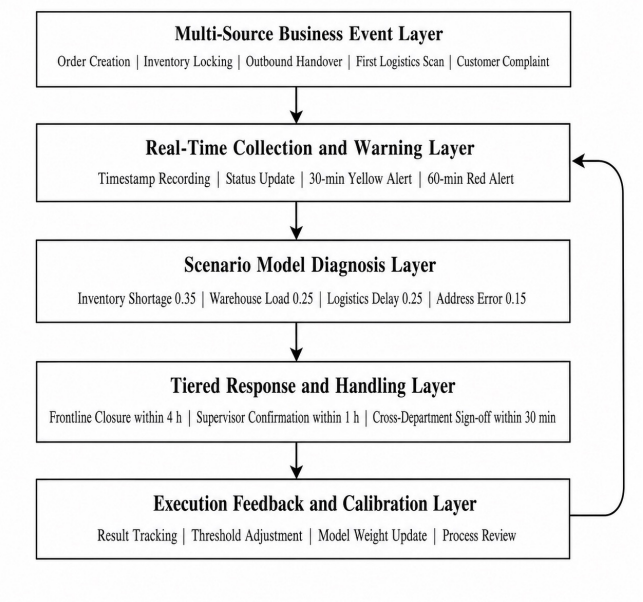

Figure 1. Enterprise Data Analysis Framework Driving the Process of Responding to Operational Decisions.

3. Application Verification and Optimization Control of the Enterprise Data Analysis Framework

3.1 Comparative Verification of Order Fulfillment Scenarios

Anonymized cross-regional retail enterprises selected the order fulfillment records for 8 consecutive weeks as the pilot sample [8]. The 4 weeks before the framework was launched and the 4 weeks after the launch were used as the control samples. The sample fields covered 8 types of information: order creation, payment confirmation, inventory locking, picking start, outbound handover, first scan of logistics, abnormal closure, and customer level. The system set a yellow warning for 30 minutes and a red warning for 60 minutes at the commitment delivery node. After an abnormal order was generated, it was simultaneously pushed to the warehouse, logistics, and customer service positions. The model sorted the probabilities of four reasons: inventory gap, warehouse load, logistics delay, and address anomaly. The operation personnel first verified the highest probability field and then executed cross-warehouse allocation, adjustment of picking priority, reassignment of carriers, or customer notification. The pilot records showed that the time for abnormal discovery decreased from 6.2 hours to 0.8 hours, the time for reason determination decreased from 4.5 hours to 1.3 hours, the closed-loop completion time decreased from 18.6 hours to 7.4 hours, and the number of manual verifications per order decreased from 5.4 times to 2.1 times, as shown in Table 1.

Table 1. Comparison of Response Efficiency Before and After Applying the Enterprise Data Analytics Framework

Indicator	Traditional Reporting Mode	Data Analytics Framework Mode	Change	Decision Implication
Anomaly Detection Time	6.2 hours	0.8 hours	Reduced by 87.1%	Anomalies enter the response chain earlier
Cause Identification Time	4.5 hours	1.3 hours	Reduced by 71.1%	Verification sequence becomes clearer
Solution Confirmation Time	3.8 hours	1.1 hours	Reduced by 71.1%	Role-based response becomes faster
Closed-loop Completion Time	18.6 hours	7.4 hours	Reduced by 60.2%	Handling cycle is significantly shortened
Alert Accuracy	68.0%	86.5%	Increased by 18.5 percentage points	Judgment quality is improved
Manual Verification Frequency	5.4 times/order	2.1 times/order	Reduced by 61.1%	Communication and confirmation costs are reduced

3.2 Data Analysis of Inventory Scheduling Scenarios

Inventory scheduling scenarios should be established with rolling calculation tables based on SKU granularity. The fields include the sales volume in the past 90 days, 7-day demand forecast, in-transit purchase volume, available inventory in regional warehouses, warehouse occupancy rate, safety inventory line, minimum order quantity, and transportation timeliness. The system updates the forecast results at 0 o'clock every day. If the predicted sales volume of a certain SKU in the next 7 days exceeds the safety inventory by 30%, and the available inventory in this warehouse is lower than the 3-day demand, a shortage risk mark will be generated; if the inventory turnover days of the same model in adjacent warehouses exceed 45 days and the warehouse occupancy rate is higher than 85%, it will enter the cross-warehouse allocation candidate pool. The scheduling personnel first screen the plans based on the conditions of transportation timeliness ≤ 48 hours, allocation cost lower than the additional procurement cost by 8%, and the inventory coverage days after the arrival of the receiving warehouse not exceeding 14 days. Then, the system calculates the recommended allocation quantity; if the allocation threshold is not met for a certain SKU, it will be transferred to the replenishment application. The purchase quantity will be calculated based on "predicted sales volume in 7 days + safety inventory - existing inventory - in-transit quantity" and will be simultaneously verified with the minimum order quantity and the supplier delivery cycle, shifting the inventory response from experience-based replenishment to cross-warehouse collaborative calculation [9].

3.3 Model Feedback Drives Continuous Correction

After the model is launched, a calibration ledger should be established in the order of "warning record - disposal action - actual result - parameter writeback". Each abnormal task must be closed with the final cause, adopted solution, actual time consumption, responsible node, and result status recorded to form a data sample for re-training. The system can set weekly review rules. If the false alarm rate of delay warnings for a certain type of order exceeds 15% for two consecutive weeks, the corresponding threshold sensitivity will be lowered, and the weights of fields such as inventory gap, warehouse load, and logistics delay will be recalculated; if the deviation rate of inventory prediction exceeds 20% for three consecutive weeks, variables such as promotional calendar, seasonal fluctuations, channel order structure, and supplier delivery period changes need to be added to avoid model bias caused by using old samples. During monthly review, technical personnel and operation positions jointly extract the top 50 overdue handling records, and verify the trigger point of the warning, cause ranking, response level, and closing duration for each record. Missed sample records will be added to the training set, and frequently misreported fields will be included in the rule revision list. In the next cycle, the accuracy rate of warnings, rule hit rate, and handling timeout rate will be retested.

4. Conclusion

The improvement of operational decision-making response efficiency by the enterprise data analysis framework lies in integrating scattered business data, scenario indicators, model diagnosis, and handling actions into the same operational chain. The framework construction should start from high-frequency scenarios such as order fulfillment, inventory scheduling, supply chain delivery, and customer service. First, unify the data standards and key event fields, and then shorten the cycle of anomaly discovery, cause location, and solution confirmation by means of real-time collection, weighted diagnosis, and grading rules. Pilot data indicates that event-level analysis and feedback calibration can reduce manual verification, compress the closed-loop time, and enhance the accuracy of collaboration among operational positions. In subsequent applications, enterprises also need to continuously monitor data quality, model drift, and rule hit situations, and write the handling results back to the training samples and parameter tables, so that the data analysis framework can maintain stable iterative capabilities in the face of changes in the operational environment.

References

[1] Hang Y, Wang K, et al. Optimising calculation logic in emergency management: a framework for strategic decision-making. Systems. 2026;14(2):139.

[2] Akintola SA, Adewuyi IO, Juliet IO, et al. Integrating data-driven continuous improvement frameworks within ERP-enabled manufacturing environments. J Eng Res Rep. 2025;27(11):353-368.

[3] Agbodike OK. From data lakes to decision-making: leveraging artificial intelligence for enterprise governance, risk management,

and strategic value creation in the digital economy. Asian J Adv Res Rep. 2025;19(10):32-41.

[4] Agbodike OK. Beyond compliance: how AI-powered data governance can transform enterprise decision-making, risk mitigation, and sustainable growth. South Asian J Soc Stud Econ. 2025;22(9):342-349.

[5] Aldossari S, Mokhtar AU, Ghani ATA, et al. Empowering Saudi manufacturing small and medium enterprises: a framework for big data analytics adoption and its impact on decision-making. SAGE Open. 2025;15(3).

[6] Appalapuram RSV. The lakehouse paradigm: converging data lakes and warehouses for integrated enterprise analytics. J Comput Sci Technol Stud. 2025;7(4):641-648.

[7] Yuan G, Ximu Y. Data analysis framework of tourism enterprise human resource management system based on MySQL and fuzzy clustering. Int J Syst Assur Eng Manag. 2023;14(5):1647-1659.

[8] Jinqian P, Liyuan B. Construction of enterprise business management analysis framework based on big data technology. Heliyon. 2023;9(6):e17144.

[9] Tom S, Angelo P, Mike C, et al. Quantifying the benefits of using decision models with response time and accuracy data. Behav Res Methods. 2020;52(5):1-14.