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The Concept and Characteristics of Data Assets

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Abstract

This paper systematically investigates valuation models for data assets, exploring their conceptual characteristics, theoretical foundations, valuation methods, and associated challenges and prospects. First, it defines the core features of data assets, including legal controllability, scenario dependency, and value derivability, and reviews their classification systems as well as current management challenges related to ownership, valuation, and circulation. Second, building upon traditional asset valuation theories (cost, income, and market approaches), the study analyzes the unique attributes of data assets across technical, economic, and institutional dimensions, proposing an integrated "Technology-Economics-Institutions" tripartite valuation framework that incorporates dynamic adjustments and interdisciplinary methodologies. Furthermore, the paper elaborates on five valuation models: the income approach (e.g., excess earnings method enhanced by grey forecasting), the market approach (relying on the maturity of data trading platforms), the cost approach (focusing on historical and replacement costs), the risk-based approach (employing system dynamics to assess uncertainty), and hybrid models (optimized via machine learning). Finally, the research highlights that data quality, technological advancements, legal-ethical considerations, and financialization trends are pivotal to the future evolution of valuation systems. Recommendations include standardized governance, blockchain and AI applications, legislative clarity on ownership, and securitization innovations to advance dynamic and market-driven data asset valuation. This study provides theoretical and practical insights into value discovery and capitalization of data assets.

Keywords

Data Assets; Valuation Models; Income Approach; Hybrid Valuation; Asset Securitization.

1. The Concept and Characteristics of Data Assets

1.1. Definition of Data Assets

As a new type of production factor in the digital economy era, the definition of data assets has evolved from a broad resource-based perspective to an asset-oriented attribute. Early studies, from the perspective of scientific journal practices, proposed that data assets must satisfy three key criteria: lawful control by a legal entity, monetary measurability, and the ability to generate economic benefits, emphasizing compliance and copyright ownership issues [1]. Further distinctions have been made among data, data resources, and data assets, clarifying that data assets must possess characteristics such as legal controllability, measurability, and the potential for future economic benefits. Essentially, they represent the assetized form of processed data resources [2].

Drawing on the resource orchestration theory framework, data assets can be defined as "the outcomes of an organization’s systematic management and value transformation of data elements based on dynamic objectives," highlighting their process-driven value creation [3]. Synthesizing existing research, the core characteristics of data assets can be summarized as:

Ownership controllability (legal rights and compliance),

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Scenario dependency (contextual value realization),Non-physicality (intangible nature), and Value derivability (potential for multi-layered value extraction).

Moreover, defining data assets requires balancing multidimensional considerations, including legal compliance (e.g., Interim Measures for the Management of Generative AI Services), accounting recognition (e.g., Provisional Accounting Standards for Enterprise Data Resources), and technical feasibility (e.g., privacy-preserving computation).

1.2. Classification of Data Assets

The classification system for data assets continues to evolve with application scenarios and governance needs. Qiu Xiaojie et al. (2025) proposed a two-dimensional taxonomy based on source (internal/external) and purpose (transactional/self-use), emphasizing the market liquidity of transactional data assets [40]. Li Xiaoxiang et al. (2024), from a lifecycle perspective, categorized data assets into three stages: resourceization, assetization, and capitalization, corresponding to the progressive forms of "raw data → structured resources → financialized capital" [4].

Zhang Qian (2025) incorporated ownership complexity [3] and introduced a classification framework based on entity type (enterprises, governments, individuals) and data generation characteristics (production, circulation, usage). For instance, in scientific publishing, Shen Xibin et al. (2024) identified content data assets such as full-text articles, metadata, and user behavior data [5].

Additionally, Xue Qian et al. (2024) aligned with accounting standards by dividing recognized data assets into intangible assets (e.g., annotated datasets for knowledge services) and inventory (e.g., standardized datasets for trading). This diversity in classification reflects the intersection of technological, legal, and economic attributes inherent in data assets.

1.3. Current Status of Data Asset Management and Utilization

Current data asset management faces three major challenges: ownership, valuation, and circulation. Zhao Zhigang (2025) and Lü Meng et al. (2024) observed that while financial practices (e.g., data-backed financing, securitization) accelerate value realization, the "accounting recognition + financing" model adopted by local government financing vehicles carries risks of valuation bubbles and regulatory arbitrage [1].

Using event study methodology, Zhang Qian (2025) demonstrated that data-asset-related stocks exhibit positive market reactions (significant cumulative abnormal returns) during policy windows, reflecting investor optimism. However, this also exposes speculative behaviors due to opaque disclosures [3]. Wu Hengguang et al. (2025) emphasized that unresolved issues-such as ownership attribution (e.g., multi-contributor rights allocation), valuation disputes (cost methods undervaluing assets, income methods relying on hypothetical scenarios), and security risks (e.g., inadequate de-identification of biomedical data)-hinder large-scale adoption [2].

From a growth theory perspective, Xue Qian et al. (2024) argued that the network effects and synergistic potential of data assets remain underutilized. Enterprises must bridge the gap from resource management to value leapfrogging through data governance (e.g., "knowledge indexing"), technology integration (e.g., orchestration mechanisms), and institutional innovation (e.g., "digital fixed assets" accounting) [6].

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2. Theoretical Foundations of Data Asset Valuation

2.1. Overview of Traditional Asset Valuation Models

Traditional asset valuation theory is primarily based on three core methodologies: the cost approach, income approach, and market approach (Ouyang & Yu, 2024). The cost approach, which relies on historical or replacement costs, is particularly applicable to data assets with traceable investment inputs, as demonstrated in the accounting practices of commercial bank data resources and initial valuation of government data assets (Wang & Li, 2024). However, this method has significant limitations in capturing the appreciation potential and reusable value of data assets (Chen et al., 2025).

The income approach estimates value by discounting future economic benefits, requiring scenario-specific benefit disaggregation techniques for data assets. The Multi-Period Excess Earnings Method (MPEEM), for instance, isolates the contribution of data assets by excluding the effects of fixed and working capital. Nevertheless, the sensitivity of key parameters such as discount rates and profit allocation ratios necessitates adjustments through methods like the Analytic Hierarchy Process (AHP) or expert scoring systems.

The market approach, while theoretically sound, faces practical challenges due to the non-standardized nature of data assets and the immaturity of relevant markets (Li et al., 2024). Notably, the Excess Earnings Method, an extension of the income approach, has gained prominence in banking sector valuations through its "off-balance-sheet intangible asset segregation" mechanism. However, this method fails to adequately account for externalities (e.g., social benefits) and lacks robust cross-industry applicability (Zhang et al., 2024).

While traditional valuation methods provide a fundamental framework, they require significant adaptation to address the unique characteristics of data assets. Recent advancements include the application of machine learning techniques for parameter optimization (Zhou et al., 2024) and the incorporation of compliance-adjusted factors to reflect regulatory requirements (Du & Teng, 2024).

2.2. Unique Characteristics and Valuation Challenges of Data Assets

Data assets possess distinctive attributes that differentiate them from traditional assets, including intangibility, replicability, scenario dependency, and value volatility (Zhao et al., 2024). These characteristics manifest across three dimensions: technical, economic, and institutional.

From a technical perspective, data assets are inherently dependent on storage media and processing technologies. For instance, banking data requires real-time processing capabilities, railway data exhibits multi-source heterogeneity, and AI datasets demonstrate significant non-uniformity (Gou & Deng, 2024). Economically, while data assets exhibit non-rivalrous consumption and partial excludability, excessive encryption measures may inadvertently constrain their scale effects. Moreover, the value density of data is directly correlated with its quality dimensions, particularly completeness and timeliness.

The institutional dimension presents perhaps the most complex challenges, with fragmented property rights regimes (encompassing ownership, processing rights, and operational rights) creating intricate benefit allocation dilemmas. Additionally, the evolving regulatory landscape governing cross-border data flows introduces substantial valuation uncertainty.

Principal valuation challenges include: ambiguous property rights delineation in multi-stakeholder environments; dynamic value fluctuations driven by technological evolution, policy changes, and market demand; and significant compliance costs for sensitive sectors such as finance and healthcare, where data breaches may result in complete value erosion. These characteristics necessitate valuation models that incorporate dynamic adjustment mechanisms, risk premium factors, and multi-agent contribution analyses.

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2.3. Valuation Frameworks for Data Assets

Contemporary research has developed integrated valuation frameworks to address the complexities of data assets, which can be categorized into three paradigms:

Technology-driven frameworks employ advanced analytical techniques such as the DP-FS-BP model, which integrates data preprocessing (utilizing Random Forest imputation and Isolation Forest anomaly detection), feature selection (through LASSO regression and principal component analysis), and BP neural network prediction to quantify variable contributions. SHAP value analysis has identified research inputs and sample size as critical determinants in such models.

Scenario-adaptive frameworks emphasize industry-specific customization. The banking sector typically employs the Excess Earnings Method with AHP adjustments, while railway data valuation utilizes a hybrid cost-income approach. AI enterprises often incorporate grey forecasting models to enhance multi-period earnings projections.

Institution-embedded frameworks adopt a phased "Resourceization-Assetization-Capitalization" model. The resourceization phase focuses on cost accounting for rights clearance activities including data cleaning and classification. The assetization phase applies income-based methods to quantify scenario-specific value, while the capitalization phase explores advanced financial applications such as securitization and collateralized financing pricing.

Future valuation frameworks must integrate three fundamental principles: dynamic adjustment mechanisms (incorporating lifecycle-based earnings periods and data refresh rate decay coefficients); interdisciplinary methodological convergence (synthesizing accounting, statistical, and financial engineering approaches); and policy compliance calibration (embedding constraints from data security legislation and tax regulations).

In conclusion, the valuation of data assets requires the development of comprehensive "Technology-Economics-Institutions" tripartite models capable of addressing their inherently dynamic and context-dependent nature. This multidimensional approach represents the most promising direction for advancing both theoretical frameworks and practical valuation methodologies in this emerging field.

3. Chapter 3: Valuation Models for Data Assets

3.1. Income-Based Valuation Models

The income-based approach primarily estimates the value of data assets by forecasting their future economic benefits and discounting them to present value using methods such as discounted cash flow (DCF). Gou Lufeng (2024) investigated the valuation of data assets in artificial intelligence enterprises and proposed an excess earnings method [9]. This approach enhances the scientific rigor and operational feasibility of data asset valuation by projecting excess earnings and discounting them using the weighted average cost of capital (WACC). Furthermore, the study incorporated a grey prediction model (GM(1,1)) to improve the accuracy of earnings forecasts, providing enterprises with a robust framework for valuing data assets in the digital economy era.

3.2. Market-Based Valuation Models

Market-based models derive the value of target data assets by comparing them with similar transactions in the market. This method requires sufficient comparable transaction data to ensure reasonable and reliable valuations. Xu Hongdan (2025) examined the impact of AI policies on manufacturing firms' utilization of data elements [15], revealing that pricing mechanisms for data elements in market transactions are gradually maturing, with increasing pricing power in capital markets. Moreover, the development of data trading platforms has

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amplified the importance of market-based approaches, particularly as industry-specific data assets become increasingly tradable through big data exchanges.

3.3. Cost-Based Valuation Models

Cost-based models focus on the acquisition, storage, processing, and maintenance costs of data assets, typically employed for internal valuation purposes. Sun Ying (2025) emphasized that cost-based valuation must comprehensively consider historical costs, replacement costs, and marginal usage costs to ensure accuracy [22]. Yang Kaiyuan (2025) further suggested that cost-based assessments should incorporate data quality, completeness, and application scope to mitigate valuation biases caused by data redundancy or inefficient utilization [19]. In practice, this method is particularly suitable for startups or scenarios where data acquisition costs are high but business models remain underdeveloped.

3.4. Risk-Based Valuation Models

Risk-based approaches evaluate data assets by accounting for market volatility, security risks, and uncertainties in future earnings. For instance, Zhou Yanqiu (2024) investigated the value formation mechanisms of data assets using system dynamics modeling to analyze the impact of various risk factors [24]. The study highlighted that risk assessment must encompass not only data security and compliance but also market uncertainties, breach risks, and regulatory changes. Additionally, Yuan Zeming (2025) analyzed the relationship between data assets and organizational resilience, demonstrating that firms' data management capabilities positively correlate with their risk response capacities [32]. This indicates that data asset values are significantly influenced by enterprises' ability to navigate market and policy risks.

3.5. Hybrid Valuation Models

Hybrid models integrate multiple valuation methodologies to address complex data asset valuation needs. Yu Xinxin (2025) proposed a hybrid model based on the super-efficiency SBM method, combining income, market, and cost approaches while incorporating machine learning to enhance accuracy [24]. Similarly, Tan Zhanglu (2025) emphasized in coal mining industry research that hybrid models must account for sector-specific characteristics and data governance capabilities to measure true data asset value [21]. These studies suggest that hybrid models represent the forefront of data asset valuation, improving both scientific rigor and market acceptability in capital markets.

This comprehensive suite of valuation methodologies reflects the evolving sophistication in assessing data assets, each offering distinct advantages tailored to specific valuation contexts and industry requirements. The continued refinement of these models will be critical as data assets assume an increasingly central role in organizational value creation and economic measurement.

4. Chapter 4: Challenges and Prospects in Data Asset Valuation

4.1. The Relationship Between Data Quality and Valuation Accuracy

Data quality fundamentally determines the scientific validity and accuracy of data asset valuation, serving as a critical prerequisite for data asset capitalization and balance sheet recognition. However, the inherent heterogeneity, dynamic nature, and non-standardized characteristics of data make quality management a complex challenge. Qiu Xiaojie (2025) emphasizes that the core of enterprise data assetization lies in the standardization and quantifiability of data resources. Without guaranteed data quality, even formally recognized intangible data assets may face market skepticism regarding their valuation [40]. Lü Meng's (2024) event study analysis of the economic consequences of data asset recognition reveals that higher data quality correlates with more positive market reactions and more stable

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investor valuation assessments [39]. Nevertheless, deficiencies in data rights confirmation, governance, and management at some enterprises have led to significant valuation volatility and potential financial statement manipulation risks. Current approaches to improving data quality focus on three key dimensions: data standardization (establishing unified storage formats and management protocols to ensure interoperability), data governance mechanisms (implementing lifecycle management and quality verification), and rights confirmation and compliance (ensuring lawful data sources to mitigate legal risks).

4.2. The Impact of Technological Advancements on Valuation Models

The rapid development of AI, blockchain, cloud computing, and big data technologies is driving significant evolution in data asset valuation methodologies. Traditional approaches face limitations when applied to complex data assets: the income method struggles with accurate earnings projections, while the market approach depends on trading environments that remain underdeveloped. Zhu Qinghu (2025) highlights blockchain's role in enhancing valuation transparency through immutable transaction records [48], while Song Jianmin (2025) demonstrates how AI and machine learning can improve income method accuracy, particularly in pricing and trend prediction [47]. Key technological impacts include blockchain ensuring transaction authenticity, AI/ML optimizing earnings forecasts, and cloud-based analytics enabling dynamic value monitoring. These advancements are transitioning valuations from static assessments to real-time, adaptive models.

4.3. Legal and Ethical Considerations

Data asset valuation confronts complex legal and ethical challenges spanning rights confirmation, privacy protection, security, and cross-border flows. Yang Yuting (2025) notes that while China's accounting standards provide basic legal recognition, the absence of unified rights confirmation mechanisms continues to create ownership ambiguity [45]. Ethical concerns regarding data misuse and consumer protection further complicate assetization processes. Critical regulatory developments should address legislative clarification of data rights, privacy-preserving technologies, and cross-border governance frameworks to facilitate international transactions while ensuring compliance.

4.4. Future Development Trajectories

Future valuation systems will evolve toward greater dynamism, marketization, and financialization. Song Jianmin (2025) predicts the transition to dynamic models incorporating real-time analytics [47], while Zou Zhiyun (2025) identifies Data Asset Securitization (DAS) as a key development that will enhance liquidity and create new financing instruments [46]. Anticipated advancements include dynamic valuation models with continuous monitoring capabilities, mature securitization markets, enhanced trading infrastructure, and comprehensive policy frameworks.

5. Conclusion

While data asset valuation faces multidimensional challenges in quality assurance, technological adaptation, legal compliance, and ethical governance, ongoing improvements in data ecosystems, technical capabilities, regulatory environments, and market maturity promise increasingly precise, market-driven valuation systems. The emergence of data asset securitization may further unlock capital market potential, establishing data as a transformative financial asset class.

References

[1] Z.G. Zhao: Financialization of Data Assets: Chinese Practice and Prospects, Finance and Accounting Monthly, Vol. 46 (2025) No.4, p.33-38.

[2] H.G. Wu, C.Y. Gao and W. Jian: Theoretical Origins and Research Paths of Data Resource Accounting, Economic Perspectives, Vol. (2025) No.1, p.146-160.

[3] Q. Zhang: Logical Motivation, Practical Dilemmas and Solutions for Data Asset Accounting, Friends of Accounting, Vol. (2025) No.3, p.9-16.

[4] X.X. Li, Y.X. Liu, Y.Q. Xie and D.X. Gu: Data Orchestration: A New Theoretical Framework for Data Valuation, Information Studies: Theory & Application, Vol. (2025), p.1-11.

[5] X.B. Shen, K.X. Liu and H.X. Liu: Definition, Value and Strategies of Scientific Journal Data Assets from the Perspective of Large Models, Science-Technology & Publication, Vol. (2024) No.11, p.80-87.

[6] Q. Xue, X.Q. Zeng and Z.Y. Ouyang: Key Issues of Data Asset Accounting in the Digital Intelligence Era, The Chinese Certified Public Accountant, Vol. (2024) No.10, p.105-113.

[7] M.G. Chen, Y.R. Zhao and Y.S. Liu: Valuation of Data Assets Based on Multi-Period Excess Earnings Method, Statistics & Information Forum, Vol. 40 (2025) No.2, p.3-18.

[8] C.P. Zhou, S.B. Li, Y.Z. Zhang, P.L. Yuan, Z.H. Liao and X.X. Zhang: Contribution Rate of Data Asset Valuation Indicators Based on DP-FS-BP Prediction Framework and SHAP Algorithm, Science Technology and Engineering, Vol. 24 (2024) No.33, p.14317-14329.

[9] L.F. Gou and W.D. Deng: Research on Data Asset Valuation of AI Enterprises: A Case Study of Hikvision, The Chinese Certified Public Accountant, Vol. (2024) No.11, p.106-110.

[10] J. Du and D.N. Teng: Discussion on Data Element Valuation and Tax-Related Issues, Taxation Research, Vol. (2024) No.11, p.61-67.

[11] S. Zhang, S.A. Zhao and R.T. Yan: Research on Enterprise Data Asset Value Realization and Financial Support Models, Southwest Finance, Vol. (2024) No.10, p.42-52.

[12] S. Wang and B.Y. Li: Review of Theories and Methods for Data Asset Value Accounting, Statistics and Decision, Vol. 40 (2024) No.20, p.43-48.

[13] H.J. Li, W.G. Yue, W.F. Shi, Y.H. Wu and J.Q. Wang: Railway Data Asset Valuation Method Considering Behavioral Characteristics of Market Participants, Railway Transport and Economy, Vol. 46 (2024) No.12, p.191-198.

[14] Z.G. Zhao, J.Y. Zeng and Y.X. Liu: Systematic Investigation of Value Characteristics and Attributes of Enterprise Data Assets, Friends of Accounting, Vol. (2024) No.20, p.128-134.

[15] H.D. Xu and J.H. Wang: Artificial Intelligence and New Quality Productivity in Manufacturing Enterprises: Based on Double Machine Learning Model, Soft Science, Vol. (2025), p.1-14.

[16] X.X. Zhang: "Data Element × Publishing": From Digital Publishing to Data Publishing, Documentation, Information & Knowledge, Vol. (2025), p.1-10.

[17] M.G. Chen, Y.R. Zhao and Y.S. Liu: Valuation of Data Assets Based on Multi-Period Excess Earnings Method, Statistics & Information Forum, Vol. 40 (2025) No.2, p.3-18.

[18] Q.W. Wang, K.Y. Wang and X.Y. Wang: Selection of Accounting Measurement Attributes for Enterprise Data Assets: Based on Data Asset Classification, Finance and Accounting Monthly, Vol. 46 (2025) No.4, p.67-73.

[19] K.Y. Yang and Y.N. Luo: Data Assetization and Enterprise Innovation Performance: Empirical Evidence Based on Text Analysis, Finance and Economy, Vol. (2025) No.1, p.40-52.

[20] Z.M. Yuan, Q. Yin and C. Huang: Data Assets and Enterprise Resilience: Effects and Mechanisms, Economic Survey, Vol. (2025), p.1-13.

[21] Z.L. Tan, M.J. Wang and Z.H. Ye: Research on Methodology System and Implementation Framework of Intelligent Coal Mine Data Governance, Coal Science and Technology, Vol. (2025), p.1-13.

ISSN: 2688-9323

[22] Y. Sun and X. Zhao: Data Asset Management and Enterprise Collaborative Innovation: Based on the Perspective of Innovation Resource Agglomeration, Journal of Industrial Technological Economics, Vol. 44 (2025) No.2, p.78-87.

[23] F. Dai and X. Zhao: Mechanism and Path of Enterprise Data Asset Value Creation: A Decision-Making Perspective, Communication of Finance and Accounting, Vol. (2025), p.1-8.

[24] X.X. Yu, Y. Zheng and Q.T. Yu: How Do Data Asset Elements Empower Enterprises' New Quality Productivity? Empirical Analysis Based on Super-Efficiency SBM Method, Enterprise Economy, Vol. 44 (2025) No.1, p.130-139.

[25] D. He, C. Zhao and M. Pang: Research on the Influence of Enterprise Network Position on Data Asset Information Disclosure, Journal of Industrial Technological Economics, Vol. 44 (2025) No.1, p.75-84.

[26] Y.Q. Zhou, L. Chen, Y.K. Mao and F. Ju: Formation Mechanism and System Simulation of Data Asset Value, Science Research Management, Vol. 42 (2024) No.6, p.52-60.

[27] C.P. Zhou, S.B. Li, Y.Z. Zhang, P.L. Yuan, Z.H. Liao and X.X. Zhang: Contribution Rate of Data Asset Valuation Indicators Based on DP-FS-BP Prediction Framework and SHAP Algorithm, Science Technology and Engineering, Vol. 24 (2024) No.33, p.14317-14329.

[28] R.H. Ouyang and M.X. Yu: Application of Excess Earnings Method in Commercial Bank Data Asset Valuation, Price: Theory & Practice, Vol. (2024) No.10, p.60-69+226.

[29] R.J. Huo: Research on the Construction Path of Data Governance System in Library Intelligent Transformation, Library and Information Service, Vol. 68 (2024) No.22, p.37-44.

[30] L.F. Gou and W.D. Deng: Research on Data Asset Valuation of AI Enterprises: A Case Study of Hikvision, The Chinese Certified Public Accountant, Vol. (2024) No.11, p.106-110.

[31] B. Niu, Y.Q. Du, X. Yu and N.H. Zhao: Data Asset Information Disclosure and Bond Financing Costs, Journal of Guangdong University of Finance & Economics, Vol. 39 (2024) No.5, p.88-101.

[32] Z.M. Yuan, Q. Yin and C. Huang: Research on the Impact of Data Assets on Enterprise Labor Income Share, Journal of Guangdong University of Finance & Economics, Vol. 39 (2024) No.5, p.72-87.

[33] X.C. Yang, S.D. Song and J. Guo: Pricing Methods for Data Assets: Research Based on Network Evolutionary Game Between Supply and Demand Sides, Science and Technology Management Research, Vol. 44 (2024) No.19, p.169-180.

[34] J.Y. Zhu, Z.Q. Shen, J.Y. Bai and Y.Y. Li: Difficulties and Countermeasures of Data Asset Audit in Financial Statement Audit, Friends of Accounting, Vol. (2025) No.5, p.15-24.

[35] F. Dai and X. Zhao: Mechanism and Path of Enterprise Data Asset Value Creation: A Decision-Making Perspective, Communication of Finance and Accounting, Vol. (2025), p.1-8.

[36] Z.F. Shi: Evaluation and Marketization Discussion of State-Owned Data Assets, Financial Circles, Vol. (2025) No.3, p.15-17.

[37] Y.F. Li: Thoughts on Data Asset Accounting Issues, Business Observation, Vol. 11 (2025) No.2, p.26-29.

[38] Y.X. Xiao, C. Suo, S.T. Zhang and Q.G. Meng: Data Gatekeeper: Functions, System Framework and Future Prospects, Management Review, Vol. 36 (2024) No.12, p.60-71.

[39] M. Lü, L.F. Zhao and Y.C. Zhong: Preliminary Study on Value Effects and Economic Consequences of Data Asset Accounting, Management Review, Vol. 36 (2024) No.12, p.47-59.

[40] X.J. Qiu and X.Y. Zhou: Enterprise Data Assetization: Mechanism, Path and Challenges, Friends of Accounting, Vol. (2025) No.2, p.18-24.

[41] Y.P. Zhang and Y.Y. Fu: Logical Mechanism, Operational Risks and Path of Public Data Asset Securitization, Friends of Accounting, Vol. (2025) No.6, p.25-31.

[42] X.L. Wang: Rights Confirmation, Valuation and Accounting: Data Assetization of Chinese Enterprises and Its Practical Results, Journal of Shenzhen University (Humanities & Social Sciences), Vol. 41 (2024) No.6, p.82-92.

[43] R.B. Huang: Enlightenment of UK Universities' "Data Audit Framework" to China, Studies in Science of Science, Vol. (2025), p.1-13.

ISSN: 2688-9323

[44] S. Zhang, S.A. Zhao and R.T. Yan: Research on Enterprise Data Asset Value Realization and Financial Support Models, Southwest Finance, Vol. (2024) No.10, p.42-52.

[45] Y.T. Yang: Challenges and Responses to Data Asset Accounting, Enterprise Management, Vol. (2025) No.3, p.45-49.

[46] Z.Y. Zou: Accelerating the Process of Data Production Factors with Data Asset Accounting as an Opportunity, Finance and Technology of MIIT, Vol. (2025) No.1, p.70-77.

[47] J.M. Song: Thoughts on Data Asset Accounting Empowered by New Quality Productivity, Time-Honored Brand Marketing, Vol. (2025) No.3, p.52-54.

[48] Q.H. Zhu and Y.Y. Liu: Development Trends, Innovative Practices and Suggestions for Enterprise Data Asset Financing, Communication of Finance and Accounting, Vol. (2025) No.4, p.140-143+150.

[49] Z.D. Tang and Z. Tang: Can Data Assets Create Value for Companies? A Case Study of Company F, Communication of Finance and Accounting, Vol. (2025) No.4, p.104-109+122.