

Assetization-Oriented Data Governance: An Exploratory Case Study

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ABSTRACT

Data has been considered an important asset; however, data governance remains overwhelmed with risk reduction and security considerations. This research proposes that data governance should be value-oriented for data assetization, monitoring, regulating, and managing the process of the data lifecycle for data value creation. Using an exploratory case, we demonstrate how, from an assetization perspective, data governance could incentivize multiple stakeholders' participation in the value realization of data. The result of in-depth case analysis reveals a data governance framework consisting of an assetization process, data artifacts, governance mechanisms, and infrastructures towards multiple stakeholders. Our preliminary findings not only enrich the literature on data governance but also provide theoretical and practical guidance on how to effectively manage and realize the value of data assets.

Keywords: Data governance, assetization, value realization, data artifacts, multiple stakeholders.

INTRODUCTION

According to the definition of assets in the "Conceptual Framework for Financial Reporting" issued by the International Accounting Standards Board (IFRS Framework, 2018), data assets can be defined as the data resources owned or controlled by an organization as a result of past events and from which economic benefits are expected to flow to the organization, which emphasizes both valuableness and property-right relationships (related to value creation and distribution) between data assets and stakeholders (Lee & Looverbosch, 2022). Despite the importance of data usage in business operations (Tallon *et al.*, 2013) and increasing investment in data management (Al-Ruithe *et al.*, 2019), a study released by Accenture reveals that over two-thirds of businesses are still confused about how to leverage data to create value (Accenture, 2020). One of the great challenges might lie in the lack of a framework to guide the process of transforming data into a data asset. Wang (2023) suggests that data assetization is a significant process of converting data into data assets with economic value and/or social value.

Although existing proposals and standards, such as ISO/IEC 38505 (2017), suggest that the goals of data governance should be maximizing the value of data use sustainably while minimizing relevant risks. Data governance is expected to enable organizations to lower the cost of data management and create value from data (Janssen *et al.*, 2020). However, the current practice and research on data governance focus more on risk reduction and addressing security concerns. Few studies pay attention to data governance from an assetization perspective, which may contribute to incentivizing and controlling stakeholders' participation (Battilana & Lee, 2014) in the process of data value creation and distribution.

From data to data asset, this process implies various data artifacts resulting from data usage and integration by diverse stakeholders (Li *et al.*, 2019). Moreover, the value of data could be varied for different usage scenarios (Yanlin & Haijun, 2020). For example, Uber or Didi can use traffic data to match drivers and passengers, enhancing the efficiency of travel services and increasing revenue; government agencies can use the same data to optimize road construction and improve the quality of transportation services. Hence, the data value creation and capture are not absolute but contingent upon creative resources and business partners (Laursen & Salter, 2006). Understanding the complexity of data assetization would help make data governance more value-oriented. Thus, we derive the research questions: what is the process of data assetization? and how to reshape an assetization-oriented data governance framework?

To answer this question, we conducted an in-depth case study of a Chinese "digital unicorn" company that owns rich data resources and has achieved successful operations of data assets. The preliminary findings reveal a framework of assetization-oriented data governance, including the process and drivers of data assetization, the forms and formation of data artifacts, the features of artifacts in stakeholders' activities, the governance mechanisms towards multiple stakeholders, and a data catalog-based infrastructure to support the mechanisms. This framework is expected to clarify governance objectives and mechanisms

towards value realization, and further guide companies to achieve data asset operations and management successfully, step by step.

RESEARCH BACKGROUND

Data Governance

Serrano and Zorrilla (2021) regard data as a type of critical asset, focusing on representing business activities digitally and serving as a foundation for knowledge and innovation. It provides principles and models to evaluate, direct, and monitor the use of data, aiming at maximizing data value realization and minimizing relevant risks. The framework and mechanisms of data governance are crucial to encourage the occurrence of desired behaviors for value realization and simultaneously for risk management that can ensure value co-creation and distribution (Alhassan *et al.*, 2019).

Extant research on data governance has covered significant aspects, including data policies and standards, data quality, and data privacy and security. Data policies and standards are the foundation for ensuring the effectiveness of data governance, with international regulations like COBIT emphasizing the importance of accurate and reliable financial reporting and governance rules, reflecting the attention to strategic and policy factors (Alhassan, 2019; Malik, 2013). In terms of data quality, existing research indicates that the quality of data directly affects consumer satisfaction and occupies a central position in the data governance framework (Haider, 2014; Eppler & Helfert, 2004). Quality improvement is seen as a long-term optimization process involving metadata management, data monitoring, and other processes (Khatri & Brown, 2010). Regarding data privacy and security, scholars have emphasized the importance of protecting data storage, use, and transmission on electronic media, recommending that organizations enhance their security policy standards (e.g., Karwatzki *et al.*, 2022; Bhansali, 2013; Trope & Power, 2005). In the context of the big data era, traditional data privacy and security protections face new challenges, necessitating considerations on how to promote data linkage, flow, and application while protecting privacy and security (Davidson *et al.*, 2023).

In summary, extant research mainly focuses on risk reduction in the process of data use through governance mechanisms within an organization. However, there is still limited research on how to incentivize and control both internal and external stakeholders to participate in data value realization, such as fostering innovation, increasing revenue, and gaining a competitive edge.

Data Asset and Assetization

The Economist boldly declared that "the world's most valuable resource is no longer oil, but data" (The Economist, 2017). As data becomes an indispensable resource for value creation, companies are increasingly exploring how to use data to create and capture value. The world's largest and most successful companies, such as Google, Amazon, and Uber, have built and expanded their businesses through extensive use of data. These organizations recognize that nearly any event can generate data that helps businesses analyze and improve consumer products (Siebel, 2019). Organizations investing in data capabilities experience numerous benefits, including increased revenue, optimized costs, and feedback on product development (Grover *et al.*, 2018). Therefore, data is no longer merely a factor of production but has evolved into a type of corporate asset (Birch *et al.*, 2021).

Furthermore, the effective development and utilization of data assets has become an urgent discussion topic. Existing literature extensively examines the strategic needs that businesses must meet to achieve data assetization (Awan *et al.*, 2021). For example, Li *et al.* (2022) argue that enterprises must adopt a data-driven approach to business operations, focusing on data quality, governance, and analytics. Dubey *et al.* (2019) emphasize the importance of fostering a data culture, where all members of an organization possess skills in data analysis and interpretation. Additionally, scholars highlight the need for businesses to invest in data management and analytic technologies, as well as the human capital and processes required to effectively manage data assets (e.g., Jansen *et al.*, 2017; Wamba *et al.*, 2017; Vial, 2021).

While existing research has discussed the concept of data assets and their assetization strategies to some extent, and Oveisi *et al.* (2024) provided a data lifecycle, these studies have not yet offered a comprehensive process of data assetization to contribute to data governance that ensures effective value realization of data.

RESEARCH METHOD

The case study method is particularly suitable for this research for several reasons. First, the research question is based on "how to build a data governance framework towards assetization," making it more amenable to answers through inductive methods (Pan & Tan, 2011; Walsham, 2006). Second, as this study aims to construct a new governance framework, case studies are more effective due to their advantage in exploring a new theoretical framework and concepts of governance (Siggelkow, 2007). Third, the process of data assetization is reflected in a series of complex actions; a case study is needed to uncover insights (e.g., Leonardi, 2013; Seidel *et al.*, 2013; Strong *et al.*, 2014).

Three criteria were adopted for selecting the case (Pan & Tan, 2011). Firstly, the case organization owns or possesses massive data, facilitating the study of data assetization. Secondly, the organization's scale is moderate, having a sufficient business case to show the complexity of data assetization while not being so large as to become unmanageable and overly complex for research. Such organizations are adequate for demonstrating the process of data assetization without adding unnecessary complexity due to large scale. Thirdly, one member of our research team acted as an expert in collaboration with the case organization, enabling

us to have a clearer understanding of the project. Finally, our case is valuable because the organization can provide real-world use cases of data assetization governance, offering precious first-hand materials for our research.

Case Background

XiaoAn Technology Co., Ltd. (XiaoAn Technology), located in Wuhan, Hubei Province, China, was established in 2015. It is a leading company in the intelligent two-wheel travel industry, with years of deep cultivation. XiaoAn Technology operates ten major centers, including software, hardware, products, manufacturing, business, marketing, and more. As a leading provider of intelligent electronic bicycle (e-bicycle) travel solutions in China, XiaoAn Technology is a national high-tech company that invests more than 15% of its annual revenue in research and development. The company focuses on solutions in four main business areas: e-bicycle sharing operations, courier bike rental and battery replacement, e-bicycle travel regulation, and artificial intelligence for e-bicycles.

The company has served over a hundred million shared e-bicycle terminals and more than a million shared e-bicycles. Its business covers over 500 cities nationwide, owning 60% of the shared e-bicycle market operation data in the country. As one of the first companies in China to focus on shared e-bicycle solutions, XiaoAn Technology has successively launched dozens of products and software systems suitable for shared e-bicycles, instant delivery motorcycles, smart motorcycles, and other application areas. It also offers a complete set of intelligent solutions for shared e-bicycles, serving over 500 shared e-bicycle companies nationwide. For three consecutive years, its market share has exceeded 60%.

Brief Description

XiaoAn Technology owns and possesses massive data of e-bicycle operations, but how to effectively utilize these data resources to create and add value has become a challenge for XiaoAn Technology. Due to the large volume and variety of data, the company has encountered difficulties in value co-creation within the company. As the CEO mentioned, “although we clearly recognize that data is our important asset, we were still getting lost in big data at that time”. Fortunately, since XiaoAn Technology has established partnerships with several universities and local operators, it decided to introduce external resources to co-create data value instead of protecting data from leaks. Thus, XiaoAn Technology implements a data governance initiative to facilitate the co-creation, distribution, and management of data value.

First, XiaoAn Technology gradually established a data catalog system as the data governance infrastructure that records and manages the company’s data-related information in real time. The information includes, but is not limited to, the roles, responsibilities, and activities of all stakeholders related to the use of data, enabling dynamic management of the data assetization process. In this way, XiaoAn Technology could more effectively monitor and evaluate its data resources and human behaviors.

Additionally, the company brought in external research and technical resources by collaborating with several universities and local e-bicycle operators. The inclusion of these partners provided XiaoAn Technology with a broader perspective and technical support, helping the company better analyze and utilize existing data.

Specifically, universities can leverage the data to help XiaoAn technology build models and algorithms, which result in novel and creative data products/services for local e-bicycle operators. The cospecialized data assets co-created by XiaoAn and universities can help the local operators gain deep insight into customers and optimize their services. For instance, XiaoAn Technology partnered with a university located in Beijing to co-develop a BDA (big data analytics) model and algorithm for discovering demands from users’ comments. The model and algorithm have been used to identify issues and reasons with user locating and parking behaviors, which contribute to two creative functional components of e-bicycle, i.e., “Locating E-bicycle at One Glance” and “Parking E-bicycle with One Click”. The two functions observably improve user experiences and operational efficiency, which resulted in a revenue increase of 19.9% for local e-bicycle operators. These governance measures not only improved XiaoAn Technology’s data operations management and competitiveness of data products/services, but also brought revenue and academic achievements to universities. The clarified assignment of responsibilities between XiaoAn Technology, universities, and local e-bicycle operators, as well as monitoring and evaluation of their activities based on the data catalog, has helped them successfully co-create and distribute value. Such a data governance strategy not only appropriately distributes the value of data assets but also aligns the interests between the company and its partners. By enhancing decision-making quality and optimizing business processes, XiaoAn Technology has transformed its data resources into corporate assets. These assets not only directly translate into market revenue but also enhance the overall business value of the company.

PRELIMINARY FINDINGS

Introduction of Data Governance Framework

Based on the case analysis, we have developed a preliminary framework of data governance (see Figure 1) through identifying the entire process of data assetization. This framework includes four parts: process and drivers of data assetization, forms and formation of data artifacts, governance mechanisms towards multiple stakeholders, and governance infrastructure.

First and foremost, we clearly understand that data itself has no value; it only becomes valuable when it has been well organized

and used. Thus, the data asset is not just the raw data itself, but the combination of raw data and data artifacts as analytics. Specifically, data artifacts are an analytic usage of raw data and are still in the form of data. Second, we identify three stages in the process of data assetization: data into factors of production, data into resources, and data into assets. Accordingly, data artifacts are defined as classified datasets, data products/services, and data assets (group). Third, the roles and activities of stakeholders and the features of artifacts embodied in activities (i.e., relationships between stakeholders and artifacts) are identified. Then, the governance mechanisms towards multiple stakeholders are developed.

The definition of the data assetization process, originating from the provision of raw data available, relies on the data lifecycle (Oveisi *et al.*, 2024). Thus, in the first stage, the data is to be prepared for production as factors, because raw data should be classified as organized datasets and distributed to different partners. Only in this way can data usage potentials be identified, and organizations cannot get lost in massive data. In the second stage, data capabilities should be created as organizational resources. Nevertheless, the context-specific nature of data leads to different stakeholders having different data usage needs and/or capabilities, and then different data products or services will be developed as data capabilities (e.g., data models and algorithms or data packages). Also, the potential value of data resources emerges when data usage is combined with traditional production factors such as capital, land, and technology, and this value is usually activated only in specific application scenarios. For example, large-scale mobile signaling data from telecommunications operators can not only improve operational efficiency in the cultural tourism consumption field but also help traffic management departments optimize road network flow. In the third stage, data assets should be confirmed in value distribution (e.g., in accounting) and often in the form of an asset group (as an ensemble) consisting of a dataset and products/services. As assets are time-sensitive, the value of assets fluctuates to influence the assessment, transaction, and appropriation of data assets.

In the following discussion, we will elaborate on artifact features, stakeholder activities, and corresponding governance mechanisms in each stage of data assetization.

Stage-1: Data into Factors of Production

Features of artifacts in stakeholders' activities. The stage of Data into Factors of Production refers to the procedure of transferring dispersed, fragmented, or unstructured raw data into classified datasets with potential for use, e.g., tables or documents of a subject-oriented database. The transferring procedure involves a series of activities, including data collection, storage, cleaning, pre-processing, and organizing, ultimately forming different datasets targeted at specific potential demands. These datasets further show two features in stakeholders' activities – non-consumability and incompleteness. Non-consumability means that data can be infinitely replicated between stakeholders without degradation, while incompleteness indicates that data can be used for group characteristic analysis even in an incomplete state, which also means that datasets can be reorganized for different partners, according to their demands and relevant requirements.

Governance mechanism for value preparation. Given the complexity and diversity of raw data, data availability and quality directly influence data value realization. Thus, two governance mechanisms for value preparation – data identification and classification, and sharing and access for stakeholders. Data identification management depends on the potential demands of data usage. The demands originate from the data owners and may also come from external partners, as partners can assist the data owner in discovering demands and usage scenarios. Data classification management further classifies the raw data according to the demands, forming datasets for different scenarios or subjects. Data sharing and access mechanisms formulate data sharing strategies and access methods for different stakeholders, especially the authorization and access control policies of datasets, to ensure that the entire process complies with regulations.

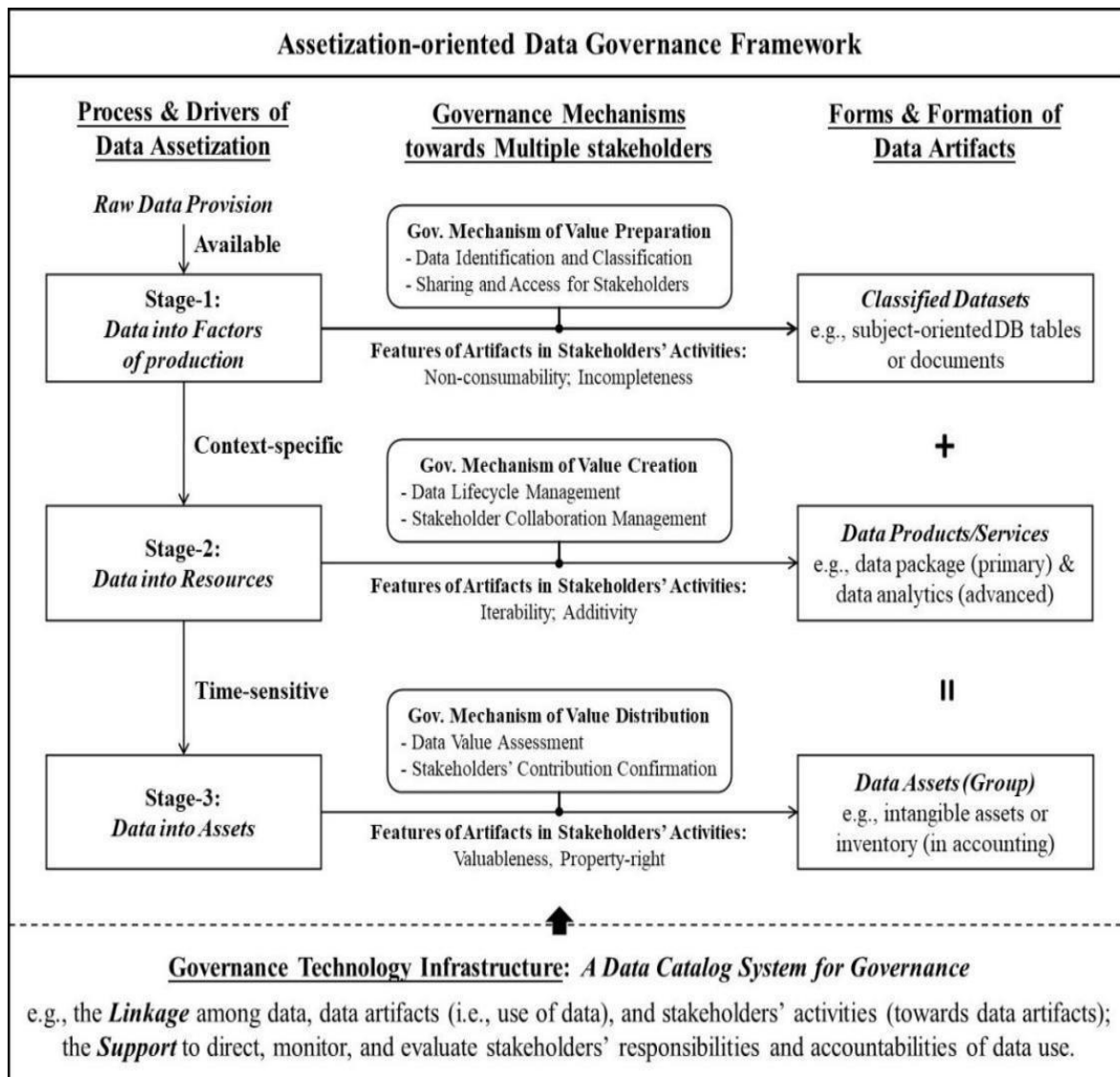


Figure 1. Preliminary Framework of Assetization-oriented Data Governance.

Stage-2: Data into Resources

Features of artifacts in stakeholders' activities. The stage of Data into Resources refers to the procedure of transforming data factors into data resources such as data products or services, which means that data capabilities have been developed and data value has been co-created. The data products or services can be categorized into two levels: the primary resources and the advanced resources. Specifically, primary data products or services provide users with basic data access and application capabilities, such as mainly include a salable database (in the form of re-organized datasets), data service APIs, or data cloud services. By contrast, advanced data products or services refer to deep business insight through data analysis, such as data analytics in the form of modeling and algorithms, data analysis reports by visualization, BDA/AI systems customized for specific business scenarios, or BDA/AI solutions integrated with cloud computing technologies. These data products or services show two features in stakeholders' activities to develop them: iterability and additivity. Iterability emphasizes the continuous version development and refinement within a project of data models or algorithms, while additivity highlights the citation relationships between projects within an organization, even the interactions or collaborations between different organizations. The features of both iterability and additivity can reflect the activity linkage of data value co-creation between multiple stakeholders.

Governance mechanism of value co-creation. The procedure of data value co-creation is a complete lifecycle, not only including the R&D phases of data resources (e.g., data products or services) mentioned in ISO/IEC 8183 (Oveisi *et al.*, 2024) but also encompassing the market and sales phases of data resources. Therefore, data lifecycle management needs to clarify activities of all stakeholders, providing rich evidence to support data value assessment. Specifically, clarifying the relationships between stakeholder activities and the intermediate or transitional forms of data resources provides evidence in support of property-right confirmation of data resources. Simultaneously, stakeholder collaboration management aims to reflect their interactions, and the interactive information provides evidence to support distinguishing their own contributions and implementing value distribution. Integrity management and audit are significant for data governance, and the governance mechanisms can also provide support in this regard.

Stage-3: Data into Assets

Features of artifacts in stakeholders' activities. The stage of Data into Assets refers to the procedure of combining data factors and corresponding data resources and translating them into data assets (group). Data assets should be confirmed in value distribution. To take accounting, for instance, the data resources can be categorized into two forms of assets – inventory and intangible assets. Inventory refers to the data resources in the form of products that are sold directly on the market or collected as direct parts of other products or services, e.g., Google collects geographical datasets and develops digital-map service APIs to sell them directly to client organizations. By contrast, intangible asset refers to data services within an organization that are used for decision-making, operations analysis, business process optimization, or enhancing customer experiences, while these data resources cannot be sold independently or their value is not easily quantified. Thus, data assets show two features in stakeholders' activities – value and property rights. The features can reflect the value assessment of data assets and the corresponding contributions between stakeholders, which determine the value distribution.

Governance mechanism of value distribution. The governance mechanisms for data asset value distribution include data value assessment and stakeholders' contribution confirmation. Specifically, data value assessment focuses on evaluating the economic or social value of data use through analyzing the evidence in the entire lifecycle. The evidence comes from all the information formed by stakeholder activities and data artifacts, during stages of data value preparation and co-creation. The assessment methods can adopt the asset evaluation approaches used in accounting. Identifying and evaluating the contributions of all stakeholders not only improves inter-organizational collaboration but also continually adds value to data assets. Furthermore, the mechanism ensures that all individuals or groups who have contributed to the value realization of data assets receive appropriate recognition and rewards.

CONCLUSION

Through an in-depth analysis of the case study of XiaoAn Technology, this paper explores the concept of assetization-oriented data governance. Our findings present a governance framework that covers the entire lifecycle of data assetization, from data elements to their transformation into data assets. The framework details the different stages of the assetization process, data artifacts and governance mechanisms oriented towards multiple stakeholders at each stage.

The case of XiaoAn Technology highlights the importance of recognizing data as a crucial organizational asset and effectively managing and utilizing it through structured governance mechanisms. By integrating external resources, organizations can expand their value creation capabilities beyond traditional boundaries, enhancing competitiveness and innovation.

Additionally, the implementation of a data catalog system at XiaoAn Technology illustrates how to construct a new data catalog to dynamically link data, data artifacts, and stakeholder activities, as well as to direct, monitor, and evaluate stakeholders' responsibilities in data usage. Therefore, our study not only provides managerial insights but also advances technical innovation.

The primary limitation of this study is the singularity of the case study, which may restrict the generalizability and applicability of our findings. To overcome this limitation, we plan to implement a two-step strategy to deepen and expand our research.

Firstly, we will continue to delve deeper into the current case of XiaoAn Technology, refining our coding processes to enrich and perfect our understanding and theoretical structure of assetization-oriented data governance. By conducting a more in-depth analysis of the existing case, we can detail the key mechanisms and dynamics within data governance, providing a solid foundation for constructing a more comprehensive governance framework.

Secondly, to enhance the broad applicability and representativeness of our research, we plan to expand the number and diversity of case studies. By replicating this study across different industries and regions, we aim to validate and optimize the assetization-oriented data governance framework, ensuring its effectiveness in various organizational and market environments. This step will help us explore and confirm the universality and flexibility of the data governance framework in different contexts.

Although this study provides valuable insights into understanding and implementing data assetization and governance, the rapid development of data and technology necessitates ongoing assessment and improvement of the existing framework to adapt to new challenges and opportunities in the digital age. Future research will include incorporating a more diverse array of case studies to provide a more comprehensive validation of the model and refine our understanding of assetization-oriented data governance across different market dynamics and industry environments.

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