Journal of Economic Surveys

WILEY

ARTICLE OPEN ACCESS

Enterprise Data Valuation—A Targeted Literature Review

Sai Krishnan Mohan[1] | Gnana Bharathy[2] | Akanksha Jalan[3]

[1]Department of Research, Rennes School of Business, Rennes, France | [2]Faculty of Engineering and IT, University of Technology Sydney, Sydney, New South Wales, Australia | [3]Department of Finance & Accounting, Rennes School of Business, Rennes, France

Correspondence: Sai Krishnan Mohan (sai-krishnan.mohan@rennes-sb.com)

Received: 11 April 2024 | **Revised:** 18 February 2025 | **Accepted:** 11 April 2025

Keywords: data as intangible asset | data valuation | enterprise data valuation | intangible assets valuation | knowledge valuation | valuation of databases

ABSTRACT

As digital transformation redefines business models, enterprise value increasingly depends on intangible assets, especially data, rather than traditional physical assets like buildings and equipment. Traditional accounting has long focused on valuing physical assets based on their anticipated future economic benefits, distinguishing between operating and capital expenditures. However, intangible assets, such as data, are more complex to evaluate due to their dependence on business context, lifecycle, and specific uses. This literature review examines data valuation as an intangible asset for accurate enterprise valuation, relevant in investments, mergers, acquisitions, and understanding enterprise worth. The article highlights multiple emerging valuation approaches, including customer transactions, lifetime value, shareholder value, and customer equity, which provide a more nuanced view of data's worth. Advanced techniques like cooperative game theory, Shapley Values, machine learning, and meta-learning frameworks are also explored as tools to quantify data value more precisely. Data quality is emphasized as a critical component of data valuation, with ongoing challenges due to regulatory uncertainties and inconsistent reporting practices. These complexities in data valuation signal a significant research opportunity to refine valuation methods as data continues to shape enterprise value across industries.

1 | Introduction

Determining an asset's objective value in monetary terms, usually through comparisons with other transactions, projected cash flows, or market trends, is known as valuation (Matthais et al. 2023). Valuation means determining an asset's objective value (in monetary terms) through comparisons with other transactions, projected cash flows, or market trends (Matthais et al. 2023). Enterprise valuation approaches vary across industries, based on differences in annualized sales growth, earnings volatility, and comparison of R&D to sales (Demirakos et al. 2004).

Digital-driven economies have catalysed the utilization of data as a primary economic asset (Güngör 2025). Current uses of data differ across industries but appear to offer better insights into business trends and, thereby, forecasting. For example, using customer data, banking companies can develop a comprehensive credit rating system, insurance companies, a personalized pricing system (Bonvino and Giorgino 2022), and healthcare, a more efficient resource allocation system (Demirakos et al. 2004). By utilizing advanced AI analytics to analyze financial data, banks equipped with better visibility of operations can offer loans at competitive rates, reducing their cost of capital (Alirezaie et al. 2024). The energy industry calculates value of data for pricing using game theory modelling (Wang and Song 2025), renewable energy prediction, system monitoring, fault detection and load forecasting (Sarker et al. 2023). The minerals (mining) industry uses data analytics for exploration, reservoir management, production engineering, pipeline monitoring, and maintenance (Sarker et al. 2023). The manufacturing industry uses data analytics for overall management on supply chains, including production control, detection of anomalies in the products and in the production process (Sarker et al. 2023). Advanced analytics is used in the procurement function of the aviation industry for cost reduction (Altundag and Wynn 2024). Big Data Analytics solutions, which include proprietary data and custom applications, offer high-level firm-specific knowledge, potentially creating long-term competitive advantages (Dahiya et al. 2022). Efficient data analytics to derive actionable insights distinguishes industry leaders from followers (Adebunmi Okechukwu Adewusi et al. 2024). As the volume of data gathered has grown exponentially over the past decade, the potential of data as an enterprise asset is acknowledged in principle (Suliman et al. 2019; Faroukhi et al. 2020; Sterk et al. 2022).

Despite its existing application in assisting business functions across several industry groups, data as an asset has received limited attention in academic research. There is a significant lack of a clear data valuation methodology in research and practice (Stein and Maass 2022). There are benefits to recognizing data assets as intangible assets in accounting information systems (Xiong et al. 2022), the value of which may be estimated through income, cost, and market value-based methods (Bendechache et al. 2023).

2 | Methodology

Data, representing the information generated by a business internally, constitutes an information asset that is considered an intangible asset under the current accounting principles (GAAP). This article explores the various methods that exist concerning data valuation and the challenges that come with them. Unlike other intangibles such as goodwill and copyrights, data forms a peculiar intangible, the value of which depends entirely on its intended use in the organisation, making valuation issues more nuanced. To the best of our knowledge, ours is the first paper that brings together a targeted literature review on data valuation. We cover themes ranging from the meaning of data, the need for its valuation, the various methods in this regard, and the underlying challenges. We conclude by identifying gaps in existing knowledge and potential areas for future research. Notably, in this article, our focus is on a single and particular intangible asset, that is, data. This focus is important given the significant differences between data and other assets that constitute intangible assets, necessitating a completely different approach to valuation.

This study used a targeted literature review approach to examine enterprise data valuation, focusing on various aspects such as valuation methodologies, implementation challenges, and business implications. A systematic search covering the review themes illustrated in Figure 1 was conducted using various databases, including Google Scholar, DOAJ, EBSCO, Emerald Insight, Research Gate, Science Direct, Scopus, and Springer.

The search phrases used were "Data as an Intangible Asset," "Data privacy valuation," "Data valuation," "Enterprise data valuation," "Intangible assets valuation," "Knowledge Valuation," Taxation of Digital Assets,'' "Taxation of Intangible Assets," "Valuation of databases," "Valuation of Formulae," and "Valuation of Equations." This literature review commenced in June 2021 with the search criteria for articles and journals on the valuation and taxation of intangible assets. Based on the searches, 408 articles were shortlisted for review. Articles/research papers that covered the targeted themes (Figure 1) were included for this review, and other articles that did not cover the targeted themes (Figure 1) were excluded.

The findings with salient references are presented thematically, covering traditional and emerging data valuation methods, challenges in data valuation, implications for businesses and policymakers, and future research directions. This approach allowed for a comprehensive analysis of enterprise data valuation, identifying current knowledge gaps and future research opportunities. The study's integrative elements allowed for a comprehensive understanding of data valuation in business contexts.

3 | Enterprise Valuation Based on Value From Customers

Data monetization is gaining prominence (Maia et al. 2024) and its market is considered large ($1.5 billion) and high growth (Machado et al. 2024). Customer Valuation Theory (CVT) focuses on generating value from customers to firms and uses the customer lifetime value (CLV) metric to estimate future customer contributions. Research on customer value has explored the volatility of future revenue contributions and has influenced profitable customer management (Kumar 2018). This necessitates the availability of high-quality customer data.

Customer relationships incorporate the value clients provide for the company (Forbes 2007). Corporate valuation techniques, such as customer lifetime value, are in higher demand due to value-based management methods. The CLV is an example of how modern financial theory has been used to assess business relationships. Although several CLV models have been created so far, there is not generally acknowledged better method (Bauer and Hammerschmidt 2005).

Wang et al. propose augmenting Cooperative Game Theory-based Data Valuation through Data Utility Learning in the context of Shapley value (Wang et al. 2022). This study was a theoretical and computational exercise to use cooperative game theory to estimate the data utility functions in unseen data combinations. It forms a theoretical basis for estimating the value of data assets and is far removed from the practical context of data valuation.

From a practical perspective, researchers (Han et al. 2021) optimized wholesale purchases based on analytics, thereby increasing returns and demonstrating the value of an analytics-based approach to customer data, which could positively impact a retailer's profit. Although this is a positive example of data valuation, it still does not offer a robust approach. Data of customers is being treated by "Big Tech" companies as techno-economic objects which can be turned into assets (Birch et al. 2021).

3.1 | Key Takeaways

The difficulty of valuing "dotcoms" led to new metrics and methods, with a popular measure based on the number of customers or "eyeballs" viewing the offering. In purely digital businesses, viewership of and interest in the company's digital products may

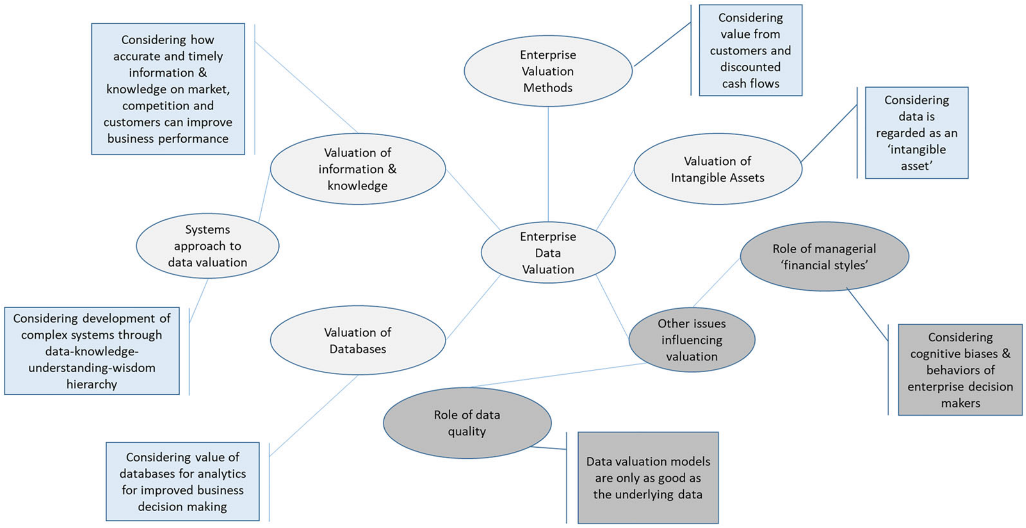

FIGURE 1 | Literature review themes. [Colour figure can be viewed at wileyonlinelibrary.com]

be the only way to estimate demand and the company's worth thereof. The discounted cash flow (DCF) approach has been used to value high-growth companies. These companies are valued based on future growth, making estimates of terminal value critical and dependent on good estimates of company growth. A high degree of subjectivity may be involved in estimating company growth factors based on market share and profit margin. Growing companies must acquire customers rapidly to gain a first-mover advantage and build markets/channels.

The focus of marketing is to provide better value to customers through better services, products, convenience, delivery, and customer satisfaction. A customer's lifetime value (CLV) depends on customer acquisition (costs), revenue over the period of retention, and revenue through cross-selling/up-selling or margin expansion. CLV measurements encourage companies to be customer-centric and focus on long-term profitability instead of short-term market share or sales growth. Hence, CLV enables greater measurement and accountability for marketing. A cost-effective customer relationship strategy would be introducing new customers to a product or service, piquing their interest, and then persuading them to buy.

Calculating the anticipated net cash flows that a company expects to receive from a customer or a particular customer segment is, in theory, a simple process. Revenue, customer acquisition costs, transaction costs, and customer retention rates are the components relevant to the calculation. However, in practice, it is difficult to estimate these components. Therefore, although CVT is well established, there is limited literature to support transitioning from or extending customer valuation to data valuation and monetization.

Big Tech companies "assetize" users and user engagement by collecting user engagement data for measurement and monetization. They state that as Big Tech increases the collection and monetization of user data, its focus on user data is reflected in the market sentiment of investors. The power of Big Tech is vested in this process of "assetizing" users rather than in the "ownership" of personal data.

A customer list can be sold (for use by the purchaser for marketing purposes), but an order backlog and customer contracts come with a guaranteed income source. The unsecured future income from clients is captured by non-contractual connections, which are softer assets. The present value of future cash flows and the amount of income an asset will produce over its useful life are factors that contribute to determining the worth of such assets. The total value these assets generate cannot be determined by valuing customer-related intangibles based on historical or replacement costs. However, estimating the expenses of replacing an intangible asset would be highly subjective. When historical expenditures and earnings data are combined, returns on marketing investment can be calculated, providing important knowledge about successful marketing strategies.

Enterprise valuation methods are established based on business from customer transactions, customer lifetime value, shareholder value, and customer equity concepts. Cohort analysis in business analysis and planning helps businesses spot opportunities to improve customer revenue by computing similarities between customers. The shareholder value (SHV) concept considers cash flows at an aggregated level, is used in valuation. However, traditional accounting tends to emphasize cost-cutting measures, which may cause staff members to overlook opportunities to boost value by enhancing customer equity (CE) drivers. A CLV approach values businesses using disaggregated cash flows at the level of individual customers or by examining profit streams produced by a single customer's value-enhancing actions, such as up-buying, cross-buying, or revenue-generating activities. The value of the customer base, which accurately represents a company's operating cash flow, is obtained by adding the "lifetime values" of all current and potential customers. Operating assets generate cash flows only when used to produce goods and services that customers buy. Consequently, CE and cash flows from non-operating assets determine the total value of a company. Marketing expenses are investments in customer assets that boost the company's value over the long term.

These valuation methods are influenced by customer and transaction (data) records maintained by the enterprise. In addition, advanced analytic techniques such as machine learning, cooperative game theory are used in the valuation of data assets.

4 | Valuation of Intangible Assets

Despite having diverse connotations, the terms "intangibles," "intangible assets," "knowledge assets," and other related concepts are used interchangeably. Non-financial, immaterial assets retained for creating or providing goods or services are intangible assets (Pastor et al. 2017). Intangible sources of anticipated financial gains or losses can be either assets or liabilities. Pastor et al. comprehensively review the literature on intangible asset valuation. They acknowledge that valuation specialists seem not to have converged on a single, universally accepted method for intangible asset valuation, despite various existing methods.

Intangible capital is the difference between intangible assets and liabilities. IFRS defines intangible assets as "Identifiable non-monetary asset without physical substance"('International Accounting Standard 38' 1998). Intangible assets can be divided into visible and hidden categories depending on whether they are' accountably' recognized. According to International Accounting Standard 38.1, identifiable and unidentified business or financial assets are a subset of intangible assets. Intangibles constitute an increasing component of corporate balance sheets. These include assets generated through research and development, investment in and training of employees, and software developments. Very few of these assets appear on the Balance Sheet, which has led to an increasing call for reform in corporate accounting. The APB Opinion No. 17 from the American Institute of Certified Public Accountants requires that intangible assets be accounted similar to methods applied for property, plant, and equipment (Canibano et al. 2000). However, given the high degree of uncertainty with the amount and timing of the future economic benefits of these assets, this accounting treatment has been questioned repeatedly.

Accounting rules do not allow intangible assets like information into the balance sheet (Evans and Price 2014; Giordani et al. 2019), even when they represent the main source of business value (Higson and Waltho 2007). Numerous studies have highlighted the need for accounting information to be supplemented with more forward-looking financial and non-financial information, particularly intangible elements that affect a company's value (García-Ayuso 2003).

The leveraging impact of intangible capital, the Internet, and information technology, and the changing US legal environment are all significant contributors to the rise in the value of intangible assets (Sullivan and Sullivan 2000). Per Sullivan and Sullivan's study, intangible assets may be valued over time utilizing a non-traditional viewpoint on the business and conventional valuation methodology.

A fair value of a company's net assets would ideally be disclosed to third-party users by financial statement preparers (Billiot and Glandon 2005). Per this article, while the market prices of most intangibles are not reported, the software sector has seemingly more openness, which enables the market to take up more of the unrecorded value. The intangible asset is documented when a cost that identifies and quantifies the intangible asset's worth is incurred. According to Billiot and Glandon, businesses involved in developing industries, where success depends on innovation and change, are more likely to invest significantly in intangible assets. These findings are consistent with Damodaran (Damodaran 2001) in that a firm's life cycle explains industry disparities. Because the costs of developing software and the industry's entry barriers are relatively low, it is simpler for many target companies to get started. The accounting treatment of investments in intangible assets is inconsistent in manufacturing firms, resulting in the "contamination" of earnings, cash flows, and return on capital, many of the primary inputs used in valuation (Damodaran 2001). Another general challenge is borrowing less money from financial institutions due to relatively lower financial leverage, due to incorrect accounting of intangible assets (Damodaran 2009).

A strategic planning methodology for valuation is proposed (Brooking 2010) using four asset categories to describe the enterprise (in terms of a "dream ticket") as it would be if the enterprise had achieved its strategic goals. The dream ticket is characterized by affirmations describing the "health" of the company's assets. As per Brooking, the following are four sets of assets used to build a "Dream Ticket" which describes how a business may look in 2–3 years:

1. Market Assets, which give the company power in the marketplace.
2. "Infrastructure Assets" cover management factors such as philosophy, culture, establishment of "financial structures" and business processes, compliance with regulatory standards, and the implementation of Information Technology systems.
3. Intellectual property assets.
4. Human-centered assets covering expertise, problem-solving capability, and managerial skills in the organization.

Intangible assets create most of a company's net worth (Green and Revilak 2009). A framework of intangible valuation areas (FIVA), an intangible asset taxonomy representing a validated set of business value drivers, is postulated (Green and Ryan 2005) as a network of interactions between intangible mechanisms, processes, representation, and goals from an organizational perspective. FIVA connects to an intangible asset valuation model termed BRAIN (Green 2012), allowing businesses to identify and link performance measurements to intangible value drivers.

Despite the simplicity of book value-based corporate valuation, its lack of connection with market or fair values makes this method unpopular or simplistic (Fernández 2001). Earnings were considered more important than book value as single-number firm valuators (Cheng and McNamara 2000). The residual income model (RIM) uses accounting data to determine a company's book value at the current time as book value at a previous time, added to the net of earnings and dividends disbursed over the time interval (Olbert 2024). Value in modern firms comes more from intangible assets than the tangible assets on the balance sheet (Penman 2009). The value of assets can be derived from both the P&L statement and the balance sheet. In the 1920s, accountants wrote up asset values in balance sheets for perceived value, but, in the market crash of 1929, they were accused of "putting water in the balance sheet" (Penman 2009). A company's miscalculation of its intangible assets may lead to high costs and a decline in its market position (Savickaitė 2014).

Using matched pair portfolio analysis and multiple regression analysis, researchers (Choi et al. 2019) state that the market positively values reported intangible assets, providing support to the requirement of valuing and reporting intangibles on the corporate Balance Sheet, rather than simply treating them as expenses in the current period. In a similar spirit, researchers (Amir et al. 1993; Chauvin and Hirschey 1994; McCarthy and Schneider 1995) report a significant and positive relationship between goodwill and a firm's market valuation. Similarly, other researchers (Kothari et al. 2002; Shi 2003) find that the value of intangibles is positively associated with the company's equity value, albeit with lower valuation coefficients, suggesting greater uncertainty compared to tangible assets. In the context of accounting choices by management in recording intangible assets on their Balance Sheet, Wyatt documents that limiting these choices for the management ends up reducing, rather than improving, the quality of the Balance Sheet through information available to investors (Wyatt 2005).

Valuing intangible assets is considered a dark art (Sharma 2012). In some industries, tangible net assets and disclosed intangible assets have a greater value than the total enterprise value. Reilly describes the considerations for a valuation analyst in valuing intangible assets (Reilly 2011). The valuation analysts frequently identify and value intangible commercial assets for ad valorem tax purposes. The intangible asset is subject to taxation in the relevant area. The valuation analyst considers, "Did I treat the right thing with the proper value? Did I use the proper valuation methodologies, techniques, and procedures?" And did the analyst succeed in achieving the assignment's goal and purpose? The valuation analyst typically prefers that the client (or the client's legal counsel) and the analyst agree to the property tax valuation assignment in writing on the specifics of the intangible asset being valued, according to the definition of the valuation assignment.

The considerations of the valuation analyst are: -

1. Why was the intangible asset valuation commissioned, and how would the results be used?
2. Who are the stakeholders, including decision makers, and what decisions will affect them?

The cost of any given asset typically does not correspond to its fair value (Catty 2012). However, an asset's replacement cost, adjusted for time to use, sets a ceiling for its fair value because this is the sum a wise investor would spend. There might be exceptions for particular objects like antiques, but fair value is meant to take precedence over emotions. Therefore, the cost approach works as a reality check.

The production and use of intangible assets rather than the investment of physical, tangible assets are now the main drivers of economic growth (Săcui and Sala 2012). A 2003 investigation of fixed asset values of Strategic Communication Management Agency revealed an estimated value significantly lower than the actual market worth (Tkachenko et al. 2018). A re-measurement after 15 years revealed that little had changed in terms of valuation. Hence, underestimating an organization's assets, particularly its intangible assets, negatively impacts the organization's ability to renew the asset because depreciation funds are calculated on the understated asset values. This makes it harder for the company to access financial resources, reduces the quantity of share capital, and impedes a proper business value assessment, in addition to overstating the company's tax base.

Assessing the intangible assets of 396 firms listed on the Vietnam stock exchange between 2010 and 2014, Binh et al. document the challenges associated with identifying the costs of sustaining or enhancing an organization's operations and those associated with establishing an intangible asset (Minh Quoc Binh et al. 2020).

Some countries tax intangible personal property owned by taxpayers. In contrast, others do not tax intangible assets such as real estate. The jurisdiction's assessment statutes and administrative decisions impact the assessor's choice of methodologies, methods, and procedures for valuing intangible assets (Reilly 2013).

Data is included as an intangible asset by the FASB. Data is a critical resource for enterprises, and it is expected that enterprise data will be accounted for and appear in balance sheets (Atkinson and McGaughey 2006). By placing a value on data and including it in the value sheet, management will develop more visibility into enterprise data assets and can manage these assets better. A study on 127 companies from 2003 to 2006 was conducted (University of British Columbia et al. 2016) to quantify the value of information technology (IT) related intangible assets, most of which are invisible on the corporate balance sheets. The definition of IT in this study includes hardware, software (both purchased internally and procured), internal services, consulting, and training. The study result suggests that companies with relatively high IT capabilities have a 45%–76% higher market value than companies with relatively lower IT capabilities.

4.1 | Key Takeaways

One of the most commonly used valuation methods, traditionally, has been based on Balance Sheet information. Within this category, the simplest metric of valuation is "Book Value." Book Value represents the net assets or net worth of a business, or simply the difference between its assets and liabilities.

Intangible assets may not have a clear physical form but can still significantly contribute to the creation of economic value. Examples include a company's reputation, culture, values, brand name, technology, and data. Intangible assets are increasingly important in determining an organization's competitiveness, worth, and expansion. Yet, a substantial portion of intangible assets are not included in the balance statements of the company, despite their apparent ability to add value. A value paradox exists in the current scenario in which intangible assets are insufficiently quantified. There is no theoretical foundation for making a clear distinction between investments in tangible assets and intangible assets from an economic standpoint. Both are potential sources of future financial gains for the company. An intangible investment is any spending that does not instantly take physical form and is designed to produce long-term advantages.

Popular valuation techniques for intangible assets are listed in the International Accounting Standard 38.1, along with three general approaches for estimating fair values of intangible assets. The direct cash flow technique discounts predicted cash flows from the intangible asset. The multi-period excess earnings technique, residual income-based valuation, and semi-qualitative approaches, such as the binomial expansion based on a decision tree and the Black-Scholes formula, are also used to evaluate intangible assets. The most reliable estimate of an intangible asset is the quoted market price in a thriving market, but intangible goods rarely have access to such a price. After the initial cost is subtracted with accumulated amortization and any impairment losses, intangible assets are revalued using fair value and multiples of this value.

Numerous studies exist on intangible assets, intangible liabilities, and their appraisal. Many of these intangible assets, particularly organizational relationships with third parties, cannot be easily transferred from one company to another. Only identifiable intangible assets that satisfy the criteria for control and the existence of predicted future economic benefits are relevant to international accounting standards. Since knowledge assets constitute a reservoir of knowledge, they are broadly considered a subset of intangible assets.

Accountability and quantification are essential for intangibles, and organizations should identify, value, care, and custody of these assets. An information audit is necessary to create an information asset register (IAR) with asset identification and recording protocols.

Due to lower costs and regulations, fewer lead-generating intangible assets, and fewer financial reporting mistakes, a firm worth may be more apparent with information disclosure regarding non-financial intangible assets. Intangibles "based in contracts or other legal rights" are the only ones the FASB has designated as eligible for disclosure. While financial reporting may become neutral as a result, there are significant constraints on verifying this. Intangibles like goodwill can quickly lose their value because they are transient or subject to competition or innovation. Quantifying value, which could make up a significant amount of corporate value, could be challenging.

Measuring intangible assets is a systematic way to create value for a business, thereby ensuring its sustainability. While intangible assets are specific and difficult to imitate, they are not utilized to their full potential as a competitive advantage. Intangible asset valuation is a standard practice, especially with brands and intellectual property. The process of valuing intangible assets is highly complex, so businesses typically measure intangible assets only as required by accounting standards, which means that the actual value of these assets may not be recorded. While models for measuring intangible assets are advantageous in enabling the measurement process, they have drawbacks, including a lack of consistency, insufficient credibility, and subjectivity. A knowledge-based approach to decision-making and business management enables an organization to detect, anticipate, and react swiftly and effectively to internal or external changes.

Since data is considered an intangible asset, research opportunities exist in data valuation, borrowing from intangible asset valuation methods. Data is regarded as an intangible enterprise asset and as an increasingly important resource for enterprises, leading to substantially greater market valuations. It also emerges that the full extent of enterprise intangible assets may be underestimated due to inadequate consideration of intangible assets such as data, leading to disadvantages in asset appraisal for corporate actions such as mergers & acquisitions (M&A), and raising external capital for business.

5 | Attributing Value to Contributing Variables in a Predictive Model

Creating a digital twin of the data's history can become the next step in data valuation and marketing, supplemented by a data asset meta-model, methodology for calculating the value of data for purchase or sale (Lu et al. 2024; Nerini et al. 2024). Marketing strategies for data that the enterprise may seek to sell/lease/provide as a service (Antohi) may also be enabled.

Stochastic control-based data valuation (Liang et al. 2024), statistical distribution based data valuation (Rammal et al. 2024; Zhou et al. 2024), and Shapley value-based data valuation (Pandl et al. 2021; Schoch et al. 2022; Garrido-Lucero et al. 2023; Liu et al. 2023; Watson et al. 2023; Cai 2024; Yang 2024) have been the subject of recent developments. Using game theory-based Shapley value estimation, researchers (Zou and Ghorbani 2019) have made progress in finding a way to equitably compensate individuals for generating data for machine learning algorithms. The Shapley value, which only provides valuations for points within a fixed data set, has been augmented by Jia etal. in the Distributional Shapley (Jia et al. 2019), and applied to value data points in the machine learning context. As the name states, the distributional Shapley value (Ghorbani et al. 2020) is defined through the data's underlying distribution, while developing a valuation function independent of a fixed dataset.

Jia et al. (2021) also developed a faster method for calculating Shapley values using K-nearest neighbors, matching existing accuracy while being more efficient. Yoon et al. (2020) created DVRL (Data Valuation using Reinforcement Learning), which learns which training samples are most useful, automatically estimates data point values, and performs better than previous methods across various tasks.

Recent applications include healthcare, where Ebiele et al. (2023) compared different methods for measuring feature importance in clinical data, and manufacturing, where Mohan et al. (2024) used Random Forest methods and Wibiral et al. (2024) used Neural Network-based methods.

5.1 | Key Takeaways

Quantifying the value of data points in a particular business domain or resolving specific problem statements is an important research area in which various machine-learning methods have been explored. Recent advancements in data valuation have made it easier to measure the contribution of each data point to machine learning models. Valuing individual data points is a bottom-up method to develop an enterprise data valuation based on aggregating individual values of critical data elements. For data evaluation, the Shapley Value (SV), a classic concept from cooperative game theory, is employed, as Shapley's value specifies a unique payoff scheme that satisfies the requirements for the concept of data value. Data valuation based on the Shapley Value fairly distributes profits among multiple data contributors and determines prospective compensation for data breaches. The distributional Shapley framework improves on the limitations of the Shapley framework for data valuations.

6 | Methods of Valuing Information

The Infonomics model introduced by Doug Laney (Laney 2017) examines information value through six distinct perspectives. These include Intrinsic Value, which considers information's inherent qualities; Business Value, focusing on its contribution to organizational objectives; Performance Value, measuring efficiency improvements; Cost Value, accounting for expenses in managing information; Market Value, representing its worth in external markets; and Economic Value, which quantifies direct financial benefits.

This framework shows perspectives on the value of information, including value derived from its utilization in business scenarios, the cost of developing the information, and its market (replacement) value. These principles can also apply to the underlying data used to make business decisions in the context of this research. Traditional enterprise valuation models depend on earnings, dividends, and assets; however, for knowledge-based enterprises (KBE), these metrics are often absent or skewed due to varying accounting practices (Johnson et al. 2003). Knowledge capitalization is crucial for enhancing short-term financial performance and long-term business excellence (Cheong et al. 2023).

Green and Revilak present "a theoretical model that identifies the path to innovation that minimizes waste (knowledge gaps) in the innovation process" (Green and Revilak 2009), enhancing innovation value, a top priority for business leaders. Green states, "The cross-pollination of value drivers generates multidimensional intangible assets that contribute to the diagnostics of productivity, competence, and resource allocation" (Green 2012). The value contributions of intangible assets can therefore be elevated into "strategic, tactical, and operational knowledge models" (Green 2012) for the company, which enable value creation.

Knowledge capitalization is a requirement: a functional paradigm that rationalizes the logic of value chains, processes, work instructions, and scripts (Lucardie 2017). A proposed knowledge valuation approach (Green 2006) uses a life cycle to dissect the business enterprise into its value drivers.

Modelling processes such as machine learning raise the value of data by eliciting underlying relationships between data elements, identifying patterns, and creating knowledge (Ciaburro and Iannace 2021). Further, the machine learning process of elevating data to knowledge aligns with the knowledge life cycle, enabling an evolution and refinement of knowledge from data (Fechter et al. 2019). Considerations on the potential of data also imply that data valuation is a dynamic process, and issues such as AI and data risk, including data privacy and ethics, must be considered as part of the valuation process (Wing 2019). Another principle of systems emphasizes the need to combine humanistic perspectives with hard or quantitative views through the collaborative participation of stakeholders. The systems engineering incorporates a range of tools and techniques that enable and facilitate stakeholder participation and collaborative processes for group decision making to ensure diverse viewpoints are considered to tackle complex challenges (Farid and Ribeiro 2015). Such a principle and approach to sweep in diverse views also aligns with ethical decision-making (Harris 2008), in addition to creating a consensual environment to assess intangible values for which no quantitative methods alone could substitute (Lu et al. 2007).

Information valuation models for "Digital Twins" (Guizzardi et al. 2024) define the following concepts, which are a class of techniques for improving process outcomes for enterprises (Table 1):

Business decision-making process involves two steps: making a decision about whether to obtain additional information and making a decision based on prior knowledge or prior information and additional information (Koski et al. 2020); the value of perfect information is always non-negative (Koski et al. 2020). The value of information (VOI) is a conceptual price threshold at which a decision maker is indecisive about whether to acquire additional information for business decisions/actions (Giordani et al. 2019). To assess the value of information (VoI) provided by each data source, it is essential to prioritize transmissions that have the greatest importance for the target applications. Giordani et al. propose using analytic hierarchy multi-criteria decision processes to predict VoI based on space, time, and quality attributes (Giordani et al. 2019).

Materiality in the context of digital objects refers to both the form and the effects of that form (Thomer and Wickett 2020). Material properties of information objects (Dourish and Mazmanian 2011) may include their "mutability, persistence, spatiality, size, durability, flexibility, and mobility." From a business standpoint, selecting data elements for valuation based on materiality requires shortlisting the most significant data points (Ning et al. 2024), leading to decision outcomes, by using machine learning techniques for predictive analytics such as random forest, XGBoost, or Shapley variables (Zheng et al. 2024).

Data elements should be prioritized based on their materiality and potential impact on decision-making outcomes (Birch et al. 2021). They should also incorporate the concept of emergence from systems engineering, considering the dynamic nature of data valuation (Vezyridis and Timmons 2021) and integrating both quantitative and qualitative methods (Stein and Maass 2022). Systems engineering is the discipline for developing complex systems, and prescribes a full lifecycle methodology from conception through design, development, deployment, monitoring, and retirement (Sillitto et al. 2018). Besides providing a structured framework for understanding and optimizing the value of data assets, systems principles also include the concept of emergence, wherein the properties of the system might be more than the sum of the parts. Systems also deal with the

TABLE 1 | Information valuation models for digital twins.

Concept (Guizzardi et al. 2024)	Description
Reasoning Value of Information (RVI)	Measures available information to analyze machinery/equipment in a process and derive the appropriate control strategy
Control Automation Value of Information (AVI)	Measures available information for automating the control of digital twins over machinery/equipment
User Value of Information (UVI)	Measures available information for human users to understand the functioning of digital twins

data-information-knowledge hierarchy (Ackoff 1989), conceptualizing data as unorganized signals for business. This holistic approach to data valuation may lead to significant changes in decision-making processes and overall business strategy.

6.1 | Key Takeaways

Valuation of data in its raw state can often be hard and misleading. The potential of the data in the context of models that could raise the value of the data through the knowledge hierarchy needs to be considered while conducting valuation exercises. The valuation of data and information assets is a complex process that goes beyond traditional financial metrics. Organizations need to adopt more holistic, complex systems-based approaches to accurately assess and leverage their data assets. These approaches should consider the entire data-to-wisdom hierarchy, considering the value of data as it transforms into information, knowledge, and wisdom. The intersection of the data-to-wisdom hierarchy and systems engineering's concept of emergence is thus critical for understanding how data valuation transcends traditional metrics. One of the ways of valuing data is to consider the potential of the data to be elevated from data to wisdom through a modelling process such as machine learning. Hence, a data valuation model for intangible assets can utilize systems engineering methodology by establishing a path from the organization's body of knowledge to valuable business outcomes.

The organized data that could ask questions, such as "what" is called information. When information is connected, it yields knowledge that could answer "how" questions, which in turn could be further distilled to contribute to understanding, answering "why" questions, leading to wisdom. This hierarchy from data to information to knowledge is in close alignment with the process of data valuation, where the value increases as raw signals or data are transformed into information and knowledge. The implication is that, when capturing the value of data, one needs to consider the potential for the data to convert to understanding and wisdom (Figure 2).

Drawing on the concept of emergence, as data translates to knowledge, the knowledge system has properties and value more than the original data ("a system is more than the sum of its parts"). Knowledge has value because of its application and usefulness, as well as its necessity and dependability, arising out of connections between information nodes. Digital knowledge bases will allow disparate applications operating on separate machines to solve complex logic without additional software or hardware. This will result in IT architectures that are flexible enough to accommodate the dynamics of complex systems, focused on the business. Companies' short-term financial performance will be enhanced by redefining "investment" to include knowledge as a factor. Conforming the valuation of knowledge to its economic value on balance sheets will alter decision-makers' mentality and spur both short-term and long-term business excellence.

A Knowledge Valuation System (KVS) of a business enterprise seeks to uncover knowledge that supports business decision-making and minimizes risks associated with acting on those decisions by emphasizing interactions between enterprise value drivers. The systems approach dictates that ethical considerations, such as data privacy and AI risks, need to be integrated into the data valuation process.

Information extracted from raw data can therefore be utilized to take "knowledgeable" enterprise actions, enabling stakeholder value creation. This premise is at the crux of valuation based on information and knowledge in a knowledge-based economy and for digital enterprises. Various methods for valuing information exist, including the intrinsic value of information, cost and economic value, and utility in business processes. Applying systems engineering approaches based on the potential for data to create enterprise value also guides the creation of valuation models.

7 | Valuation of Data

Data is often said to be the most valuable commodity of our age (Ciuriak 2019). Data has been described as the new global corporate currency or capital comparable to financial capital (Franzetti 2017). Information value quantification and asset management are critical components of the emerging idea known as "Infonomics," which Gartner (Laney 2017) employed. The Internet of Things (IoT) is revolutionizing the way we interact with and consume data, leading to an emerging market for monetized data exchanges (Suliman et al. 2019; Firouzi et al. 2022; Baghcheband et al. 2024; Shi and Duan 2024).

Miciuła et al. highlight the necessity for a synthetic and universal methodology for business valuation and indicate the consequences of not having an appropriate and standardizable methodology (Miciuła et al. 2020). Data quality must be incorporated into data valuation methods (Stein and Maass 2022; Xu et al. 2024). Poor data quality reduces the value of data assets (Sun et al. 2024) in an enterprise as the data utility reduces.

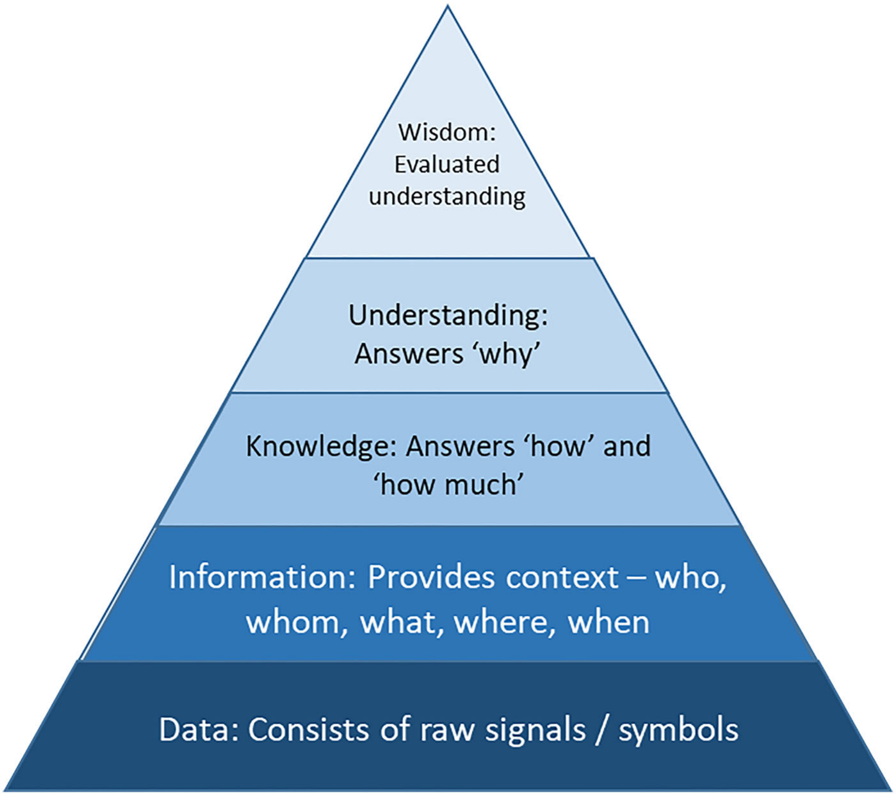

FIGURE 2 | Value creation from progressive utility of processed data. [Colour figure can be viewed at wileyonlinelibrary.com]

TABLE 2 | Business scenarios translated to financial impact.

Scenario	Business Impact	Financial Impact
Avoid penalties due to non-compliance/regulatory actions	Reduction in future one-time costs	Cost (P&L)
	Reduction in legal/litigation charges	Cost (P&L)
Develop and convert business opportunities	Develop cross-sell opportunities with existing customers	Revenue (P&L)
	Develop up-sell opportunities with existing customers	
	Identify prospects and acquire new customers	
Improve business operations	Optimize/reduce costs	Cost (P&L)
	Reduce inventory balances	Inventory (Balance Sheet)
	Reduce inventory obsolescence/surplus/reserve scenarios	Inventory (Balance Sheet)
	Improve collections from customers	Account Receivables (Balance Sheet)
	Optimize payments to vendors	Account Payables (Balance Sheet)
	Identify & improve on supply chain partnerships	Cost (P&L), Working Capital (Balance Sheet)

Determinants of the value of data (Heckman et al. 2015) include consumption aspects such as time savings, effort, and money. Qualitative valuation parameters include (Heckman et al. 2015) the data's age, the data's credibility, data elements' accuracy, and fixed and marginal cost parameters (Yuncheng Shen et al. 2016) for collecting the data, including data storage, bandwidth and operational costs, and data as a service offering.

Businesses typically estimate the value of data in terms of costs and revenues, or in the case of valuing companies whose business models are data-driven for M&A scenarios, while government approaches to data valuation focus on estimating economic benefit in making government data available to the public to fuel economic growth (Fleckenstein et al. 2023). A valuation approach based on data dimensions, which examines valuation points of respective datasets, with properties inherent to data (e.g., completeness, accuracy) and contextual to value data (e.g., frequency of use, ownership) is also proposed by these researchers (Fleckenstein et al. 2023).

There is a rise in vehicle connectivity technologies, resulting in exponential growth in vehicle data (Sterk et al. 2022). To monetize connected car data, businesses must evolve their business model and organization design, including technology architecture and infrastructure (Sterk et al. 2022).

Data is regarded as the currency of the digital economy for sustainable business development (Tian 2024). Sathanathan proposes a practical approach to data valuation driven by KPIs (Sathananthan 2018), including the information's utility, cost, and risk to businesses.

Data value is a composite of three sources: asset value, activity value, and expected future value (Short and Todd 2018). Per Short and Todd, companies can choose between top-down or bottom-up valuation processes. Analytics used to be a competitive advantage and is now becoming a table stakes for businesses to execute competitively (Fitzgerald 2015). A data valuation index for scientific and technological data based on authority, influence, attention, domain relevance, integrity, timeliness, novelty, and domain intersectionality can be developed (Zeng et al. 2020).

Data is central to finance and is a key consideration for entrepreneurs starting a new firm (Veldkamp 2022). Data has become a valuable economic resource (Coyle and Manley 2024); in 2021, seven of the top 10 global enterprises by stock market capitalization were data-driven businesses. To assist nations in creating digital development policies, the OECD Going Digital Toolkit (Ker and Mazzini 2020) highlights the significance of evaluating data value and compiling case studies of data valuation.

The importance of data in the industrial context led to the need for consistent and comprehensive measurement of data-driven value addition by manufacturing companies (Stein et al. 2021). In a study aimed at reducing uncertainty electricity in load demand (Wang et al. 2021), a data valuation approach is proposed based on mitigation of risks in decision-making, reducing uncertainty and enhancing profits.

Data is becoming a vital resource for creating value because of the tremendous rise in its significance brought about by digitalization. There are currently insufficient ideas and useful techniques for the financial valuation of data, which prevents it from being managed per the fundamentals of company management. A structural equation modeling field study (Bodendorf and Franke 2024) demonstrated that determining data value is multifaceted and hierarchical, with three main dimensions: cost, benefit, and quality-oriented.

A literature survey (Bendechache et al. 2023) reveals that insufficiently accepted dimensions and generalized data value models are being developed to assess the value of data. This is in stark contrast to the related but more specialized developments in data quality. Due to the lack of standard validation platforms and techniques, industrial deployment, reproducibility, job comparison, and rate of advancement are hampered. Data valuation is being proposed as a business capability based on the emerging studies' open group architecture framework (TOGAF) standard (Hafner et al. 2024). A data value vocabulary called DaVe (Attard et al. 2019) is developed, allowing the integration of metrics spanning data value dimensions (meta-data) across different tools. An emerging study also proposes data valuation using meta-data and stakeholder perceptions as a qualitative valuation method (Ebiele et al. 2024).

7.1 | Key Takeaways

Data monetization results through using data for quantifiable economic gain. Data is the primary value source in a "Data Economy." Data monetization entails efficient and timely utilization of corporate data, combining insights to add value to current and potential clients. Companies must decide on an acceptable business model to convert their data and analytics strategy to benefit from data monetization.

Big data enables companies to improve business processes, reduce costs, and increase operating margins using big data. The ability to create machine knowledge capital will enable market share capture: this follows from when even a small advantage can lead to market share dominance and rent capture. Internet of Things (IoT) devices can generate valuable data that can be sold to interested users, paving the way for a centralized platform for managing and monetizing this data. However, implementing a secure, cost-efficient, automatic data monetization solution for IoT data can be challenging. Businesses need to establish resources for data monetization, including high-performance computing, Human Machine Interfaces (HMI), enabled by physical infrastructure where applicable, such as 5G data towers, and digital infrastructure, including data platforms. While IoT data is collected and processed, Personally Identifiable Information (PII) and sensitive geolocation data need protection with privacy and ethics safeguards while enhancing customer-centricity and collaboration.

Understanding the value of data could benefit businesses in three ways:

- It could enable them to develop new digitally based business models.
- It could also help them make more informed decisions regarding data-related investments.
- It could provide transparency regarding the value of data.

This idea of valuation and a practical method of valuing data and information is demonstrated with the help of the Data-Information-Knowledge-Wisdom (DIKW) framework. In addition, some valuation strategies emphasize the potential threats to data security. In contrast, other methods in Sathanathan's article examine how revenue or costs are impacted, both with and without a particular category of information. This research

TABLE 3 | Business impact traceable to enterprise KPIs.

Scenario	Business impact	KPI
Avoid penalties due to non-compliance/regulatory actions	Reduction in future one-time costs	Functional costs
	Reduction in legal/litigation charges	
Develop and convert business opportunities	Develop cross-sell opportunities with existing customers	Number of orders Sales Pipeline Growth
	Develop up-sell opportunities with existing customers	
	Identify prospects and acquire new customers	Number of (unique) customers
Improve business operations	Optimize/reduce costs	Functional Costs
	Reduce inventory balances	Inventory Days of Supply (DOS)
	Reduce inventory obsolescence/surplus/reserve scenarios	Inventory Days of Supply (DOS), Inactive/Obsolete/Surplus Inventory (IOS)
	Improve collections from customers	Days Sales Outstanding (DSO)
	Optimize payments to vendors	Days Payable Outstanding (DPO)
	Identify & improve on supply chain partnerships	Cash conversion cycle (CCC)

TABLE 4 | Business impact traceable to enterprise master datasets.

Business scenario	Business impact	Enterprise dataset
Reduction in future one-time costs (due to regulatory penalties)	GDPR/CCPA/equivalent country-level regulations	Customer master, contact master, Legal functional cost
	ITAR, Potential sanctions due to trade with banned customers/parties/countries	Product master, material master, legal functional cost
Develop cross-sell opportunities with existing customers	Marketing & Sales	Customer master, product master
Develop up-sell opportunities with existing customers	Marketing & Sales	Customer master, product master
Identify prospects and acquire new customers	Marketing & Sales	Customer master

includes incorporating many "Key Prediction Indicators" since future benefits can be considered a component of the wisdom gained from existing knowledge, a specific kind of analysis, or data. The phases of collecting data, information, knowledge, and understanding will be mapped out for the valuation methods. The key performance indicators for valuation show performance relative to the past or the current status, but they do not focus as much on the predictive aspect. Other valuation methods are identified for each phase involved in the process that these people are working on. Key prediction indicators will be implemented as a component of the wisdom phase valuation. This strategy will result in a simplified and practical approach that businesses can use in the most practical manner possible. Because of this, this valuation method is connected to the utilization of data analytics.

The challenges faced in getting broad performance from analytics efforts include finding, cleaning, and structuring data for analysis. It is a long process, taking time to build a foundation. The data itself may be private, confidential, and non-public information, and the company must ensure that it is leveraging it for the benefit of the ecosystem while protecting the companies that produced the data.

As seen by how the COVID-19 epidemic was handled in the United Kingdom and other countries, the public sector and policymaking have benefited from the broad availability of data and analytics. Organizations that own particular data sets, businesses that provide data services, and investors who factor dataset assets into mergers and acquisitions or stock market values understand the worth of data.

Data use is defined by its application, with the frequency of use affecting its value. Tangible assets generally have decreasing returns to use, while data can increase in value as it is used. The major data costs include data capture, storage, and maintenance, while the marginal costs of using data may be negligible. The right data, available at the right time, can be of high value to businesses.

While there is no generally accepted definition of how balance sheets should include data assets, data assets can be valued based on observable market-based transactions, income generated, or the cost incurred for asset development or replacement. Companies can embed data valuation into enterprise-wide strategies by making valuation policies explicit and shareable. Companies can manually classify selected data sets by value through internal security audits or data volume assessments.

Data valuation is crucial to business strategy, particularly in acquiring, selling, or dividing business units with significant data assets. Companies attempt to monetize data assets through sale or licensing to third parties. To monetize their data assets, companies must establish methods to acquire and develop valuation expertise within their organizations.

Establishing a data valuation practice requires pre-set criteria of data quality and business usage of datasets, deriving a monetary value based on data preparation/processing and transaction costs, and sharing criteria-based data valuation in relevant management reports.

Approaches for data valuation have been proposed considering the following:

1. Cost of acquisition & storage.
2. Exchange value.
3. Intangible asset value in the market capitalization of a firm.

Organizations are more likely to adopt a monetary data value determination when subject to institutional forces (coercive, normative, and mimetic) that impact their behavior. The business scenarios influenced by data are summarized as the following areas:

- Avoid penalties due to non-compliance/regulatory actions.
- Develop and convert business opportunities.
- Improve business operations.

The above-mentioned areas may be traced to financial outcomes for the enterprise as follows (Table 2):

Apart from the aforementioned scenarios, financial impacts that can be measured and tracked through financial statements, business impact through data can also be tracked through Enterprise Key Performance Indicators (KPI) and Management Accounting, such as in the following examples (Table 3):

Observing changes in these KPIs and financial metrics because of data-driven decisions is critical to identifying data influencing decision-making. Some of these data can be enterprise master data and illustrated in the examples in Table 4.

Areas where data enables business decisions are subject to analytics practice maturity how the individual enterprises can utilize data analytics as a competitive advantage. In addition, there is considerable extant literature dealing with the valuation of personal data, the “activity” and “exchange” value of data, valuation of data from machines and internet of things enabled devices—which can be categorized as value of data to business process, supplement the valuation theories on information and knowledge.

8 | Valuation of Databases

A case study on database valuation (King 2007) states that it takes art, not science, to create a valuation opinion. Evaluation criteria for data persistence in an enterprise data warehouse (EDW) are based on data volume, frequency of data usage, and changes (Winsemann 2011). Trademarks, brands, secret techniques, and tangible assets have historically been a client-side business’s top assets & customer interactions are increasingly piquing the interest of investors with the Institute of Chartered Accountants for England and Wales (ICAEW) and the IDM Data Council collaborating on the acceptance of value of databases (Reed 2007).

8.1 | Key Takeaways

A database is a collection of information or other content organized to make each item individually accessible. Databases, which serve as a customer and lead information repository, can be identified, valued, protected, and transformed into a tax-efficient asset.

Databases are not sold separately from the businesses that possess them, unless the data is being leased or sold outright—such as potential prospect lists for marketing campaigns. Calculating a database’s fair market value is the traditional method for determining its value. A database could be considered a depreciating asset because data decay, that is, the potential for timely action based on information available, starts reducing in value from the moment it is created. However, a database’s value for training analytical models increases over time based on increasing data volume, veracity, and relevance to business.

It is important to comprehend the value associated with the construction and upkeep of databases. The cost approach frequently underestimates value and is typically the least relevant in analyzing marketing assets. The kind, quality, and quantity of the data always influence and sometimes constrain the choice of the valuation approach.

The characteristics of a database must be able to be defined, protected, licensed, or sold for it to be considered an intangible asset. Database rights cover the control of the extraction and reuse of database contents. Value reflects the existence of a distinct, transferable legal right pertaining to data assets. In the case of commercial data sets, this might include revaluing the database every three years. Intangible asset valuation can be done using cost-based, income-based, and market-based methods. Based on

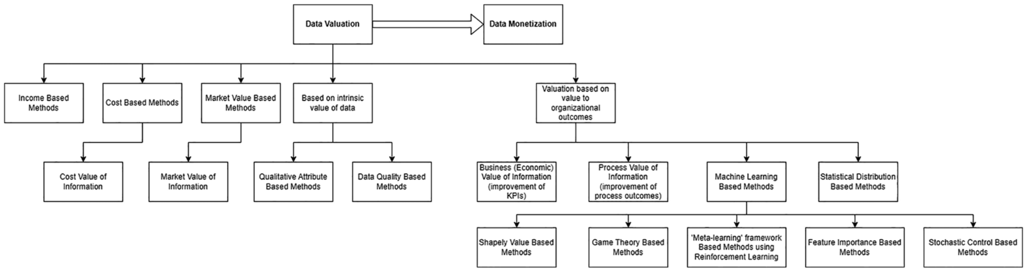

FIGURE 3 | Key drivers for enterprise data valuation.

TABLE 5 | Data valuation methods aligned to end-uses.

Use for valuation	Focus area	Data valuation methods
IP value useful for licensing and royalties/amortized recovery	Cost of Data Creation—if this is a time-sensitive and involved operation	Cost-based methods
Benchmark value useful for Pre-M&A/Pre-IPO/IP Divestment	Market Value of Data Asset	Market value-based methods
Goodwill value paid for the Data Asset when acquired by another firm	Disposal of Data Asset	Market value-based methods
Economic value is useful during and end of the lifecycle of the Data Asset	Income Based	Income-based methods
Improved business performance enabled by data science/analytics	Prioritization of data elements for enterprise data management initiatives	Valuation based on the intrinsic value of data
		Valuation based on value to organizational outcomes

the anticipated income for the asset's anticipated life, the net present value of a database may be determined.

9 | Big Data Valuation

As noted by Dunham, big data analytics (BDA) encompasses the ability to analyze vast quantities of information, which can lead to significant insights and innovations in business practices (Dunham 2015). Big data is an all-encompassing term that encompasses the seismic shift in analytics. The methods used by professional appraisers are continuously evolving. Dell's article investigates the applications of regression analysis in the context of an evidence-based approach to valuation (Dell 2017).

BDA aims to create an information ecosystem that aids in decision optimization and generates business insights (Ji-fan Ren et al. 2017). Ji-fan et al. define information quality as the exhaustiveness, precision, format, and currency of data for big data analytics.

A conceptual framework for estimating the economic value of big data is proposed (Nani 2023), which includes using databases as accounting units and costing methods derived from database user-based metrics (Ylinen et al. 2022). Big Data Value Chains (Faroukhi et al. 2020) describe the data flow within organizations relying on big data to extract valuable insights, and they have emerged to face new data-related challenges such as high volume, velocity, and variety.

9.1 | Key Takeaways

In contrast to the valuation of databases, the valuation of big data deals with data that has a relatively higher volume, variety, veracity, and velocity than data commonly held in enterprise databases. Concepts of big data value chains and the relationships between the business and financial values of data are proposed to develop valuation methods for big data for the enterprise.

9.2 | Role of Managerial "Financial Styles" on Financial and Valuation Metrics

Creating an environment that appreciates data-driven decision-making and propels organizational transformation requires establishing a data-driven culture (Ochuba et al. 2024). Most managers' financial decision behaviors are determined by factors they are unaware of, which could have far-reaching implications on the selection, development, and management of leaders at all levels (Ted Prince 2008).

9.3 | Key Takeaways

People possess unique "financial" characteristics, which generate an internal calculus for decision-making. The resulting "financial signature" of decisions reveals an individual's behavioral propensity to generate capital. Prince's model disaggregates individual financial behavior into constituent managerial styles with distinct

TABLE 6 | A comparison of data valuation methods.

	Cost-based methods	Market-based methods	Income-based methods	Valuation based on the intrinsic value of data	Valuation based on value to organizational outcomes
Benefits	Easy to compute, based on data acquisition and database development costs.	Useful for business models involving the sale or lease of data.	Easy to establish in a digital sales-driven business model, where analytic insights contribute to customer acquisition and/or income generation.	Easy to compute, based on data quality measurements.	Direct linkage established to KPIs and business process outcomes. Scientific and repeatable valuation methods using machine learning methods.
Trade-offs	Likely to yield the least valuation outcome as the benefits of data utilization are not considered.	Market value is dependent on the precedence of sale/leasing costs of similar data and hence may be challenging to determine.	Income attribution to multiple parties in the sales channel may be complex—depending on the enterprise value chain.	The scarcity of data may be challenging to determine beyond enterprise boundaries.	Space-time complexity of machine learning models increases for the valuation of large datasets—increasing time and compute infrastructure requirements for valuation.

TABLE 7 | Potential research opportunities.

S No#	Potential research opportunities
1	Usage of distributed Shapley value and machine learning methods for enterprise data valuation
2	A comparison of data, information, and knowledge valuation methods for enterprises, with the merits and challenges of using the valuation methods mentioned in Table 5
3	Impacts on financial reporting, including Information Content, Fundamental Analysis of the value of corporate securities, discretionary versus non-discretionary disclosures, and recognition versus disclosure based on data valuation

but recognizable financial and valuation effects, permitting a behaviorally essentialist approach to financial value creation.

10 | Synthesis and Discussion

The digital transformation of enterprises has challenged traditional asset valuation approaches, leading to a shift in how value is created and demanding an equivalent shift in how it is measured and managed. Traditional valuation approaches, grounded in tangible assets, are becoming inadequate for modern digital and data enterprises. For example, customer-based metrics like Customer Lifetime Value (CLV) and Customer Equity (CE) reflect this shift, emphasizing data's utility and transformational potential in the customer analytics space.

The value of data changes based on context, model utility, network effects, and adaptability from the data processing perspective. This "value plasticity" challenges traditional asset valuation approaches, highlighting the complexity of enterprise data valuation. We know that the concept of scarcity works differently in the case of data to physical assets, and even many digital assets. First, the data can be replicated like other digital assets, challenging the concept of material scarcity. At the same time, certain scarce data can be highly valuable to humans owing to its scarcity. At the same time, machine learning models require a certain level of high-quality abundance with variety for model performance. Model performance requires balanced, high-quality datasets. The scarcity could potentially introduce imbalanced classes in target variables (like rare events in fraud detection) and biases in protected demographics.

In addition, data valuation faces theoretical tensions due to divergent priorities from financial and technical perspectives (also at times coinciding with business vs. academic). Financial valuation tends to be more static and seeks standardization and comparability (Fleckenstein et al. 2023), but is often subjective, being influenced by the evaluator's perspective and the context in which data is utilized (De Araújo et al. 2023).

Technical, data analytics-centric approaches tend to be more data-driven and as dynamic as the data cadence allows, but are narrower in scope as they focus on insight generation in the given context, making standardization difficult (Ferreira et al. 2011). The complexity of the technical models also creates a "paradox" where increased technical understanding complicates assigning consistent financial value to data (Fleckenstein et al. 2023). Business and academic viewpoints also differ, with academia developing elaborate models (Fleckenstein et al. 2023) and businesses prioritizing simplicity (Hafner and Silva 2024). While the simplicity of traditional approaches is attractive, valuation should not merely be a static assessment but rather a reflection of the evolving nature of data as it transitions through various stages of utility (Hees et al. 2021).

Theoretical frameworks such as information economics and systems theory provide critical insights into data valuation. With its concepts of asymmetric information and network externalities, information economics helps explain why traditional methods may underestimate data's unique value. Systems theory, particularly the data-information-knowledge hierarchy, underscores data's transformative potential, suggesting that valuation should account for data's capacity to evolve from raw information into valuable business insights.

It is also important to incorporate ethical and governance frameworks into data valuation practices, as pointed out by Jiroušek and Shenoy (Jiroušek and Shenoy 2014). Ethics and governance have limited coverage under the current paradigms and would naturally come into consideration when adopting a systems perspective.

These differences and tensions underscore the challenges of establishing a universally accepted value for data but point to a need for hybrid frameworks that integrate financial, technical, and systems perspectives, creating a balanced approach that serves both practical and theoretical ends.

11 | Conclusion and Directions for Future Research

The review identifies promising areas for future research in enterprise data valuation, including standardization of valuation methods, integration of data valuation with financial reporting, use of AI and machine learning in valuation, data quality and data value relationships, regulatory and ethical considerations, industry-specific data valuation models, dynamic data valuation, organizational impact, data ecosystems and value networks, and validation studies. These research directions aim to address current knowledge gaps and advance the field of enterprise data valuation, ultimately leading to more effective management and leveraging of data assets in the digital economy. The review also suggests exploring the impact of data valuation on data privacy regulations and the ethical dimensions of monetizing certain types of data. The research also aims to explore data ecosystems and value networks, enabling more effective management and leveraging of data assets in the digital economy.

Traditional financial statements do not provide complete information on the enterprises' intangible determinants of performance (Canibano et al. 2000). The CPA Journal (Collins 2020) states, "Most businesses have processes to manage physical or other assets that appear on their current financial statements. Because data is an intangible asset not recognized by modern accounting standards, it is often not managed as an asset. There is no good reason not to measure and manage data as the asset it is. Turning data into information will probably become the most critical operation of every business soon if it is not already. Organizations must begin managing data and its information as real assets." This indicates, from a finance professional's perspective, the need to treat, measure, and maintain data as an enterprise asset, even if data valuation is not a recognized practice from a financial standards perspective. While data as an asset does not yet have formal treatment from a GAAP/IFRS perspective, this viewpoint creates the space for accounting treatment for data as an asset from a management accounting perspective. Despite its rising importance in value generation, data as an intangible asset does not find a place in enterprises' balance sheets. Businesses tend to be ineffective in protecting data because they may misunderstand its value (Sidgman and Crompton 2016).

As we have seen earlier, the information systems and data views are important lenses often ignored in favour of traditional valuation techniques. Valuing data through the financial lens as a standalone asset is fraught with risks, as data valuation depends on the context and purpose, and the processing that could be applied. A systems view, which is also capable of incorporating intangibles (but not necessarily capable of assigning financial values) and the dynamic and evidence-based data view, must be combined with traditional finance-based valuation methods to improve the reliability of valuation estimates.

Customer valuation techniques are crucial for managing the acquisition and retention of profitable customers, as they link marketing initiatives and potential income streams, ultimately determining a company's worth. Customer-based valuation (CLV) is a fundamental tool for assessing business relationships and determining the value of a company. Valuation due diligence procedures, considering factors like industry benchmarks and the relative age of intangible assets are crucial in determining the value of intangible assets. The development of data valuation methods (Figure 3) is essential for businesses to assess the value of their data assets, considering factors such as usage, market, cost, and income. Data monetization is the use of data for quantifiable economic gain, and companies must decide on appropriate business models to align their data and analytics strategy for data monetization.

Various models for the valuation of intangible assets exist, as illustrated in Figure 3. Selecting an appropriate data valuation approach can depend on the relevant business uses and focus areas as shown in Table 5:

An approach comparing the outcome of various valuation methods (Table 6) and using mixed-method approaches may be considered for data valuation, incorporating the strengths of the respective methods for the relevant purpose (Table 5).

During the literature survey, the researchers did not encounter a significant body of work covering enterprise case study-based valuation methodology to validate the effectiveness of valuation methods. The following research opportunities are identified based on the literature review, in Table 7:

The digital revolution in business has led to a transformation in business models and changes in business asset structures.

Large businesses today, including LinkedIn (Microsoft), Facebook, Google, and Amazon, have significantly more intangible assets, including data, than their "brick and mortar" or fixed assets. Governments worldwide are also taking notice of the increasing digital transformation with the sale/purchase of digital assets and the establishment of taxation regulations accordingly.

Multiple parties, including finance professionals, researchers/academia, and consulting companies such as Gartner, have called out the need for data valuation and treating data as an asset. While multiple methods for data valuation are suggested, implementing data valuation as a practice and communicating the value of data as part of enterprise valuation remains an area primed for innovation and breakthrough.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

All articles and data that support this literature review are referenced in the references section of the article.

References

Ackoff, R. L. 1989. "From Data to Wisdom." *Journal of Applied Systems Analysis* 16, no. 1: 3–9.

Adewusi, A. O., U. I. Okoli, E. Adaga, T. Olorunsogo, O. F. Asuzu, and D. O. Daraojimba. 2024. "Business Intelligence in the Era of Big Data: A Review of Analytical Tools and Competitive Advantage." *Computer Science & IT Research Journal* 5, no. 2: 415–431. https://doi.org/10.51594/csitrj.v5i2.791.

Alirezaie, M., W. Hoffman, P. Zabihi, H. Rahnama, and A. Pentland. 2024. "Decentralized Data and Artificial Intelligence Orchestration for Transparent and Efficient Small and Medium-Sized Enterprises Trade Financing." *Journal of Risk and Financial Management* 17, no. 1: 38. https://doi.org/10.3390/jrfm17010038.

Altundag, A., and M. Wynn. 2024. "Advanced Analytics and Data Management in the Procurement Function: An Aviation Industry Case Study." *Electronics* 13, no. 8: 1554. https://doi.org/10.3390/electronics13081554.

Amir, E., T. S. Harris, and E. K. Venuti. 1993. "A Comparison of the Value-Relevance of U.S. Versus Non-U.S. GAAP Accounting Measures Using Form 20-F Reconciliations." *Journal of Accounting Research* 31: 230. https://doi.org/10.2307/2491172.

Antohi, T. "A Data Marketing and Valuation Approach.".

Atkinson, K., and R. McGaughey. 2006. "Accounting for Data: A Shortcoming in Accounting for Intangible Assets." *Academy of Accounting and Financial Studies Journal* 10, no. 2.

Attard, J., and R. Brennan. 2019. "DaVe: a semantic data value vocabulary to enable data value characterisation." In Enterprise Information Systems: 20th International Conference, ICEIS 2018, Funchal, Madeira, Portugal, March 21-24, 2018, Revised Selected Papers 20 (239–261). Springer International Publishing.

Baghcheband, H., C. Soares, and L. P. Reis. 2024. "Machine Learning Data Market Based on Multiagent Systems." *IEEE Internet Computing* 28, no. 4: 7–13. https://doi.org/10.1109/MIC.2024.3399049.

Bauer, H. H., and M. Hammerschmidt. 2005. "Customer-based corporate valuation: Integrating the concepts of customer equity and shareholder value." *Management Decision* 43, no. 3: 331–348. Available at: https://doi.org/10.1108/00251740510589733.

Bendechache, M., J. Attard, M. Ebiele, and R. Brennan. 2023. "A Systematic Survey of Data Value: Models, Metrics, Applications and Research Challenges." *IEEE Access* 11: 104966–104983. https://doi.org/10.1109/ACCESS.2023.3315588.

Billiot, M. J., and S. Glandon. 2005. "The Impact of Undisclosed Intangible Assets on Firm Value." *Journal of Accounting & Finance Research* 13: 2.

Birch, K., D. Cochrane, and C. Ward. 2021. "Data as Asset? The Measurement, Governance, and Valuation of Digital Personal Data by Big Tech." *Big Data & Society* 8, no. 1: 205395172110173. https://doi.org/10.1177/20539517211017308.

Bodendorf, F., and J. Franke. 2024. "What Is the Business Value of Your Data? A Multi-Perspective Empirical Study on Monetary Valuation Factors and Methods for Data Governance." *Data & Knowledge Engineering* 149: 102242. https://doi.org/10.1016/j.datak.2023.102242.

Bonvino, C., and M. Giorgino. 2022. "Economics of Data Systematic Review for Planning Strategies in the InsurTech Industry." *European Conference on Innovation and Entrepreneurship* 17, no. 1: 66–75. https://doi.org/10.34190/ecie.17.1.597.

Brooking, A. 2010. March. "On the importance of managing intangible assets as part of corporate strategy." In *The Proceedings of the 2nd European Conference on Intellectual Capital* (p. 137).

Cai, H. 2024. "CHG Shapley: Efficient Data Valuation and Selection towards Trustworthy Machine Learning." arXiv. Available at: https://doi.org/10.48550/ARXIV.2406.11730.

Canibano, L., M. Garcia-Ayuso, and P. Sanchez. 2000. "Accounting for Intangibles: A Literature Review." *Journal of Accounting Literature* 19: 102–130.

Catty, J. 2012. "Valuing Intangible Assets by the Cost Approach.".

Chauvin, K. W., and M. Hirschey. 1994. "Goodwill, Profitability, and the Market Value of the Firm." *Journal of Accounting and Public Policy* 13, no. 2: 159–180. https://doi.org/10.1016/0278-4254(94)90018-3.

Cheng, C. S. A., and R. McNamara. 2000. "The Valuation Accuracy of the Price-Earnings and Price-Book Benchmark Valuation Methods." *Review of Quantitative Finance and Accounting* 15, no. 4: 349–370. https://doi.org/10.1023/A:1012050524545.

Cheong, H., B. Kim, and I. U. Vaquero. 2023. "A Data Valuation Model to Estimate the Investment Value of Platform Companies: Based on Discounted Cash Flow." *Journal of Risk and Financial Management* 16, no. 6: 293. https://doi.org/10.3390/jrfm16060293.

Choi, J. P., D.-S. Jeon, and B.-C. Kim. 2019. "Privacy and Personal Data Collection With Information Externalities." *Journal of Public Economics* 173: 113–124. https://doi.org/10.1016/j.jpubeco.2019.02.001.

Ciaburro, G., and G. Iannace. 2021. "Machine Learning-Based Algorithms to Knowledge Extraction From Time Series Data: A Review." *Data* 6, no. 6: 55. https://doi.org/10.3390/data6060055.

Ciuriak, D. 2019. "Unpacking the Valuation of Data in the Data-Driven Economy." Available at SSRN 3379133.

Collins, V., and J. Lanz. 2019. "Managing data as an asset." *The CPA Journal* 89, no. 6: pp.22–27.

Coyle, D., and A. Manley. 2024. "What Is the Value of Data? A Review of Empirical Methods." *Journal of Economic Surveys* 38, no. 4: pp.1317–1337.

Dahiya, R., S. Le, J. K. Ring, and K. Watson. 2022. "Big Data Analytics and Competitive Advantage: The Strategic Role of Firm-Specific Knowledge." *Journal of Strategy and Management* 15, no. 2: 175–193.

Damodaran, A. 2009. "Valuing Companies With intangible assets." *Stern School of Business* p.10.

Damodaran, A. 2009. "Valuing Companies With Intangible Assets." Available at: https://pages.stern.nyu.edu/~adamodar/pdfiles/papers/intangibles.pdf.

De Araújo, J. A. R., A. Souza, A. Clemente, and V. L. Crisóstomo. 2023. "Firm Valuation in Brazil: Evidence of Overvaluation in the Valuation

Reports." *Contribuciones a Las Ciencias Sociales* 16, no. 7: 5591–5614. https://doi.org/10.55905/revconv.16n.7-024.

Dell, G. 2017. "Regression, Critical Thinking, and the Valuation Problem Today." *Appraisal Journal* 85, no. 3.

Demirakos, E. G., N. C. Strong, and M. Walker. 2004. "What Valuation Models Do Analysts Use?" *Accounting Horizons* 18, no. 4: 221–240. https://doi.org/10.2308/acch.2004.18.4.221.

Dourish, P., and M. Mazmanian. 2011. June. "Media as material: Information representations as material foundations for organizational practice." In Third international symposium on process organization studies (Vol. 92).

Dunham, I. M. 2015. "Big Data: A Revolution That Will Transform How We Live, Work, and Think." *AAG Review of Books* 3, no. 1: 19–21. https://doi.org/10.1080/2325548X.2015.985533.

Ebiele, M., M. Bendechache, M. Ward, et al. 2023. November. "The Impact of Data Valuation on Feature Importance in Classification Models." In *International Conference on Computing and Communication Networks* (601–617). Singapore: Springer Nature Singapore.

Ebiele, M., M. Bendechache, E. Clinton, and R. Brennan. 2024. Personalization of Dataset Retrieval Results using a Metadata-based Data Valuation Method. arXiv preprint arXiv:2407.15546.

Evans, N., and J. Price. 2014. "Why Organisations Cannot Justify the Effective Management of Their Information Assets." European Conference on Management, Leadership & Governance, 78–85. Academic Conferences International Limited.

Farid, A. M., and L. Ribeiro. 2015. "An Axiomatic Design of a Multiagent Reconfigurable Mechatronic System Architecture." *IEEE Transactions on Industrial Informatics* 11, no. 5: 1142–1155. https://doi.org/10.1109/TII.2015.2470528.

Faroukhi, A. Z., I. El Alaoui, Y. Gahi, and A. Amine. 2020. "Big Data Monetization Throughout Big Data Value Chain: A Comprehensive Review." *Journal of Big Data* 7, no. 1: 3. https://doi.org/10.1186/s40537-019-0281-5.

Fechter, M., T. Dietz, and T. Bauernhansl. 2019. August. "Cost calculation model for reconfigurable, hybrid assembly systems." In 2019 IEEE 15th International Conference on Automation Science and Engineering (CASE) (836–841). IEEE.

Fernández, P. 2007. "Company valuation methods. The most common errors in valuations." *IESE Business School* 449: 1–27.

Ferreira, L. N. et al. 2011. "Do Portuguese and UK Health State Values Differ Across Valuation Methods?" *Quality of Life Research* 20, no. 4: 609–619. https://doi.org/10.1007/s11136-010-9785-3.

Firouzi, F., B. Farahani, M. Barzegari, and M. Daneshmand. 2022. "AI-Driven Data Monetization: The Other Face of Data in IoT-Based Smart and Connected Health." *IEEE Internet of Things Journal* 9, no. 8: 5581–5599. https://doi.org/10.1109/JIOT.2020.3027971.

Fitzgerald, M. 2015. "Viewing Data as a Liquid Asset." *MIT Sloan Management Review* 57, no. 2: 1–4. http://mitsmr.com/1WCNOji.

Fleckenstein, M., A. Obaidi, and N. Tryfona. 2023. "A Review of Data Valuation Approaches and Building and Scoring a Data Valuation Model." *Harvard Data Science Review* 5, no. 1. https://doi.org/10.1162/99608f92.c18db966.

Forbes, T. 2007. "Valuing Customers." *Journal of Database Marketing & Customer Strategy Management* 15, no. 1: 4–10.

Franzetti, A. 2017. Data monetization in the big data era: Evidence from the Italian market.

García-Ayuso, M. 2003. "Factors Explaining the Inefficient Valuation of Intangibles." *Accounting, Auditing & Accountability Journal* 16, no. 1: 57–69. https://doi.org/10.1108/09513570310464282.

Garrido Lucero, F., B. Heymann, M. Vono, P. Loiseau, and V. Perchet. 2024. "Du-shapley: A shapley value proxy for efficient dataset valuation." *Advances in Neural Information Processing Systems* 37: pp. 1973–2000.

Ghorbani, A., and J. Zou. 2019. May. "Data shapley: Equitable valuation of data for machine learning." In International conference on machine learning (2242–2251). PMLR.

Ghorbani, A., M. Kim, and J. Zou. 2020. "November. A distributional framework for data valuation." In International Conference on Machine Learning (3535–3544). PMLR.

Giordani, M., T. Higuchi, A. Zanella, O. Altintas, and M. Zorzi. 2019. July. "A framework to assess value of information in future vehicular networks." In Proceedings of the 1st acm mobihoc workshop on technologies, models, and protocols for cooperative connected cars (31–36).

Green, A. 2006. "Building Blocks to a Knowledge Valuation System (KVS)." *VINE* 36, no. 2: 146–154. https://doi.org/10.1108/03055720610682951.

Green, A. 2012. *Measuring Organization Vitals that are Essential to Sustain the Life of the Organization*. Arcada University of Applied Sciences Helsinki Finland, p.529.

Green, A., and A. Revilak. 2009. April. "Measuring Innovation From the Source to the Value." In Proceedings of the European Conference on Intellectual Capital (228–235).

Green, A., and J. Ryan. 2005. "A Framework of Intangible Valuation Areas (FIVA): Aligning Business Strategy and Intangible Assets." *Journal of Intellectual Capital* 6: 43–52. https://doi.org/10.1108/14691930510574654.

Guizzardi G., Santoro F., Mouratidis H., and Soffer P. eds. 2024. "Advanced Information Systems Engineering: 36th International Conference, CAiSE 2024." Limassol, Cyprus, June 3–7, 2024. Proceedings (Vol. 14663). Springer Nature.

Güngör, D. 2025. "The Economic Implications of Data Monetization in a Digital-First Economy." *Next Generation Journal for the Young Researchers* 8, no. 1: 175. https://doi.org/10.62802/y1eqqs51.

Hafner, M., M. Mira Da Silva, and H. A. Proper. 2024. "Towards a Reference Ontology for a Data Valuation Business Capability." *Enterprise Information Systems* 18, no. 7: 2358920. https://doi.org/10.1080/17517575.2024.2358920.

Hafner, M., M. Mira Da Silva, and H. A. Proper. 2024. "Towards a Reference Ontology for a Data Valuation Business Capability." *Enterprise Information Systems* 18, no. 7: 2358920. https://doi.org/10.1080/17517575.2024.2358920.

Han, L., J. Kazempour, and P. Pinson. 2021. June. "Monetizing customer load data for an energy retailer: A cooperative game approach." In *2021 IEEE Madrid PowerTech* (1–6). IEEE.

Harris. 2008. "The Good Engineer: Giving Virtue Its Due in Engineering Ethics." *Science and Engineering Ethics* 14, no. 2: 153–164. https://doi.org/10.1007/s11948-008-9068-3.

Heckman, J. R., E. L. Boehmer, E. H. Peters, M. Davaloo, and N. G. Kurup. 2015. A pricing model for data markets. IConference 2015 Proceedings.

Higson, C., and D. Waltho. 2007. *Valuing Information as an Asset*. Harvard Business School Press. http://faculty.london.edu/chigson/research/InformationAsset.pdf.

'International Accounting Standard 38'. 1998. IFRS Foundation. Available at: https://www.ifrs.org/content/dam/ifrs/publications/pdf-standards/english/2021/issued/part-a/ias-38-intangible-assets.pdf.

Jia, R., D. Dao, B. Wang, et al. 2019. April. "Towards efficient data valuation based on the shapley value." In The 22nd International Conference on Artificial Intelligence and Statistics (1167–1176). PMLR.

Jia, R., F. Wu, X. Sun, et al. 2021. "Scalability vs. utility: Do we have to sacrifice one for the other in data importance quantification?." In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (8239–8247).

Ji-fan Ren, S. et al. 2017. "Modelling Quality Dynamics, Business Value and Firm Performance in a Big Data Analytics Environment." *International Journal of Production Research* 55, no. 17: 5011–5026. https://doi.org/10.1080/00207543.2016.1154209.

Jiroušek, R., and P. Shenoy. 2014. "Compositional Models in Valuation-Based Systems." *International Journal of Approximate Reasoning* 55, no. 1: 277–293. https://doi.org/10.1016/j.ijar.2013.02.002.

Johnson, L. D., E. H. Neave, and B. Pazderka. 2003. "Knowledge, Innovation and Share Value." *International Journal of Management Reviews* 4, no. 2: 101–134. https://doi.org/10.1111/1468-2370.00080.

Ker, D., and E. Mazzini. 2020. *Perspectives on the value of data and data flows*, no. 299: OECD Publishing.

King, K. 2007. "A Case Study in the Valuation of a Database." *Journal of Database Marketing & Customer Strategy Management* 14, no. 2: 110–119. https://doi.org/10.1057/palgrave.dbm.3250041.

Koski, V. et al. 2020. "The value of perfect and imperfect information in lake monitoring and management." *Science of The Total Environment* 726: p. 138396. Available at: https://doi.org/10.1016/j.scitotenv.2020.138396.

Kothari, S. P., T. E. Laguerre, and A. J. Leone. 2002. "Capitalization versus Expensing: Evidence on the Uncertainty of Future Earnings From Capital Expenditures versus R&D Outlays." *Review of Accounting Studies* 7, no. 4: 355–382. https://doi.org/10.1023/A:1020764227390.

Kumar, V. 2018. "A Theory of Customer Valuation: Concepts, Metrics, Strategy, and Implementation." *Journal of Marketing* 82, no. 1: 1–19. Available at: https://journals.sagepub.com/doi/abs/10.1509/jm.17.0208.

Laney, D. B. 2017. *Infonomics: How to Monetize, Manage, and Measure Information as an Asset for Competitive Advantage*. Routledge.

Liang, Z., H. Gao, and J. Zhang. 2024. Neural Dynamic Data Valuation. arXiv preprint arXiv:2404.19557.

Liu, Z., H. A. Just, X. Chang, X. Chen, and R. Jia. 2023. July. "2d-shapley: A framework for fragmented data valuation." In International Conference on Machine Learning (21730–21755). PMLR.

Lu, C., B. Huang, S. P. Karimireddy, P. Vepakomma, M. Jordan, and R. Raskar. 2024. DAVED: Data Acquisition via Experimental Design for Data Markets. arXiv preprint arXiv:2403.13893.

Lu, S. C.-Y., W. Elmaraghy, G. Schuh, and R. Wilhelm. 2007. "A Scientific Foundation of Collaborative Engineering." *CIRP Annals* 56, no. 2: 605–634. https://doi.org/10.1016/j.cirp.2007.10.010.

Lucardie, L. 2017. April. "Disclosing the Economic Value of Knowledge. A Functional Paradigm." In European Conference on Intangibles and Intellectual Capital (p. 190). Academic Conferences International Limited.

Machado, M. P., C. O. Klingenberg, J. L. Abreu, R. Barbastefano, and D. P. Lacerda. 2024. "Business processes for data monetization: an exploratory analysis and proposition of design patterns." *Business Process Management Journal*. https://doi.org/10.1108/BPMJ-02-2024-0079.

Maia, C. R., A. C. G. Maçada, G. L. Lunardi, and A. R. Sengik. 2024. "Data Monetization Capability: From the Systematic Literature Review to the Proposition of a Multidimensional Model." *Revista De Administração Da UFSM* 17, no. 2: e6. https://doi.org/10.5902/1983465986416.

Pohl, M., C. Haertel, D. Staegemann, and K. Turowski. 2023. "Data Valuation Methods—A Literature Review." Annual Americas Conference on Information Systems (AMCIS 2023). pp 3466–3470. https://www.proceedings.com/content/073/073940webtoc.pdf.

McCarthy, M. G., and D. K. Schneider. 1995. "Market Perception of Goodwill: Some Empirical Evidence." *Accounting and Business Research* 26, no. 1: 69–81. https://doi.org/10.1080/00014788.1995.9729499.

Miciuła, I., M. Kadłubek, and P. Stępień. 2020. "Modern Methods of Business Valuation—Case Study and New Concepts." *Sustainability* 12, no. 7: 2699. https://doi.org/10.3390/su12072699.

Minh Quoc Binh, Q., N. Minh Ha, and N. Thi Huyen Trang. 2020. "Application of an Intangible Asset Valuation Model Using Panel Data for Listed Enterprises in Vietnam." *Investment Management and Financial Innovations* 17, no. 1: 304–316. Available at: https://doi.org/10.21511/imfi.17(1).2020.26.

Mohan, S. K., G. Bharathy, and A. Jalan. 2024. Functional Data Valuation Paradigm for Enterprises-Case Studies from the Manufacturing Sector. Available at SSRN 4915651.

Nani, A. 2023. "Valuing Big Data: An Analysis of Current Regulations and Proposal of Frameworks." *International Journal of Accounting Information Systems* 51: 100637. https://doi.org/10.1016/j.accinf.2023.100637.

Nerini, F. P., P. Bajardi, and A. Panisson. 2024. "Value Is in the Eye of the Beholder: A Framework for an Equitable Graph Data Evaluation." In *The 2024 ACM Conference on Fairness, Accountability, and Transparency*. *FAccT '24: The 2024 ACM Conference on Fairness, Accountability, and Transparency*, Rio de Janeiro Brazil: ACM, 467–479. https://doi.org/10.1145/3630106.3658919.

Ning, Y., S. Li, Y. Y. Ng, et al. 2024. "Variable Importance Analysis With Interpretable Machine Learning for Fair Risk Prediction." *PLOS Digital Health* 3, no. 7: e0000542. https://doi.org/10.1371/journal.pdig.0000542.

Ochuba, N. A., O. O. Amoo, E. S. Okafor, O. Akinrinola, and F. O. Usman. 2024. "Strategies for leveraging big data and analytics for business development: a comprehensive review Across sectors." *Computer Science & IT Research Journal* 5, no. 3: 562–575.

Olbert, L. 2024. "Industry-Specific Stock Valuation Methods—A Literature Review." *Journal of Accounting Literature* 47, no. 5: 52–70. https://doi.org/10.1108/JAL-04-2023-0065.

Pandl, K. D. et al. 2021. "Trustworthy machine learning for health care: scalable data valuation With the shapley value." in Proceedings of the Conference on Health, Inference, and Learning. ACM CHIL '21: ACM Conference on Health, Inference, and Learning, Virtual Event USA: ACM, 47–57. Available at: https://doi.org/10.1145/3450439.3451861.

Pastor, D., J. Glova, F. Lipták, and V. Kováč. 2017. "Intangibles and Methods for Their Valuation in Financial Terms: Literature Review." *Intangible Capital* 13, no. 2: 387. https://doi.org/10.3926/ic.752.

Penman, S. H. 2009. "Accounting for Intangible Assets: There Is Also an Income Statement." *Abacus* 45, no. 3: 358–371. https://doi.org/10.1111/j.1467-6281.2009.00293.x.

Rammal, M. R., R. Zhou, and S. Diggavi. 2024. "Reframing Data Value for Large Language Models Through the Lens of Plausibility." arXiv. https://doi.org/10.48550/ARXIV.2409.00284.

Reed, D. 2007. "Database Valuation: Putting a Price on Your Prime Asset." *Journal of Database Marketing & Customer Strategy Management* 14, no. 2: 104–109. https://doi.org/10.1057/palgrave.dbm.3250048.

Reilly, R. F. 2011. "Defining the Intangible Asset Valuation Assignment." *Journal of Property Tax Assessment & Administration* 8, no. 4: 45–59. Available at: https://willamette.com/pubs/presentations/reilly_journal_of_property_assessment_article_2012.pdf.

Reilly, R. F. 2013. "Intangible Asset Valuation Due Diligence Procedures." *Journal of Property Tax Assessment & Administration* 10, no. 2: 23–26.

Săcui, V., and D. Sala. 2012. "Economic Properties of Intangible Assets. The Value Paradox." *Review of International Comparative Management* 13, no. 5: p. 793. Available at: https://www.proquest.com/docview/2158168555?sourcetype=Conference%20Papers%20&%20Proceedings.

Sarker, S., M. S. Arefin, M. D Kowsher, T. Bhuiyan, P. K. Dhar, and O. H-J. Kwon. 2023. "A Comprehensive Review on Big Data for Industries: Challenges and Opportunities." *IEEE Access* 11: 744–769. https://doi.org/10.1109/ACCESS.2022.3232526.

Sathananthan, S. 2018. "Data Valuation Considering Knowledge Transformation, Process Models and Data Models." In *2018 12th International Conference on Research Challenges in Information Science (RCIS)*. *2018 12th International Conference on Research Challenges in Information Science (RCIS)*, Nantes: IEEE, 1–5. https://doi.org/10.1109/RCIS.2018.8406649.

Savickaitė, Ž. 2014. "The Evaluation of Company's Intangible Assets' Influence for Business Value." *International Journal of Economic Sciences and Applied Research* 7, no. 3: 133–155.

Schoch, S., H. Xu, and Y. Ji. 2022. “CS-Shapley: class-wise Shapley values for data valuation in classification.” *Advances in Neural Information Processing Systems* 35: 34574–34585.

Sharma, N. 2012. “Intangible Assets: A Study of Valuation Methods.” *BVIMR Management Edge* 5, no. 1.

Shen, Y., B. Guo, Y. Shen, X. Duan, X. Dong, and H. Zhang. 2016. “A Pricing Model for Big Personal Data.” *Tsinghua Science and Technology* 21, no. 5: 482–490. https://doi.org/10.1109/TST.2016.7590317.

Shi, C. 2003. “On the Trade-Off Between the Future Benefits and Riskiness of R&D: A Bondholders' Perspective.” *Journal of Accounting and Economics* 35, no. 2: 227–254. https://doi.org/10.1016/S0165-4101(03)00020-X.

Shi, X., and H. Duan. 2024. “Data Valuation and Pricing in Internet of Things: Survey and Vision.” In *2024 IEEE International Conference on Smart Internet of Things (SmartIoT). 2024 IEEE International Conference on Smart Internet of Things (SmartIoT)*, Shenzhen, China: IEEE, 547–554. https://doi.org/10.1109/SmartIoT62235.2024.00090.

Short, J. E., and S. Todd. 2018. “What's Your Data Worth?” In *MIT Sloan Management Review, How to Go Digital*, 49–58. The MIT Press. https://doi.org/10.7551/mitpress/11633.003.0010.

Sidgman, J., and M. Crompton. 2016. “Valuing Personal Data to Foster Privacy: A Thought Experiment and Opportunities for Research.” *Journal of Information Systems* 30, no. 2: 169–181. https://doi.org/10.2308/isys-51429.

Sillitto, H., J. Martin, R. Griego, et al. 2018. “A fresh look at Systems Engineering–what is it, how should it work?.” *Insight (American Society of Ophthalmic Registered Nurses)* 21, no. 3: 44–51.

Stein, H., L. Holst, V. Stich, and W. Maass. 2021. “From qualitative to quantitative data valuation in manufacturing companies.” In Advances in Production Management Systems. Artificial Intelligence for Sustainable and Resilient Production Systems: IFIP WG 5.7 International Conference, APMS 2021, Nantes, France, September 5–9, 2021, Proceedings, Part II (172–180). Springer International Publishing.

Stein, H., and W. Maass. 2022. “Requirements for Data Valuation Methods.” in: Proc. of 55th HICSS. Hawaii: pp. 6155–6164.

Sterk, F., D. Dann, and C. Weinhardt. 2022. January. Monetizing Car Data: A Literature Review on Data-Driven Business Models in the Connected Car Domain. *In HICSS* 1–10.

Sullivan, P. H., and P. H. Sullivan. 2000. “Valuing intangibles companies—An intellectual capital approach.” *Journal of Intellectual Capital* 1, no. 4: 328–340. Available at: https://doi.org/10.1108/14691930010359234.

Suliman, A., Z. Husain, M. Abououf, M. Alblooshi, and K. Salah. 2019. “Monetization of IoT Data Using Smart Contracts.” *IET Networks* 8, no. 1: 32–37. https://doi.org/10.1049/iet-net.2018.5026.

Sun, Y., J. Shen, and Y. Kwon. 2024. “2D-OOB: Attributing Data Contribution Through Joint Valuation Framework.” arXiv. https://doi.org/10.48550/ARXIV.2408.03572.

Ted Prince, E. 2008. “Research Note: How the Financial Styles of Managers Impact Financial and Valuation Metrics.” *Review of Accounting and Finance* 7, no. 2: 193–205. https://doi.org/10.1108/14757700810874155.

Thomer, A. K., and K. M. Wickett. 2020. “Relational Data Paradigms: What Do We Learn by Taking the Materiality of Databases Seriously?,” *Big Data & Society* 7, no. 1: 205395172093483. https://doi.org/10.1177/2053951720934838.

Tian, X. 2024. “Research on Data Asset Valuation Pricing and the Path to Sustainable Business Development in a Green Economy.” *Advances in Economics, Management and Political Sciences* 138, no. 1: 28–33. https://doi.org/10.54254/2754-1169/2024.19331.

Tkachenko, E., E. Rogova, V. Kokh, and S. Bodrunov. 2018. November. “The valuation of intangible assets based on the intellectual capital leverages concept.” In Proceedings of the International Conference on Intellectual Capital, Knowledge Management, and Organizational Learning, ICICKM (319–329).

University of British Columbia. Saunders, A., and E. Brynjolfsson. 2016. “Valuing Information Technology Related Intangible Assets.” *MIS Quarterly* 40, no. 1: 83–110. https://doi.org/10.25300/MISQ/2016/40.1.04.

Van Hees, S., C. Greubel, E. Moors, and A. Peine. 2021. “Valuation in Health and Ageing Innovation Practices.” *Ageing and Society* 43, no. 9: 2022–2040. https://doi.org/10.1017/s0144686X21001483.

Veldkamp, L. 2022. “Valuing Data as an Asset.” Columbia Business School.

Vezyridis, P., and S. Timmons. 2021. “E-Infrastructures and the Divergent Assetization of Public Health Data: Expectations, Uncertainties, and Asymmetries.” *Social Studies of Science* 51, no. 4: 606–627. https://doi.org/10.1177/0306312721989818.

Wang, B., Q. Guo, T. Yang, L. Xu, and H. Sun. 2021. “Data Valuation for Decision-Making With Uncertainty in Energy Transactions: A Case of the Two-Settlement Market System.” *Applied Energy* 288: 116643. https://doi.org/10.1016/j.apenergy.2021.116643.

Wang, T., Y. Yang, and R. Jia. 2021. Improving cooperative game theory-based data valuation via data utility learning. arXiv preprint arXiv:2107.06336.

Wang, Z., and J. Song. 2025. “Data Monetization Pathways and Complex Dynamic Game Equilibrium Analysis in the Energy Industry.” *IEEE Transactions on Industry Applications* 61, no. 1: 1725–1734. https://doi.org/10.1109/TIA.2024.3430246.

Watson, L., Z. Kujawa, R. Andreeva, H. T. Yang, T. Elahi, and R. Sarkar. 2023. Accelerated Shapley Value Approximation for Data Evaluation. arXiv preprint arXiv:2311.05346.

Wibiral, T., M. K. Belaid, M. Rabus, and A. Scherp. 2024. LossVal: Efficient Data Valuation for Neural Networks. arXiv preprint arXiv:2412.04158.

Wing, J. M. 2019. “The data life cycle.” *Harvard Data Science Review* 1, no. 1: 6. https://doi.org/10.1162/99608f92.e26845b4.

Winsemann, T. 2011. “Valuation Factors for the Necessity of Data Persistence in Enterprise Data Warehouses on In-Memory Databases.” In CAiSE (Doctoral Consortium) (3–14).

Wyatt, A. 2005. “Accounting Recognition of Intangible Assets: Theory and Evidence on Economic Determinants.” *Accounting Review* 80, no. 3: 967–1003. https://doi.org/10.2308/accr.2005.80.3.967.

Xiong, F., M. Xie, L. Zhao, C. Li, and X. Fan. 2022. “Recognition and Evaluation of Data as Intangible Assets.” *SAGE Open* 12, no. 2: 215824402210946. https://doi.org/10.1177/21582440221094600.

Xu, L., J. Chen, S. Chang, C. Wang, and B. O. Li. 2024. “Toward Quality-Aware Data Valuation in Learning Algorithms: Practices, Challenges, and beyond.” *IEEE Network* 38, no. 5: 213–219. https://doi.org/10.1109/MNET.2023.3336959.

Yang, Y. 2024. “Bridging Efficacy and Efficiency: Innovations in Shapley Value Estimation for Model-Agnostic Data Valuation in Machine Learning.” In S.U. Jan (ed.) *Fourth International Conference on Signal Processing and Machine Learning (CONF-SPML 2024). Fourth International Conference on Signal Processing and Machine Learning (CONF-SPML 2024)*, Chicago, United States: SPIE, 8. https://doi.org/10.1117/12.3027116.

Ylinen, M., M. Järvenpää, and A. Myllymäki. 2022. “Data Balance Sheet in OP Financial Group.” In *Responsible Finance and Digitalization*, edited by P. Kalmi, T. Auvinen, and M. Järvenpää, 123–139. 1st ed. Routledge. https://doi.org/10.4324/9781003144427-10.

Yoon, J., S. Arik, and T. Pfister. 2020. November. “Data valuation using reinforcement learning.” In International Conference on Machine Learning (10842–10851). PMLR.

Zeng, W., X. Wang, R. Xiao, and F. Yuan. 2020. “Study on Data Valuation Oriented to Identification of Scientific and Technological Frontier.” *Procedia Computer Science* 174: 66–71. https://doi.org/10.1016/j.procs.2020.06.057.

Zheng, X., X. Chang, R. Jia, and Y. Tan. 2024. Towards Data Valuation via Asymmetric Data Shapley. arXiv preprint arXiv:2411.00388.

Zhou, X., O. Wu, M. K. Ng, and H. Jiang. 2024. Data Valuation by Leveraging Global and Local Statistical Information. arXiv preprint arXiv:2405.17464.