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Accounting for Data: A Framework for Valuing and Reporting Digital Intangible Assets

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Abstract
In the digital economy, data has become a central driver of enterprise value, yet prevailing accounting frameworks fail to recognize or report internally generated data as an intangible asset. This omission creates a significant disconnect between the financial statements of data-driven firms and their underlying economic reality. This study introduces the Extended Asset Recognition Model (EARM), a conceptual framework designed to enable the recognition, valuation, and disclosure of proprietary data assets in corporate financial reporting.
Grounded in existing accounting theory and informed by stakeholder perspectives, the model integrates asset recognition criteria with flexible valuation approaches including cost, market, and income-based methods tailored to the unique attributes of data. Through hypothetical applications involving firms such as Amazon and Meta, the paper demonstrates how data can be reliably valued and accounted for using structured assumptions and revenue attribution analysis. It also addresses challenges of verification, auditability, and ethical concerns around privacy and data governance. The study concludes with policy recommendations for international standard-setting bodies, including the IASB and FASB, and emphasizes the need for cross-disciplinary collaboration to align financial reporting with the realities of the digital age. By enabling data to be treated as a measurable and reportable asset, this research contributes to the modernization of intangible asset accounting and enhances the relevance and transparency of financial statements in the 21st-century economy.

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1. Introduction

In the 21st-century digital economy, data has emerged as one of the most valuable economic assets, often surpassing traditional resources in both strategic significance and financial impact. Businesses are increasingly generating, collecting, and utilizing vast volumes of data to enhance operational efficiency, deliver personalized experiences, predict market behavior, and develop new revenue streams (Brynjolfsson & McAfee, 2014; Marr, 2015) [2, 10]. From e-commerce platforms and social media networks to logistics providers and fintech companies, the monetization of data has become central to competitive advantage and enterprise valuation.

Despite this paradigm shift, traditional accounting systems have largely failed to adapt. Prevailing standards under the International Financial Reporting Standards (IFRS), particularly IAS 38 Intangible Assets, and the U.S. Generally Accepted Accounting Principles (GAAP) provide limited guidance on internally generated data assets (IASB, 2004) [7].

These frameworks focus predominantly on identifiable, separately acquired intangible assets and often exclude internally developed data due to challenges in measurability, reliability, and verification. As a result, the financial statements of data-driven companies do not reflect the economic reality of their data holdings, creating a significant valuation gap and potentially misguiding stakeholders (Lev & Gu, 2016; Cañibano & Sánchez, 2009) [9, 3].

This discrepancy is especially critical in the case of platform-based and data-intensive firms such as Google (Alphabet), Meta (formerly Facebook), Amazon, and Microsoft, whose business models rely heavily on the systematic collection, analysis, and commercialization of user and behavioral data. These organizations derive substantial value from proprietary algorithms, real-time customer data, and targeted advertising mechanisms. Yet, the absence of accounting recognition for these data assets not only obscures the true financial position of the firm but also limits comparability, impairs transparency, and complicates investment decision-making (Barth & Schipper, 2008; Lev, 2001) [1, 8].

The motivation for this study arises from the growing urgency to modernize financial reporting standards in light of digital transformation and data-centric business practices. As policymakers, investors, regulators, and auditors grapple with questions about data ownership, privacy, monetization, and accountability, it becomes imperative that accounting theory and practice evolve accordingly.

Therefore, the primary objective of this research is to propose a conceptual framework for recognizing, measuring, and reporting digital data as an intangible asset in corporate financial statements. This framework is designed to bridge the existing gap between accounting representation and economic substance by integrating traditional valuation models with the unique characteristics of data assets. The proposed model seeks to address issues of asset identification, measurement approaches (e.g., cost, income, and market-based), capitalization criteria, impairment testing, and disclosure guidelines, while also considering the broader implications for regulatory policy and standard-setting bodies such as the Financial Accounting Standards Board (FASB) and the International Accounting Standards Board (IASB).

Ultimately, this study contributes to the emerging discourse on "accounting for the digital economy" by challenging conventional notions of asset recognition and by redefining the financial narrative of modern, data-intensive enterprises.

2. Literature Review

The emergence of data as a strategic asset in the global economy has posed a formidable challenge to traditional accounting frameworks. For decades, the accounting profession has struggled with the recognition, measurement, and disclosure of intangible assets, particularly those that are internally generated. As the economic architecture of business shifts decisively toward platform-based, data-centric models, these challenges have become more acute. The limitations of prevailing standards in capturing the value of non-physical, digital assets risk rendering financial statements increasingly irrelevant, especially for technology firms that dominate capital markets.

This section reviews the state of the literature on accounting standards and valuation practices related to intangible assets, with a specific focus on data assets. It traces the evolution of accounting recognition criteria, critiques current regulatory frameworks, and highlights prior scholarly attempts to conceptualize the economic valuation of digital intangibles, such as proprietary datasets and algorithms.

2.1. Existing accounting standards for intangible assets

Under current international and U.S. accounting regimes, intangible assets are subject to well-established recognition criteria. The International Accounting Standards Board (IASB), through IAS 38 Intangible Assets, defines an intangible asset as "an identifiable non-monetary asset without physical substance" that is controlled by the entity and expected to yield future economic benefits (IASB, 2004) [7]. Similarly, FASB ASC 350 provides guidance on the accounting treatment of intangible assets and goodwill, particularly in the context of business combinations, acquisitions, and impairment testing.

However, both standards were formulated in an era where intangibles were typically understood to be acquired externally for instance, through licensing agreements, intellectual property purchases, or mergers and acquisitions. As a result, these standards prioritize assets that have clear acquisition costs or observable market prices, thereby rendering most internally generated intangibles ineligible for capitalization. Specifically, internally developed datasets, customer behavior insights, and proprietary algorithms are excluded from financial statements unless they are acquired through business transactions. This exclusion stems from the difficulty of attributing a reliable cost and the absence of active markets for such assets (Barth & Schipper, 2008) [1].

While this conservative approach safeguards auditability and comparability, it often comes at the expense of relevance and representational faithfulness particularly in the case of digital-first enterprises, whose value creation mechanisms are deeply embedded in their ability to collect, analyze, and monetize data.

2.2. Limitations of current frameworks in recognizing data assets

The principal criticism of IAS 38 and ASC 350 in the digital era lies in their inability to account for the economic substance of internally generated data. In many firms, particularly those operating within the digital platform economy, data is not acquired in discrete transactions but rather accumulated passively through continuous interaction with users, customers, or digital systems. This means that while the data may drive significant business value, it fails to meet the recognition threshold under current accounting standards due to the lack of a traceable acquisition cost or fair value benchmark.

Lev and Gu (2016) [9] characterize this disconnect as a form of "accounting dark matter" a phenomenon where economically significant resources exist and operate, yet are invisible in financial reporting systems. This problem is especially pronounced in sectors such as e-commerce, social media, digital advertising, and fintech, where user data forms the backbone of competitive strategy, pricing models, and customer acquisition. These firms often report massive discrepancies between book value and market capitalization, reflecting investor awareness of unrecognized intangible value that is not captured in audited financial statements.

Furthermore, the multi-use nature of data its ability to be copied, analyzed, and reused across multiple business processes challenges the linear accounting models designed for physical or single-use assets. Unlike tangible inventory or capital equipment, data can generate non-diminishing, compounding returns over time, making its exclusion from asset reporting a severe distortion of financial reality (Brynjolfsson & McAfee, 2014) [2].

2.3 The economic value of big data and proprietary algorithms

In contemporary economic thought, data has been increasingly recognized as a productive factor on par with labor, capital, and land. It plays a direct role in enhancing organizational productivity, driving innovation, and enabling hyper-personalized consumer engagement. Firms like Amazon, for example, leverage customer data to refine supply chain operations, streamline logistics, and boost customer retention. Meta (formerly Facebook) uses real-time behavioral data and engagement patterns to power its targeted advertising engine, which accounts for the vast majority of its revenue.

According to Marr (2015) [10], big data analytics has transformed the nature of strategic decision-making across industries, enabling firms to identify demand signals, detect fraud, and optimize pricing in real time. The economic utility of data is further amplified when combined with machine learning and artificial intelligence (AI) tools that allow firms to transform raw information into predictive and prescriptive insights (Schroeck *et al.*, 2012) [12]. These proprietary systems, which rely heavily on training datasets, represent long-term sources of competitive advantage and should, from an economic standpoint, be treated as assets with measurable value.

Yet, despite these realities, formal financial statements remain silent on the contributions of such assets. This silence contributes to information asymmetry, impairs investor judgment, and complicates valuation in capital markets (Lev, 2001) [8]. The lack of visibility into these core value drivers has prompted scholars, practitioners, and regulators to advocate for urgent reforms in the treatment of data within accounting systems.

2.4 Prior research on digital asset valuation

Recognizing the limitations of conventional accounting, several researchers have explored methodologies for the valuation of digital intangibles. Much of this literature builds upon established valuation techniques used for intellectual property (IP), software, customer relationships, and brand equity, adapting them to the context of data assets. Damodaran (2009) [4], for example, supports the use of income-based valuation models particularly discounted cash flow (DCF) to estimate the future economic benefits attributable to intangible resources.

Other scholars have examined cost-based approaches, wherein development costs for data collection, cleaning, structuring, and storage are capitalized, provided they can be reliably tracked. Market-based methods, while theoretically useful, are harder to implement due to the lack of active markets and the idiosyncratic nature of proprietary data. This is especially true in cases where data is tied to specific algorithms, platforms, or user interfaces that limit transferability.

A key theme in the literature is the notion that data, as a non-rival, non-depleting, and context-dependent resource, demands a bespoke valuation framework. Scholars such as Cañibano and Sánchez (2009) [3] emphasize that existing models fail to account for the scalability, multidimensionality, and evolving utility of data over time. The absence of standardization also complicates external validation, regulatory oversight, and cross-firm comparability.

In conclusion, while progress has been made in developing theoretical models for valuing digital assets, these efforts remain fragmented and largely disconnected from mainstream accounting practice. The literature reveals a consensus on the economic centrality of data but highlights a critical gap in its formal recognition and measurement. Bridging this gap is essential not only for improving the accuracy of financial statements but also for aligning accounting with the informational architecture of the modern enterprise.

3. Methodology

This study adopts a qualitative and conceptual research design to develop a framework for the recognition and valuation of data as an intangible asset in corporate financial reporting. The objective is not merely to critique existing accounting practices but to construct a structured, theoretically grounded model that integrates principles from accounting theory, economic valuation, and digital business strategy. Given the complexity and evolving nature of data assets, a multi-method approach is employed, consisting of conceptual synthesis, comparative corporate analysis, and illustrative valuation modeling.

3.1 Conceptual framework development

The foundation of this research lies in the qualitative synthesis of existing accounting and valuation theories, particularly those governing intangible asset recognition under IFRS and U.S. GAAP. By examining the limitations of IAS 38 (IASB, 2004) [7] and FASB ASC 350 in addressing internally generated digital assets, the study develops an Extended Asset Recognition Model (EARM) tailored specifically to the characteristics of data.

This conceptual framework is informed by the relevance–reliability trade-off in accounting standards (Barth & Schipper, 2008) [1], and incorporates stakeholder perspectives from investors, regulators, and digital platform operators. Additionally, interdisciplinary insights from information economics, intellectual capital theory, and data governance literature are integrated to capture the multi-dimensional nature of data as a strategic asset (Lev, 2001; Brynjolfsson & McAfee, 2014) [8, 2].

3.2 Comparative analysis of financial disclosures

To understand current industry practices, a comparative case study of data-driven firms is conducted. The study analyzes publicly available financial reports and disclosures from Alphabet (Google), Meta (Facebook), and Amazon, focusing on how these firms report data-related expenditures, intangible assets, and customer relationship metrics. Key areas of focus include:

- Capitalized versus expensed data-related costs
- Disclosures on proprietary algorithms and data infrastructure
- Narrative reporting around data monetization strategies
- Market capitalization versus book value disparities

These firms are selected because of their high dependency on proprietary data and their strategic use of analytics for business growth. The case analysis highlights the inconsistencies, omissions, and voluntary disclosures that illustrate the inadequacy of current accounting standards in reflecting the economic substance of data assets.

3.3. Application of valuation techniques in hypothetical models

To demonstrate the applicability of the proposed framework, the study presents hypothetical valuation models using three widely accepted approaches in intangible asset valuation: the cost approach, the market approach, and the income approach (Damodaran, 2009; OECD, 2015) [4, 11]. These models are applied to simulated data-driven asset scenarios, such as:

- A user behavior dataset collected over a multi-year period
- A proprietary recommendation engine trained on consumer inputs
- A customer relationship management (CRM) database used in targeted marketing

Each approach is adapted to suit the non-physical, non-rivalrous, and often non-transferable characteristics of data. For example, the income approach estimates future economic benefits derived from data-enabled revenue streams, while the cost approach focuses on the historical development costs, including infrastructure, labor, and compliance expenditures. The market approach, though limited by the scarcity of active markets for data, draws from comparable data asset transactions (e.g., in mergers and acquisitions).
Through these models, the study evaluates the feasibility, limitations, and policy implications of incorporating data valuation into formal financial statements. The outputs of these hypothetical models will inform the proposed recognition and measurement criteria embedded in the EARM framework.

Conclusion of Methodology

By combining conceptual development, empirical disclosure analysis, and applied valuation modeling, this methodological design ensures both theoretical rigor and practical relevance. It provides a robust foundation for proposing policy-relevant reforms to accounting standards and contributes a novel tool for corporate decision-makers, auditors, and regulators engaged in the evolving landscape of data-centric financial reporting.

4. Theoretical Framework

In light of the limitations in existing accounting standards and the economic significance of data, this study introduces a proposed theoretical model the Extended Asset Recognition Model (EARM) to guide the accounting treatment of digital data assets. The model builds upon foundational asset recognition principles while adapting them to the distinct attributes of internally generated, non-physical data. It is designed to enhance the relevance, reliability, and comparability of financial reporting in the context of data-intensive enterprises. The EARM is grounded in existing accounting theory and supported by stakeholder theory and the relevance–reliability trade-off that underpins standard-setting decisions (Barth & Schipper, 2008) [1].

4.1. The Extended Asset Recognition Model (EARM)

The EARM framework consists of four integrated components: recognition criteria, measurement bases, impairment and derecognition rules, and disclosure guidelines. Together, these elements offer a comprehensive approach to the valuation and reporting of digital data assets.

4.1.1. Recognition Criteria for Data Assets

To qualify for recognition under the EARM, a data asset must meet the following criteria:

- **Identifiability:** The data must be clearly defined and separable from other business activities or assets.
- **Control:** The entity must have exclusive legal or contractual rights to access, use, or restrict others from using the data (e.g., proprietary databases or algorithm-specific training datasets).
- **Future Economic Benefits:** The data must be expected to generate future economic benefits through cost savings, revenue generation, or strategic decision-making advantages (IASB, 2004) [7].
- **Reliable Measurement:** The value of the data must be measurable with reasonable accuracy using established valuation techniques.

These criteria extend and adapt those of IAS 38 while considering the non-traditional, dynamic, and replicable nature of data as an asset class (Lev & Gu, 2016) [9].

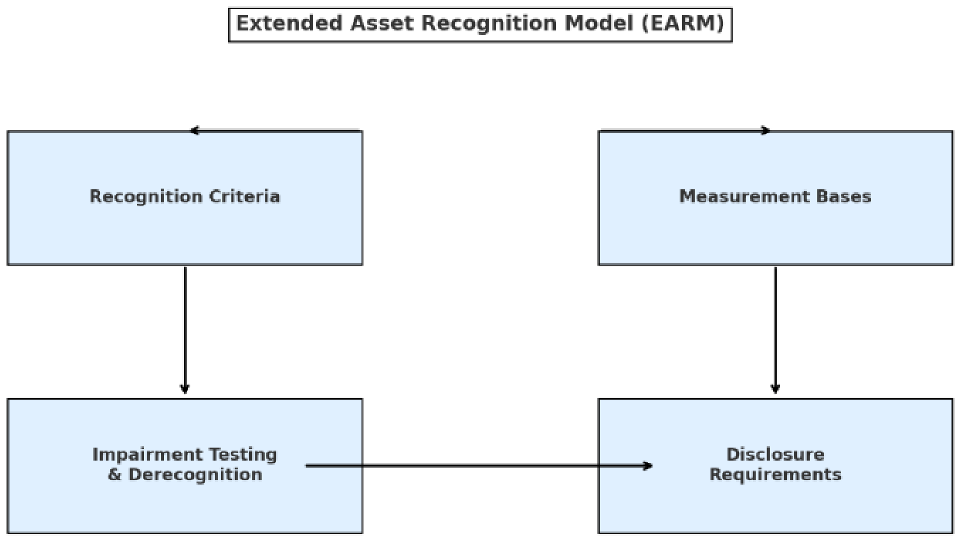

Fig 1: The Extended Asset Recognition Model (EARM) for Internally Generated Data Assets

(This figure illustrates the conceptual structure of the Extended Asset Recognition Model (EARM), comprising four interdependent components: (1) Recognition Criteria, (2) Measurement Bases, (3) Impairment Testing and Derecognition, and (4) Disclosure Requirements. These components collectively form the foundation for valuing and reporting internally generated data assets in financial statements. The directional arrows indicate the logical progression and feedback loops among the elements, emphasizing the model's dynamic and integrative nature. Positioned centrally in the financial reporting process, the EARM ensures that data assets are assessed through a balanced lens of relevance, reliability, and regulatory compliance.).

4.1.2. Suggested Measurement Bases

Given the difficulty in assigning a single measurement model to all types of data, EARM proposes a multi-model approach, allowing for flexibility based on asset type, usage, and availability of inputs:

- **Cost Approach:** Applicable where data is developed internally and development costs (e.g., collection, cleaning, storage, and processing) can be tracked and capitalized.
- **Replacement Cost:** Suitable for estimating the current cost to reproduce the dataset, especially for technical or operational databases.
- **Fair Value (Market Approach):** Used when there is an observable transaction or active market for comparable data assets, such as customer lists sold in mergers and acquisitions.
- **Income Approach:** Involves discounted future cash flows attributable to the data asset, particularly where data directly generates monetizable outcomes (Damodaran, 2009) [4].

The selection of measurement basis must align with the faithful representation and cost-benefit considerations emphasized in conceptual accounting frameworks (FASB, 2010) [5].

4.1.3. Impairment Testing and Derecognition

Data assets recognized under EARM must be subject to periodic impairment testing, particularly when the economic utility or legal enforceability of the data diminishes. For instance, data may lose value due to:

- Regulatory changes (e.g., data privacy laws limiting usage)
- Technological obsolescence
- Reduced relevance in predictive models

EARM recommends impairment testing annually or upon trigger events, in alignment with the treatment of goodwill and other indefinite-lived intangibles. Derecognition would occur if the asset is no longer expected to generate economic benefits or if control is lost.

4.1.4. Disclosure Requirements

To ensure transparency and comparability, EARM includes enhanced disclosure obligations, including:

- A description of the nature and purpose of the data asset
- Basis for recognition and measurement
- Valuation method used, along with key assumptions and sensitivities
- Amortization or impairment policy
- Any legal or regulatory restrictions associated with the asset's usage

Such disclosures are intended to reduce information asymmetry between data-intensive firms and their stakeholders, providing a clearer view of how proprietary data contributes to firm value (Cañibano & Sánchez, 2009) [3].

4.2. Integration with Stakeholder Theory and Relevance–Reliability Trade-Off

The EARM framework is conceptually supported by stakeholder theory, which emphasizes the need for accounting information to serve a broad set of users investors, regulators, creditors, analysts, and even consumers who have a stake in understanding the sources of organizational value (Freeman, 1984) [6]. In data-driven business models, stakeholders increasingly demand insights into how data is collected, governed, and monetized, making its disclosure a matter of public and regulatory interest.

Additionally, EARM acknowledges the relevance–reliability trade-off inherent in financial reporting. While measuring data assets may involve estimation uncertainty, excluding them altogether results in systematic underrepresentation of organizational value. As Barth and Schipper (2008) [1] argue, relevance must be balanced with reliability, but not sacrificed altogether. By proposing structured measurement models, rigorous recognition criteria, and robust disclosure requirements, the EARM seeks to mitigate estimation risks while enhancing the decision-usefulness of financial reports.

Conclusion of theoretical framework

The Extended Asset Recognition Model (EARM) provides a structured, theoretically grounded foundation for the accounting treatment of data assets. By addressing recognition, valuation, impairment, and disclosure in a unified framework, it offers a practical pathway for integrating digital intangibles into the core of financial reporting. The model not only enhances the representational faithfulness of financial statements but also aligns with evolving stakeholder expectations and economic realities in the digital era.

5. Practical application and case analysis

To bridge theory and practice, this section applies the Extended Asset Recognition Model (EARM) in hypothetical yet realistic scenarios inspired by operational practices of data-centric firms. The goal is to demonstrate how data assets could be recognized, measured, and disclosed in financial statements using the EARM framework. The case analyses of Amazon and Meta illustrate how internally generated data may qualify for recognition, and how its valuation can be aligned with economic contributions to revenue and strategic advantage.

5.1. Hypothetical scenario 1: Customer data valuation at amazon

Amazon.com, Inc. utilizes customer transaction data, product reviews, browsing history, and purchase patterns to optimize its recommendation algorithms and supply chain logistics. These datasets are proprietary, continuously updated, and embedded in Amazon's operational infrastructure.

Assumptions

- Amazon collects and stores data on 300 million users annually.

- The development and storage cost per user's data record is estimated at $3 (includes cloud storage, security, and engineering).
- The average revenue increase attributable to personalized recommendations per user is $5/year.
- Estimated useful life of the dataset is 3 years.

Valuation Using Cost and Income Approaches

- **Cost-based capitalized value:** 300 million users × $3 = $900 million
- **Income-based present value (simplified DCF):** Annual incremental revenue = 300M × $5 = $1.5 billion Discount rate: 10% PV ≈ $3.73 billion over 3 years

Proposed Recognition

Given that the data is identifiable, under Amazon's control, expected to generate future economic benefits, and can be reliably measured, it meets the EARM recognition criteria.

Table 1: Sample Journal Entry (Cost Approach)

Date	Account	Debit ($)	Credit ($)
12/31/2020	Data Asset-Customer Database	900,000,000	
	Cash/Accrued Expenses		900,000,000

Amortization over three years would follow straight-line or usage-based methods.

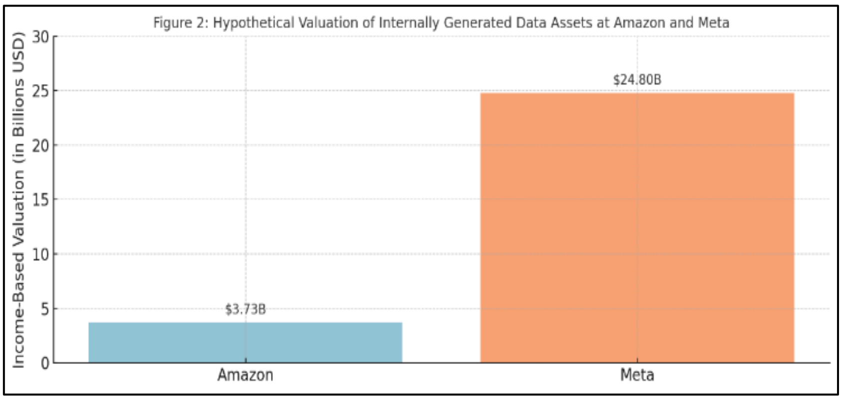

Fig 2: Hypothetical Valuation of Internally Generated Data Assets at Amazon and Meta

(This figure presents a comparative income-based valuation of data assets at Amazon and Meta. It highlights Amazon's customer dataset valued at approximately $3.73 billion and Meta's ad-targeting dataset at $24.8 billion, based on projected revenue streams and discounted cash flow analysis. The visual emphasizes the substantial economic value of internally generated data and supports its recognition as a financial asset under the EARM framework.)

5.2. Hypothetical scenario 2: Meta's ad-targeting dataset

Meta Platforms, Inc. (formerly Facebook) derives a significant portion of its revenue through targeted advertising based on behavioral data. This includes user engagement, clickstreams, location, and social interactions.

Assumptions

- Meta tracks data from 2.8 billion monthly active users.
- Ad revenue directly attributable to targeting algorithms is $40 billion/year.
- Attribution analysis estimates that 35% of this revenue depends specifically on its proprietary targeting datasets.
- Useful life of the dataset is 2 years due to regulatory changes and algorithm refresh rates.

Valuation Using Income Approach

- Data-dependent revenue = $40B × 35% = $14 billion/year
- Two-year discounted cash flow (10%): PV ≈ $24.8 billion

Given the direct revenue link and control over the asset, Meta's ad-targeting dataset would qualify for recognition under the EARM, particularly using the income approach due to its clear monetization strategy.

Table 2: Sample Journal Entry (Income Approach, Fair Value Estimate)

Date	Account	Debit ($)	Credit ($)
12/31/2020	Intangible Asset – Ad Dataset	24,800,000,000	
	Fair Value Reserve / Deferred Income		24,800,000,000

5.3. Sample Disclosure Notes

Note X: Recognition of internally generated data assets

During the reporting period, the company recognized two internally generated data assets: (1) a customer behavioral dataset used in algorithmic recommendations, and (2) a proprietary ad-targeting dataset. Recognition was based on the Extended Asset Recognition Model (EARM), developed to enhance reporting relevance for data-intensive activities. The assets were valued using a combination of cost-based and income-based methods, with expected useful lives of three and two years, respectively. Impairment will be tested annually or upon regulatory triggers affecting data utility or access rights.

Note Y: Key assumptions in valuation

The valuation models assume a 10% discount rate, stable user engagement patterns, and continued legal control over data usage. Any material changes in data governance laws (e.g., GDPR, CCPA) may result in impairment or derecognition of recognized data assets.

5.4. Implications and Challenges

While these scenarios demonstrate the technical feasibility of recognizing data assets, they also highlight practical challenges:

- Estimating future economic benefits with precision is inherently uncertain.
- Regulatory risks, such as privacy law changes, may shorten asset life or restrict usage.
- There is a lack of active markets for benchmarking fair value, particularly for proprietary datasets.

Nonetheless, these challenges are not insurmountable and are analogous to those encountered in the valuation of other complex intangibles, such as goodwill, software, and brand equity (Lev, 2001) [8]. The structured application of EARM ensures that data asset reporting can be approached with discipline, transparency, and auditability.

Conclusion of Section 5

The practical application of the EARM framework reveals that internally generated data when properly identified and valued can be treated as a legitimate financial asset. By applying structured valuation models to hypothetical data assets at Amazon and Meta, this section provides a tangible blueprint for how organizations might recognize and report data in a way that aligns with both accounting theory and economic reality.

6. Challenges and Policy implications

While the Extended Asset Recognition Model (EARM) offers a conceptual and operational framework for recognizing data as a reportable intangible asset, its real-world implementation presents significant challenges both technical and ethical. These obstacles must be understood not as reasons for inaction, but as critical dimensions of a much-needed reform in financial reporting and intangible asset accounting.

6.1. Verification, Standardization, and Auditability

A core principle of asset recognition is that the value of an asset must be measurable and verifiable by external auditors. Internally generated data poses difficulties in this regard because:

- Collection processes are often opaque, especially when integrated with broader digital infrastructure.
- Cost tracking is inconsistent, as firms rarely account separately for the time, storage, and labor associated with data generation.
- Market comparable are scarce, which limits the application of fair value estimation.

Without standardized practices, two firms may treat identical datasets differently, one capitalizing and disclosing it, another expensing or ignoring it. This undermines comparability and introduces material subjectivity into audit procedures (Barth & Schipper, 2008) [1]. To address this, a regulatory blueprint must include uniform data classification systems, standard cost categories, and industry-specific benchmarks.

6.2. Ethical Considerations: Privacy, Ownership, and Data Governance

Accounting for data also raises ethical questions that are largely absent from traditional asset accounting. Unlike physical or financial assets, data often involves personally identifiable information (PII) collected from users, which introduces a tension between asset recognition and individual privacy.

Three primary ethical concerns emerge

- **Ownership ambiguity:** Who owns the data the company that collects it or the user who generates it?
- **Consent and rights:** Can a firm recognize an asset based on user behavior if consent for commercial use is not explicit or revocable?
- **Compliance with data protection laws:** Recognized data assets may become subject to legal discovery, cross-border transfer restrictions, or forced deletion, which adds risk to their continued recognition.

As data becomes a line item on the balance sheet, robust internal governance structures and clear privacy policies will become essential to maintaining ethical and legal compliance. Firms will need to establish a data ethics committee or similar oversight body to monitor the intersection of data monetization and stakeholder rights (OECD, 2015; Freeman, 1984) [11].

6.3. Recommendations for IASB and FASB

To address the growing misalignment between economic substance and financial reporting, both the International Accounting Standards Board (IASB) and the Financial Accounting Standards Board (FASB) should prioritize a modernization of intangible asset standards with specific guidance on data assets.

Recommended actions include

1. Issue an exposure draft on accounting for internally generated data, inviting input from technology firms, auditors, and regulators.
2. Amend IAS 38 and ASC 350 to include a dedicated section on digital intangibles, including definitions, recognition thresholds, and valuation techniques.
3. Encourage voluntary disclosures of data valuation methodologies in Management Discussion & Analysis (MD&A) sections, as a precursor to mandatory reporting.
4. Incorporate guidance on non-financial risks, such as cybersecurity and regulatory compliance, within asset impairment and derecognition criteria.

Such reforms would align financial statements more closely with the underlying value drivers of modern enterprises and enhance investor confidence in the representational faithfulness of reported figures.

6.4 Policy Impacts on tax reporting, investment, and valuation

Recognizing data as an intangible asset would also have wide-ranging policy implications:

- **Tax Reporting:** Capitalized data assets may qualify for depreciation or amortization, altering corporate taxable income. Conversely, aggressive valuations could prompt scrutiny from tax authorities and necessitate new IRS guidelines.
- **Investor Decision-Making:** Investors would benefit from enhanced visibility into data-driven business models, enabling more accurate valuation and risk assessment. Transparency in data valuation would bridge the gap between market capitalization and book value (Lev & Gu, 2016) [9].
- **Corporate Valuation and M&A:** In mergers and acquisitions, data assets would assume a more central

role in deal structuring, pricing, and post-acquisition integration. Standardizing valuation methods would improve due diligence quality and reduce post-deal disputes.

These impacts reinforce the urgency for coordinated reform among accounting bodies, regulatory agencies, and policymakers. In the absence of structured guidance, companies risk either underreporting economically critical assets or misrepresenting their value, both of which threaten financial stability and market integrity.

Conclusion of Section 6

Recognizing data as a reportable asset marks a turning point in accounting thought, but it requires careful navigation of legal, ethical, and technical complexities. Verification and auditability remain significant hurdles, yet they can be addressed through standardization. Ethical concerns about privacy and consent must be handled through transparent governance and compliance frameworks. Most critically, accounting standards must evolve to reflect the digital realities of 21st-century enterprise. Only through thoughtful reform can data be responsibly integrated into the financial language of business, enabling fairer taxation, better-informed investors, and more accurate assessments of corporate value.

7. Conclusion

The digital economy has fundamentally transformed the structure and valuation of modern enterprises. In this new paradigm, data is no longer merely an operational byproduct, it is a central driver of innovation, efficiency, and profitability. Yet, accounting systems remain rooted in legacy frameworks that are ill-equipped to recognize or report the economic value of internally generated data assets. This misalignment creates a growing disconnect between the economic substance of businesses and their financial representation, particularly for technology-driven firms like Amazon, Meta, and Alphabet.

This study addressed this critical gap by proposing the Extended Asset Recognition Model (EARM) a conceptual and practical framework that defines how data assets can be identified, measured, tested for impairment, and disclosed under a structured accounting approach. By combining qualitative synthesis, case-based analysis, and hypothetical valuation models, the research demonstrates that data assets can meet the fundamental recognition criteria when appropriately assessed. The framework provides guidance on valuation methods such as the cost, income, and market approaches and offers disclosure formats that enhance transparency and comparability.

The study's primary contribution lies in its attempt to modernize intangible asset accounting in a way that is theoretically grounded, operationally feasible, and ethically responsible. By integrating stakeholder theory and the relevance reliability trade-off, the model balances the need for faithful representation with the challenges of valuation uncertainty. Furthermore, the study underscores the ethical and legal complexities surrounding data ownership, user consent, and privacy issues that must be addressed alongside technical reforms.

In aligning accounting practice with digital-era economic realities, the research advances a crucial dialogue on the future of financial reporting. If accounting is to remain the "language of business," it must evolve to articulate the value of intangible and algorithmically mediated resources that dominate the contemporary corporate landscape.

Finally, this study calls for cross-disciplinary collaboration in future research and policy-making. Recognizing and valuing data as an asset involves more than accounting; it demands insights from information technology (e.g., data architecture, AI), law (e.g., privacy and intellectual property), and economics (e.g., valuation theory and utility). The harmonization of these domains is essential to build robust frameworks that can guide not only corporate practice but also international standard-setting, taxation, and capital market regulation.

As data continues to shape global economies and redefine enterprise value, the evolution of accounting standards is not just desirable it is imperative. This manuscript serves as a foundational step toward that transformation.

8. References

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