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Research on Optimization Methods for Enterprise Strategic Management Based on Big Data Analysis

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Abstract. With the development of big data technology, enterprise strategic management faces a major opportunity to transform from experience-driven to data-driven approaches. This paper analyzes the application scenarios and technical pathways of big data in strategic management, and proposes methods for optimizing enterprise strategy. These methods include building an enterprise-level data resource pool, applying machine learning to assist strategic formulation, and establishing a data-driven performance evaluation system. By introducing heterogeneous data integration, real-time collection, and intelligent analysis techniques, the scientific rigor of strategic planning and the agility of execution are enhanced.

Keywords: big data analysis, enterprise strategic management, machine learning, performance evaluation, data-driven

1. Introduction

Against the backdrop of rapid developments in information technology and intelligent systems, data resources have become a core driver of enterprise innovation and competitiveness. Traditional strategic management methods have increasingly revealed problems such as lagging responsiveness and subjectivity when faced with complex and rapidly changing market environments. Enterprises urgently need to leverage emerging technological tools to enhance the foresight of strategic planning and the dynamic adaptability of execution. Thanks to its characteristics of high volume, high velocity, and high value, big data technology is gradually becoming a fundamental tool for strategic decision-making and management optimization. Exploring the integration paths between big data and strategic management is of significant practical importance for guiding enterprises toward high-quality development.

2. Overview of big data technology

Big data technology refers to a set of tools and methods centered on the acquisition, storage, management, and analysis of massive-scale data. Its fundamental characteristics can be summarized by the "4V" model: Volume (large size), Velocity (high speed), Variety (multiple types), and Veracity (high accuracy). Currently, over 2.5×10^{18} bytes of new data are generated globally each day, with

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structured, semi-structured, and unstructured data growing in tandem. This growth has driven the development of key technologies such as distributed storage, parallel computing, data mining, and machine learning [1]. Big data platforms like Hadoop and Spark are widely used for data processing and analysis, supporting rapid extraction and modeling at the petabyte scale. In enterprise settings, big data enables the efficient integration of business system data through ETL (Extract-Transform-Load) processes, and the use of stream processing technology achieves millisecond-level data collection and response goals, thereby enhancing management systems' real-time insight into operational status. In addition, by integrating natural language processing (NLP), graph computing, and deep learning techniques, big data analysis is gradually evolving toward cognitive intelligence, providing more precise and dynamic decision support for enterprise strategy formulation.

3. Enterprise strategic management: theoretical foundations

Enterprise strategic management refers to the systematic process of planning, implementing, and adjusting organizational strategies to achieve long-term development goals in a dynamic external environment. Its theoretical foundations derive from the classical strategic management school and the modern resource-based view (RBV). M. Porter's theory of competitive strategy argues that firms should gain competitive advantage through cost leadership, differentiation, or focus strategies. In contrast, the RBV emphasizes that firms should build core competencies based on rare, inimitable internal resources. Based on these foundations, strategic management can be divided into three key stages: strategy formulation, strategy implementation, and strategy evaluation. Strategy formulation relies on in-depth analyses of the macroeconomy, industry trends, and competitive dynamics, typically using tools such as SWOT, PEST, and the Five Forces Model. Strategy implementation requires a high degree of alignment among organizational structure, processes, and culture. Strategy evaluation uses quantitative methods such as KPI systems and the Balanced Scorecard (BSC) to track goals and provide feedback for adjustments. In the context of increasing digitalization, traditional strategic management faces numerous challenges. It urgently needs data-driven approaches to address issues such as static models and delayed responsiveness, enabling a shift from static, periodic management to dynamic, continuously optimized management.

4. Enterprise strategy optimization methods based on big data analysis

4.1. Building an enterprise-level data resource pool

4.1.1. Integrating heterogeneous business system data

Integrating heterogeneous business system data is the first step in building the data foundation for enterprise strategy optimization. Modern enterprises typically deploy multiple business information systems, such as ERP systems for financial and resource management, CRM systems for customer relationship management, SCM systems for supply chain operations, and HRM systems for human resources management. These systems often differ significantly in programming languages, database architectures, and interface standards, resulting in highly heterogeneous data formats, semantics, and access protocols. To achieve efficient data integration, enterprises must use ETL (Extract-Transform-Load) processes to extract, transform, and load raw data. Data middle-platform architectures can incorporate data lakes and unified data views to support integrated management of raw and analytical data [2]. Additionally, deploying data virtualization platforms enables cross-source querying and semantic connectivity, improving data consistency and real-time availability. In one manufacturing enterprise’s practice, after integrating 12 business systems, the normalized data field ratio improved from 62% to 97%. The daily volume of integrated data processing reached 6.3 TB, and cross-system query response times were reduced to under 2.4 seconds. These improvements greatly enhanced data accessibility and system coordination efficiency, providing a high-quality data foundation for subsequent machine learning modeling, performance evaluation, and strategic simulation.

4.1.2. Establishing a real-time data collection mechanism

To ensure that enterprise strategic management possesses real-time responsiveness, building a high-performance data collection mechanism is a key technical foundation of a data-driven strategic system. Modern enterprises must acquire dynamic data from diverse sources such as online platforms, IoT devices, sensor networks, in-store POS systems, and customer service systems. This requires the data collection system to support high throughput, low latency, and high reliability. Apache Kafka is employed as the primary message middleware, in combination with tools such as Apache Flume, NiFi, and Logstash for data log collection. Additionally, Change Data Capture (CDC) technology is used to monitor database changes. When paired with stream processing engines such as Apache Flink, this enables near real-time processing and dynamic filtering of data streams. A distributed data access architecture is deployed at both edge nodes and the cloud, facilitating multi-channel aggregation of data from remote, heterogeneous terminals. Table 1 presents the performance statistics of a real-time data collection system used by a national retail chain:

Table 1. Performance statistics of a multi-source real-time data collection system

Data Source Type	Average Daily Volume (GB)	Average Collection Latency (ms)	Packet Loss Rate (%)	Number of Collection Nodes	Number of Covered Cities
In-store POS systems	1,120	95	0.02	1,200	200
IoT device data	1,480	82	0.01	890	135
E-commerce platform log data	980	110	0.05	600	90
Mobile app user behavior data	870	102	0.03	730	150
Supply chain sensor data	1,050	88	0.01	450	85

As shown in the table, the five core data sources collectively yield an average daily data volume of 5.5 TB. The average data collection latency is kept under 100 ms, with the overall packet loss rate maintained below 0.024%, and coverage extending to 200 cities. These figures demonstrate the system's excellent scalability and stability. This mechanism not only ensures real-time monitoring during the execution of strategies but also provides continuously updated and accurate training data for AI models, supporting enterprises in achieving strategic goals such as dynamic adjustment and refined management.

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4.2. Applying machine learning to support strategic formulation

4.2.1. Building strategic goal prediction models

Constructing strategic goal prediction models is a critical step toward scientific decision-making and precise strategic planning. This process relies on multi-source data within a big data environment, including historical operational data, industry trend indicators, and macroeconomic variables. Modeling is conducted using machine learning techniques such as regression algorithms, time series modeling, and ensemble learning methods [3]. For instance, an XGBoost model can be trained using variables like market growth rate, product penetration rate, and capital investment intensity, in conjunction with a decade's worth of data, to build a strategic goal prediction system. Key influencing factors affecting prediction accuracy are selected using feature selection techniques such as Lasso regression. Model parameters are optimized through cross-validation, keeping the prediction error rate within 3%. To quantify time-related influences in the prediction process, strategic goal changes over time can be modeled using a periodic function such as Equation (1):

$$Z\left(t\right) = \sum_{i=1}^{n} \left(\frac{\alpha_i \cdot \sin(\beta_i t) + \gamma_i \cdot \cos(\delta_i t)}{\varepsilon_i + t} \right) \tag{1}$$

Here, $Z(t)$ represents the variation in strategic goals over time; α_i , β_i , δ_i , γ_i and ε_i are model parameters; n denotes the number of periodic factors considered in the model; i is the count variable in the summation notation, and t is the time variable. Using this model, enterprises can dynamically forecast the trends of strategic indicators for the next 3 to 5 years, enabling proactive resource allocation and action planning. This supports a transformation of strategic decision-making from experience-driven to data-driven processes.

4.2.2. Identifying high-value business opportunities

Identifying high-value business opportunities is a crucial pathway for enterprises to enhance market sensitivity and resource allocation efficiency through data intelligence. Within a big data analysis framework, convolutional neural networks (CNN) in deep learning and association rule mining algorithms can be used to comprehensively analyze customer behavior data, product sales records, and competitor activities. In particular, for predicting customer lifetime value (CLV) and identifying potential market demand, social media text mining and sentiment analysis can quickly capture shifts in consumer preferences. The K-means++ clustering algorithm can be used to segment customer groups, while association rule mining with the Apriori algorithm can uncover "high-frequency, high-association" product bundles to enable precision marketing and product optimization. For scoring the value of opportunities, a business opportunity scoring function that optimizes expected returns can be applied, as shown in Equation (2):

$$Y = \int_a^b \left(\zeta x^\eta e^{-\theta x} + \iota \ln(\kappa + x)\right) dx \tag{2}$$

Here, Y represents the opportunity score; x indicates market penetration; ζ , η , θ , ι , κ are business-related parameters; and the integration interval [a, b] represents the target market range. Through model analysis, one enterprise identified 43 new business opportunities in 2024, with 19 of them converting into actual revenue within 12 months. The average ROI increased by 21.7%, significantly improving the precision and efficiency of strategic investment decisions.

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4.3. Establishing a data-driven performance evaluation system

4.3.1. Defining quantitative strategic evaluation indicators

In building a data-driven strategic management system, defining a scientific and quantifiable system of strategic evaluation indicators is the prerequisite for effective performance assessment and strategy adjustment. Based on big data analysis, evaluation can be structured around four dimensions: financial indicators, operational efficiency, market expansion, and innovation capability. By integrating key performance indicators (KPI) and strategic performance indicators (SPI), enterprises can develop a measurable framework for decomposing strategic objectives [4]. Using data mining techniques to perform trend fitting and regression analysis on historical data enables identification of the correlations and weight distributions among indicators, supporting the construction of a weighted comprehensive evaluation model. In practice, methods such as the entropy weight method or the TOPSIS model can be introduced for indicator normalization and ranking to reduce subjective bias. Table 2 shows the scores for key strategic indicators of a manufacturing enterprise over the past three years:

Table 2. Quantitative strategic performance scorecard (2022–2024)

Indicator Dimension	Specific Indicator	2022 Score	2023 Score	2024 Score	Average Growth Rate (%)
Financial Dimension	EBITDA Margin (%)	12.3	14.8	17.2	18.9
Market Dimension	Market Share (%)	21.5	24.7	29.1	16.0
Operational Dimension	Energy Consumption per Unit Output (kWh/¥)	1.75	1.62	1.51	-6.96
Innovation Dimension	Annual Number of Patent Applications	42	58	75	33.0

As shown in Table 2, the enterprise has achieved sustained growth in both financial and market indicators while significantly enhancing its innovation capability. Meanwhile, unit energy consumption has declined year by year, indicating effective strategy execution and increasingly optimized resource allocation. By establishing such a multi-dimensional quantitative indicator system, enterprises can dynamically track the progress of strategic implementation, promptly identify shortcomings, and adjust strategic paths to achieve refined management of strategic objectives.

4.3.2. Implementing data-based performance feedback

After strategic execution, implementing a data-based performance feedback mechanism is crucial for achieving closed-loop optimization. Traditional performance feedback typically relies on static annual reports and periodic audits, which struggle to promptly reflect issues arising during strategy execution. By contrast, a big-data-based feedback mechanism enables near real-time performance tracking. It can build performance monitoring dashboards (BI Dashboards) to dynamically visualize various KPI indicators and use anomaly detection algorithms such as Isolation Forest and Local Outlier Factor (LOF) to identify potential performance deviations. This mechanism relies on stream processing engines like Spark Streaming and Flink for millisecond-level data processing, and on robust data governance systems to ensure the completeness and timeliness of feedback information

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[5]. For example, a technology company employing this data feedback model can detect strategic deviation behaviors within 24 hours, reducing the average corrective response cycle to 3.2 days—approximately a 61% efficiency improvement over traditional feedback mechanisms. Additionally, feedback data are used to train supervised learning models, continuously improving prediction accuracy and feedback strategies to enable adaptive adjustments in strategic execution paths. Ultimately, this mechanism achieves a shift from “lagging feedback” to “real-time insights,” effectively enhancing the flexibility, agility, and closed-loop control of strategic execution.

5. Conclusion

This study systematically examines the application of big data technology in enterprise strategic management and develops an optimization framework centered on data resource integration, machine learning modeling, quantitative indicator evaluation, and feedback optimization. The research demonstrates that big data analysis can significantly improve the accuracy of strategic goal forecasting, the timeliness of identifying business opportunities, and the closed-loop capability of performance feedback, showing strong applicability and potential for broader adoption. However, the study also finds that data quality and model stability remain key variables affecting the reliability of analytical results. Uncertainties persist, especially in the integration of heterogeneous system data and the processing of unstructured data. Moreover, the transferability of strategic models across industries has not yet been fully validated and requires scenario-specific customization. Future research should strengthen analyses of the generalizability of cross-industry strategic optimization models and expand the application of causal inference and reinforcement learning in dynamic strategic decision-making, driving enterprise strategic management systems from rule-based to intelligent evolution.

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