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Concepts, Accounting Treatment and Pricing of Data Assets

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Abstract

In the era of digital economy, data assets, as one of the important nodes in the valorization of data elements, have received a great deal of attention from policymakers, academics and the industry. Due to the public goods attributes of data resources such as non-exclusivity and non-competitiveness, there are many new challenges in the accounting treatment and pricing of data assets, which have a significant impact on corporate financial reporting, enterprise value assessment and stakeholder decision-making. In the macro context where the usefulness of accounting information is being questioned, the importance of a clear and persuasive definition of the concept of data assets and a discussion on the accounting treatment and pricing of data assets has become more prominent. This paper aims to address the following research questions based on sorting out the conceptual evolution and characteristics of data assets: what is the definition of data assets? Is it necessary and how to adjust or design accounting standards to regulate the accounting treatment of data assets? How can data assets be reasonably priced? This paper summarizes the conceptual evolution of data assets based on the development stage of the digital economy, and characterizes the characteristics of data assets based on the analysis of data resources. Combined with the characteristics of data assets, it provides useful insights into the reform of their accounting treatment. This paper helps to enrich and develop the accounting theory of data assets, provide theoretical basis for the accounting treatment and pricing of data assets, and obtain theoretical support for the corporate governance and policy making practice of data assets.

1. Introduction

The wave of global technological revolution is driving enterprises to undergo digital and intelligent transformation. The application of technologies such as industrial internet, cloud services, and smart workshop has triggered the growth of global data stock. Thanks to a complete industrial system and government policy support, China's data stock is growing most rapidly, with an average annual growth rate about 3% faster than that of the world. The importance of data in social governance of the government, business activities of enterprises and financial credit is increasing day by day. As the application scenarios of data resources expand, the existence of data resources goes beyond pure information carriers, and data valorization has received the attention of many scholars. With the establishment of market mechanisms and legal norms around data, the discussion on the asset attributes of data has become hotter and hotter, and the inclusion of data assets in the table has become a consensus among academics, industry and policy makers. The focus on data assets reflects the strategic importance of data elements in the context of the current digital economy.

The origin of the concept of data assets can be traced back to 1974, when all digital records of an enterprise were defined as data assets (Peterson & Richard, 1974).In 2009, the International Data Management Association (IDMA) declared that data is an essential corporate asset in the information age, highlighting the urgent need for effective data management in all organizations (Fisher, 2009). On this basis, Brackett & Earley (2017) suggested that data assets are inexhaustible and undiminished long-term resources for organizations. Since then, the connotation of the concept of data assets has evolved and expanded, reflecting the fact that in the context of digital transformation, the academic community has gradually recognized the key role played by data resources in business operations through recognition, analysis, summarization, and abstraction of practical experience. Although existing research has generally recognized data assets as an important resource for enterprises. However, there is still no consensus on basic issues such as the concept, accounting treatment and pricing of data assets in both academia and industry. This is one of the important reasons why it is difficult to advance the practice related to data assets in depth.

In order to bridge academic differences, this paper systematically examines the academic literature on enterprise data assets published in the last five years, proposes a conceptual evolution timeline of enterprise data assets, identifies data asset accounting treatments, and analyzes the advantages and disadvantages of different pricing models. On this basis, this paper proposes feasible next research directions based on practice development and policy needs.

The possible marginal contributions of this paper are the following two: first, it clarifies the connotation of the data asset concept and its evolution. By combing through the established literature, this paper reveals the emergence of asset attributes in the concept of data assets. Based on the core characteristics of data resources such as non-exclusivity, non-competitiveness, unlimited replicability, extensibility, heterogeneity and dynamism, this paper provides a conceptual foundation for the precise definition of the concept of data assets, which helps to clarify the boundaries between data assets and other types of assets, and establishes a foundation for the accounting treatment and pricing research of data assets. Second, it expands the theoretical horizon of data asset pricing. After assessing the applicability of commonly used pricing methods such as market method, income method and cost method in current data asset pricing, this paper concludes that traditional pricing methods and models are difficult to apply. This paper also summarizes the application of machine learning and other technologies in data asset pricing research, which helps to promote the theoretical research on data asset pricing and provides some inspiration for data asset pricing and enterprise value assessment.

The rest of the paper is organized as follows. Section II describes the concepts and characteristics of data assets. Section III describes the accounting recognition of enterprise data assets. Section IV describes the measurement and amortization of enterprise data assets. Section V summarizes the pricing model of enterprise data assets. Finally, a research framework and future outlook for enterprise data assets are presented.

2. Concepts and Characteristics of Data Assets

2.1 The Concept of Data Assets and its Evolution

2.1.1 Early concepts: valuable records of data resources

In the era of digital economy, data elements have become an important driving force for economic development. As an emerging asset type, the concept and definition of data asset is a hot topic in current research. This paper summarizes and analyzes the relevant literature and concludes that the concept of data assets has generally experienced a "ladder-type" evolution from simple data records to emerging asset types with important strategic value.

In the early days, data assets were mainly regarded as a kind of valuable data resources that could bring future economic benefits to enterprises and were recorded and archived in a certain form. At the initial stage of the evolution of the data asset concept, academics and industry crudely viewed all data records within an enterprise as data assets, believing that data records, as long as they were recorded in a certain form, would be able to bring future economic benefits to the enterprise. This early understanding was largely derived from library and laboratory data resource management experience and did not follow the traditional logic of accounting.

According to the logic of accounting, all types of resources owned or controlled by an enterprise can be considered as "assets" for the purpose of balance sheet accounting. The only requirement is that these resources are capable of generating future inflows of economic benefits to the enterprise. In this way of thinking, data resources can be "rightfully" included in the category of enterprise assets. Since data in the early days came mainly from the enterprise, were stored within the enterprise, and were predominantly structured, data records within the enterprise were regarded as data assets.

At the same time, research on data resource management in information management has provided theoretical support for the evolution of the concept of data assets. Early scholars focused on considering data resources as strategic resources of enterprises, arguing that enterprises need to plan reasonably, organize effectively and manage centrally data in order to give full play to the role of data resources. In these studies, data are categorized as resources, assuming that there is potential value in data resources and that enterprises need to manage and utilize them. These views provide the theoretical basis for recognizing data as "assets".

Thus, the early concept of data assets can be summarized as follows: data assets are data resources generated within an enterprise and recorded in a certain form, which are capable of generating an inflow of future economic benefits for the enterprise. The value of data assets is mainly reflected in the utilization of data, such as decision support and operational efficiency improvement (Tambe, 2014).

The concept of data assets at this stage focuses on the value of data resources themselves and emphasizes the rationality of the existence of data assets as a kind of asset. However, at the same time, there are certain limitations: first, it only considers data resources within the enterprise; second, it focuses on static data records and ignores the dynamic attributes of data assets; and third, it lacks an in-depth analysis of the value of data assets. With the development of data technology and the rise of digital economy, this concept needs to evolve to keep pace with the times.

2.1.2 Conceptual expansion: driven by big data and artificial intelligence technologies

With the rapid development of information technology, the rise of emerging technologies such as big data and artificial intelligence has greatly promoted the expansion and deepening of the concept of data assets. During this period, data assets are no longer narrowly viewed as static data records within an enterprise, but show unique dynamic attributes and broad application prospects.

The rise of big data technology makes data assets no longer limited to structured data, but also includes a large amount of unstructured data, such as web logs and social media data. At the same time, the convergence of massive heterogeneous data in the era of big data has brought new opportunities for deep mining and value discovery of data assets. Through the analysis and modeling of big data, enterprises can discover the hidden knowledge and laws, so as to formulate more targeted business strategies and improve the scientific and forward-looking decision-making. The value of data assets is no longer limited to the utilization of existing data, but is more reflected in the value creation brought about by the discovery of new knowledge and new patterns through big data analysis.

On the other hand, breakthroughs in artificial intelligence technology have further expanded the concept of data assets. By learning from a large amount of manually labeled data, AI algorithms can generate models with practical significance and revolutionize enterprise data application scenarios. At this point, data is no longer a passive object to be utilized, but a key raw material for AI training and learning, and the basis for the creation of AI. Data assets play an indispensable role in all aspects of the construction, training, and optimization of AI systems. With the wide application of AI technology in various industries, the value and importance of data assets are increasing day by day.

Under the dual impetus of big data and artificial intelligence technology, the concept of data assets has taken a qualitative leap. Data assets are no longer simple data records, but part of an enterprise's core competitiveness, and are the key support for enterprises to realize intelligent operation and innovative development. The value of data assets is no longer only reflected in the utilization of existing data, but also lies in the value created by discovering new knowledge, new modes and new application scenarios through big data analysis and intelligent algorithms. At this time, the concept of data assets expands to all kinds of products formed based on data, such as algorithms and models. However, algorithms, especially those manifested in the form of software, can form intangible assets such as patents, which intersect with the recognition of established intangible assets of enterprises. However, the concept and definition of data assets has still not been formalized.

2.1.3 Globalization and informatization: further expansion of the concept of data assets

At the beginning of the 21st century, under the tide of globalization and informationization, the concept of data assets experienced further expansion and deepening. During this period, data assets were no longer limited to traditional data storage, but focused on data life cycle management; at the same time, the governance of data assets by enterprises also moved towards systematization, shifting from single data storage to all-round data asset management.

Globalization has brought new connotations to the concept of data assets. In this context, data not only exists within enterprises, but also breaks through geographic and industry boundaries and becomes an important resource flowing across borders. Enterprises need to collect data from all over the world and clean and mine heterogeneous data in order to fully release its potential value. Data assets are no longer the accumulation of data within a single enterprise, but a global resource. Mastering and utilizing high-quality data assets from all over the world has become the key for enterprises to remain competitive.

At the same time, the wave of informatization has promoted the concept of data assets from single data storage to full life cycle management. Enterprises need to build a full-life-cycle management system for data assets, systematically managing all aspects from data collection, cleaning, and storage to data application, privacy protection, and compliance (Zhao et al., 2023). Only in this way can the quality of data assets and the effective utilization of data be ensured. At this point, the concept of data assets is no longer limited to the valuable data itself, but is more concerned with how to systematize governance and standardized management of data assets to maximize the release of the value potential of data assets.

Under the dual influence of globalization and informatization, data asset management has also undergone a fundamental transformation, rising from single data storage to a comprehensive governance system that requires consideration from multiple perspectives, including data quality, data security, data privacy, and data use (Ruckelshausen et al., 2024). The management of data assets is no longer simply technical, but more concerned with strategic, legal, ethical and other aspects. The construction of a data governance system aims to enable the efficient flow and compliant use of massive heterogeneous data assets from all over the world, and ultimately maximize the value creation of data assets.

In general, under the general trend of globalization and informatization, the concept of data assets has been formalized in academic research, although no expansion has occurred. At this stage, data assets are no longer limited to the accumulation of data in a single enterprise or a single geographic region, but have become an important resource that can flow globally. At the same time, enterprise management of data assets has also risen from a single link of storage to a systematic governance of the whole life cycle. This new conceptual perspective not only enriches the understanding of the connotation of data assets, but also points out the direction for value creation and sustainable utilization of data assets.

2.1.4 Driving national strategies: management and utilization of data assets

Since 2019, with the rapid accumulation and wide application of data in various fields, the importance of data assets has become increasingly prominent, and their management and utilization has risen to the level of national strategy. The Chinese government realizes that mastering and utilizing data assets is not only related to improving the level of government governance and public services, but also key to safeguarding national security and promoting socio-economic development. Accordingly, a series of relevant policies have been introduced in recent years to promote the standardized management and efficient utilization of data assets.

In August 2020, *the State Council issued the Guiding Opinions on Strengthening the Management of Data Assets* (hereinafter referred to as the *Guiding Opinions*), explicitly elevating data assets to a new type of national strategic resources. The Guiding Opinions aim to strengthen the top-level design, improve the institutional mechanism for data asset management, promote the integration, circulation and open sharing of data resources, and enhance the service capacity and value creation of data assets. This marks the Chinese government's formal incorporation of data assets into the national strategic system, and its management and utilization as an important factor of production.

The promotion of the management and utilization of data assets at the national level focuses on the following aspects: first, the formulation of a top-level design and the overall deployment of data asset management. The second is to improve the institutional mechanism for data asset management. Through the introduction of relevant laws and regulations, the property rights and utilization rights of data assets are clarified, and a data property rights protection system in line with national conditions is established. Once again, it is to increase the openness and sharing of data assets. The government encourages and supports the open sharing of public data assets, promotes the integration and convergence of public data such as government data, transportation data, meteorological data, etc., and establishes data resource catalogs and trading platforms to promote the orderly circulation and efficient use of data assets. Finally, the government has also actively promoted the deep integration of data assets with new technologies. By increasing investment in new technologies such as big data, artificial intelligence, and industrial internet, it has improved the ability to develop, utilize, and create value from data assets. It is also strengthening the construction of data infrastructure and data security guarantee systems to create a favourable environment for the efficient utilization of data assets.

At this stage, the academic concept of data assets can be divided into the “asset attribute theory” and the “production factor theory” (Li et al., 2022). According to the former, a data asset is a current data resource that is controlled by an enterprise due to past events and has the potential to bring economic benefits to the enterprise. For example, although the marginal value of the personal data of a single Facebook user is close to zero, the aggregated personal data satisfies the profitability requirement of an asset. The latter argues that, along with the change of social production mode, data assets have changed from the elements of commodity circulation to the elements of social production, and as the elements of production, data itself cannot be directly used to produce economic goods, but it can play a role in the production process. However, the former does not clarify the boundary between digital assets and data assets, while the latter is too general and does not conform to the traditional definition of “asset” in accounting research. Based on the above analysis, this paper considers data assets to be data resources in electronic or physical form that meet the definition of “asset”.

The management and utilization of data assets has become an important part of the current national strategy, and the integrated integration of data assets into the national governance system, which in turn promotes the development of the digital economy and the smart economy, helps to enhance the competitiveness and comprehensive strength of the country, and injects new impetus into the high-quality development of the economy and society.

2.2 Characterization of Data Assets

The characteristics of data assets are related to the properties of the main data itself. A comprehensive understanding of the characteristics of data assets is of great significance to the correct understanding of the conceptual connotation of data assets, the definition of research, and the formulation of targeted management policies and operational strategies.

First, data assets have the attribute of (quasi) public goods. As an information carrier, data tend not to be consumed exclusively in the process of production and consumption, and the same data can be used and output value by multiple subjects at the same time, with non-competition and non-exclusivity. This makes data assets to some extent characterized as public goods. However, unlike typical public goods, the acquisition and utilization of data assets usually requires certain search, integration and processing costs. There is a certain degree of exclusivity in data assets at this stage. In addition, data assets also have spillover effects in theory, and the accumulation of data by a single subject can bring positive externalities to society. The above characteristics determine that data assets have the dual attributes of private goods and public goods.

Secondly, data assets have unlimited reproducibility and extensibility. Through replication and dissemination, the same data assets can be reused by different subjects, and the data assets themselves will not be impaired, which is significantly different from the “disposable” characteristics of traditional tangible assets. At the same time, data assets also have a high degree of scalability. Through integration, analysis and processing, new data assets or knowledge products can be derived from the original data, bringing a constant stream of added value. This characteristic not only lays the foundation for the efficient diffusion and utilization of data assets, but also provides a new model for its value realization.

Third, data assets are heterogeneous and dynamic. Different data assets differ greatly in terms of quality, source and processing methods, which determines their inherent heterogeneity. At the same time, new data are constantly generated, and the value and use of data are constantly changing, so the accumulation of data assets is itself a dynamic development process. This requires continuous assessment and management of data assets to ensure their quality and timeliness and to maximize their potential value.

Fourth, the value of data assets is mainly reflected in the hidden economic value. Compared with the explicit economic value that can directly create revenue, data assets are more often reflected in decision optimization, operational efficiency improvement and other hidden economic value. The hidden value is often difficult to be measured directly by monetary value, and needs to be assessed with the help of appropriate models. This characteristic brings challenges to the value realization and pricing of data assets.

In summary, data assets, as an emerging asset class, have unique characteristics that determine that managing and utilizing data assets requires methods and paths different from those of traditional assets. Facing up to its characteristics such as public product attributes, unlimited replicability, extensibility, heterogeneity, dynamism and hidden economic value is crucial to giving full play to the utility of data assets and maximizing their value.

3. Accounting Recognition of Data Assets

3.1 Challenges and Difficulties in the Recognition of Data Assets

As a new form of asset, the recognition of data assets faces many "dilemmas". Only by clearly recognizing the challenges can we contribute accounting wisdom to the reasonable recognition of data assets. From the perspective of accounting, this paper summarizes and analyzes the accounting recognition problems of data assets based on their own special attributes.

Firstly, the infinite replicability and extensibility of data assets pose challenges to their recognition. Unlike tangible assets, data assets do not rely on physical forms to exert economic value, making it difficult for enterprises to directly measure their economic value. The same data can be reused by multiple entities and can also be transformed into new data derivatives through certain means. This makes the accounting recognition of data assets complex. In the balance sheet, should we recognize the original data or the data derivatives? If the former, we need to solve the problem of cash flow attribution. If the latter, it is easy to incentivize enterprises to falsely recognize or duplicate recognize data assets to fabricate assets.

Secondly, the ownership attribution contradiction of data assets poses obstacles to accounting recognition. Traditional asset theory regards ownership as the key premise of asset recognition, but the ownership of data assets is often highly uncertain. On the one hand, the existing legal system and property rights protection practices have not paid much attention to data assets. On the other hand, the non-exclusivity of data leads to blurred ownership boundaries. The same data asset may have multiple users and controlling entities. The lack of a clear ownership basis will inevitably affect the accurate classification and recognition of data assets.

Thirdly, the heterogeneity and dynamics of data assets increase the complexity of recognition. Data assets from different sources have significant differences in quality, format, and standards. Enterprises need to incur huge costs if they apply the same recognition criteria to heterogeneous data assets. At the same time, data assets are a constantly changing and developing process. New data is constantly generated, and demands continue to change. This high degree of dynamics brings greater difficulties to the definition and recognition of data assets.

In summary, the current mainstream asset recognition theory mainly targets traditional tangible assets, and may have insufficient applicability when dealing with new intangible assets like data assets. For example, existing accounting standards lack targeted guidance on data asset accounting and measurement; related statistical standards have also failed to fully cover the scope of data assets, leading to their value being severely underestimated. The lag of theory undoubtedly increases the resistance to the recognition of data assets.

3.2 Basic Principles of Data Asset Recognition

3.2.1 Compliance Principle

The recognition of data assets should be highly consistent with current laws and regulations, unified accounting standards, and relevant standards. We should avoid making exceptions or special treatments. This is not only the basic requirement for the compliance of recognition work, but also the proper meaning of maintaining the fairness and justice of the capital market and promoting the rational allocation of resources.

3.2.2 Objectivity Principle

In the process of recognition, enterprises should break away from subjective assumptions and adhere to an objective and fair attitude and standards to truly and completely reflect the actual situation of data assets. Objectivity requires the establishment of a scientific evaluation system in practice, and the scientific measurement of the economic value and use value of data assets through reasonable models and methods. At the same time, it is also necessary to maintain the consistency and replicability of asset evaluation to avoid randomness. Only by basing the recognition on objective facts can we truly reflect the intrinsic value of data assets.

3.2.3 Prudence Principle

Given the high complexity of data assets, enterprises need to maintain a prudent and cautious attitude in the process of recognition. On the one hand, we need to limit the scope of recognized data assets. For data resources whose asset conditions cannot be objectively judged, we should adopt a prudent and strict attitude and not recognize them. On the other hand, in the measurement and recognition of data assets, enterprises also need to operate cautiously and avoid adopting overly optimistic or aggressive measurement methods, which may lead to overestimation or underestimation of asset value. The prudence principle can maximize the avoidance of uncertainty risks and ensure the reliability and robustness of recognition results.

3.2.4 Unity Principle

Due to the high heterogeneity of data assets, if there is a lack of unified standards and norms, it is likely to lead to contradictory and inconsistent recognition results. Accounting standards need to establish a unified data asset recognition framework for the whole society and the whole industry, clearly defining unified classification standards, entry principles, accounting methods, etc., so as to ensure the unity of theory and practice at the macro level. As an important part of future economic development, the recognition of data assets must adhere to unity, which is not only the need for improving efficiency, but also the necessary condition for ensuring fairness and justice in the capital market.

In summary, compliance, objectivity, prudence, and unity are the basic principles guiding the recognition of data assets. This not only helps enterprises to complete asset recognition in a standardized and orderly manner, but also lays a solid foundation for the subsequent management and trading of data assets.

4. Measurement Methods of Data Assets

4.1 Initial Measurement and Subsequent Measurement of Data Assets

The measurement of data assets is an important step in incorporating data assets into the enterprise financial accounting system and truly exerting their economic value. Data asset measurement can be divided into two stages: initial measurement and subsequent measurement, each with different measurement focuses and technical paths.

The core task of initial measurement is to accurately reflect the cost paid by the enterprise when obtaining data assets. Initial measurement mainly includes two situations: one is that the enterprise obtains data assets through external purchase, and the recognized data assets are the fair value of the purchase or the obtained license; the other is that the enterprise obtains data assets through independent creation or collection, and the recognized data assets are the sum of all expenditures incurred in the process of data acquisition, processing, and sorting.
In the initial measurement stage, enterprises need to pay attention to the following principles: the first is the principle of consideration, that is, data assets should be booked at the actual consideration paid; the second is the principle of integrity, that is, all expenditures directly related to the formation of data assets should be fully accounted for to ensure the integrity of the measurement results; the third is the principle of timeliness, that is, initial measurement should be strictly carried out according to the time node when the ownership of data assets is obtained to avoid lagging or advancing; the fourth is the principle of prudence, that is, for expenditures that are difficult to judge, we should adhere to the conservative and prudent principle to avoid overestimation of asset value.

Compared with initial measurement, subsequent measurement is a more complex process, which not only needs to consider the intrinsic changes in the value of data assets, but also needs to comprehensively consider the changes in external environment and usage conditions. From the perspective of measurement methods, this paper believes that the current data assets should choose the cost model, and can be changed to the fair value model after the development of the data trading market matures. The cost model is based on the initial measurement of data assets as the base, deducting the subsequent amortization amount to form the carrying amount of the asset; the fair value model is based on the transaction price of the asset in the active market to determine the fair value. Both measurement methods have their advantages and disadvantages. The cost model is simple to operate and has strong information availability, but it cannot reflect the real value changes of data assets due to the abandonment of market value factors. The fair value model is more realistic and credible, but it faces high complexity in valuation, uncertainty in the selection of models and parameters, and requires periodic re-measurement, with high costs.

In addition to choosing a reasonable measurement model, the subsequent measurement stage also needs to consider the factors of data asset duration, usage status, technical conditions, etc. Standards need to establish a sound impairment test mechanism to timely identify and provision impairment losses of data assets, avoid the overvaluation of carrying amount, and also pay attention to the external changes in the value of data assets. For example, changes in the market conditions of data and the innovation of data value realization paths may require enterprises to make corresponding adjustments to the value of data assets.

4.2 Amortization Methods of Data Assets

In terms of data asset amortization, the main issues involve the selection of amortization period and amortization method. The determination of the amortization period needs to consider factors such as the service life of data assets, the speed of technical updates, and market competition. Generally speaking, the service life of data assets is short, so the amortization period should also be shortened accordingly. In addition, since the value of data assets often changes over time, the value change of data assets also needs to be considered when determining the amortization period.

The selection of amortization methods mainly depends on the usage characteristics and value realization methods of data assets. Common amortization methods include straight-line method, declining balance method, and unit of production method. Among them, the straight-line method is suitable for situations where the use effect of data assets is relatively stable; the declining balance method is suitable for situations where the value of data assets gradually decreases over time; the unit of production method is suitable for situations where the value of data assets is closely related to its output benefits. In actual operations, enterprises can choose a suitable amortization method according to their own actual situation to accurately reflect the value consumption of data assets.

As an intangible asset, data assets, like other intangible assets, need to be systematically amortized within their service life to reasonably amortize their initial value or subsequent revalued value. Reasonable amortization not only helps to more accurately reflect the value realization process of data assets, but also facilitates the cost accounting and performance evaluation of enterprises.

The basis of amortization is the service life of data assets. The service life refers to the expected period of time during which data assets create economic benefits for the enterprise, usually measured in years or months. Determining the service life is a complex process that requires comprehensive consideration of various factors, such as the technical update cycle of data assets, the life cycle of products or services, laws and regulations, and competition. Due to the diversity of influencing factors, enterprises need to carefully evaluate and make timely adjustments to the service life according to changes.

After determining the service life, the next step is to choose an appropriate amortization method. At present, the straight-line method and the production method are commonly used for the amortization of intangible assets. The straight-line method evenly amortizes the amortization amount to each period, that is, the amortization amount of each period is equal; the production method allocates the amortization amount according to the proportion of the actual use or output quantity of the asset to the expected total quantity, which is a form of the work-to-cost method.

For data assets, the selection of amortization methods needs to be combined with the usage and value realization methods of the assets themselves. If the value realization of data assets is unrelated to the actual usage or utilization intensity, the straight-line method can be adopted to amortize evenly over time; if the value realization of data assets mainly comes from the business output or usage activities related to it, it may be more reasonable to choose the production method to make the amortization amount close to the actual output value.

No matter which method is adopted, the amortization process should pay special attention to the impairment signs of data assets. Unlike tangible assets, data assets do not undergo physical wear and tear, but their value may be impaired due to technical updates and changes in demand. Therefore, enterprises need to establish a regular impairment test mechanism to ensure that the value of data assets is not overvalued. Once impairment is found, impairment provisions should be timely recognized, and the amortization number of future periods should be adjusted accordingly.

In addition, in special cases, enterprises can also adopt flexible amortization policies according to the actual situation of data assets. For example, for core data assets with reliable quality and long service life, the amortization period can be extended; for some data assets with uncertain service life, the perpetual retention method can be applied to avoid unnecessary amortization costs. Amortization policies should be tailored to the specific characteristics of data assets and achieve maximum economic rationality within the framework of accounting standards.

5. Pricing Models of Data Assets

With the deepening of digital transformation, data has evolved from a simple information carrier to an asset with important value. With the joint efforts of many researchers and practitioners, the concept of data assets is gradually becoming clear, the research content is continuously expanding, and how to reasonably price data assets have also become a common concern of academia and industry. The value of data assets is reflected in their ability to bring economic benefits to enterprises, promote social development, and become an important driving force for innovation. However, the characteristics of data assets make the pricing problem difficult to be effectively solved. The value of data assets not only depends on themselves, but also is affected by various factors such as technology and liquidity.

5.1 Theoretical Foundation of Data Asset Pricing

Reasonable pricing is a key link in realizing the maximum value of data assets. However, as a new type of asset, the theoretical foundation of data asset pricing is still full of blanks and dilemmas, and it is urgent for us to innovate and break through on the basis of existing theories.

The theoretical foundation of data asset pricing can be traced back to traditional asset pricing theory. Asset pricing theory mainly originates from two disciplines: finance and microeconomics. Its core is to seek a balance between risk and return, and to explain and predict the reasonable price level of assets.

In the field of finance, the Capital Asset Pricing Model (CAPM) and the Arbitrage Pricing Theory (APT) lay the foundation for data asset pricing. CAPM explains the relationship between the risk and expected return of securities, and only systematic risk should be priced. APT further introduces multi-factor analysis to explore the relationship between various risk factors and return. These two major theories not only provide analytical tools for asset pricing in financial markets, but also provide a theoretical framework for general asset pricing.

Microeconomics focuses on the market equilibrium of supply and demand and explains the mechanism of price formation. According to the marginal utility theory, the price of an asset should be equal to the ratio of its marginal utility to the marginal utility of individuals. This theory reveals the basic logic of price formation, that is, asset pricing should reflect the marginal value of the asset to consumers.

The above traditional asset pricing theories lay an important theoretical foundation for data asset pricing. However, how to effectively apply these theories to data asset pricing and innovate and apply them is still a huge challenge. For example, the current lack of a mature trading market and public quotation information for data assets brings obstacles to the application of asset pricing theory based on market investment portfolio. At the same time, data assets have infinite replicability, and their value is mainly reflected in externalities in the process of utilization, which is significantly different from traditional tangible assets. Moreover, data assets also have higher heterogeneity and dynamics, making it difficult to have a universal methodology for their pricing.

Therefore, on the basis of drawing lessons from traditional theories, it is urgent to establish new pricing models and measurement paths innovatively combined with the characteristics of data assets. For example, scholars can try to construct pricing models from the perspectives of marginal revenue, depreciation law, and value externality of data assets; they can also develop novel data asset valuation methods based on big data analysis and artificial intelligence technology. At the same time, with the rise of the data trading market, how to introduce market supply and demand laws into data asset pricing will also be a new theoretical proposition.

5.2 Methods and Models of Data Asset Pricing

The value of data assets is reflected in their ability to bring economic benefits to enterprises, promote social development, and become an important driving force for innovation. However, the characteristics of data assets such as public goods attribute make the pricing of data assets complex and challenging. From the perspective of data quality, the value of data assets depends on their accuracy, integrity, and availability. High-quality data assets can bring higher value returns to enterprises, so their pricing should also be correspondingly increased. At the same time, the value of data assets is also closely related to the industry and application scenarios they are in. Different industries and application scenarios may have different demands and value cognition for data assets, so these factors need to be fully considered in the pricing process.

From a technical perspective, the pricing models of data assets can draw on traditional asset valuation methods, such as the cost method, income method, and market method, etc. The cost method mainly focuses on the acquisition, processing, and maintenance costs of data assets, and takes these costs as the basis for the value of data assets. The main idea of applying the cost method to data asset pricing is to calculate the present value sum of all historical costs of data asset acquisition, storage, processing, etc. as its value. The cost method has the advantages of being intuitive and easy to operate, but it also has the disadvantage of failing to reflect the future returns of data assets. The income method focuses on the potential returns that data assets can bring to enterprises, and evaluates the value of data assets through predicting future returns. The specific approach is to first scientifically predict the future income stream that data assets can create, and then choose an appropriate discount rate to discount it to the present value, which is the value of data assets. The advantage of the income method is that it conforms to the economic value theory and can better reflect the intrinsic value of data assets. The disadvantage is that it has high requirements for income forecasting and discount rate selection, and there is a certain subjectivity. The market method determines the value of data assets by comparing the transaction prices of similar data assets in the market. When the data trading market becomes more and more active, it is undoubtedly the most direct and effective way to price data assets by referring to market prices (Dalessandro et al., 2014). However, due to the current immaturity of the data asset trading market, it is difficult to find real comparable transaction examples, which brings certain limitations to the application of the market method.

In practical applications, it is necessary to comprehensively consider factors such as supply and demand, customer perception, data quality, industry and application scenarios, and technical methods, and adopt appropriate methods to reasonably price data assets. In addition to traditional asset valuation methods, the advancement of computer technology also provides new ideas for the pricing of data assets. For example, methods based on big data analysis can mine the value characteristics of data assets by analyzing a large amount of historical transaction data, thus providing a basis for pricing. In addition, artificial intelligence and machine learning technology can also be applied to the pricing process of data assets, and models can be trained to predict the value of data assets. With the development of big data and artificial intelligence and other technologies, the accuracy of data asset pricing models can be further improved.

In recent years, academia and industry have also been actively exploring and innovating new models for data asset pricing to better adapt to the special attributes of data assets. For example, the data valuation model based on LINMAP, the analytic hierarchy process pricing model considering the dynamic characteristics and flow process of data assets, the disintermediation pricing model based on blockchain, the data asset value measurement model based on data value chain theory, the pricing model based on database storage (Nani, 2023), and the pricing model based on user utility function (Liao & Li, 2023), etc., are all beneficial attempts to price and value data assets under the condition of immature market transactions.

5.3 Uncertainty in Data Asset Pricing

The uncertainty of data asset pricing is mainly reflected in the following four aspects.

Firstly, the multi-source heterogeneity of data assets itself leads to high uncertainty in pricing. Data assets from different sources and fields have significant differences in quality, format, and standards, making it difficult to apply the same pricing model and parameters to heterogeneous data assets with feasible costs. Even for the same type of data assets, their value may vary greatly due to differences in collection time and processing methods. The existence of heterogeneity means that it is impossible to establish a unified and concise general pricing system, but it is necessary to adopt a flexible pricing model according to local conditions.

Secondly, the dynamic characteristics of data assets also bring considerable uncertainty to pricing. Unlike relatively static tangible assets, data assets are a continuous dynamic process. New data is constantly generated, and demand and application scenarios are also constantly changing. Therefore, the value of the same data asset may fluctuate with the change of time and conditions. This requires enterprises to timely evaluate dynamic factors, re-evaluate their value, and minimize the lag and uncertainty of pricing as much as possible.

Thirdly, the diversified value realization paths of data assets are also a source of uncertainty. Unlike other assets, the value of data assets can not only be realized through direct trading, but also indirectly reflected through internal use, technological innovation, and other channels. For example, the value of data assets applied to enterprise decision support and customer experience improvement is often difficult to quantify quickly, which brings difficulties to pricing work.

Fourth, the lack of a mature data trading market is also a major factor contributing to pricing uncertainty. Currently, the data trading market is still in its infancy, with low activity and transparency, and a scarcity of relevant trading information and data. Under such circumstances, it is difficult for pricing methodologies based on the market approach to be truly effective, thus increasing the risk of pricing uncertainty. This uncertainty is expected to be mitigated as the data trading market becomes more active in the future.

6. Conclusion

With the increasingly important role of data in modern society, its value as a new type of asset is also receiving more and more attention. At present, the concept of data assets has evolved from a single data information to an asset with economic and social value. Its research content not only includes the valuation methods of data assets, but also involves many aspects such as information disclosure, market allocation, and value realization of data assets. At the same time, the pricing mechanism of data assets is also a research hotspot. In future research, we need to further deepen our understanding of data assets, explore more scientific and reasonable valuation methods, and promote the value realization and development of data assets and the digital economy.

The concept of data assets as an intangible asset is still under discussion in academia. On the one hand, data assets are understood as data collections with potential or actual value, which can bring economic benefits to enterprises; on the other hand, the definition of data assets also involves the tradability and control ability of data, emphasizing their legal ownership issues. Although there are various definitions, the consensus is that data assets need to have a certain amount, quality, and value density, and can be transformed into decision information or operational guidance in specific scenarios.

In terms of research content, the research on data assets is shifting from a single valuation model to more complex market behavior analysis and institutional construction. In particular, the issue of market allocation of enterprise data elements has attracted widespread attention. How to realize the effective circulation and value transformation of data while ensuring data security and privacy has become an urgent problem to be solved. At the same time, the heterogeneity of data assets and their impact on regional economic growth have also become important research fields, revealing the key role of digital technology level and data liquidity.

Regarding the valuation methods of data assets, the combination of traditional asset valuation methods and modern science and technology provides a new perspective for the pricing of data assets. However, due to the particularity of data assets, such as infinite replicability and dynamics, traditional valuation methods face challenges. The application of emerging technologies such as blockchain provides a possible solution to the problems of data asset reliability and ownership, bringing new opportunities to the research on the pricing mechanism of data assets. In addition, the research on the deep opening of government data and the coordinated development of digital industrialization and industrial digitalization provides new ideas for the primary processing and effective circulation of public data. These studies not only broaden the exploration of data asset path, but also provide new theoretical support for the value transformation of data assets.

In summary, data assets, as a research object in the interdisciplinary field, the establishment of the concept definition, value evaluation, and pricing mechanism is a multi-dimensional and dynamically evolving process. Future research needs to further deepen the understanding of the characteristics of data assets, explore more scientific and reasonable evaluation models, and promote the efficient circulation and maximum value of data assets through technological innovation and institutional design. In this process, interdisciplinary cooperation, technological innovation, and in-depth analysis of existing laws and regulations will be indispensable.

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