Exploring Data Value Assessment: A Survey Method and Investigation of the Perceived Relative Importance of Data Value Dimensions

Conference Paper · January 2019

DOI: 10.5220/0007723402000207

5 authors, including:

Rob Brennan
Dublin City University

Judie Attard
Trinity College Dublin

Markus Helfert
National University of Ireland, Maynooth

Exploring Data Value Assessment: A Survey Method and Investigation of the Perceived Relative Importance of Data Value Dimensions

Rob Brennan[1][a], Judie Attard[2][b] , Plamen Petkov[1][c] , Tadhg Nagle[3][d] and Markus Helfert[4][e]
[1]*ADAPT Centre, School of Computing, Dublin City University, Dublin 9, Ireland*
[2]*ADAPT Centre, School of Computer Science and Statistics, Trinity College Dublin, Dublin 2, Ireland*
[3] *Department of Accounting, Finance and Information Systems, University College Cork, Ireland*
[4] *LERO Centre, School of Computing, Dublin City University, Dublin 9, Ireland*
{rob.brennan, markus.helfert}@dcu.ie, {judie.attard, plamen.petkov}@adaptcentre.ie, t.nagle@ucc.ie

Keywords: Data Value, Business-IT Alignment, Business Value of IT, Data Governance.

Abstract: This paper describes the development and execution of a data value assessment survey of data professionals and academics. Its purpose was to explore more effective data value assessment techniques and to better understand the perceived relative importance of data value dimensions for data practitioners. This is important because despite the current deep interest in data value, there is a lack of data value assessment techniques and no clear understanding of how individual data value dimensions contribute to a holistic model of data value. A total of 34 datasets were assessed in a field study of 20 organisations in a range of sectors from finance to aviation. It was found that in 17 out of 20 of the organisations contacted that no data value assessment had previously taken place. All the datasets evaluated were considered valuable organisational assets and the operational impact of data was identified as the most important data value dimension. These results can inform the community's search for data value models and assessment techniques. It also assists further development of capability maturity models for data value assessment and monitoring. This is to our knowledge the first publication of the underlying data for a multi-organization data value assessment and as such it represents a new stage in the evolution of evidence-based data valuation.

1 INTRODUCTION

Trends such as Big Data have popularised the need for enterprises to become more data driven and increased the need for a better understanding of what that means (The Economist, 2017). This is in line with the view that while organizations claim that data is a strategic asset, they fail to articulate its value, resulting in missed opportunities, fundamental data problems (such as data quality), and ultimately unsuccessful projects (Nagle and Sammon, 2017). Even defining data value has proved problematic with many defintions in but no agreed consensus as yet.

Despite this lack of clarity on how to quantify data value, the literature highlights data value chains as a way to organise enterprises. These echo manufacturing value chains (Crié and Micheaux, 2006), and depict a process-orientated view of data (e.g. defining activities from acquisition to distribution). However, data value chains do not specify the capabilities needed to manage or optimise value creation (Rayport and Sviokla, 1995). It has been observed (Otto, 2015) that measures for managing data as a strategic resource have focused on technology aspects such as data architecture or analytics. However, a technology first attitude towards data can cause more problems than solutions (Nagle and Sammon, 2017).

Articulating and communicating the value of data within organizations in ways that lead to successful

[a] https://orcid.org/0000-0001-8236-362X
[b] https://orcid.org/0000-0001-7507-1864
[c] https://orcid.org/0000-0002-1757-7987
[d] https://orcid.org/0000-0002-6123-7349
[e] https://orcid.org/0000-0001-6546-6408

projects, depends on an understanding of the context of use, the value creation process, data value measures, and hence the nature of data value. The focus of this paper is on data value assessment or quantification. It is possible to locate application-specific data value assessment metrics in the literature (Higson and Waltho, 2010). However, there is a lack of understanding of how data value dimensions combine into data valuations (Viscusi, G., and Batini, 2014) and how they contribute to undoubtedly complex data value creation processes (Moody and Walsh, 1999). Effective data value management must start with practical data value assessment techniques (Brennan et al., 2018).

In previous work (Brennan et al., 2018) we identified the data value assessment and monitoring capability within an organisation as critical to successfully managing data value. In this paper we seek to answer the research questions (i) to what extent do organisations value their data? and (ii) to what extent can manual data value assessment survey techniques inform us about the key dimensions of data value? To address these questions we (i) idenify a key manual data value assessment survey method from the literature, (ii) describe our further development of the assessment method and (iii) provide initial results from applying the method in 20 academic and business environments.

The contributions of the paper are providing evidence from a field survey that data value assessment is needed, development of a manual data value assessment survey and the first published set of responses for such an assessment. We have augmented the survey questions from previous work with more detailed ones on specific aspects of each data value dimension and with a set of self-reflective questions to establish the impact of participating in the assessment process. This is itself an indicator of the potential for organizational change.

The rest of this paper is structured as follows: section 2 provides background on data value with a focus on assessment and monitoring, section 3 describes the structure and development of our data value assesment survey, section 4 presents an evaluation of the relative importance of data value dimesions using our data value assesment survey for a set of 34 datasets acrosss multiple organisations and finally section 5 provides our conclusions.

2 BACKGROUND

Data value assessment should aim to be holistic in measuring the dimensions of data value for an organization. Unfortunately, there are a wide range of known dimensions of data value (Viscusi, G., and Batini, 2014) and there is not yet a consensus on their definitions, how they are related, or how data value metrics in information systems relate to monetary value (as measured in accounting-based measures of value). Viscusi and Batini break data value down into information capacity and information utility (Viscusi, G., and Batini, 2014). Capacity is then subdivided into quality, structure, diffusion and infrastructure. In their scheme, utility is based on financial value, pertinence and transaction costs. In contrast, the models of (Moody and Walsh, 1999) and (Tallon, 2013) strongly emphasize usage as a key dimension of value. It is in usage-based data value that the most progress has been made for practical data value monitoring systems. Hence, we give it prominence below.

Ease of measurement is another important concept to consider. Some data value dimensions have well known metrics and may even have recommended data or metadata formats, for example the W3C's data quality vocabulary (Albertoni et al., 2016) and DaVe, the Data Value Vocabulary (Attard and Brennan, 2018). Other data value dimensions, such as business utility or impact are very difficult to measure since they depend on having models and information about the business processes, outcomes and dependencies to identify measurable metrics for the contribution of datasets to profit or operating efficiencies.

Moody et al. (Moody and Walsh, 1999) defined seven "laws" of information (which we just refer to as data in the widest sense) that explained information's unique behaviour and relation to business value, whilst also highlighting the importance of meta-data. Moody identifies three methods of data (information) valuation – utility, market price and cost (of collection) – and concludes that utility is in theory best, but impractical and thus cost-based estimation is the most effective method. Most research on information value merely seeks to identify dimensions or characteristics without defining a mathematical theory of data value. Many of these dimensions overlap with data quality dimensions. For example, (Ahituv, 1989) suggests: timeliness (dimensions: recency, response time, and frequency), contents (dimensions: accuracy, relevance, level of aggregation and exhaustiveness), format (dimensions: media, color, structure, presentation), and cost.

There are documented uses of data value assessment and monitoring for enhanced control of elements of the data value chain, especially in the application areas of file-storage management

(Wijnhoven et al.., 2014), information lifecycle management (Chen, 2005), information pricing (Rao and Ng, 2016), data governance (Tallon, 2010) (Stander, 2015), and data quality management (Evan et al., 2010). We used these examples from practice as the basis for our data value monitoring capability maturity model (Brennan et al., 2018).

In 2006 Sajko et al. defined a structured manual data value assessment method for security risk assessment (Sajko et al., 2006) and unlike the previous methods that focus on automated or theoretical data value assessment, a structured questionnaire is used to drive a stakeholder assessment of the importance (value) of organisational data assets as part of a workshop to determine which assets should receive the most attention in the creation of a data security solution. The five questions provided are each aligned with a single data value dimension: operational impact (utility), replacement costs, competitive advantage, regulatory risk and timeliness. They are framed in terms that are suitable for business stakeholders to easily relate to. Compared to the general formulations of data value dimensions discussed above, there are two significant omissions in the data value dimensions selected: data utilisation and data quality which is generally included by all holistic models of data value. Sajko et al. also provide a suggested scoring system for the Likert-style responses to the questions and establish a threshold to determine whether or not a given data asset is "organisationally valuable". The simplicity and engaging nature of this method is very attractive for deploying a first level data assessment method in an organisation to (i) establish baselines for the evaluation of automated methods, (ii) act as a first assessment of data value from local domain experts that are aware of the business use of data assets but who may struggle with linking value either to more abstract data value dimensions or choosing appropriate data value metrics and (iii) to stimulate organisational awareness of data value. Although Sajko et al. report that the method has been applied many times unfortunately it provides no example data on responses.

3 DATA VALUE ASSESSMENT SURVEY DESIGN

This section discusses the development of an enhanced form of Sajko et al.'s data value assessment survey to investigate our research question and support the wider use case of data value-driven digital transformation rather than security risk assessment.

Three enhanced questionnaires were iteratively developed ranging from 11 to 28 questions per dataset. The survey prototypes were created using Google Forms. In order to study data value and its dimensions, the questionnaires were divided into five major dimensions of value:

1. Operational Impact (Utility);
2. Dataset Replacement Costs;
3. Competitive Advantage;
4. Regulatory Risk;
5. Timeliness.

These are based on the structured manual data value assessment method by Sajko et al. (Sajko et al., 2006). All three questionnaires covered these dimensions. In addition to evaluating data value itself, every survey included a section on self-reflection on the manual assessment process itself. This is where the impact of performing the assessment on the organization was self-evaluated. In two of the three forms of the survey, participants could add evaluations of multiple datasets or data assets, but this was dispensed with for the final survey as it was found most respondents (66%) only entered data for a single dataset and it was hoped that a shorter survey would increase the response rate.

Questions were mainly multiple choice; however, some open-ended questions were also included. In toyal 23 new questions developed and these were formulated based on (a) the desired addition of data quality and utilization dimensions and (b) the approach of the data value map (Nagle and Sammon, 2017). Thus, the objective with these questions was to go beyond the passive collection of data and to act as spur to insight and discussion with the participants. The addition of data quality and utilization dimensions of value is grounded in our ongoing survey of the data value literature to support the data value vocabulary initiative (Attard and Brennan, 2018). Most questions asked the participant to rate the importance of an event with respect to their dataset in terms of business impact in an increasing level of severity that may be converted to a Likert-like scale.

During the first iteration, the description of the survey and its purposes was presented to a test group of data science postgraduate students with a range of backgrounds to improve the understandability of the study. Information related the ethics and the impact of the study were included based on their feedback.

The first versions of the questionnaire consisted of a high number of questions (28). After discussing the complexity and the number of questions, the authors decided to also produce a short form survey in order to reduce completion and minimise inaccurate responses (e.g. by participant unable to understand a question due to its complexity or by answering a question without taking the necessary time to understand it). The authors also decided to keep and use two versions of the questionnaire (long and short form), as the long one may generate more insight into data value assessment and analysis of the meta-questions could provide feedback on which form respondents preferred or found more effective.

The next review criteria were related to the types of questions included. For example, to ensure that the survey includes questions which cover all possible data value dimensions, open form answer options were added in addition to predefined lists of potential answers. The authors also agreed to place simpler questions (e.g. questions related to capture technology-centric metrics such as data volume, and access rate) at the beginning of the questionnaire and more difficult at the end (e.g. questions that capture business user satisfaction or require understanding of the value creation process). The rationale behind this was to avoid people become flustered and quit answering questions at very early stage of the survey.

4. VALIDATION OF DATA VALUE DIMESIONS

This section describes the use of our survey to investigate the hypothesis that given a set of data value assessments (responses) targeted at specific data value dimensions that we could gather evidence for which dimensions are seen as most important for contributing to data value in an operational setting.

4.1 Method

A wide-scale, multi-organization data value assessment survey was conducted to gather further evidence about the relative importance of different data value dimensions to an organization. The primary means of data collection for our research was a questionnaire. The structure of this questionnaire is outlined in the previous section, and information on participation criteria and sampling is provided below. The Likert-type scoring scale provided for the questionnaire results by Sajko et al. is used to convert the survey results into numerical scores to enable easy comparison of the results.

By allowing participants to evaluate their own datasets we recorded the overall responses per data value dimension (as each question targets a specific dimension). Lower scores in these cases indicate less important dimensions of value for specific datasets. When the survey results are taken as a whole these are an indicator of the relative importance of each dimension for the operational datasets evaluated. Following (Sajko et al.., 2006) this gives some insight into the relative importance of datasets within an organization and may even indicate trends in the relative importance of the dimensions themselves in a business setting. In addition, the reflective questions were analyzed to indicate the organizational impact of participating in the data value assessment exercise.

The participants were a mix of enterprise data professionals (16) drawn from a wide range of industries (finance, aviation, publishing, legal, ICT) and computer science postgraduate students (4) used for initial testing. Recruitment was through the network of past professional association with the Cork University Business School Master’s degrees for practitioners, participation in the Data Value Workshop at Semantics 2018 in Vienna[6], Austria and the clients and partners of Castlebridge data governance consultancy[7]. This was a broad range of participants with data governance backgrounds.

Non-probabilistic sampling methods were used to recruit participants. Key decision makers were contacted in the participating organisations and asked to complete the questionnaire or forward it to relevant staff. An open call for participation in the questionnaire was made in the Data Value Workshop (3 responses).

The questionnaires received 20 responses, all of whom had completed at least one dataset data value assessment. In total 34 datasets were assessed. This was made up of 12 short-form questionnaires that assessed a total of 20 datasets and 8 long-form questionnaires that assessed 14 datasets.

4.2 Results

The results of this multi-organization data value assessment activity are presented in the following paragraphs and associated tables and are discussed and interpreted in the next subsection. In all cases the value score columns are based on the methodology of Sajko et al. but the raw data from user responses is also presented in the tables to enable other interpretations.

Operational Impact Data Value Dimension (Utility): In table 1 the results of the common question for operational impact are summarized. The most popular impact selected across all data assets (59%) is that there would be a major impact on operations. The mean score calculated is also the highest value for any dimension examined.

[6] http://2018.datavalue.adaptcentre.ie/cfp.html

[7] https://www.castlebridge.ie/

Replacement Cost Data Value Dimension (Cost): In table 2 we see the results of this common question across all three questionnaires. This features a much more even spread of answers, so this implies that replacement costs for data are more variable than the operational impact of losing data. However, the fact that the highest impact answer is the most popular (35% of respondents) ensures that the weighted mean score for this dimension is still high at 2.88.

Competitive Advantage (Market Value) Data Value Dimension: Once again (table 3) the strongest (most valuable) response it's the most popular one at 35% of respondents but it is notable that a large fraction of the respondents (18%) estimate that their data is of no use to their competitors. This depresses the mean score for this dimension to 2.35.

Competitive Advantage (Market Value) Data Value Dimension: This dimension (table 4) captures the likelihood that an organization is keeping data for auditing purposes that have a potential penalty associated with non-compliance. It is a kind of inverse value as if not properly maintained then these datasets will become a liability for the organization. For 50% of the datasets assessed there were potential sanctions or strict sanctions if the data was not maintained. However, the large number of lower category responses see that the mean score continues to drop slightly and is at 2.32 for this dimension.

Timeliness Data Value Dimension: Unfortunately, the sample size (20) for this question (table 5) is smaller than the others as the longer variant questionnaire had a cluster of related questions about the effect of time on data that do not easily map onto the question presented in the short survey based on Sajko et al. hence only the short survey results are presented here. Nonetheless it can be seen that many datasets (45%) do not exhibit the property of data value decreasing over time. One omission from Sajko et al.'s methodology (Sajko et al.., 2006) was the ability to account for datasets that rise in value over time. Hence in the longer version of the questionnaire we asked this and 50% (N=14) of the datasets surveyed were recorded as increasing in value over time. It is possible to combine the results in table 5 with this result to get an overall value of 47% (N=34) of datasets are seen to either retain their value or increase in value over time.

Self-Reflection on the Data Value Assessment Process: The survey was accompanied by open questions leaving the ability for the respondent to provide additional context or rationale for their answers (Table 6). One participant did not complete this part of the survey and hence the sample size drops to 19. The vast majority of respondents had never taken part in a data valuation exercise before (89%) and found the process simple (95%).

Overall Valuation: Using Sajko et al.'s method the 34 data valuation surveys can be scored using the Likert-type scale and weights of 0, 1, 2, 3 and 4 for the possible answers (figure 1).

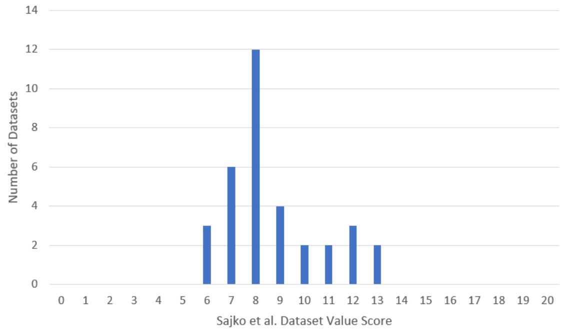

Figure 1: Histogram of the Sajko et al data value scores calculated for the 34 datasets assessed in the field study.

4.3 Discussion

This is to our knowledge the first publication of the data behind a multi-organization data value assessment and as such it represents a new stage in the evolution of evidence-based data valuation. It is notable that 82% of the datasets which were assessed would score 7 or more on the valuation scale of Sajko. et al. and hence be assessed as "business private information" and thus is valuable.

It is an interesting feature of this survey that the aggregate results can be interpreted as an indication of the relative importance (figure 2). From the figure the operational impact of data for an organization (for the datasets evaluated) is the most important dimension and after that it is the combination of timeliness and replacement costs that dominate. Given the reported importance of timeliness it is perhaps significant that under the assessment scheme of Sajko et al. (Sajko et al.., 2006) there was no concept of data value rising over time, in comparison to the results reported by our respondents.

This may be a feature of the differences between 2018 and 2006 when Sajko et al. developed their assessment scheme. It is also important to recognize that Sajko et al. constructed the survey for the use case of security threat assessment, i.e. to understand which data assets most needed protection, whereas we are investigating data value for its general use in data management. The specific use cases are laid out in our definition of a data value ontology (Attard and Brennan, 2018) and include value monitoring value-driven data governance, data quality, data curation.

Table 1: Operational Impact (Utility) – What happens if you do not have this data anymore?

Answer	Responses	Value Score	(N = 34) % Datasets
Nothing special	2	0	6%
Some non-essential processes are late	1	1	3%
Imperfections are noticeable, but fixable	4	2	12%
New costs appear	7	3	21%
There is a bigger halt to operations and wrong decisions are likely- new urgent action is necessary	20	4	59%
	Mean:	3.24	

Table 2: Replacement Cost - What is the cost of replacing this data or production of the new equivalent data?

Answer	Responses	Value Score	(N = 34) % Datasets
Negligibly small	2	0	6%
Cost exists but it is low	0	1	0%
Higher costs appear	10	2	29%
Cost is hardly tolerable	10	3	29%
Intolerably high costs	12	4	35%
	Mean:	2.88	

Table 3: Competitive Advantage (Market Value) - What happens if your competitor has the same data?

Answer	Responses	Value Score	(N = 34) % Datasets
Nothing	6	0	18%
Competitor has all unimportant data about our company available	3	1	9%
Competitor has insight in our important business processes	10	2	29%
Competitor can reach the company	3	3	9%
Competitor gets competitive advantage	12	4	35%
	Mean:	2.35	

Table 4: Regulatory Risk - Is there any obligation to keep this data and any consequences for the organization if it loses it?

Answer	Responses	Value Score	(N = 34) % Datasets
There are none	8	0	24%
It is necessary to keep the data for a brief period	2	1	6%
The organizations should keep the data but without consequences	7	2	21%
Keeping the data is obligatory and the company can suffer sanctions	5	3	15%
Keeping the data is obligatory and the sanctions are strict	12	4	35%
	Mean:	2.32	

Table 5: Timeliness - Does the data value fall in the course of time?

Answer	Responses	Value Score	(N = 34) % Datasets
Very quickly	1	0	5%
Quickly	5	1	25%
After 1 year	0	2	0%
After a few years	5	3	25%
Does not fall at all	9	4	45%
	Mean:	2.8	

Table 6: Self-reflection Questions (per participant rather than per-dataset)

Question	Answer	Responses	(N = 34) % Datasets
1. Have you been previously asked to value your data?	Yes	2	11%
	No	17	89%
2. Do you think the Data Value Questionnaire has changed your perception on data value?	Yes	8	42%
	No	11	58%
3. In the future, will you change how your data is stored, maintained, or secured?	Yes	6	32%
	No	12	63%
4. Was the Data Value Questionnaire easy to answer?	Yes	18	95%
	No	1	5%

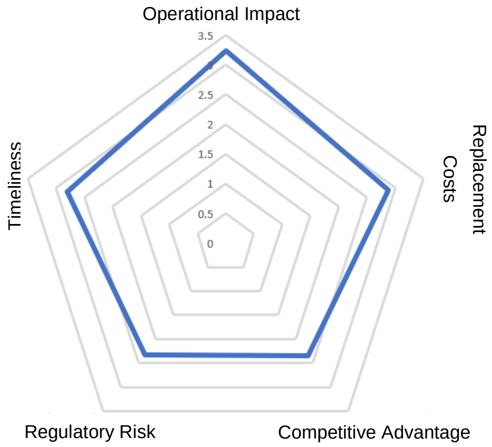

Figure 2: Radar plot of the Highest Mean Scores for the Data Value Dimensions Assessed by the Survey

A new use case that is gaining attention is the use of data value assessments in corporate merger and acquisition processes.

Given that 18 of the respondents were practitioners, it was surprising to see change in perception the survey generated. Given the simplicity of the survey and the fact that it changed the perception of 42% of respondents, points to fragility or uncertainty in how practitioners perceive data value. This may be partially explained by the low number of data valuations carried out by the respondents, but it is still surprising given the backdrop of current data trends like AI, machine learning and big data, all of which portraying the potential to unlock the value in organizational data. However, if practitioners do not understand this value in the first place, initiating data projects becomes a random exercise and delivering a successful one becomes problematic. How can data projects be on a successful trajectory if the value of data is not understood upfront or throughout the project.

5 CONCLUSIONS

Our key conclusion, from this initial field study, is that while organisations acknowledge that they hold significant value in data (82% of the datasets assessed were classified as valuable) but interestingly very rarely are asked to place a value their data (89% of respondents had never previously been asked to perform a data value assessment). It also seems that their understanding of data value is fragile as 42% of respondents suggested that engaging in our simple assessment process changed their opinions on data value. This indicates that the answer to our first research question is that organisations do value data in theory but not often in practice. More data needs to be collected to support this initial finding.

Our previous capability maturity model (CMM) for data value monitoring and assessment (Brennan et al., 2018) suggested a hierarchy of data value dimensions, i.e. Utility (including Operational Impact), Context (including Timeliness and Competitive Advantage), Usage and Quality, Cost (including replacement costs). The analysis here of the data value assessment survey provides further evidence of this hierarchy - usage and cost are the easiest to implement but utility or operational value is the most important dimension for organizations. This contributes to our second research question and indicates that manual survey-based methods are worth deploying to gather further evidence.

The survey results indicate an impact on practitioners by performing data value assessments. This is encouraging as next we intend to provide an online tool for conducting assessments and allowing organisations to compare their performance to others in terms of the CMM and hence recommend strategies for improving data value assessment and monitoring in their organisation.

ACKNOWLEDGEMENTS

This research was partially supported by Science Foundation Ireland and co-funded by the European Regional Development Fund through the ADAPT Centre for Digital Content Technology [grant number 13/RC/2106] and grant 13/RC/2094 co-funded under the European Regional Development Fund through the Southern and Eastern Regional Operational Programme to Lero - the Irish Software Research Centre (www.lero.ie). This paper has also received funding from the European Union's Horizon 2020 research and innovation programme under the Marie Sklodowska-Curie grant agreement No. 713567 (EDGE). The authors wish to thank Dr Pieter De Leenheer of Collibra, Nora Murphy and Laura Tierney for their assistance in this research.

REFERENCES

Ahituv, N. (1989) Assessing the Value of Information: Problems and Approaches, *International Conference on Information Systems (ICIS)*, Available at: https://aisel.aisnet.org/icis1989/45

Albertoni, R., Isaac, A., Guéret, C., Debattista, J., Lee, D., Mihindukulasooriya, N., and Zaveri, A. (2016). Data Quality Vocabulary (DQV). Retrieved from http://www.w3.org/TR/vocab-dqv/

Attard, J., Brennan, R. (2018) A Semantic Data Value Vocabulary Supporting Data Value Assessment and Measurement Integration, *20th International Conference on Enterprise Information Systems, (ICEIS)*, 133—144.

Brennan, R., Attard, J., Helfurt, M. (2018) Management of Data Value Chains, a Value Monitoring Capability Maturity Model, *20th International Conference on Enterprise Information Systems (ICEIS)*, 573-584.

Chen, Y. (2005). Information Valuation for Information Lifecycle Management. In *Second International Conference on Autonomic Computing (ICAC'05)*. https://doi.org/10.1109/ICAC.2005.35

Crié, D., & Micheaux, A. (2006). From customer data to value: What is lacking in the information chain? Journal of Database Marketing & Customer Strategy Management, 13(4), 282–299.

Economist, The (2017), *"The world's most valuable resource is no longer oil, but data," Economist, May 6, 2017*. Retrieved from https://www.economist.com/news/leaders/21721656-data-economy-demands-new-approach-antitrust-rules-worlds-most-valuable-resource

Even, A., Shankaranarayanan, G., and Berger, P. D. (2010). Evaluating a model for cost-effective data quality management in a real-world CRM setting.

Higson, C.; and Waltho, D. (2010) Valuing Information as an Asset. *Sas the Power To Know*, 1–17. Available online http://www.eurim.org.uk/activities/ig/InformationAsset.pdf (Accessed on 13 10 2018)

Laney, D. (2011). Infonomics : The Economics of Information and Principles of Information Asset Management. *The Fifth MIT Information Quality Industry Symposium, July 13-15, 2011*, 590–603.

Moody, D., and Walsh, P. (1999). Measuring The Value Of Information: An Asset Valuation Approach. *Seventh European Conference on Information Systems (ECIS'99)*, 1–17. https://doi.org/citeulike:9316228

Nagle, T.; Sammon, D. (2017) The Data Value Map: A Framework for Developing Shared Understanding On Data Initiatives. *25th European Conference on Information Systems (ECIS)*, 1439-1452.

Otto, B. (2015). Quality and Value of the Data Resource in Large Enterprises. *Information Systems Management*, *32*(3), 234–251.

Pipino, L. L., Lee, Y. W., Wang, R. Y. (2002) Data quality assessment. *Communications of the ACM*, 45(4), 211-218. DOI: http://dx.doi.org/10.1145/505248.506010

Rao, D., and Ng, W. K. (2016). Information Pricing: A Utility Based Pricing Mechanism. Proceedings - 2016 IEEE 14th International Conference on Dependable, Autonomic and Secure Computing, DASC 2016, 2016 IEEE 14th International Conference on Pervasive Intelligence and Computing, PICom 2016, 754–760.

Rayport, J. F., and Sviokla, J. J. (1995). Exploiting the Virtual Value Chain. Harvard Business Review, 73, 75.

Sajko, M., Kornelije, R., Miroslav, B. (2006) How to calculate information value for effective security risk assessment, *Journal of Information and Organizational Sciences*, 30(2), 263-278. Available at: https://www.researchgate.net/publication/26596362_How_to_calculate_information_value_for_effective_security_risk_assessment.

Stander, J. B. (2015). The Modern Asset : Big Data and Information Valuation, MSc, Stellenbosch University, South Africa

Tallon, P. P. (2013). Corporate governance of big data: Perspectives on value, risk, and cost. *Computer*, *46*(6), 32–38. https://doi.org/10.1109/MC.2013.155

Tallon P., Scannell, R. (2007) Information Lifecycle Management, *Communications of the ACM*, 65-69.

Turczyk, L. A., Heckmann, O., and Steinmetz, R. (2007). File Valuation in Information Lifecycle Management. *Managing Worldwide Operations and Communications with Information Technology*, 347–351.

Viscusi, G., and Batini, C. (2014). Digital Information Asset Evaluation: Characteristics and Dimensions (pp. 77–86). Springer, Cham.

Wijnhoven, F., Amrit, C., Dietz, P. (2014) Value-based File Retention: File Attributes as File Value and Information Waste Indicators, *ACM journal of data and information quality*, 4 (4). 15:1--15:17. ISSN 1936-1955