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RESEARCH ON THE VALUATION OF INTERNET ENTERPRISE DATA ASSETS BASED ON VALUE CHAIN THEORY

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Abstract. As data assets grow strategically important yet remain difficult to value in internet enterprises, this study analyzes the factors influencing their valuation. Using value chain theory and a system dynamics model, it uncovers the mechanisms of value formation. Results show that data asset value is realized dynamically across stages – collection, analysis, mining, and application – shaped by internal attributes and external factors. The process follows a diminishing marginal return pattern and exhibits significant value lag. Therefore, data asset assessment should account for the full life-cycle, intrinsic properties, and technological conditions.

Keywords: system dynamics, data assets, value chain, value assessment, lag effect, simulation modeling.

JEL Classification: C63, L86, L22, G32, C53, C61.

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1. Introduction

In the digital economy, the rapid growth of data assets has made their evaluation crucial for unlocking data value, facilitating circulation, and standardizing market development. On the government side, data assets have emerged as a key driver of global economic transformation, with major economies such as the United States, the European Union, and China recognizing their importance in measuring economic and technological strength. On the corporate side, data assets are gradually becoming the core competitiveness of internet companies such as Apple, Google, Microsoft, Alibaba, Tencent, and others. These data assets not only include user behavior and transaction data but also high-value information processed through big data analytics, artificial intelligence, and other technologies. These assets help optimize products, enhance user experience, and drive data-based decision-making, which is crucial for maintaining a competitive edge. As data assetization accelerates, more enterprises have begun to emphasize the accumulation and utilization of data assets. The digital economy, fueled by data resources and digital technology, is emerging as a major growth driver. However, accurately valuing data assets – a prerequisite for realizing their value – remains a major challenge (Hu & Xu, 2022). Characterized by virtuality, exclusivity, processability, and value variability, data assets are shaped by factors such as cost, scenario, market, and quality. Traditional valuation methods are often ill-suited for such assets. This study therefore applies value chain theory to examine the value composition and key influencing factors of data assets in internet enterprises. A system dynamics model is developed to address evaluation challenges. Through simulation, the study explores value changes across stages and identifies the dynamic evolution of data elements under external factors like technology and policy, thereby supporting assetization and offering practical insights for valuation and market development.

The potential contributions of this paper include:

- First, from a research perspective, it innovatively examines the value of data assets in internet companies based on data value chain theory. By integrating both internal and external features of data, it expands current research scope and offers a new viewpoint on data valuation.
- Second, in terms of research methodology, it introduces system dynamics to develop a quantitative model for assessing data asset value and capturing its dynamics. Combined with cost, market, and income approaches, this enhances the objectivity and reliability of valuation.
- Third, regarding research findings, the study analyzes key interactions affecting data value, reveals the trend of diminishing returns, and highlights scenario-specific patterns. These insights not only support data asset valuation theoretically but also enrich the methodological framework, promoting further development in the field.

2. Theoretical framework

The term "data asset" was first introduced by Peterson (2012), but as an emerging concept, its definition remains relatively vague. By reviewing the existing research, this paper argues that a data asset is characterized by the following: (1) it is a data resource stored in a specific format on a medium; (2) it is controlled or held by a specific entity; and (3) it possesses asset-related characteristics with the potential to create economic value for enterprises.

2.1. Factors affecting the value of data assets

2.1.1. Economic factors

The economic factors of data assets typically include acquisition cost, revenue, transaction price, and market application. Costs and benefits directly reflect the value of data assets, while other factors impact them.

Data cost is evaluated based on the data life-cycle theory, covering collection, transmission, storage, processing, and use (Acquisti et al., 2020). It is categorized into acquisition, storage and management, mining and analysis, and application security costs (Abbas et al., 2021). Generally, higher costs contribute to higher data transaction prices. As a novel production factor, data not only directly generates social value but also reduces transaction costs when integrated with other factors. This integration promotes economies of scale, improves efficiency, and enhances total factor productivity (Mahajan, 2022). For internet enterprises, sustained management and application turn data into valuable assets, enabling capital gains through transactions. Data also carries significant internal innovation value (Nolin, 2020), supporting management, operations, and decision-making. By analyzing its role across business scenarios, data aids decision-making and indirectly affects cash flow. Using data to refine products and services increases revenue and reduces costs, particularly in digital environments. This establishes a value chain linking talent, technology, capital, and management, driving productivity through optimized processes and service enhancements, thereby improving profitability.

2.1.2. Non-economic factors

Non-economic factors such as data quality and technology aid comprehensive valuation. Some scholars prioritize data quality and quantity, while others stress technology, legal frameworks, and risks. Gill (2024) tie value realization to stakeholders, and Xiong et al. (2022) emphasize organizational management and skilled professionals. The data ecosystem involves numerous internal and external factors throughout its life-cycle, complicating value confirmation. This paper classifies these factors into inherent attributes and external characteristics.

(1) Intrinsic properties

The inherent attributes of data assets include data quality, data size, scarcity, freshness, and privacy (Pei, 2020).

Data quality is a crucial factor influencing the realization of data value. High-quality data yields richer insights and empowers operators to make more informed decisions.

The scale of data serves as the foundation for data mining and analysis generally enhances potential value (De Amicis & Batini, 2004). However, some argue that a large amount of data does not necessarily imply an increase in information content or data value; on the contrary, it may lead to an overflow of information waste.

Scarcity refers to the relationship between supply and demand of data. Data in short supply holds higher value and can be crucial for innovation and differentiation. Freshness refers to the validity period of data. newer data is more likely to produce effective value. Privacy, often measured using Shannon's information theory (Shannon, 1948), determines the privacy content of data using information entropy and then expresses the value of data through privacy metrics. These attributes show that date's marginal value varies across contexts, as supported by recent research (Farboodi et al., 2025).

(2) External Characteristics

Given the openness of digital assets, external factors such as organizational management, digital technology, and the external environment also impact their value.

Organizational management factors refer to the data literacy of data users. Data literacy encompasses the awareness and ability of data users to recognize the value of data, manage it ethically, and apply it effectively through analysis and mining. The effectiveness of data analysis hinges on appropriate interpretation methods, which translate complex results into actionable insights, enabling users to make informed decisions. Variations in users' data knowledge and analytical skills also influence their value judgments. The connotation and mechanism of data literacy varies by industry, and its impact on value needs to be analyzed in the context of specific scenarios. Low-literate companies may only realize static cost savings, while high-literate companies can trigger value-added innovation through predictive maintenance. For Internet companies, data literacy focuses on agile iteration and user insights. In a typical product optimization scenario, data users are required to quickly turn analytics into action. The value transfer path of data literacy is to shorten the cycle of "data-insight-action", which directly enhances the value of user life-cycle.

Digital technology factors pertain to technological investment and data analytic capabilities. Raw data are often complex, featuring diverse formats and lacking direct connections between different indicators and parameters, which limits their immediate economic value. Efficient utilization of data resources necessitates ample computational power and suitable algorithmic support (Li & Wu, 2021). Strong analytic capabilities help enterprises uncover correlations, generate predictive insights, and provide decision-makers with more accurate information, driving corporate growth and success. Thus, data technology capabilities constitute a vital source and necessary avenue for realizing data value.

External environmental factors encompass moral constraints, data security, regulatory policies, and other factors (Cong et al., 2021). Data assets are vulnerable to data leakage and unauthorized use during their utilization, posing security risks that can diminish or even eradicate their value. Furthermore, data is also subject to regulatory and policy risks, which concern whether the acquisition, utilization, and trading of data assets comply with relevant laws and regulations. Consequently, certain data may lose all value due to the introduction of a specific policy document or legal regulation, while others may experience a surge in value as a result. A summary of these influencing factors is presented in Table 1.

Table 1. Classification of factors influencing data asset value

Factors Affecting the Value of Data Assets			Source of Viewpoint
Economic Factors	Cost	Collection Cost	Acquisti et al. (2020)
		Storage Management Cost	Abbas et al. (2021), Mahajan (2022)
		Mining and Analyzing Costs	Nolin (2020), Acemoglu et al. (2022)
		Security Cost	Abbas et al. (2021), Bounie et al. (2021), Choe et al. (2018)
	Benefits	Internal Innovation	Cong et al. (2021), De Nijs (2017), Jones and Tonetti (2020)
		Data Trading	Goldfarb and Tucker (2019), Abbas et al. (2021)
Non-Economic Factors	Intrinsic properties	Quality	De Amicis and Batini (2004), Zhu et al. (2021)
		Scale	Pei (2020), Li et al. (2018)
		Privacy Level	Shannon (1948)
		Scarcity	Laney (2011), Liu et al. (2019)
		Freshness	Liu et al. (2019), Jung and Park (2019)
	External Characteristics	Technical Factors	Gill (2024), Xiong et al. (2022)
		Organizational Factors	Peng and Bing (2020), Gill (2024), Xiong et al. (2022)
		Market Environmental Factors	Cong et al. (2021), Laney (2011), Liu et al. (2025)

2.2. Pathways to value creation of data assets

As a general commodity, data assets possess value, exchange value, and use value (Pei, 2020). The use value of data is primarily manifested in the collection and utilization of data by various enterprises, aiding in efficient need analysis and decision-making. Exchange value, grounded in its use value, reflects the market price of data, traded through licensing or transfer, yielding direct economic benefits. To better evaluate the exchange value and use value of data assets, this paper employs a value chain analysis method to dissect the process of realizing data value.

Chinese scholars such as Xu et al. (2022) argue that data elements can participate in production activities and generate value along four stages: data collection, data storage, data analysis, and data utilization. Based on this, Hu and Xu (2022) constructed a data value chain comprising four phases: data collection, storage, analysis, and application. Each stage reflects a dynamic process of value creation, transforming raw data from low-value forms into structured, high-value assets for decision-making or external sale.

Therefore, this paper argues that when internet enterprises apply digital technologies and explore and analyze their data assets along the various stages of the value chain, influenced by external factors such as organization and environment, this potential value gradually becomes apparent.

However, despite these valuable contributions, several gaps remain in the existing literature. First, most current studies adopt static or linear models to assess data asset value, lacking a dynamic and system-level perspective. Second, although the concept of the data value chain has been widely discussed, few studies have incorporated it into theoretical modeling frameworks to analyze how data value is formed. Third, the interaction between internal data attributes, and external environmental factors, has not been sufficiently explored. These gaps underscore the need for an integrated and dynamic modeling approach grounded in value chain theory and system dynamics to better capture the complex process of data asset valuation in internet enterprises.

3. Model construction

This section delineates the methodology and structural framework for modeling the value assessment of data assets. It begins by establishing the theoretical foundation and research design, defines system boundaries and research hypotheses, conducts causality analysis, constructs the system flow diagram and finally sets simulation equations.

3.1. Methodological basis and research design

System dynamics utilizes causal feedback diagrams for systematic analysis of complex systems and quantitative simulations of models through system flowcharts. It can dynamically reflect the functions and behaviors of systems, offering numerous advantages in studying dynamic, multi-stage, and non-linear systems (Forrester, 1958). It has been widely applied in various asset evaluations and price forecasting studies. For example, Vaish et al. (2011) proposed a novel information asset valuation technique using system dynamics, studying and calculating three important variables of information assets on a test platform; Gu and Li (2022) utilized system dynamics to explore value creation in digital innovation ecosystems within complex socio-technical environments. This approach is consistent with recent research that emphasizes integrating value chain–based variable extraction with systematic modeling frameworks for data valuation (Hafner et al., 2025), and has been successfully applied in enterprise contexts using analytic hierarchy process combined with multi-period excess earnings methods (Yang et al., 2025). Data assets, influenced by their inherent attributes and external characteristics, exhibit value fluctuations over time. Traditional methods such as the cost, income, and market approaches fail to capture the dynamic and non-linear nature of data assets. System dynamics, on the other hand, can reflect the causality of internet enterprise data assets from the perspectives of costs and benefits. It systematically reconstructs the transfer and value-added processes of data throughout the various stages of data asset collection, storage, mining, and application, revealing the operational laws governing the value realization system of enterprise data assets.

Building on this methodological foundation, this study employs a structured research design based on data value chain theory. It conceptualizes data asset value realization as a multi-stage dynamic process encompassing four core stages: collection, storage, mining, and application. These stages constitute the backbone of the value creation mechanism and are influenced by diverse internal attributes and external environmental factors. Figure 1 visualizes this conceptual framework, illustrating the transformation of raw data into valuable assets through iterative value-adding processes and contextual enablers.

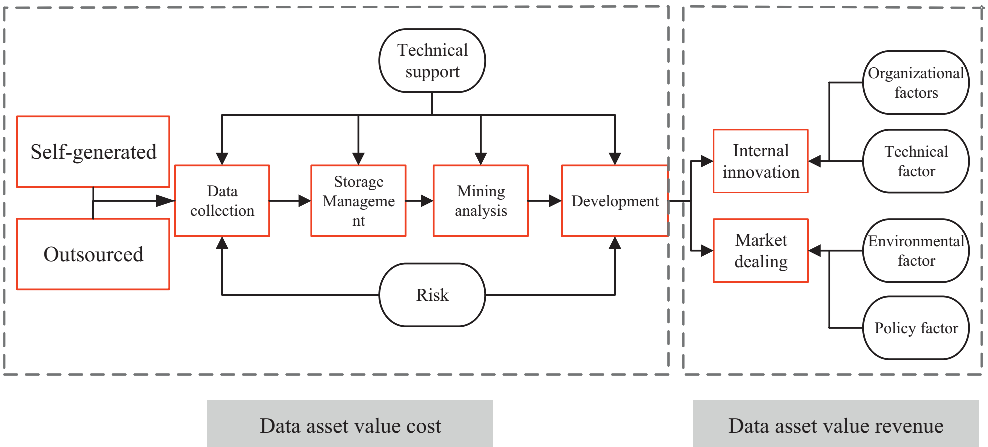


Figure 1. Flow chart of data asset value creation

This integrated framework bridges conceptual analysis with modeling, serving as a foundation for translating value chain theory into a dynamic simulation approach. It provides a coherent logic for mapping the evolution of data assets and supports the development of a system-level model that captures the complex interactions driving value creation in internet enterprises.

3.2. System boundaries and research hypotheses

Establishing system boundaries is the foundation for conducting system dynamics simulation modeling. This paper includes the process of realizing data asset value and its influencing factors within the system boundaries. To clarify the scope of the system study and key factors, this paper makes the following basic assumptions about the system:

Hypothesis 1: Based on Marx's theory of value creation, digital assets also possess both use value and value attributes. The use value of digital assets lies in their ability to generate revenue and reduce costs. Therefore, this paper adopts the net present value of cost-benefit analysis as an indicator of the value of data assets.

Hypothesis 2: It is assumed that there exists an absolute standard of data quality, which is independent of specific usage scenarios. In contrast, contextual assessments are based on subjective judgments, where indicator scores reflect how these subjective judgments influence data usage and decision-making.

Hypothesis 3: Different business decisions require varying levels of data quality. Consequently, this paper hypothesizes that analyzed and processed data assets can be applied to suitable application scenarios.

Hypothesis 4: Data can realize its value through data trading. Market environmental factors impact the value of data that is sold. It is assumed that when engaging in external data sales, data owners are able to ensure compliance and security measures to protect data assets.

3.3. Causality analysis

The causality diagram is essential for constructing the system flowchart, illustrating the structure among system elements through qualitative analysis (Gu & Li, 2022). It consists of arrows showing causality direction and loops indicating feedback. Causality can be classified into two polarities: positive (+) and negative (–). Positive (+) causality reinforces relationships, while negative (–) causality weakens them. Based on the preceding analysis of data asset value creation and influencing factors, a causality diagram for data asset value is constructed, as shown in Figure 2.

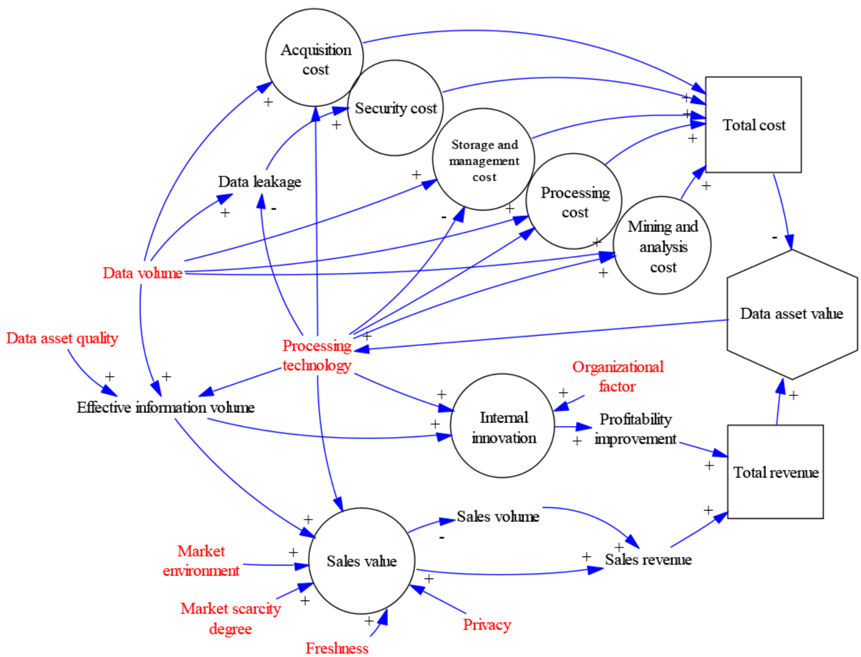


Figure 2. Causal relationship diagram of data asset value

In Figure 2, we consider the process from data generation to application, taking into account both the costs throughout the entire value creation process and the future revenue from data application. This process is influenced by factors such as data quality, freshness, and organizational factors, and incurs various data costs. The net present value resulting from these costs and revenues constitutes the value of data assets. This paper unfolds data asset valuation from two aspects: "cost value" and "revenue value." The cost value reflects the investment costs, while the revenue value reflects the economic benefits. Together, they comprise the total value of data assets.

3.3.1. Cost subsystem

By mining, analyzing, and utilizing data elements, information interaction biases and transaction costs can be reduced, as illustrated in Figure 3. The cost subsystem reflects the process where data assets influence their value through costs. Based on the data life-cycle theory, the costs of data assets are categorized into four types: acquisition, storage and management, mining and analysis, and application security.

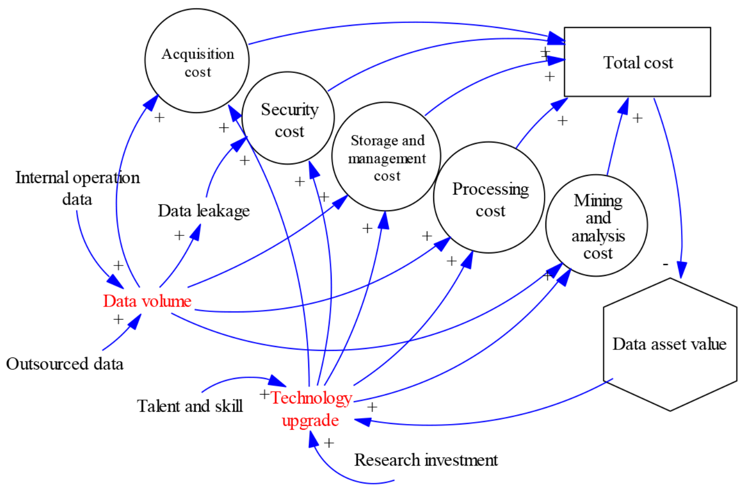


Figure 3. Causal loop of cost subsystem

This process relies on the support of data technology, encompassing acquisition, storage, processing, mining, and protection (Schaefer et al., 2014). Additionally, the scale of data impacts costs, which in turn affects the value of data assets. As the net present value continues to accumulate, it prompts increased technological investment, forming a feedback loop where technology enhances, costs decrease, and the value of data assets improves.

3.3.2. Revenue subsystem

Data revenue primarily comprises indirect income from internal efficiency improvements and direct income from data sales. "Internal efficiency improvement through data" refers to applying data to business decision-making and operational management, enhancing the scientificity and accuracy of decisions, and achieving internal efficiency improvements within organizations by establishing data-driven decision-making mechanisms and intelligent business processes (Cloud Computing and Big Data..., 2021). As shown in Figure 4, the revenue subsystem reflects the process by which data assets influence their value through revenue.

Environmental factors such as national policies and societal recognition of the data's value will impact the data's value. A large data scale does not equate to high information content or data value; therefore, enhancing data quality and mining capabilities is essential. Furthermore, attention must be paid to the synergy between mining and privacy protection to avoid inhibiting the value of data assets through negative feedback loops. When data revenue increases, the net present value also rises, prompting increased technological investment, thereby forming a positive feedback loop where data analysis capabilities improve, data quality enhances, revenue gradually increases, and the value of data assets continuously improves.

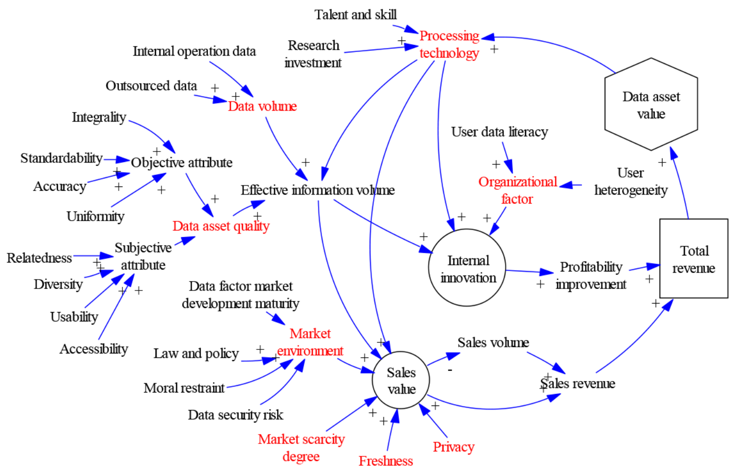


Figure 4. Causal loop of revenue subsystem

3.4. System flow diagram

The causality diagram reflects the qualitative relationships among the elements of the data asset value realization system, while the system flow diagram quantitatively analyzes the dynamic interaction. Stocks, flows, auxiliary variables, and constants are the most basic variables in a system flow diagram. Flows represent the rate of change or transfer between stocks, represented by double-headed arrows with indications of flow direction and rate. Auxiliary variables describe the system's state or influence its behavior but are not directly affected by external factors, while constants represent fixed parameters that remain unchanged throughout the model's operation. Based on the causality diagram and analysis of the cost and revenue subsystems, this paper constructs a comprehensive system flow diagram for the data asset value system, as shown in Figure 5.

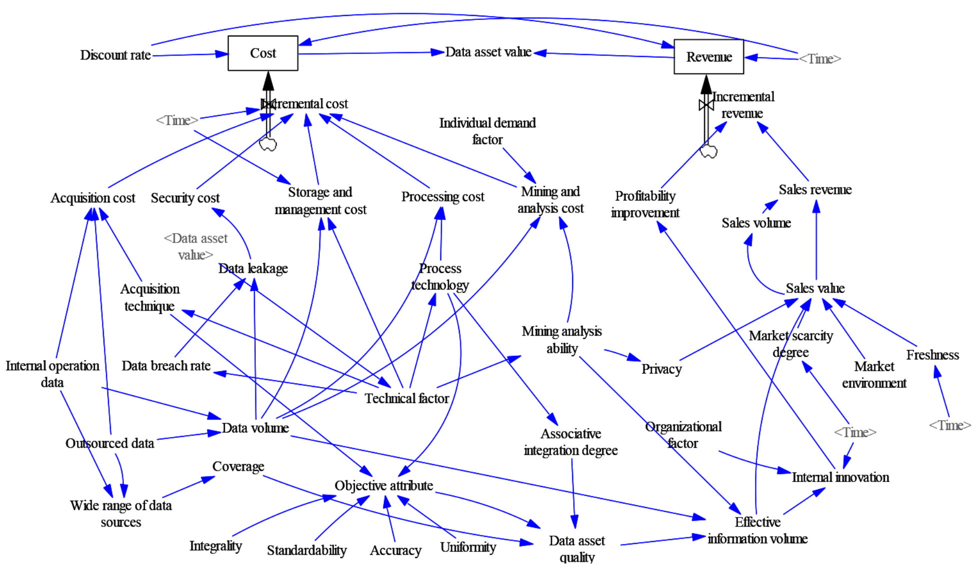


Figure 5. Flow chart of value stock of data assets

3.5. Simulation equation setting

Due to the limited data involving the main variables of this model, it is difficult to estimate the parameters through it. Therefore, this paper first sets the preliminary values based on the logical relationships described in the causal feedback diagram, and then derives the parameter values based on the equilibrium state of the system, finally determining the relationships between variables, as shown in Table 2.

Table 2. Simulation equation setting

Variable Type	Parametric Equation	Unit	Equation specification
Level Variable	Cost = INTEG (Incremental cost/(1+ Discount rate)) ^ Time, 0)	Million	Referring to the perspective of the "White Paper on Data Asset Management 5.0", costs are divided into acquisition, processing, storage management, mining and analysis, and security costs (Cloud Computing and Big Data..., 2021)
	Revenue = INTEG (Incremental Revenue / (1+Discount rate)^Time,0)	Million	Revenue is divided into data sales revenue and profit enhancement brought by internal corporate decisions
Rate Variable Auxiliary	Cost variation = IFTHEN ELSE (Time < 1, Processing cost +Storage and management cost + Mining and analysis cost + security cost + acquisition cost, Storage and management cost + Mining and analysis cost + security cost)	Million	The first month's cost includes processing, storage and management, mining and analysis, security costs, and acquisition costs. After one month, the cost only needs to calculate storage and management costs, mining analysis costs, and security costs.
	Revenue-variation = Sales revenue + Profitability improvement	Million	Monthly revenue includes data sales revenue and internal decision-making revenue (Abbas et al., 2021)
	Data asset value = revenue – cost	Million	The net present value from benefits and costs is central to data asset valuation
	Acquisition cost = (internal operation data *0.15 + outsourced data *0.17)/(0.1 + acquisition technology)	Million	The acquisition cost is the weighted sum of internal operational data and purchased data. The cost of data collection, transmission, and purchase is only incurred in the first month. With the continuous maturity of data collection technology, costs are gradually decreasing
	Processing cost = (2+LN (data volume + 1)) /(0.1 + processing technology)	Million	The processing cost consists of two parts: fixed basic costs and costs related to data volume. Although processing costs rise with increased data, the rate of increase slows. Higher processing technology levels also reduce per-unit costs
	Storage management cost = LN (data volume) * (1 – technical factors/20) ^ Time	Million	The cost of storage management is directly proportional to the natural logarithm of data volume, showing a non-linear relationship. Technological progress can reduce costs, and this reduction will gradually slow down over time

Continued Table 2

Variable Type	Parametric Equation	Unit	Equation specification
	Data mining and analysis cost = LN (data volume + 1) *2.4* personalized demand factor/(0.1 + data mining and analysis capability)	Million	The costs of data modeling, analysis, and visualization occur monthly. However, monthly demands cause cost fluctuations (Gu & Li, 2022)
	Security cost = SMOOTHI (Data breach *0.24, 2, 0)	Million	The IBM 2022 Data Breach Cost Report estimates that in regulated industries, 24% of data breach costs are incurred more than two years after the data breach occurred, due to the risk losses caused by data breaches or external regulatory penalties
	Effective Information Quantity = SMOOTHI (Data Asset Quality * 2.5) * (Data Quantity * 0.216) ^ Data Mining and Analysis Capability * 12.45,1,0)	Dmnl	The quantity of effective information is a function of data asset quality, data quantity, and data mining and analysis capabilities, adjusted dynamically using the SMOOTHI function (De Amicis & Batini, 2004). 2.5 is the coefficient of influence of data asset quality, 0.216 is the coefficient of influence of data quantity and 12.45 is the amplification coefficient of data mining and analysis capabilities
	Internal innovation = organizational factors * effective information * 0.03/ (1+200 x EXP (–0.2 x Time))	Dmnl	The level of internal innovation is determined by organization and the quantity of effective information, with an adjustment factor that varies over time. As time passes, the difficulty of innovation may increase, thus requiring more organizational factors and effective information the multiplier effect of big data by Schaefer et al. (2014), with the extreme value of the multiplier effect set as a = 0.03, B = 200, and the proportionality coefficient I = 0.2
	Selling Value = (Effective Information Volume/23.45)* (Freshness + Privacy + Market Scarcity)/20) * Environmental Factors	Million	The value of data sales is influenced by environmental factors such as the amount of effective information provided by the data, market scarcity, freshness, privacy concerns, policy implementation, and laws and regulations
	Selling revenue = quantity sold * selling value	Million	The sales revenue of data products is calculated by multiplying the quantity sold by the selling price
	Data asset quality = objective attributes * correlation integration * coverage/125	Dmnl	Data quality assessment is divided into two aspects: objective and subjective dimension assessment. Objective attributes include normalization, completeness, accuracy, consistency, etc. (China National Information Technology Standardization Network (SAC/ TC 28), 2018); while the subjective dimension refers to the applicability of data such as relevance, diversity, etc. (Laney, 2011)

End of Table 2

Variable Type	Parametric Equation	Unit	Equation specification
Cons-tant	Monthly discount rate = 0.78%	Dmnl	data assets have a higher discount rate due to greater uncertainty in economic returns. This article adopts a market comparison method, averaging the discount rates of similar data assets, resulting in an annual discount rate of 9.8% The monthly discount rate is then calculated as 0.78%, based on the formula (1 + monthly discount rate) ^ 12 = 1 + annual discount rate
	Normality = (amount of data in the data-set that meets the data specification requirements/total number of data records) * 100%	Dmnl	The degree to which the data conforms to data standards, business rules, metadata, or authoritative reference data (China National Information Technology Standardization Network (SAC/TC 28), 2018)
	Environmental factors = RANDOM NORMAL (0.7,1,0.8, 0.02,4)	Dmnl	Environmental factors have uncertainty, so random functions are used for setting

Note: Dmnl is dimensionless.

4. Model simulation and result analysis

This section examines the robustness of the model and simulates the dynamic evolution of data asset value. It includes model validation, simulation of value realization trends, sensitivity analysis of key influencing factors, and scenario simulations across different market development stages.

4.1. Model verification

The simulation time for the original scenario is set to 50 months, with a step size of 1 month, using Vensim PLE software. the effectiveness of the model is examined through operational verification, extreme condition testing, model structural stability testing, sensitivity testing, and other methods.

(1) Operational verification: Structural operational verification and dimensional consistency verification can be performed through the software's built-in unit verification and model verification features (Liu et al., 2020). The results indicate that it has passed the inspection.

(2) Extreme condition test: When the data volume is 0, the enterprise cannot obtain effective information from the data, resulting in an effective information volume of 0. When the quality of data assets is 0, the data assets lose their selling value, and the selling value becomes 0. The extreme condition test results align with reality.

(3) Stability testing of model structure: Referring to the integral error testing method adopted by Ke et al. (2020), taking the value of data assets as an example, the simulation step sizes are set to 0.5, 1, and 1.25 to test the stability of the model structure. The results, presented in Figure 6, show that the trend of data asset value changes remains consistent under different simulation step sizes, with no significant abnormalities, indicating that the test has been passed.

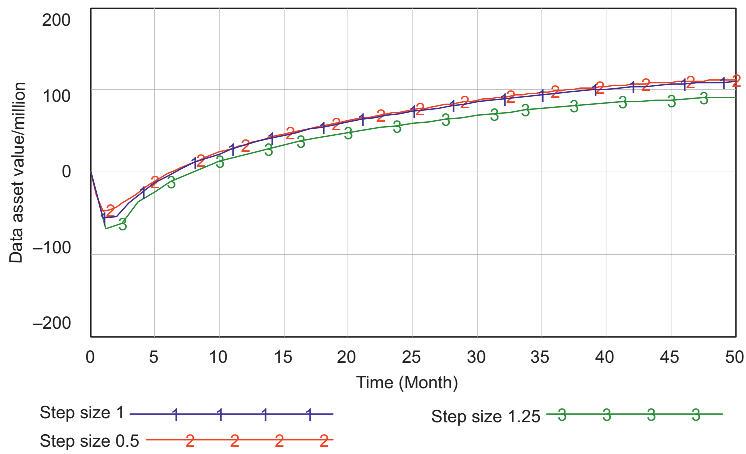


Figure 6. Results of model structure stability test

(4) Sensitivity testing: The technical factors are increased by 5% and 10% respectively, and decreased by 5% and 10%, using data asset quality as an example for sensitivity testing. The results, presented in Figure 7, demonstrate that the stronger the technical factors, the higher the data asset quality. This indicates that for an enterprise to continuously improve its data asset quality, it must continually enhance its technical capabilities, which aligns with the actual situation.

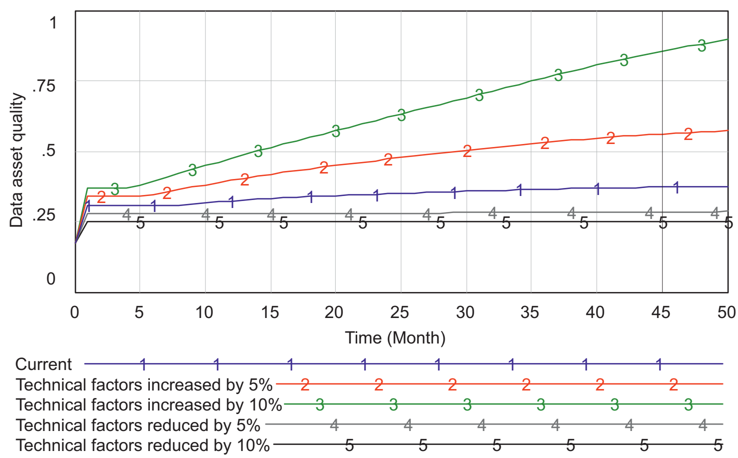
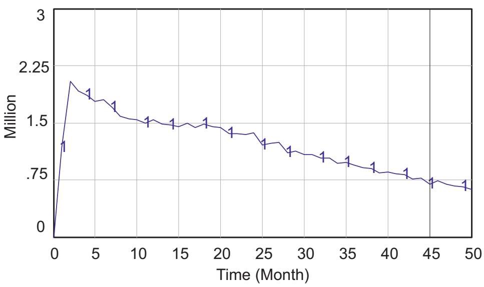


Figure 7. Sensitivity test results

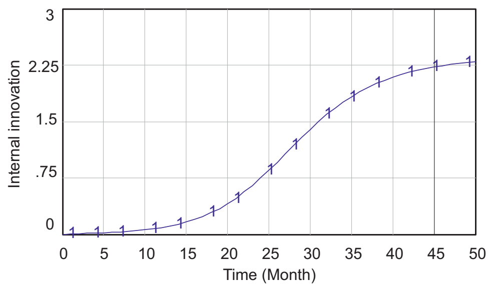
4.2. Simulation

Through simulating the system flowchart, this paper aims to reveal the changing trend of the data asset value evaluation system. As shown in Figure 8, the simulation focuses on six variables: selling value, internal innovation, technical factors, effective information quantity, data asset quality, and freshness. With the continuous improvement of technology, the quality of data assets has been continuously enhanced, leading to a continuous increase in the amount of effective information obtained from the data, and internal innovation has also been continuously promoted. However, the evolution of the overall decision-making effect resembles the famous "S"-shaped diffusion curve of new technology proposed by Griliches (1957).

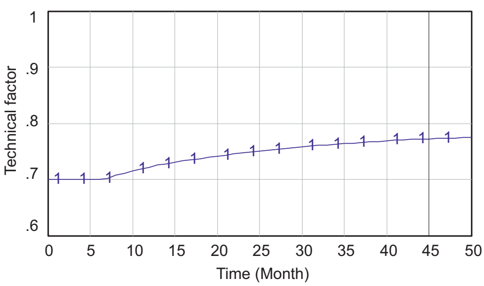
The simulation results indicate that the impact of big data applications on business is relatively limited and grows slowly in the initial stage. However, as enterprises and the market gradually recognize the potential value of data, the application diffusion accelerates, entering an "inflection point" where its influence rapidly increases. Once the widespread application of data reaches a saturation point, its value-added effect stabilizes, with the growth rate gradually slowing down and stabilizing. Furthermore, the simulation study shows that data can achieve high monetization in the short term. However, due to the reproducibility and multiple transactions of data, the supply significantly increases, leading to a rapid decline in scarcity. Additionally, as time passes, the freshness of data rapidly decreases. These two factors contribute to the gradual decline in the sale value of data, which may ultimately no longer contribute substantially to the actual revenue of businesses. This finding provides



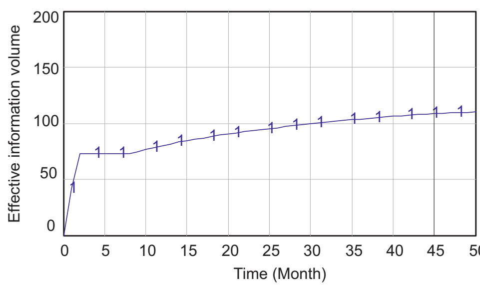
a) Sale Value



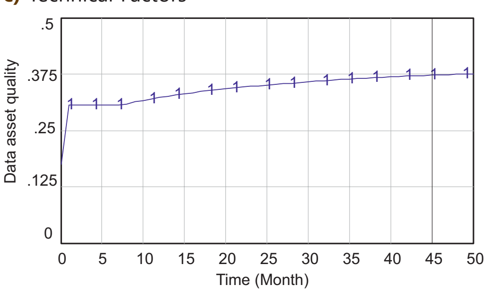
b) Internal Innovation



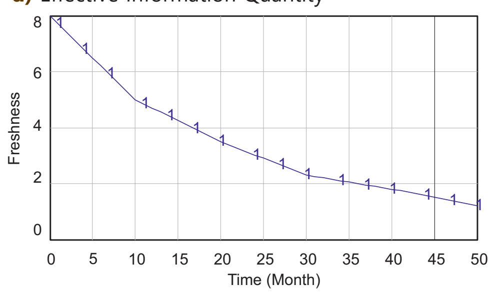
c) Technical Factors



d) Effective Information Quantity



e) Data asset quality



f) Freshness

Figure 8. Simulation results of data asset value release

insights for enterprises on how to maximize data monetization in the short term and reveals the critical time windows that must be considered in data asset management.

As shown in Figure 9, during the stage of exploring the potential value of data, enterprises typically hold a relatively small scale of data assets, and the full potential of these assets to drive profitability and asset realization has yet to be realized. At this stage, substantial cost investment yields minimal revenue, resulting in a negative data asset value. However, as time progresses, we enter a phase of explosive growth in data value. With the continuous accumulation of data, enhanced analysis and processing capabilities, and increased promotion of data assets through organizational and environmental factors, data returns experience a significant surge.

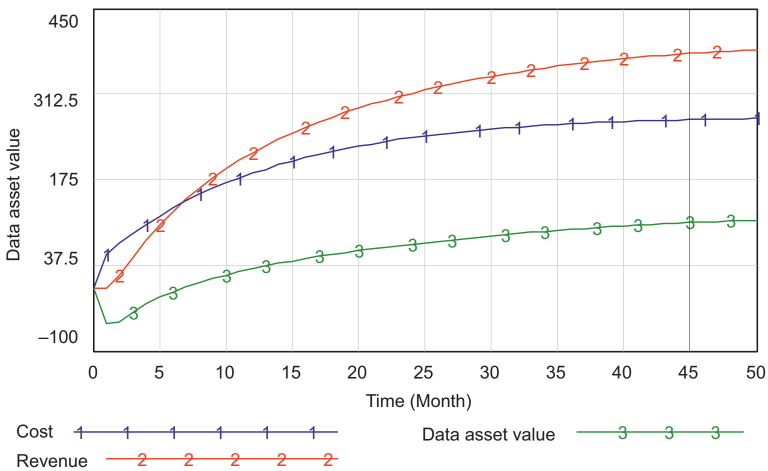
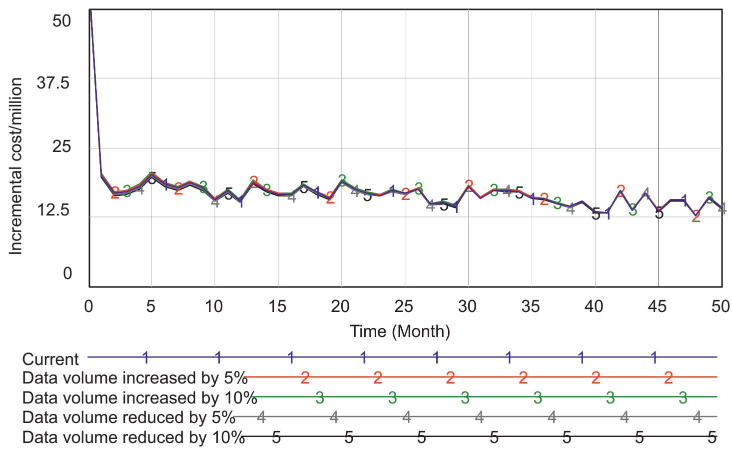


Figure 9. Cost benefit simulation results

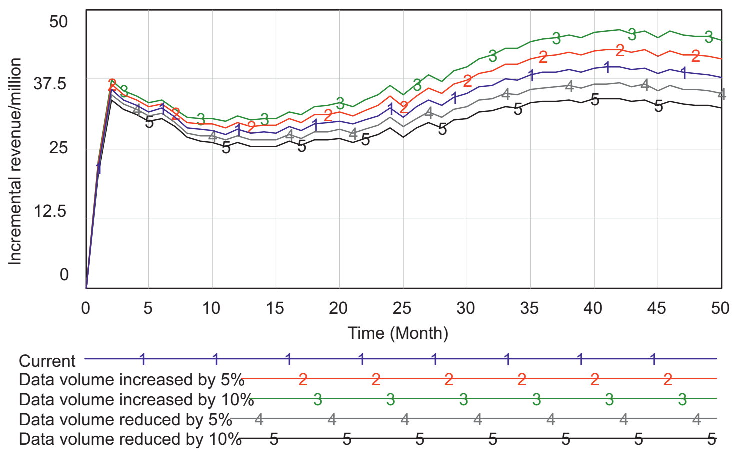
The simulation results indicate that the variation curve of data value differs from the traditional "U"-shaped marginal cost curve in economics (Wang, 2022). Despite the high initial fixed costs associated with data, due to its non-rivalrous nature and near-zero marginal cost characteristics, enterprises can achieve significant scale effects and economies of scope through large-scale data applications (Sama et al., 2022), thereby breaking through the limitation of increasing marginal costs in traditional economics. Consequently, the cumulative curve of data costs grows rapidly at first and then gradually slows down. As data monetization improves, corporate profits increase, enhancing data asset value. However, when data enters a saturation phase with reduced freshness, its value and corresponding revenue gradually decline. This variation holds significant implications for practical businesses, suggesting that enterprises should grasp the data life-cycle, maximize data monetization during peak value growth, and be vigilant against the risk of diminishing value caused by data aging.

4.3. Sensitivity analysis

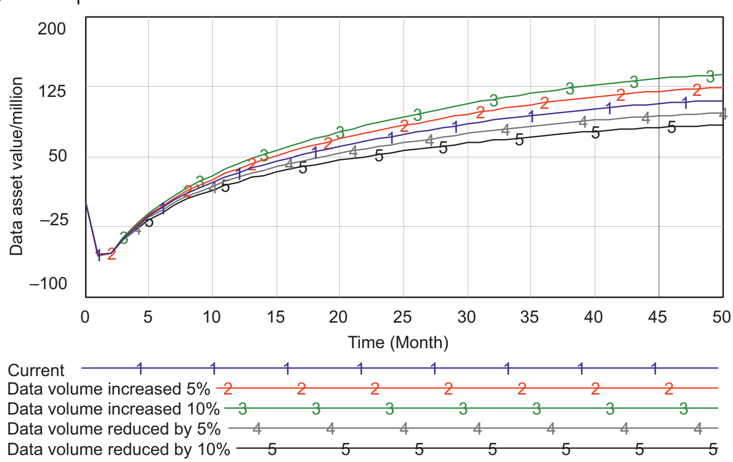
To quantify the impact of critical variables on data asset value, this subsection conducts sensitivity tests on intrinsic attributes (data volume and quality) and external characteristics (technology, environment, and organization). The sensitivity ranges of ±5% and ±10% were selected following established practices in system dynamics modeling, which recommend



a) The impact of data volume on cost increment



b) The impact of data volume on revenue increment



c) The impact of data volume on the value of data assets

Figure 10. Sensitivity analysis of data volume

using plausible parameter variations to assess model robustness (Sterman, 2000). These ranges also align with commonly used variation levels in similar simulation studies and reflect realistic fluctuations in enterprise data management contexts.

4.3.1. Data self attributes

(1) Data volume

By adjusting the data volume – reducing it by 10%, then 5%, and increasing it by 5% and 10% – while keeping all other variables constant, we obtained five simulation curves depicting cost increment, revenue increment, and data asset value. These curves are presented in Figure 10.

As shown in Figure 10a, the cost increment peaks initially, then declines and stabilizes with slight fluctuations. The simulation results indicate that high costs associated with data collection and processing. However, the non-competitiveness and reproducibility of data during its usage lead to diminishing marginal costs, potentially even reaching zero. As data accumulates into big data, it further reduce data costs, resulting in an "L"-shaped curve between data volume and cost.

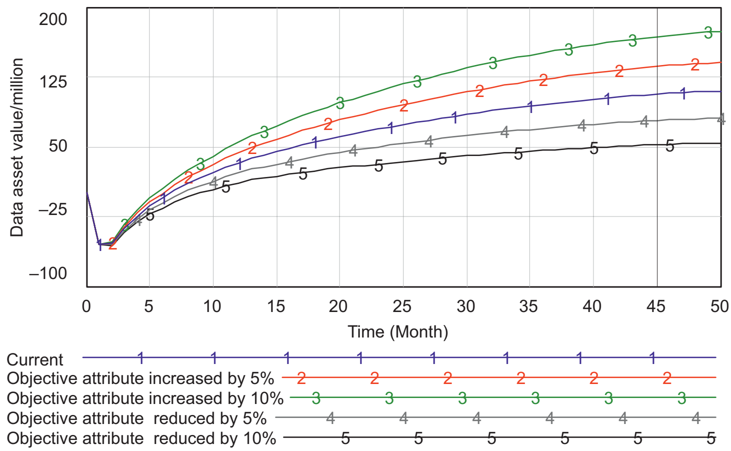
As depicted in Figure 10b, when a single enterprise possesses more data assets, these assets interact and generate new data assets, leading to a gradual increase in the marginal utility created by data, exhibiting an increasing returns effect of "1+1>2" (Wang et al., 2022).

As depicted in Figure 10c, when the data volume is small, the amount of effective information gained through data analysis is insufficient to support better decision-making by enterprises, thereby failing to enhance profitability effectively. At this stage, high costs and low returns result in data asset values remaining negative for an extended period. However, when the data volume reaches a certain scale, the economic value generated covers both the fixed and variable costs of data management and operation, generating revenue for the enterprise. Thus, the scale of data is fundamental to realizing value appreciation of data assets. Consequently, enterprises can leverage this attribute by collecting data as comprehensively and promptly as possible to create economies of scale and elevate the value of their data assets.

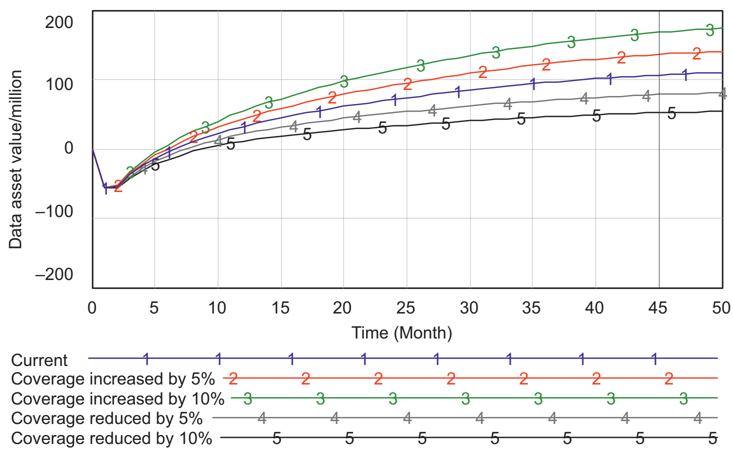
(2) Data Asset Quality

Reduce the objective attributes, coverage, and correlation integration levels of the data by 10%, 5%, and 5% respectively, while keeping other variables constant. The five simulated curves of data asset value are shown in Figure 11. As shown in Figures 11a–c, curve 3 indicating the highest levels. Among them, curve 3 represents the highest objective attributes, coverage, and correlation integration of data, indicating that improving data asset quality can significantly enhance their value.

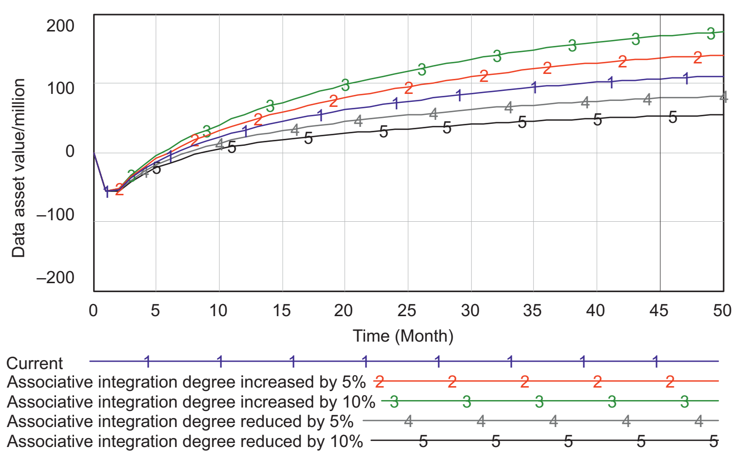
The simulation results show that, as an important part of data value creation, enterprises can utilize standardized, complete, and accurate data to assist in scientific decision - making, improve data returns, and thereby enhance the value of their data assets when the objective attributes of data are improved. Similarly, when the correlation between data elements and the coverage of data in relevant business areas are insufficient, the information value is limited, resulting in lower data worth. As the diversity and quantity of data increase, economies of scope emerge. It is evident that the quality of data assets serves as the cornerstone for their value appreciation.



a) The impact of objective attributes of data on the value of data assets



b) The impact of coverage on the value of data assets



c) The impact of correlation integration on the value of data assets

Figure 11. Sensitivity analysis of data asset quality

4.3.2. External attributes of data

(1) Digital Technology Factors

By reducing the technological factors by 5%, 10%, and increasing them by 5%, 10% respectively, five simulated curves were obtained as shown in Figure 12. Technological factors significantly influence data asset value growth, when technological factors increase by 10% in curve 3, the growth in data asset value is most pronounced. Conversely, in curve 5 where technological factors decrease by 10%, the growth in data asset value nearly stagnates, with the curve approaching a horizontal line and even showing a decline in the initial stages.

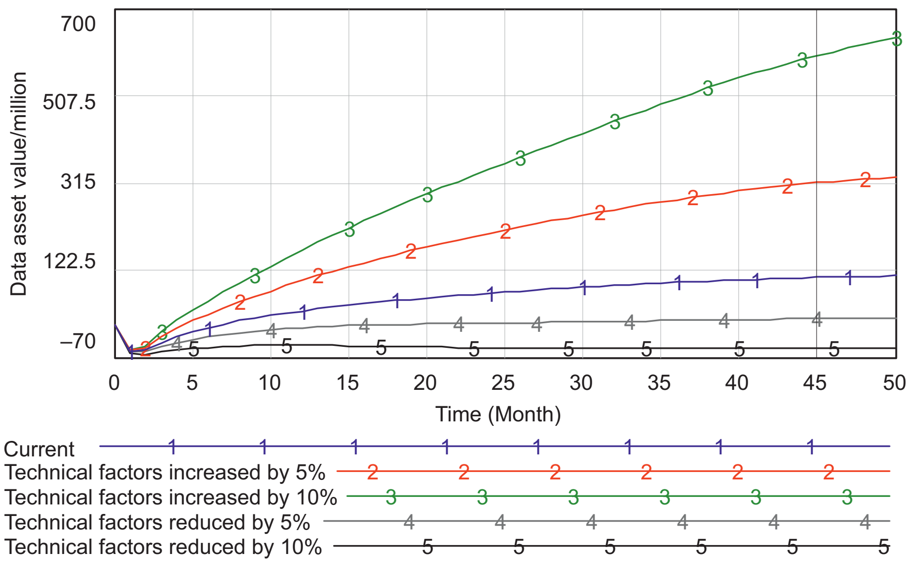


Figure 12. Sensitivity analysis of technical factors

The simulation results indicate that the value of data often stems from its processing and mining, which are further analyzed to form knowledge, ultimately enhancing support for business decision-making or enabling external sales. When the level of big data analytic technology is low, costs are high, and data asset returns are not significant, potentially resulting in negative data asset value. However, as technology iterates and upgrades, data analysis capabilities improve, the value of data assets is gradually unleashed. Thus, a company's technological proficiency in data plays a crucial driving role in the exploitation of its data asset value.

(2) External Environmental Factors

By reducing the environmental factors by 5%, 10%, and increasing them by 5%, 10% respectively, five simulation curves are obtained as shown in Figure 13. When the environmental factors are increased, the value of data assets shows significant growth at all stages, especially in the initial and mid-stages, where the growth rate is the fastest.

The simulation results indicate that firstly, when the environment for realizing the value of data assets is not mature enough, i.e., data ownership is ambiguous, laws and regulations are inadequate, or there are privacy breaches, the value of data assets is relatively low. Secondly, as the data factor trading market continues to develop and relevant laws and regulations are constantly improved, the net present value accumulation of data assets increases, and their value is enhanced. Therefore, when laws and regulations are more robust, and privacy breaches are minimized, enterprises apply data assets more effectively, gaining more user trust. As a result, the value of data assets becomes relatively higher. It can be seen that the environment for realizing the value of data assets plays a crucial role in ensuring the achievement of such value.

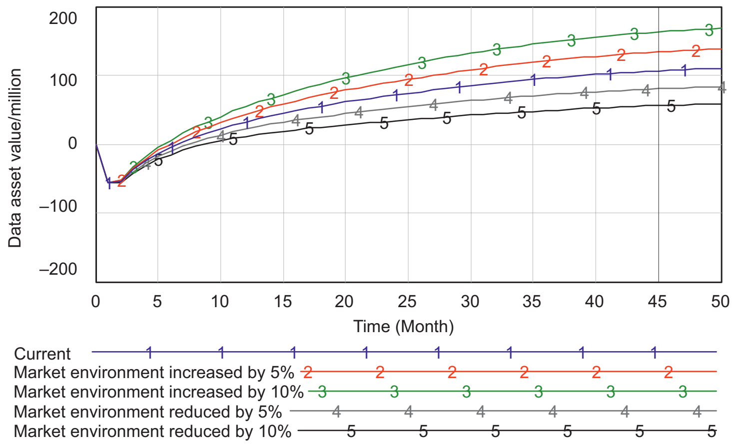


Figure 13. Sensitivity analysis of environmental factors

(3) Organizational Management Factors

By adjusting the organizational factors by –5%, –10%, +5%, and +10% respectively, five simulation curves are generated as depicted in Figure 14. Data value starts negative and increases rapidly at first. The growth rate then slows in the mid-stage, though still rising. Finally, the rate decelerates further, leading to a stable curve.

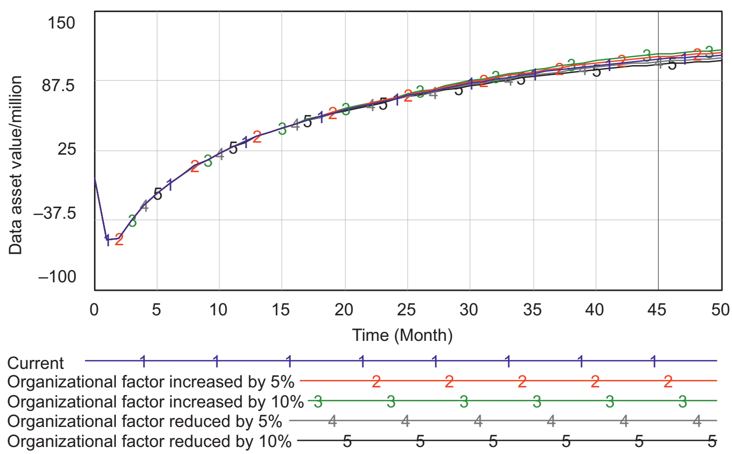


Figure 14. Sensitivity analysis of organizational factors

The simulation outcomes reveal that these factors exert an influence on the value of data assets by shaping the scientific rigor of decision-making. Given that the effectiveness of decision-making follows an "S"-shaped curve (Forrester, 1958), in other words, the impact of organizational factors is relatively modest in the initial phase. While maintaining necessary quality, data-driven decisions increasingly rely on the diversity of application scenarios and data users. Moreover, as data users' data literacy enhances, the quality of decision-making also improves, thereby elevating the value of data (Mingers, 2006). Consequently, the data literacy of data users plays a pivotal supporting role in boosting the value of data assets.

4.4. Market simulation

With the development of the digital economy, the data asset market is continually evolving. Currently, China's data asset market is still in its infancy (Li & Wu, 2021), leading to significant differences across various stages of the market in terms of technical factors, data volume, data breaches, objective data attributes, coverage, and other aspects. These differences have a crucial impact on the valuation of data assets.

Based on the unique characteristics of different stages in the data market, by adjusting the five primary influencing factors – technical factors, data volume, data breaches, objective data attributes, and coverage – we obtain three simulated curves depicting the initial, growth, and mature stages, as illustrated in Figure 15. In the initial stage, data asset values remain nearly identical across various markets, with the various levels of influencing factors yet to take full effect.

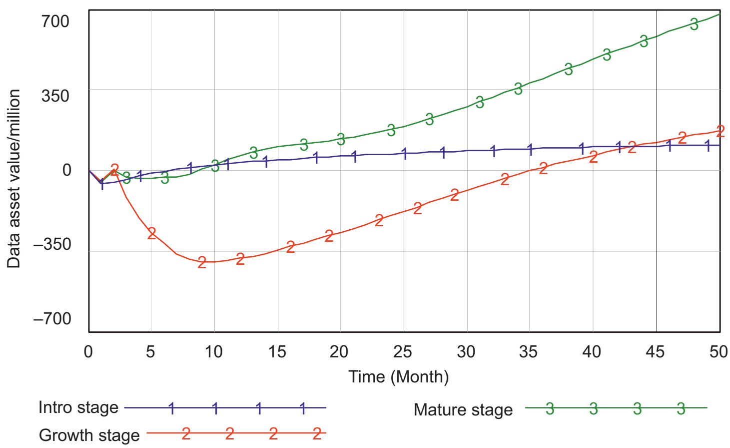


Figure 15. Comparative analysis of data asset value at different market stages

As time passes during the initial stage, factors such as technological shortages, limited data volume, high levels of data breaches, poor objective data attributes, and low coverage contribute to constrained capabilities in data processing, analysis, and application. This results in even less information available for analysis and decision-making, further limiting the scope and depth of data asset applications. The representativeness and universality of data are constrained, limiting their application scenarios and potential markets within enterprises. Collectively, these factors maintain the value of data assets at a relatively low level, with no apparent growth trend.

In the growth stage, as the market recognizes the potential of new technologies and data assets, investors in the early and mid-stages exhibit overly optimistic sentiment, triggering a rapid increase in the value of data assets. However, due to the high investment costs associated with technological upgrades, data collection, and maintaining data privacy, along with the time lag in realizing the full value of data assets, returns eventually fall far below investment costs, leading to a sharp decline in value. Notably, emerging technologies such as blockchain and artificial intelligence (AI) may influence these dynamics. Blockchain's decentralized ledger and cryptographic mechanisms can significantly mitigate the risk of data breaches, enhance transaction transparency, and reduce certain compliance and privacy protection costs (Li et al., 2018). Concurrently, AI technologies enhance data standardization and consistency through automated data cleansing and semantic analysis, thereby improving the accuracy and reliability of information processing (Grger, 2021). Nevertheless, with time and market adjustments, data usage intensifies and appreciates, resulting in declining marginal costs, rising marginal returns, especially for AI-driven data mining capabilities break through traditional limitations resulting in a rapid surge in data asset value (Sama et al., 2022). These effects, while not explicitly modeled as independent variables in this study, align with our findings on the importance of technological factors in shaping data asset value.

In the mature stage, the market has a clear grasp of the significance of data assets as a cornerstone of enterprise value. The technology for data analysis and processing has matured, and data-driven products and services have become widely adopted. The widespread application of blockchain technology has further consolidated the trust mechanism of data assets, while AI technology has made the management, evaluation and monetization of data assets an integral part of the daily operation of enterprises by strengthening data standardization and intelligent analysis, driving its value up steadily. This demonstrates that the fluctuation in data asset value is a complex process, shaped by various internal and external factors. Across different markets, the value of data assets exhibits diverse trends of change. Understanding these influencing factors and their interplay can facilitate more effective evaluation and management of data asset value.

5. Discussion

This study contributes to the growing body of research on data asset valuation by addressing several theoretical and methodological gaps in the existing literature. Prior studies have predominantly relied on static valuation approaches such as cost, income, or market-based methods, which are insufficient to capture the dynamic, multi-stage nature of data value creation in internet enterprises. In contrast, this research adopts a system dynamics modeling approach grounded in value chain theory to simulate the evolution and transformation of data assets over time.

First, this study provides a dynamic and process-oriented perspective on data asset valuation by reconstructing the full life-cycle of data value creation. By modeling the flows of value across data collection, storage, mining, and application stages, the research offers a comprehensive understanding of how data assets undergo continuous value enhancement. This approach enables a more accurate reflection of the mechanisms through which data assets generate utility and economic benefit, particularly in digital business ecosystems.

Second, the study reveals the mechanisms that underpin data asset value formation. The findings confirm that data scale is a foundational condition for value creation, while data quality plays a critical role in value enhancement. Additionally, the study highlights the time-sensitive nature of data, indicating a clear pattern of diminishing value as data freshness declines. Notably, the simulation identifies an S-shaped diffusion curve in the impact of technical inputs on value realization, illustrating the nonlinear and delayed effects of digital capabilities. Organizational and environmental factors also serve as essential enablers, reinforcing the importance of ecosystem-level support for effective data asset management.

Third, this research advances the theoretical framework of data asset valuation. It contributes by clarifying the core concepts of data asset value and its generation mechanisms, systematizing the internal and external factors that influence value realization, and providing a robust simulation-based methodology for analyzing their interactions. The incorporation of sensitivity analysis and scenario-based simulations further enhances the explanatory power of the model, offering new pathways for future research on data-driven strategy and policy design.

Collectively, these contributions fill key gaps in the literature by moving beyond static valuation methods and offering a theory-driven, simulated approach that captures the complexity and dynamism of data asset value creation in the digital age.

6. Conclusions and implications

Based on the data value chain, this paper constructs a system dynamics model for data asset value, conducting research on data asset value assessment with a focus on internal attributes and external characteristics. The research results indicate the following:

Firstly, the realization of data value is a dynamic flow spanning various stages of data collection, analysis, mining, and application. Relying on the data value chain, it undergoes continuous value appreciation, ultimately achieving the value of data assets.

Secondly, the value of data assets is influenced by multiple factors. Specifically, the larger the data volume and the higher the data quality, the greater the data value. External characteristics, such as technology, organization, and environment, also have indispensable impacts on data value, with technology factors exerting a greater influence than environmental and organizational factors.

Thirdly, there exists a diminishing law of data value. Data assets exhibit characteristics of diminishing marginal costs and increasing returns, with fresher data holding higher value.

Lastly, there is a significant lag effect in the release of data asset value. In the initial stages, the application and impact of data assets are not fully apparent. However, after undergoing potential exploration and explosive growth, the immense value embedded is widely excavated, entering a stage of convergence and saturation, and ultimately completing the release of value.

These findings offer practical implications for data governance and enterprise strategy. Decision-makers should evaluate data assets from a life-cycle perspective, break down value-added stages, clarify empowerment phases, and assess value more precisely. Valuation is a multifaceted task involving internal decision-making, external application, and the integration of key factors such as technology and organization. Context-specific approaches that combine complementary methods are essential for reliable valuation in real-world settings.

Despite its contributions, this study has certain limitations, as it relies on generalized assumptions and causal structures that may not fully capture cross-industry heterogeneity in data asset valuation, and it omits uncertainties such as user behavior shifts or regulatory changes that could affect value realization. Future research could develop industry-specific models, integrate stochastic elements and scenario analyses to address uncertainties, and conduct empirical validation through longitudinal and cross-industry studies to enhance the robustness and practical relevance of simulation-based value assessment.

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Author contributions

Shen was key in conceptualizing the study, developing the methodology, and conducting the analysis. All authors contributed to drafting the manuscript, Peng and Fang were respon-sible for reviewing and editing it.

Declaration of competing interests

Authors have no conflict of interest to declare.

References

Abbas, A. E., Agahari, W., Ven, M. V. D., Eijk, Z. V., & Reuver, G. A. D. (2021). *Business data sharing through data marketplaces*: *A systematic literature review*. University of Maribor Press. https://doi.org/10.18690/978-961-286-485-9.6

Acemoglu, D., Makhdoumi, A., Malekian, A., & Ozdaglar, A. (2022). Too much data: Prices and inefficiencies in data markets. *American Economic Journal*: *Microeconomics*, *14*(4), 218–256. https://doi.org/10.1257/mic.20200200

Acquisti, A., Brandimarte, L., & Loewenstein, G. (2020). Secrets and likes: The drive for privacy and the difficulty of achieving it in the digital age. *Journal of Consumer Psychology*, *30*(4), 736–758. https://doi.org/10.1002/jcpy.1191

Bounie, D., Dubus, A., & Waelbroeck, P. (2021). Selling strategic information in digital competitive markets. *The RAND Journal of Economics*, *52*(2), 283–313. https://doi.org/10.1111/1756-2171.12369

China National Information Technology Standardization Network (SAC/TC 28). (2018). *Information technology – evaluation indicators for data quality* (*GB/T 36344-2018*). State Administration for Market Regulation; Standardization Administration of the People's Republic of China.

Choe, C., King, S., & Matsushima, N. (2018). Pricing with cookies: Behavior-based price discrimination and spatial competition. *Management Science*, *64*(12), 5669–5687. https://doi.org/10.1287/mnsc.2017.2873

Cloud Computing and Big Data Research Institute of China Academy of Information and Communications Technology. (2021). *Data asset management practice white paper* (*Version 5.0*) (pp. 22–23). China Academy of Information and Communications Technology.

Cong, L. W., Xie, D., & Zhang, L. (2021). Knowledge accumulation, privacy, and growth in a data economy. *Management Science*, *67*(10), 6480–6492. https://doi.org/10.1287/mnsc.2021.3986

De Amicis, F., & Batini, C. (2004). A methodology for data quality assessment on financial data. *Studies in Communication Sciences*, *4*(2), 115–137.

De Nijs, R. (2017). Behavior-based price discrimination and customer information sharing. *International Journal of Industrial Organization*, *50*, 319–334. https://doi.org/10.1016/j.ijindorg.2016.12.003

Farboodi, M., Singal, D., Veldkamp, L., & Venkateswaran, V. (2025). Valuing financial data. *The Review of Financial Studies*, *38*(3), 938–980. https://doi.org/10.1093/rfs/hhae034

Forrester, J. W. (1958). Industrial dynamics: A major breakthrough for decision makers. *Harvard Business Review*, *36*(4). https://doi.org/10.1007/978-3-642-27922-5_13

Gill, A. Q. (2024). The digital ecosystem information framework: Insights from action design research. *Journal of Information Science*, *50*(1), 85–88. https://doi.org/10.1177/01655515221086593

Goldfarb, A., & Tucker, C. (2019). Digital economics. *Journal of Economic Literature*, *57*(1), 3–43. https://doi.org/10.1257/jel.20171452

Griliches, Z. (1957). *Hybrid corn*: *An exploration in economics of technological change* [Doctoral dissertation, The University of Chicago]. https://doi.org/10.2307/1905380

Grger, C. (2021). There is no ai without data. industry experiences on the data challenges of ai and call for a data ecosystem for industrial enterprises. *Communications of the ACM*, *64*(11), 98–108. https://doi.org/10.1145/3448247

Gu, B., & Li, R. Y. (2022). Value Creation pathes of digital innovation ecosystem based system dynamics. *Systems Engineering*, *40*(3), 56–65.

Hafner, M., Mira da Silva, M., & Proper, H. A. (2025). Data valuation as a business capability: From research to practice. *Information Systems and e-Business Management*. https://doi.org/10.1007/s10257-025-00701-w

Hu, Y., & Xu, X. (2022). Research on the statistical measurement of business data assets. *Statistical Research*, *9*, 3–18. https://doi.org/10.19343/j.cnki.11–1302/c.2022.09.001

Jones, C. I., & Tonetti, C. (2020). Nonrivalry and the economics of data. *American Economic Review*, *110*(9), 2819–2858. https://doi.org/10.1257/aer.20191330

Jung, K., & Park, S. (2019). Privacy bargaining with fairness: Privacy-price negotiation system for applying differential privacy in data market environments. In *2019 IEEE International Conference on Big Data* (*Big Data*) (pp. 1389–1394). IEEE. https://doi.org/10.1109/BigData47090.2019.9006101

Ke, X. L., Guo, H. X., Gong, X. G., & L, X. (2020). Early Warning Simulation of Urban Ecological Security Based on System Dynamics in Wuhan City. *Management Review*, *32*(4), 262–273. https://doi.org/10.14120/j.cnki.cn11-5057/f.2020.04.022

Laney, D. (2011). Infonomics: The economics of information and principles of information asset management. In *The fifth MIT information quality industry symposium* (vol. 9(2), pp. 590–603). Cambridge.

Li, Z., & Wu, Y. (2021). Data factor market cultivation and digital economy development – A political economy based perspective. *Academic Research*, (7), 114–120.

Li, L., Liu, J., Cheng, L., Qiu, S., & Zhang, Z. (2018). Creditcoin: A privacy-preserving blockchain-based incentive announcement network for communications of smart vehicles. *IEEE Transactions on Intelligent Transportation Systems*, *19*(99), 2204–2220. https://doi.org/10.1109/TITS.2017.2777990

Liu, E., Ma, S., & Veldkamp, L. (2025). Data sales and data dilution. *Journal of Financial Economics*, *169*, Article 104053. https://doi.org/10.1016/j.jfineco.2025.104053

Liu, K., Qiu, X., Chen, W., Chen, X., & Zheng, Z. (2019). Optimal pricing mechanism for data market in blockchain-enhanced Internet of Things. *IEEE Internet of Things Journal*, *6*(6), 9748–9761. https://doi.org/10.1109/JIOT.2019.2931370

Liu, K., Yang, D., Wang, G., & Zhou, Z. (2020). Policy modeling and simulation on ecological civilization construction in China based on system dynamics. *Chinese Journal of Managent Science*, *28*, 209–220. https://doi.org/10.16381/j.cnki.issn1003-207x.2020.08.019

Mahajan, S. (2022). Data marketplaces: A solution for personal data control and ownership?. *Sustainability*, *14*(24), Article 16884. https://doi.org/10.3390/su142416884

Mingers, J. (2006). *Realising systems thinking*: *Knowledge and action in management science*. Springer Science & Business Media.

Nolin, J. M. (2020). Data as oil, infrastructure or asset? Three metaphors of data as economic value. *Journal of Information*, *Communication and Ethics in Society*, *18*(1), 28–43. https://doi.org/10.1108/JICES-04-2019-0044

Pei, J. (2020). A survey on data pricing: from economics to data science. *IEEE Transactions on knowledge and Data Engineering*, *34*(10), 4586–4608. https://doi.org/10.1109/TKDE.2020.3045927

Peng, C., & Bing, C. (2020). Evaluation model of power data assets based on ewm-topsis. In *2020 5th International Conference on Mechanical*, *Control and Computer Engineering* (*ICMCCE*) (pp. 1379–1382). IEEE. https://doi.org/10.1109/ICMCCE51767.2020.00302

Peterson, R. E. (2012). A cross section study of the demand for money: The United States, 1960-62. *Journal of Finance*, *29*(1), 73–88. https://doi.org/10.1111/j.1540-6261.1974.tb00025.x

Sama, L. M., Stefanidis, A., & Casselman, R. M. (2022). Rethinking corporate governance in the digital economy: The role of stewardship. *Business Horizons*, *65*(5), 535–546. https://doi.org/10.1016/j.bushor.2021.08.001

Schaefer, A., Schiess, D., & Wehrli, R. (2014). Long-term growth driven by a sequence of general purpose technologies. *Economic Modelling*, *37*, 23–31. https://doi.org/10.2139/ssrn.1894588

Shannon, C. E. (1948). A mathematical theory of communication. *The Bell System Technical Journal*, *27*(3), 379–423. https://doi.org/10.1002/j.1538-7305.1948.tb01338.x

Sterman, J. D. (2000). *Business dynamics*: *Systems thinking and modeling for a complex world*. McGraw-Hill.

Vaish, A., Prabhakar, A., Mishra, H., Dayal, N., Singh, S. K., Goel, U., & Coull, N. (2011). Quantifying information dynamics through a new valuation system. *Information Management* & *Computer Security*, *19*(5), 313–332. https://doi.org/10.1108/09685221111188601

Wang, C. W. (2022). Deep integration of digital economy and real economy: Core dynamics, major problems, trends and responses. *Frontiers*, *18*, 12–21. https://doi.org/10.16619/j.cnki.rmltxsqy.2022.18.002

Wang, C. X., Zhang, W. D., & Yan, M. (2022). Is more data always better – An interdisciplinary analysis of the nature of returns to data. *China Industrial Economics*, *7*, 44–64. https://doi.org/10.19581/j.cnki.ciejournal.2022.07.016

Xiong, F., Xie, M., Zhao, L., Li, C., & Fan, X. (2022). Recognition and evaluation of data as intangible assets. *SAGE Open*, *12*(2). https://doi.org/10.1177/21582440221094600

Xu, X. C., Zhang, Z. W., & Hu, Y. R. (2022). Research on deriving measures of data assets in national accounts. *Journal of Management World*, *38*(2), 16–30. https://doi.org/10.3969/j.issn.1002-5502.2022.02.003

Yang, L., Qiu, S., Zhu, N., & Yu, Z. (2025). Valuation of enterprise big data assets in the digital economy: A case study of Shunfeng Holdings. *Platforms*, *3*(3), Article 13. https://doi.org/10.3390/platforms3030013

Zhu, S., Dong, T., & Luo, X. R. (2021). A longitudinal study of the actual value of big data and analytics: The role of industry environment. *International Journal of Information Management*, *60*, Article 102389. https://doi.org/10.1016/j.ijinfomgt.2021.102389