Scholar Publishing Group
International Journal of Business Management and Economics and Trade
https://doi.org/10.38007/IJBMET.2026.070114
ISSN 2790-0959 Vol. 7, Issue 1:117-126

Construction and Application of Interpretable Enterprise Performance Prediction Model Based on Multi-Source Operational Data

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Keywords: Multi source operational data; Enterprise performance prediction model; Data quality governance; Data compliance governance; Matching governance strategies.

Abstract: This study focuses on the challenge of balancing data development and compliant circulation in the digital economy era. In response to the gaps in existing research on the connotation of data business governance, the impact path of strategies on performance, and participant behavior interaction, an interpretable enterprise performance prediction model based on multi-source operational data is constructed. Adopting typological analysis, econometric analysis, and behavioral empirical analysis, following the technical route of "problem posing theoretical construction empirical testing application implementation". The results showed that enterprise data business governance needs to take into account both data quality and data compliance dimensions, covering first, second, and third level governance dimensions (such as data intrinsic quality governance, data infringement risk, etc.). Strategies are divided into data quality governance (asset management, supply chain management) and data compliance governance (compliance management), and different business types (providers, transformers, etc.) have different forms of strategies; Governance strategies enhance performance through synergistic effects - data asset management directly/indirectly promotes financial performance, supply chain management enhances the role of resource scale, compliance management strengthens innovation impact, and platform complementarity, user scale, and compliance services enhance platform performance through paths such as improving perceived revenue/value, influencing revenue and value, and strengthening fairness; The strategy needs to match the technical, market, and regulatory resource needs of participants to drive value appreciation and monetization. The final model enriches the research on data governance at the theoretical level, expands the resource-based view, and provides guidance for the healthy development of data element markets, enterprise value realization, and the construction of ecological data trading platforms at the practical level.

1 Introduction

In the era of digital economy, data serves as a fundamental strategic resource for promoting economic transformation, enhancing governance capabilities, and reshaping competitive advantages.

The balance between its development and compliant circulation has become a key challenge. Although policies encourage the development and utilization of data elements to cultivate data merchants and improve the industrial ecosystem, the contradiction between data value development and compliance risks is becoming increasingly prominent - data processing capabilities [1] can develop products to achieve supply-demand matching and obtain benefits, while regulatory constraints such as data rights protection, fair market competition, and data security increase potential regulatory risks. Although existing research involves enterprise data business types, governance frameworks, and performance driving factors, there are significant gaps in the integration of multi-source operational data, the differential impact mechanism of governance strategies on financial and relationship performance, and the interaction between governance strategies and participant behavior. Specifically, the connotation and dimensions of data business governance are not clear, and there is no integration of data quality and compliance construction system; The research on the impact path of governance strategies on financial performance is insufficient, especially the analysis of the differentiated role of supply chain management and compliance management in different stages of business processes.The research contribution is reflected in both theoretical and practical aspects: enriching research in the field of data governance at the theoretical level, expanding the connotation of resource-based view, and improving the perspective of participant behavior in the field of data trading and circulation; At the practical level, provide governance solutions for the healthy development of the data element market, guide enterprises to formulate effective strategies to realize the value realization of data, and provide practical guidance for the construction of ecological data trading platforms. The research adopts a systematic methodology that combines typological analysis[2], econometric analysis, and behavioral empirical analysis. The technical route follows the logic of "problem posing theoretical construction empirical testing application implementation", forming a complete research loop, and ultimately constructing an interpretable enterprise performance prediction model, providing scientific guidance for value mining and risk management of multi-source operational data.

2 Correlation theory

2.1 The connotation of enterprise data business

In the era of digital economy, data, as a strategic resource and new production factor, has its potential economic value released through management and development, becoming a key path for enterprises to create profits. Enterprise data business can be defined as an economic activity that utilizes data to create value. Its value realization usually goes through three stages: data resource utilization, productization, and commodification: the resource utilization stage focuses on the accumulation and integration of raw data, the productization stage transforms data resources into data products with specific functions (such as reports and analysis tools) through processing capabilities, and the commodification stage ensures the compliant circulation of products and the completion of market transactions.From the perspective of business types, it is mainly divided into data sales business and data matching business. The data sales business directly generates revenue through the transaction of data resources or products, including data resource sales (such as datasets, APIs) and data product sales (such as data application services). The former relies on the enterprise's own raw data for direct monetization, while the latter requires dual transformation from productization to commodification, emphasizing processing capabilities, compliance management, and customer demand matching. The data matching business attracts both supply and demand sides by building a trading platform, indirectly realizing profits through network effects. Its core goal is not financial performance, but to enhance relationship performance by increasing participants' willingness to continue trading - a stable and sufficient supply and demand side is the basic condition for the operation of such business, without which the business is difficult to sustain. The two types of businesses together constitute the main path of enterprise data value, corresponding to different strategic orientations of direct revenue acquisition and ecological construction.

2.2 Enterprise Data Business Governance and Performance Evaluation System

Enterprise data business governance achieves the dual goals of maximizing data value and minimizing risks by organizing and coordinating business process activities, with the core of balancing revenue creation and risk management. The value of data is reflected in the benefits brought by data resources, products, and transactions, and its evaluation depends on data quality - including intrinsic quality (accuracy, completeness), scenario quality (ability to complete specific scenario tasks), and acquisition quality (sustainability); Data risk[3] focuses on compliance control, avoiding infringement, monopoly, and security regulatory risks, and ensuring cross-border circulation compliance. Governance strategies are divided into data quality management and compliance management: the former is achieved through data asset management (expanding resource scale) and supply chain management (improving supplier heterogeneity and customer concentration), requiring the integration of complementary resources and processing capabilities; The latter prevents legal risks and ensures sustainable business operations by [4]and relational performance [5] - Financial performance is applicable to enterprises that maximize revenue through data processing and sales, and measures profitability and operational efficiency using indicators such as return on total assets; Relationship performance is applicable to platform based enterprises that promote supply and demand side transactions. It evaluates participant satisfaction and platform activity through indicators such as sustained trading willingness, reflecting platform attractiveness and ecological health, and together constitutes a complete dimension of business optimization and strategic decision-making.

3 Research method

3.1 Resource foundation and value logic of enterprise data business governance

The resource-based view points out that enterprise resources include tangible assets (such as funds and equipment) and intangible assets (such as technology and organizational capabilities), among which heterogeneous resources[6]are the source of competitive advantage, and it is necessary to identify and integrate internal and external resources to build sustainable advantages. As a new type of production factor, data's resource characteristics make it the foundation for enterprises to expand new businesses and gain competitive advantages. However, it needs to be coordinated with other resources to release value - for example, data resources need to be combined with technology, management, customers, and other resources to transform into high-value data products to improve performance. The value of data follows the path of "resource asset commodification capitalization": the resource stage improves quality through data acquisition, preprocessing, and storage; During the assetization stage, tradable data products are formed through deep processing; Realize the circulation of data products in factor markets during the commercialization stage; The capitalization stage releases economic and social value through financial attributes. The process of value creation is influenced by both internal factors (technology, organizational structure, strategic orientation) and external factors (institutional environment, market competition, cooperation pressure). The output is reflected in data value, economic value (such as main business performance and market performance), and social value (such as employment opportunities and circular economy performance). It is necessary to balance value creation and risk control through governance strategies to maximize data value and minimize risks.

3.2 Theoretical framework of stakeholders and organizational legitimacy

The stakeholder theory[7]advocates that enterprises need to balance the demands of multiple stakeholders, meet the needs of shareholders, employees, consumers, suppliers and other stakeholders through effective governance strategies, and ensure sustained and stable operation. The core idea includes: creating value for stakeholders to avoid short-term profit seeking or low efficiency; Core stakeholders directly participate in business operations and influence business objectives through specialized investments. The theory of organizational legitimacy focuses on the interaction between organizational behavior and institutional environment, emphasizing that enterprises need to adapt to institutional pressures such as coercion, imitation, and standardization, and obtain legitimacy resources through compliance management. Legitimacy is divided into practical legitimacy (stakeholder support), moral legitimacy (social moral judgment), and cognitive legitimacy (public understanding and acceptance). Enterprises need to respond to external regulatory requirements through data compliance management to ensure business compliance and operation, while meeting the technical and market resource needs of stakeholders such as data providers and demanders, and building a sustainable business operation mechanism.

3.3 Analysis of Governance Objectives and Differences in Enterprise Data Business

Enterprise data business governance focuses on governance objectives, exploring the differences in data quality governance and data compliance governance goals for different types of data businesses. The study first raises research questions about the types of data businesses and governance objectives. Based on the perspective of data assetization, a business process model is constructed to identify four types of data businesses through different stages of system combination. Subsequently, from the perspective of integrating data resources and user resources, identify the key dimensions that affect business choices - data resource control ability (low/high) and user demand knowledge level (transactional/preference based), and deeply explore the resource control ability that enterprises need to possess when choosing specific businesses and the matching level of user demand. Ultimately, based on the goals of maximizing value and minimizing risk, it is clear that data quality and data compliance are key governance objectives, and the differences between data quality governance objectives (intrinsic quality, acquisition quality, scenario quality) and data compliance governance objectives (infringement, monopoly, security) in the implementation of each type of business are systematically analyzed. Data business governance is the starting point for sustainable operation of enterprises, requiring clear governance goals, coordination of process activities, improvement of quality, and ensuring compliance to achieve maximum value and minimize risks. It promotes the compliant circulation of high-value data commodities in factor markets, optimizes factor allocation, and leverages data resources to drive the big data industry, which is crucial for stable business operations and realizing data value realization. However, in practice, there are challenges such as unclear promotion paths, vague type selection, and lack of risk governance capabilities, which make it difficult for enterprises to match suitable business types, and even lead to operational interruptions or limited value release due to governance failures. Therefore, enterprises need to select appropriate business types, clarify governance objectives to meet the requirements of commodity circulation, and enhance user purchasing willingness to create conditions for obtaining data revenue and new competitive advantages. Although the academic community has explored macro governance frameworks and business types, it has not delved into the governance objectives of type selection and implementation risks. Existing research often divides businesses from the perspective of a single data resource, such as dividing them into platform markets and unilateral markets based on differences in data subjects, or dividing them into three models based on processing levels: data suppliers, service providers, and intermediaries. A few studies suggest combining data resources with user resources to identify business types, such as providing nine types of businesses by combining product types (sales data, analysis, services) with customer types (current customers, value chain participants, arbitrary participants). When choosing a business, it is necessary to consider its own resources, capabilities, and user needs, while also addressing governance challenges such as data quality, privacy, security, and monopolies. Overall, existing research focuses on single perspective classification, without analyzing business processes from the perspective of data and user integration, nor identifying business types based on stage combination systems, analyzing specific requirements, and addressing differences in governance objectives during implementation. To address the above issues, the research is carried out through three core contents: firstly, by combining trading practices, industry dynamics, and domestic and foreign research, the key factors affecting business are sorted out. From the perspective of data assetization and business processes, the three key stages of data resource utilization, productization, and commodification are identified, and the business type is clarified based on the combination of stages; Secondly, extract the key dimensions that influence the selection, and delve into the specific requirements of each type of business in terms of data resource control capabilities and user demand knowledge levels; Finally, identify governance objectives as improving data quality and ensuring data compliance, and further explore the differences in governance objectives among different business implementations.

4 Results and discussion

4.1 Three stages of data assetization and four types of business governance framework

Enterprise data business focuses on economic activities that use data to create value. Its process can be divided into three core stages: data resource utilization, data productization, and data commodification. The specific model is shown in Figure 1.

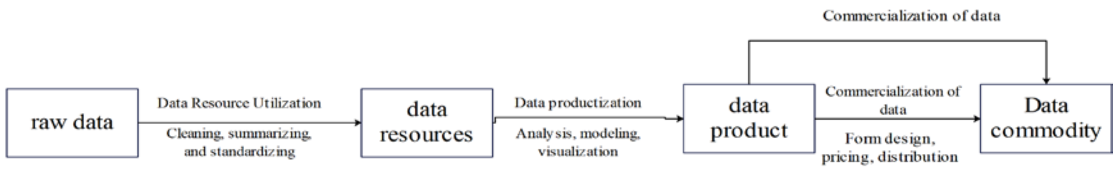

Figure 1 Enterprise data business process model from the perspective of data assetization

The data resource stage transforms raw data into usable data resources through sub processes such as data cleaning, summarization, and standardization; In the data productization stage, data resources are deeply processed into universal or customized data products through data analysis, modeling, visualization, and other operations; In the stage of data commodification, data resources or products are traded and circulated in the factor market through form design, pricing strategies, distribution methods, etc., to achieve data revenue. Based on the above process stage combination, enterprise data business can be divided into four categories: providers, transformers, integrators, facilitators, and classification logic. Providers mainly rely on their own raw data and directly sell data resources through the stages of data resource utilization and commercialization, in order to obtain basic income at a low price; Transformers integrate internal data resources on the basis of their existing main business, complete the entire process of resource utilization, productization, and commodification, and develop high priced data products to empower their main business or expand revenue; The integrator focuses on specific external data needs, and through the stages of data productization and commodification, integrates external data resources into customized products to meet specific user needs; The facilitator builds a trading platform and provides data trading services, with commission or membership fees as the main source of income, to promote supply-demand matching and compliant circulation. There are significant differences in data acquisition sources, product forms, and revenue sources among the four types of businesses: providers mainly rely on internal data, product forms are data resources, and revenue comes from resource sales; Transitioners are led by internal data, with products in the form of data products and revenue coming from product sales; The integrator integrates external data, and the product is in the form of a data product, with revenue also coming from product sales; The facilitator gathers external data, and the product is in the form of transaction services, with revenue mainly based on transaction commissions. In terms of governance objectives, data quality and data compliance are core dimensions. Data quality governance covers intrinsic quality, acquisition quality, and scenario quality; Data compliance governance involves risks of infringement, monopoly, and security. There are differences in governance objectives among different business types, and targeted strategies need to be developed based on their own data resource control capabilities (such as ownership, access rights, rule making) and user demand knowledge levels (transactional or preference based) to achieve maximum value and minimize risk.

4.2 Model experiment

This study collected sample data through questionnaire surveys, focusing on analyzing the sample characteristics of participants in data trading platforms, including the basic characteristics of questionnaire respondents and the basic characteristics of sample enterprises. The basic characteristics of the questionnaire respondents show that 54.5% are male and 45.5% are female in terms of gender distribution; The age groups are mainly concentrated between 25-34 years old (47.1%) and 35-44 years old (38.8%); Positions include executive team (21.5%), department heads (16.5%), business supervisors (15.7%), project leaders (13.2%), and ordinary employees (32.2%); The departments involved include Sales Department (22.3%), Marketing Department (17.4%), Decision making Department (11.6%), Technology Department (11.6%), Product Department (10.7%), Data Department (9.9%), etc., covering the entire process of data business (relevant statistics are shown in Table 1)

Title1 Basic Characteristics of Questionnaire Respondents

Variable	Category	Frequency	Percentage (%)
Gender	Male	66	54.5
	Female	55	45.5
Age Group	18-24 years old	4	3.3
	25-34 years old	57	47.1
	35-44 years old	47	38.8
	45-54 years old	10	8.3
	55+ years old	3	2.5
Position	Executive Team	26	21.5
	Department Head	20	16.5
	Business Supervisor	19	15.7
	Project Leader	16	13.2
	General Staff	39	32.2
	Other	1	0.8
Department	Sales Department	27	22.3
	Marketing Department	21	17.4
	Decision-Making Department	14	11.6
	Technology Department	14	11.6

Variable	Category	Frequency	Percentage (%)
	Product Department	13	10.7
	Data Department	12	9.9
	Project Department	6	5.0
	Development Department	4	3.3
	Business Department	3	2.5
	HR Department	3	2.5
	Brand Department	2	1.7
	Compliance Department	1	0.8
	Education Department	1	0.8

In terms of basic characteristics of sample enterprises, the most commonly used data trading platforms include the International Big Data Exchange (15.7%), Shanghai Data Exchange (11.6%), Anhui Data Exchange (10.7%), etc; The industry is mainly focused on information transmission, software, and information technology services (76%), with also wholesale and retail, manufacturing, etc; The types of data products sold are diverse, including datasets (60.3%), data application services (52.1%), APIs (46.3%), data processing services (44.6%), data analysis tools (38.0%), industry research reports (38.0%), etc. Enterprises often choose to sell a combination of 2-7 data products.

4.3 Effect analysis

Sample feature analysis covers the basic characteristics of questionnaire respondents and enterprises. The characteristics of questionnaire respondents include gender (54.5% male, 45.5% female), age distribution (47.1% 25-34 years old, 38.8% 35-44 years old, 8.3% 45-54 years old), position (21.5% executive team, 16.5% department director, 15.7% business supervisor, 13.2% project leader, 32.2% ordinary employee), and department (22.3% sales department, 17.4% marketing department, 11.6% decision-making department, 11.6% technology department, 10.7% product department, 9.9% data department, etc.). The basic characteristics of enterprises involve commonly used data trading platforms (Beijing International Big Data Exchange accounts for 15.7%, Shanghai Data Exchange accounts for 11.6%, Anhui Data Exchange accounts for 10.7%, etc.), industries (information transmission, software, and information technology services account for 76%, wholesale and retail accounts for 3.3%, manufacturing accounts for 3.3%, etc.), and types of data products sold (datasets account for 60.3%, data application services account for 52.1%, APIs account for 46.3%, etc.).The reliability and validity tests of variable measurement show that the reliability of each construct combination is greater than 0.7, and the Cronbach's alpha coefficients[8]are all greater than 0.7, indicating high internal consistency of the measurement. The standardized factor loading range is 0.797-0.984, all of which are greater than the 0.7 threshold; The average variance extraction (AVE) values are all greater than the 0.5 threshold, indicating good convergent validity [9]. The discriminant validity was validated by comparing the correlation coefficients between AVE square roots and constructs. The AVE square roots of each construct were greater than the correlation coefficients with other constructs, indicating that the measurement has good discriminant validity. The path coefficient test was conducted using Bootstrap analysis with SmartPLS 4 software, and the results showed standardized path coefficients and significance levels (such as platform complementarity on data product valuation fairness path coefficient 0.407, $p<0.001$); The platform data compliance service has a perceived service price fairness path coefficient of 0.377, $p<0.001$, etc. The predictive ability of the model is evaluated by the R^2 value, and the endogenous variable R^2 ranges from 0.19 to 0.67, indicating that the explanatory power of the model is appropriate or relatively high. The common method bias test used the labeled variable method and the control variable method. There was no significant difference in the correlation coefficient matrix before and after correction. After adding the control variable, the path coefficient was consistent with the original model, indicating that the empirical results were not severely affected by the common method bias, and the hypothesis test results were reliable.

5 Conclusion

The construction and application of interpretable enterprise performance prediction models based on multi-source operational data need to revolve around the core dimensions of enterprise data business governance. Enterprise data business governance needs to balance the two key dimensions of data quality and data compliance. The governance objectives cover the first level dimension (data quality governance, data compliance governance), the second level dimension (data intrinsic quality governance, data scenario quality governance, data acquisition quality governance; data infringement risk, data monopoly risk, data security risk), and the third level dimension (data source infringement/usage infringement; monopoly agreement/operator concentration/abuse of market dominance; data cross-border security). Governance strategies are divided into data quality governance strategies (data asset management, data supply chain management) and data compliance governance strategies (data compliance management), and different types of data businesses (providers, transformers, integrators, facilitators) There are differences in the specific forms of governance strategies, such as data sales enterprises focusing on data resource scale, supplier heterogeneity, customer concentration, and data compliance, while data matching enterprises focus on platform complementarity, platform data user scale, platform data compliance services, and cognitive legitimacy. The data quality governance strategy and data compliance governance strategy enhance data business performance through synergistic effects: data asset management directly promotes the financial performance of data resource sales business through the scale of data resources, or indirectly improves the financial performance of data product sales business through data product innovation; Data supply chain management enhances the promotion effect of data resource scale on financial performance by improving supplier heterogeneity and customer concentration; Effective data compliance management ensures that data product innovation has a stronger positive impact on financial performance. At the same time, in terms of relationship performance on data trading platforms, platform complementarity, data user scale, and data compliance services can ultimately improve platform relationship performance by enhancing participants' perceived benefits/value, influencing perceived benefits and value, and strengthening perceived service price fairness. The innovation of data products and the resource demands of participants are key variables that affect the effectiveness of governance strategies. Governance strategies need to be effectively matched with the technical resource demands of participants (platform complementarity matching), market resource demands (data user scale matching), and regulatory resource demands (data compliance management matching) to drive data value appreciation, accelerate value realization, ensure transaction security, and enhance perception of valuation fairness. Regulatory agencies should dynamically evaluate the compliance level of data business, classify supervision, and promote the construction of the data industry ecosystem. Specifically, a data business compliance evaluation system should be established to systematically measure potential risks from three levels: data infringement (focusing on whether the data acquisition and use stage infringes on the legitimate rights and interests of the original data subject), data monopoly [10] (focusing on examining monopoly agreements, abuse of market dominance, and concentration of operators), and data security (focusing on preventing cross-border data security risks). At the same time, platform design should be extended to the scale of data users, data compliance services, and other aspects. By matching governance strategies with participant resource needs, it can drive the cultivation and development of the data trading ecosystem, and ultimately construct an interpretable enterprise performance prediction model to achieve effective integration and application of multi-source operational data.

References

[1] *Ukezeki Y, Inoue S, Fujimura N, et al. Data processing capability of polarization dynamics in ferroelectric-gate transistor-based physical reservoir computing[J]. APPLIED PHYSICS EXPRESS, 2025, 18(8):081001.*

[2] *Marucci A. A Typological Analysis Method for Rural Dwellings: Architectural Features, Historical Transformations, and Landscape Integration: The Case of "Capo Due Rami", Italy[J]. Land, 2025, 14. DOI:10. 3390/land14020374.*

[3] *Hong, Y. (2025). Architecture Design and Performance Optimization of a Large-scale Online Simulation Platform for Business Decision-making. Advances in Computer and Communication, 6(4).*

[4] *Ye, J. (2025). Application of Nerve Signal Tracking Technology in Rehabilitation of Spinal Cord Injury. Artificial Intelligence and Digital Technology, 2(1), 171-177.*

[5] *Truong, T. H. (2025). Research on the Application of Digital Healthcare Platforms in Chronic Disease Management. Advances in Computer and Communication, 6(5).*

[6] *Ye, J. (2025). Optimization and Application of Gesture Classification Algorithm Based on EMG. Journal of Computer, Signal, and System Research, 2(5), 41-47.*

[7] *Yin, J. (2026). Research on a CLO Secondary Market Spread Volatility Prediction Model Based on RoBERTa Sentiment Factors. Advances in Computer and Communication, 7(1).*

[8] *Liu, H. (2025). Research on the Evaluation of User Safety Intervention Measures Based on Causal Inference. Engineering Advances, 5(4).*

[9] *Wang, B. (2025). Strategies and Practices for Load Test Optimization in Distributed Systems. SCIENTIFIC JOURNAL OF TECHNOLOGY Учредители: Boya Century Publishing, 7(2), 132-137.*

[10] *Wang, B. (2025). Application of Efficient Load Test Strategies in Infrastructure. Journal of Computer, Signal, and System Research, 2(4), 69-75.*

[11] *Qi, Y. (2026). The AI optimization path for payment gateway operations in the Global Financial Market. Financial Economics Insights, 3(1), 67-73.*

[12] *Wu, W. (2025, June). Construction and optimization of intelligent gateway software management platform based on jenkins cluster management under cloud edge integration architecture in industrial internet of things. In International Conference on 6G Communications Networking and Signal Processing (pp. 633-645). Singapore: Springer Nature Singapore.*

[13] *Wu, L. (2025, December). Design and Application of Automatic Data Set Generation Tool Based on KLEE in Embedded Memory Management Performance Test Framework. In 2025 IEEE 17th International Conference on Computational Intelligence and Communication Networks (CICN) (pp. 1111-1117). IEEE.*

[14] *Qi, Y. (2025, October). Research on Privacy Protection of AI Models in Big Data Using Differential Privacy Technology. In 2025 2nd International Conference on Software, Systems and Information Technology (SSITCON) (pp. 1-5). IEEE.*

[15] *Hua, X. (2024, November). Design and Implementation of a Game QoE Monitoring and Evaluation System Driven by Network Traffic Analysis. In International Conference on Cognitive based Information Processing and Applications (pp. 149-161). Singapore: Springer Nature Singapore.*

[16] *Huang, J. (2025, August). Research on Multi-Model Fusion Machine Learning Demand Intelligent Forecasting System in Cloud Computing Environment. In 2025 2nd International Conference on Intelligent Algorithms for Computational Intelligence Systems (IACIS) (pp. 1-7). IEEE.*

[17] *Zhou, Y. (2024, November). Construction of a Multi-factor Quantitative Stock Selection System for the New Energy Industry Based on Microservices Architecture and Machine Learning Components. In International Conference on Cognitive based Information Processing and Applications (pp. 163-174). Singapore: Springer Nature Singapore.*

[18] *Sun, Q. (2026). Research on Lightweight Intelligent Dialogue Systems Based on Semantic Entity Enhanced Intention Recognition and Rule Retrieval Generation Hybrid Models.*

[19] *Wang, Y. (2026). Research on the Application of Artificial Intelligence in Supply Chain Risk Early Warning.*

[20] *Liu, H. (2026). Research on Dynamic Price Prediction of E-commerce Based on Time Series Modeling.*

[21] *Yu, X. (2026). Strategy Models and Practical Research of Growth Marketing under the Background of Digital Transformation.*

[22] *Yin, J. (2026). Research on Financial Time Series Prediction and Multiscale Correlation Based on the Fusion of Network Big Data and Deep Learning.*

[23] *Hou, Y. (2026). Research on Server Performance Stability Assurance Mechanisms during Cross-Generation Computing Platform Upgrades.*

[24] *Han, X. (2026). Research on Process Decision-Making Behavior under Incomplete Information Conditions in Automobile Manufacturing Systems.*

[25] *Yu, X. (2026). Exploration of Multi-Channel Conversion Path Optimization Methods Based on A/B Testing.*

[26] *Zheng, H. (2026). Research on Edge Computing Network Task Scheduling and Resource Management Optimization Based on Artificial Intelligence Technology.*

[27] *Zhixian Zhang. Research on Model Engineering Integration Methods for AI Systems Based on Data-Driven Intelligence. International Journal of Big Data Intelligent Technology (2026), Vol. 7, Issue 1: 140-149.*

[28] *Ma, X. (2026). Research on End-To-End Reliability Modeling and Optimization of Service Grid.*

[29] *Zinuo Wang. Value Reassessment Logic of Resource-Based Enterprises in the Context of Energy Transition. International Journal of Social Sciences and Economic Management (2026), Vol. 7, Issue 1: 141-149.*

[30] *Zelin Wang. Data Analysis and Risk in Supply Chain Management. International Journal of Social Sciences and Economic Management (2026), Vol. 7, Issue 1: 132-140.*