Summary and Evaluation of the Data Valuation Model  
Fleckenstein, Obaidi, & Tryfona (2023)

Introduction

Fleckenstein, Obaidi, and Tryfona (2023) address the challenge of assigning value to data—an intangible asset that organisations now regard as a key driver of decision-making and innovation. Acknowledging the absence of a universally accepted valuation standard, the authors present a framework categorising valuation methods into three models: market-based, economic, and dimensional. They proceed to build and empirically test a dimensional model.

The proposed approach aligns with the UVA Data Science Framework developed by Keller et al. (2020), particularly in its emphasis on stakeholder engagement, fitness-for-use assessment, and ethical data governance throughout the data lifecycle. This connection supports the argument that Fleckenstein et al.’s model is not only theoretically sound but also practically aligned with current best practices in the data science discipline.

Advantages of the Data Valuation Model

1. Comprehensive Framework

The authors present a flexible taxonomy of market-based, economic, and dimensional models adaptable to organisational needs. This layered approach mirrors the "Problem Definition" and "Decision Support" stages of Keller et al.'s (2020) UVA framework, where stakeholder requirements and intended outcomes determine the analytical method.

2. Practical Dimensional Model

The dimensional model introduces a survey-based scoring mechanism using key attributes such as ownership, cost, usage, age, privacy, data quality, and volume/variety. This methodology helps organisations assess datasets consistently and compare them transparently. As in the UVA framework, this stage mirrors "Fitness-for-Use" and "Modelling", where data are evaluated based on relevance, usability, and context (Keller et al., 2020).

3. Contextual Sensitivity

The model accounts for differences in stakeholder priorities. For example, a public health researcher may value COVID-19 data for its timeliness, while a policymaker might prioritise completeness or regulatory compliance. This reflects the multi-stakeholder perspective encouraged by the UVA model’s "Stakeholder Engagement" and "Ethics and Governance" principles.

4. Decision Support in Data Investment

Fleckenstein et al.’s model provides decision-makers with a means to:  
- Compare the relative value of datasets  
- Assess return on investment for data integration  
- Prioritise datasets for retention or procurement

This aligns with Keller et al.'s final stage—Decision Support & Communication—where findings guide strategic planning.

5. Promotes Data Management Maturity As McAfee and Brynjolfsson (2012) emphasise, data-driven organisations consistently outperform their peers, with higher productivity and profitability. This highlights the competitive value of adopting systematic data practices like those encouraged by Fleckenstein et al.'s model.

The scoring model encourages organisations to adopt data governance practices that align with industry frameworks such as DAMA and CMMI. Measurable indicators like completeness, timeliness, and duplication support organisational growth towards data maturity—a theme also emphasised in the UVA model’s ethical and quality assurance components.

Disadvantages and Limitations

1. No Standard Monetary Valuation

While the dimensional model enables comparative scoring, it does not produce direct monetary valuations. This limits its application in scenarios involving financial reporting or licensing, where market-based methods remain necessary.

2. Subjectivity in Weighting and Scoring

Despite using structured surveys, the model is subject to stakeholder bias. Different organisations may assign varying weights, causing inconsistencies across sectors. This aligns with Acquisti, John and Loewenstein (2013), who demonstrate that individuals value privacy inconsistently based on how it is framed, reinforcing the challenges of reliably scoring sensitive dimensions.

3. Complexity and Cost of Implementation.

These challenges are particularly significant for SMEs, which often lack the infrastructure, skills, and strategic alignment required to effectively operationalise big data valuation models (Mikalef et al., 2019).

The model's full implementation requires time and technical expertise, including survey design, stakeholder interviews, and data cleansing. This can introduce resource constraints, particularly for small to medium-sized enterprises (SMEs). Similarly, Keller et al. (2020) note the cost and complexity of ensuring data is fit for purpose across all lifecycle stages.

4. Limited Real-World Testing

Although applied to datasets from diverse domains, the sample remains relatively small. Broader testing across other sectors (e.g., finance, retail, manufacturing) is needed for generalisation and model refinement.

5. Evolving Nature of Dimensions

Attributes such as data utility, privacy, and ownership are highly context-dependent and influenced by changing technologies and regulations. For instance, the rise of AI governance or updates to GDPR may shift how these dimensions are interpreted or prioritised, challenging the model’s long-term applicability.

6. Difficulty Capturing Intangible Benefits

Specific datasets yield indirect or long-term benefits, including greater trust and innovation. These elements are difficult to quantify through scoring alone. As Acquisti et al. (2013) argue, the non-monetary aspects of privacy, such as autonomy and dignity, often elude traditional valuation mechanisms, suggesting caution when interpreting low privacy scores.

A combined analysis of the weaknesses and threats reveals recurring issues around subjectivity, scalability, and long-term applicability. For instance, the reliance on stakeholder input for weighting dimensions, while adaptable, opens the model to inconsistency, particularly across sectors with varying priorities. Moreover, the evolving nature of regulatory and technological landscapes introduces uncertainty into how dimensions like privacy and utility will be perceived over time. Unmitigated, these risks could reduce the model’s credibility for data governance and investment.

Conclusion:

Organisations, especially SMEs, should align their valuation models with business goals and foster a data-driven culture (Mikalef et al., 2019; McAfee and Brynjolfsson, 2012).

The dimensional valuation model presented by Fleckenstein et al. offers a structured, practical, and stakeholder-oriented solution for assessing the relative value of data. By leveraging dimensions such as usage, cost, and privacy, the model enables transparent comparison between datasets and supports informed internal decision-making. When viewed through the lens of the UVA Data Science Framework (Keller et al., 2020), the model aligns well with modern data science practices, particularly in areas such as stakeholder needs, ethical governance, and contextual fitness for use.

However, its limitations—including the lack of monetary output, the need for subjective weighting, and implementation cost—suggest that it should be used as a complementary tool rather than a standalone solution. In high-stakes contexts such as mergers and acquisitions, commercial licensing, or regulatory audits, the dimensional model should be integrated with market-based or economic models to provide a more complete valuation strategy.

Word count 1001

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