Requirements for Data Valuation Methods

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Abstract

Data is considered the most significant intangible asset for the 21st century enterprise. Serving as key asset for ever-increasing digital transformation and entrepreneurship, they ensure economic success through empowering new technologies, services and business models. Despite their high relevance, there exist neither consistent valuation methods nor specific requirements for developing such methods. Data valuation is crucial in order to better understand their value and, for example, incorporating them into financial statements. Existing literature indicates relationship between data value and quality. Thereupon, we conducted semi-structured expert interviews to gain insights on data valuation methods in connection with data quality. This results in 11 requirements for data valuation methods and seven value-driving quality criteria. Furthermore, several challenges for future data valuation are derived from the empirical results.

1. Introduction

Data are crucial for success of digital transformation and entrepreneurship. Representing raw material for information, processed through information systems (IS), they enable enterprises to improve processes and decision-making, offer new data-driven services, and create new business models [1][2]. Using and analyzing data is considered to enhance enterprise productivity and realize business value [3]. With digital entrepreneurship arising, data gain more importance in terms of economic value creation, resulting in higher prices, more sales, cost savings as well as new business models from new products or services [4][5].

Existing measurement tools struggle to keep up in valuing data in a consistent and comprehensible way [6]. Despite their high relevance, data are rarely reported in annual financial statements [7] - due to inconsistent and lacking reliable valuation methods. Consequently, stock market valuations increasingly diverged from their measured book value [8]. Moody and Walsh describe difficulties in transferring accounting principles, i.e., valuation methods, from the sphere of physical to intangible assets such as data [9]. Furthermore, existing quantitative valuation approaches in accounting (i.e. market-, income- and cost-based approaches) are rarely used in practice to value data [10]. IS literature mainly proposes qualitative methods for measuring data value [11][12][13][14]. However, existing quantitative methods don't measure monetary value of data. Merely the quantitative methods by Möller et al. [15] and Saunders and Brynjolfsson [8] approach the quantitative valuation of data. They define costs, usage and data quality as main influencing factors on data value. To the best of the authors' knowledge, specific requirements for data valuation methods are nonexistent. Furthermore, data quality represents a multi-dimensional concept composed of numerous quality criteria. Most research focuses on the importance and impact of different quality criteria with only implicit connection to data value [16][17][14]. So far, there exists no research examining the influence of specific quality criteria on data value with using empirical study results.

Without data valuation and lacking options to calculate returns on data-related infrastructure investments, enterprises are unable to present their data assets in financial statements. Thereby, misjudging opportunities in investing in digital technologies in order to collect, store and process data increases. Quantitative valuation of data will (1) equip enterprises, analysts and investors with a better basis for investment decisions [18], (2) enable to develop novel or enhance existing products, services or business models beyond simple process optimization [19], (3) improve creditworthiness of enterprises and (4) provide a basis for adjusting accounting standards in order to represent all relevant assets in financial statements. In general, placing a value on data and reflecting it in enterprises' financial statement will contribute to management's capability to manage it [20].

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This work aims to derive requirements for quantitative data valuation methods and, in doing so, provide researchers with common knowledge base to develop comprehensive and consistent data valuation methods. We were specifically interested in general requirements for such methods as well as relevant data attributes to be incorporated for deriving a quantitative data value and focused on operational data in companies.

The remainder of this paper is structured as follows. We first review existing valuation methods for data and related intangible assets from accounting and IS perspective. Afterwards, we elaborate value-influencing data quality criteria from literature. Thereupon, the study design of semi-structured expert interviews is presented and results are described then. We derive requirements for data valuation methods from the interview results and summarize them within a conceptual model. Influence of data quality on data value and future challenges in data valuation are described afterwards. We conclude the paper by discussing the results and giving an outlook on future work.

2. Related Work

Moody and Walsh [9] describe difficulties in transferring accounting valuation principles from the sphere of physical to intangible assets such as data. This can be justified by specific data characteristics. Unlike physical assets, data are shareable, infinitely often replicable, gain value through usage and often dispose infinite useful life [29][9][30][31].

2.1. Data Valuation Approaches

Data can be defined as intangible asset based on International Accounting Standards' (IAS) definition: data are identifiable, non-monetary, without physical substance, controllable and provide future economic benefit. According to IAS, three basic approaches are differentiated to value intangible assets: cost, income and market approaches [32]. It is recommended in practice to apply market before income and cost methods. Nevertheless, in practice mostly the latter two are applied, mainly due to absence of active markets. Cost approaches determine a monetary value, based on costs for acquiring, (re)producing or replacing an asset. They estimate reproduction costs based on historical or replacement costs. It needs to be analyzed which costs are used for asset creation, i.e., personal costs for developing software. If applicable, a value impairment or appreciation due to quality issues or other influences is performed [32]. Alternatively, the

expected re-acquisition costs can be calculated, e.g. costs for the introduction of a brand can be estimated [33]. Income approaches determine the fair value of intangibles based on future cashflows that an asset is expected to generate for its beneficial owner over its remaining useful life [32]. The classic market-based approach derives the value of intangibles based on actual prices achievable on active markets. These are defined as markets wherein transactions for the asset or liability take place with sufficient frequency and volume to provide price information on an ongoing basis [32]. If markets for specific assets are absent, analogy methods are applied.

IS researchers implicitly approached the topic of data valuation from the early 1980s, by researching the value of information [34]. To the authors' knowledge, only few publications fully focus on the valuation of data or similar concepts. Table 1 provides an overview of these publications. The valuation methods described therein are structured on the basis of approach type (cost-, usage/-income-, or market-based) and valuation object (data, information, IT systems or related intangibles). Furthermore, key features of each method are briefly described (cf. table 1). The publications consider multiple aspects for deriving a monetary value to the valuation objects. In addition, the role of usage or utility, customer relations and quality are considered. Seven papers implement cost-based valuation methods. In addition, most of the other approach types also incorporate costs.

The literature reviewed reveals that the factors costs, usage and quality are expected to influence data value. This represents an alignment with the most common methodology for measuring IS success, which combines the dimensions of quality, usage and benefit [35]. However, the literature on this topic is sparse. Therefore, expert interviews are conducted (cf. section 3 and 4) in order to broaden and deepen insights as well as practical knowledge on valuation methods for data. In addition, the relationship between data value and data quality are examined at the interface of accounting and IS research. The next subsection reviews data quality in correlation with data value.

2.2. Derivation of Value-Influencing Data Quality Criteria

Results of the previous section point to the importance of data quality when it comes to valuing data. Measuring data quality is extensively covered in literature. Although a comprehensive analysis of the role of data quality in the scope of assessing data value is missing, it represents an influence [34]. Data scientists

Table 1. Overview of Related Research.

Paper	Approach Type	Valuation Object	Method Description
Zechmann and Möller 2016 [21]	Usage	Data	Costs and data quality as a success factor for enterprises and aim of predicting future economic benefit based on data usage.
Möller et al. 2017 [15]	Usage	Data	Usage-based valuation combined with data quality, utility, costs, opportunities and risks.
Heckman et al. 2015 [22]	Market	Data	Estimating the value of datasets on data markets by building on costs and characteristics of data, e.g.: age, periodicity, volume, format, accuracy.
Moody and Walsh 1999 [9]	Cost	Information	Modification of historical cost method based on seven laws of information.
Laney 2017 [23]	Cost; income; market	Information	Modification of the three accounting approaches and formula development to value information.
Glazer 1993 [24]	Cost	Information	Sum of (1) profits that result from increased revenues and reduced costs from future transactions that are in turn a function of information collected along with the transaction and (2) profits from information sale.
Saunders and Brynjolfsson 2016 [8]	Cost	IT System Related Intangibles	Valuing IT-related assets by including costs for capitalized software, all purchased and internally developed software, other internal IT services, IT consulting, and IT-related training.
Brynjolfsson et al. 2002 [25]	Cost	IT System Related Intangibles	Higher level of IT and IT-related organizational characteristics result in higher company value on financial markets and from the viewpoint of investors
Chircu and Kauffman 2000 [26]	Cost	IT System	Valuation by calculating cost savings through IT by distinction of potential and realized values.
Murphy and Simon 2002 [5]	Cost	IT System	Cost-benefit analysis of ERP projects including value of further intangibles, e.g., customer satisfaction.
Ahituv 1980 [27]	Usage	IT System	Utility-function based value assessment including timeliness, contents, format, sub-attributes and costs.
Nissen 1994 [28]	Usage	IT System	Valuation based on organizational process performance and IT investments.

spend 80 % of their time in analytical projects on data exploration and preparation due to lacking data quality, which leads to higher (personnel) costs [36].

The proposed framework by Wang and Strong [16] captures important aspects of data quality from a customer perspective. These aspects enable to enhance the value of data. In their survey study, they derive a conceptual framework of data quality that is differentiated into intrinsic, contextual, representational and accessibility data quality and reduced to 15 quality dimensions. Based on this, Pipino et al. describe the subjective and objective assessment of data quality and present functional forms for developing objective data quality metrics [17]. They propose 16 data quality dimensions in their work. Kahn et al. [14] propose a product service performance model for deriving information quality where they build upon the quality dimensions defined by [17]. They highlight evolving

costs when data quality is low and enterprises put effort on the improvement. Batini and Scannapieco as well as Laney present a reduced data quality framework with eight quality dimensions each [37][23]. ISO/IEC 15939 recommends data quality assessment for data products based on 15 dimensions. In order to derive the main value-influencing data quality criteria in terms of a framework, the following six-step procedure was conducted (cf. figure 1).

The following value-influencing data quality criteria result from the procedure presented in figure 1: accuracy, completeness, accessibility, consistency, timeliness, relevancy, usage degree and portability. Based on the sources reviewed, definitions of data quality criteria were derived for this work: Accuracy is defined as the degree to which data correctly represents reality [38][39]. Completeness means there exists no missing data in a data table, or it is sufficiently complete
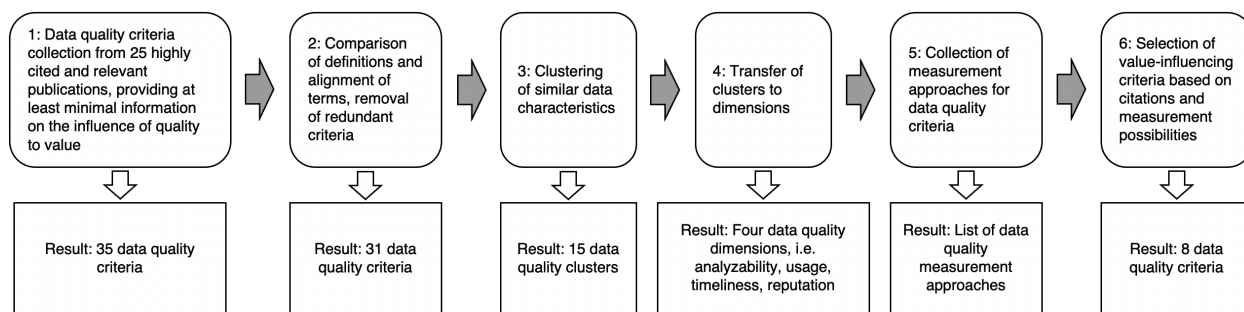
Figure 1. Elaboration of value-influencing data quality criteria.

for the task to be executed [11][37]. Accessibility describes the availability and retrievability of data [11][17] (e.g., no storage in data silos, but linked databases). Consistency is the degree to which data matches its semantic definition [11]. Timeliness means that data is current and regularly updated [11][17]. Relevance implies that data is applicable and useful for the task to be executed [17]. Usage degree describes how frequently a data set is used [40]. Portability represents transferability to other usage targets [41], e.g., sales data are additionally used for product recommendations. These quality criteria and their influence on data value will be validated within the expert interviews.

3. Study Design

3.1. Research Method

A qualitative study was designed in order to gain further insights. We adopted the method of expert interviews using a semi-structured questionnaire [42][43]. This enables to benefit from the interviewee's diverse backgrounds or perspectives and to understand their point of view towards monetary valuation of data as richly as possible [42][44]. The semi-structured composition allowed to deviate from the guideline in order to keep the discussion flowing, to pose in-depth questions and adapt the question-wording [43].

The final guideline comprises twelve questions [45]. Participants were asked about their background, when and in which context they started working on data valuation and how they value data themselves. Afterwards, they were asked about relevant factors in data valuation, how reliable they consider accounting valuation approaches and which role data quality plays in data valuation. Subsequently, participants answered how they judge the influence of specific quality criteria on data value (cf. criteria derived in 2.2). Finally, it was discussed which challenges will be most critical for future data valuation. Most questions were framed

open. Merely questions on data quality criteria influence and reliability of accounting methods were answered on a 5-Point-Likert scale, including explanation of the according choices by the experts. As a requirement, we planned to conduct interviews until data and inductive thematic saturation occurs. Data saturation relates to data collection process and describes the degree to which new data repeat what was expressed in the previous data. Inductive thematic saturation relates to the fact that no further codes or themes emerge from further interview data [46]. Furthermore, it points to sufficient number of subjects.

3.2. Selection and Acquisition of Study Subjects

For selecting the experts, two main criteria were considered: 1) background diversity, i.e., researchers and practitioners, to obtain rich perspectives on the topic and 2) depth of individual experience to maximize insights [47]. After screening publications on the topic of data valuation and monetization, existing lectures and webinars as well as workshops and white papers, nine experts were identified. To acquire qualified experts according to the selection criteria and to avoid validity issues, no more experts could have been acquired for this study. The potential interviewees received a brief explanation of the study to align the criteria fulfilment. Two experts were excluded, as the identified skills did not completely meet the selection criteria. One expert did not reply. Table 2 shows the profiles of the six selected interviewees. Similar expert interview studies also obtain five or six experts in order to gather sound empirical results [48][49]. All experts dispose excellent experience for data valuation in accounting & finance, sharing economy, management or industrial production.

3.3. Data Analysis and Threats to Validity

Interviews were guided by one of the authors of this work, appearing as a co-expert for exchange at a higher

Table 2. Interviewee Profiles.

ID	Role	Organization	Experience	Years of Experience	(1) Research (2) Practice	View
E1	Managing Director, Senior Researcher	IIoT Platform, Research Institute	Workshops, Lectures, Practical	10	(1) + (2)	Industrial Production
E2	Head of Controlling	Power Supplier	PhD value-based data valuation	7	(2)	Accounting & Finance
E3	Full Professor, Managing Director	Technical University, Cyber Security Startup	Lectures, Seminars	8	(1) + (2)	Accounting & Finance, Damage Assessment
E4	Division Manager	Research Institute Software & System Technology	Publications on Data Valuation & Economy	6	(1)	Sharing Economy & Data Ecosystems
E5	Division Manager	Research Institute Corporate Development & Business Models	Publications on Digital Asset Pricing, Webinars	5	(1)	Service Management and Industrial Production
E6	Director Valuation Department	Management Consultancy	Workshops & Lectures on Approaches for Data Valuation and Intangibles	12	(2)	Enterprise Valuation & Finance

professional level than with a layperson as interviewer [50]. From 2020-07-22 to 2020-08-12 six individual interviews were conducted in German language using Microsoft Teams. The interviews were audio-recorded and transcribed by the interviewer right after each interview using the software MAXQDA.

Thematic coding was adopted [51] using a mixture of a priori and emergent coding based on theory presented in section 2. The codes emerged from raw, transcribed interview data, combining data from all transcripts to ensure that the full data set is covered in the synthesis of findings. The coding consisted of three steps: (1) descriptive coding, (2) categorical coding and (3) analytic coding. Step one was a simple summary or labelling of relevant sentences respective phrases in a few words. Descriptive codes having things in common were combined on a higher aggregation level to categories. Finally, the connections between categories were examined in the analytic coding step. They result in method-related requirements, influence specification of quality criteria on data value and challenges for future data valuation. Within the coding, inductive thematic saturation occurred, indicating sufficient number of interviewees. After coding, the results and citations were translated into English. Maxwell identified five threats to validity in qualitative research that also apply

to our study design [52]. Threats are described in table 3 including countermeasures taken in this study to avoid them.

4. Study Results

Results are divided into three areas: valuation method-related requirements, data quality-related findings and high-level challenges in data valuation.

4.1. Data Valuation Method Requirements

After demographics, experts (E) described their approaches to data valuation. Five apply cost-based approaches and four combine cost-based approaches with a usage facet, i.e., they consider target and frequency of data usage. E6 strictly follows the IAS income method. Beneath E5 and E6 all adapted existing valuation methods by combining them with further aspects such as future cashflow calculations or data usage. This means, they favor multi-dimensional approaches, incorporating costs, data quality, type and data usage or data management aspects. For E6, traceability and objectivity respective objectifiability of the method is considered as being most important. These aspects also arise from accounting approaches, which always require traceability and objectifiability.

Table 3. Counteracting against Threats to Validity in Qualitative Research.

Threat	Description	Countermeasure
Descriptive Validity	Not all relevant data collected during an interview.	Recording of interviews; transcribing with MAXQDA; taking notes and enrich transcripts with them; verbatim transcription.
Interpretation Validity	Possible misunderstandings between subjects and interviewer.	Interviews in mother tongue of subjects and interviewer; screen-sharing of relevant definitions; background research on subjects; verified fulfilment of selection criteria in advance.
Researcher Bias and Theory Validity	Researchers interpret results of the interviews in a way that serves their goals or initial theory.	Openness to interview outcomes; starting requirements and theory development after interviews; aiming to capture rich insights from interviews.
Reactivity	Subjects behave differently because of interviewer's presence.	No avoidance possible; awareness of possible influences on observations.

Subsequently, the experts rated which accounting approach delivers the most reliable value of data, i.e., closest to a real data value that could be balanced, on a 5-point-Likert scale (1 = not reliable, 5 = highly reliable). Market-based is considered the most reliable method (mean = 4.5, standard deviation (std. dev.) =0.84), followed by income- (mean = 3.67, std. dev. = 0.52) and cost-based (mean = 2.83, std. dev. = 1.33) methods. E6 values data as a segment of other intangibles, not as standalone asset. Although the experts apply mainly cost-based approaches, the market-based one is considered most reliable. E2 states "A price available in an active market represents what everybody believes and relies on". But due to limited spread of data markets, the market-based valuation can hardly be implemented in present. In contrast, cost-based approach marks the starting point for data valuation and obtain a minimum value (E1, E3, E4). According to E4 and E6 the approach enables an objective evaluation from an internal enterprise perspective and represent an improved basis for investments in digital transformation. E2 and E5 apply modified cost-based methods in their approaches but criticize the design of existing accounting methods: the more expensive the production, processing and maintenance of data, the more value it ultimately has. High costs could also be the product of mismanagement of processes and resources, which could make a higher value seem less meaningful. Furthermore, uniqueness of data is named by E3 and E5 as being highly relevant in data valuation, as unique data represent "data treasures". In addition, E1, E2, E6 state that occasion of the valuation needs to be clear and differs in various cases. E.g., small and medium sized enterprises might have other goals in valuing data compared to large enterprises. All experts recommend to incorporate the usage aspect in future data valuation approaches. E3 and E5 propose to extend this in future by incorporating underlying business models. According to all experts, there is a relationship between data usage, quality and value: type of usage influences the required level of data quality which in turn influences data value.

Based on these results, we derived eleven requirements (R) for data valuation methods, designed to assess a quantitative data value. We transfer these requirements into a conceptual model that describes requirements for the method itself and requirements on which data characteristics to include in the method (cf. figure 2). The model includes the objects "Data", and "Valuation Methods" and shows their attributes and relationships. Valuation methods result in a "quantitative value assessment", if the specified requirements are included. Quantitative valuation methods shall be traceable (R1) and objective (R2) or at least objectifiable. In addition, they shall consider several dimensions (R3) to obtain a realistic data value. R1 - R3 thereby align with existing requirements from IAS standard. The methods should build on existing methods (R4), so they have not do be developed from scratch. Application should always take place under clear occasion (R5), i.e., data valuation has no self-purpose but is foundation to assess specific goals and outcomes. Furthermore, valuation methods shall incorporate several data attributes. Namely type of data (R6), costs (R7), usage (R8) and quality (R9). R6 - R9 enable alignment of least required criteria for data valuation. Further aspects, such as degree of uniqueness (R10) and data management (R11) also need to be recognized. Using these requirements for developing data valuation methods enables researchers to start on common ground and derive data valuation methods, resulting in a quantitative, comparable value.
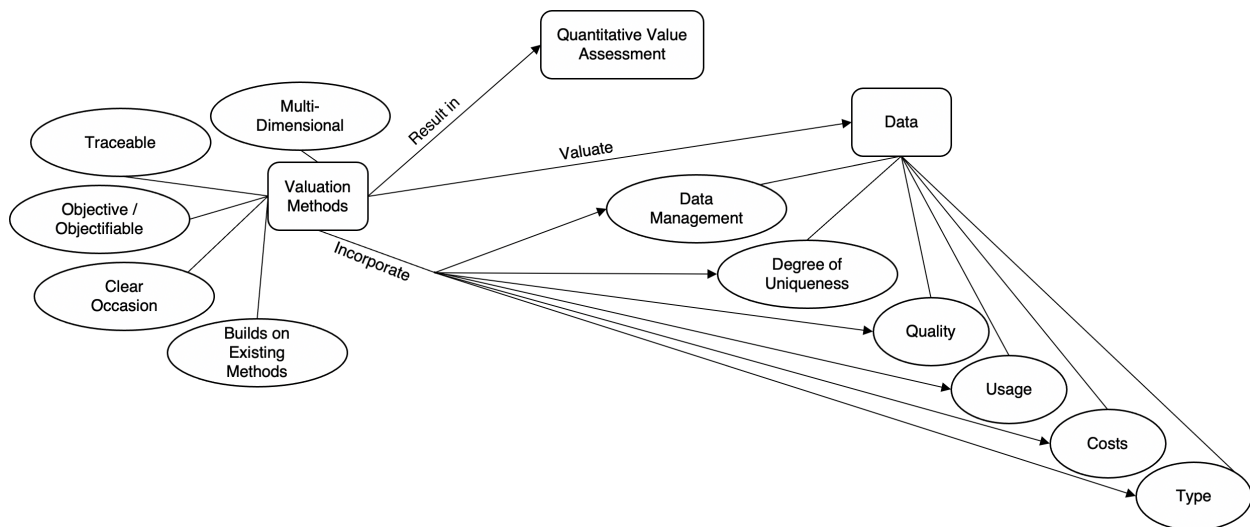
Figure 2.   Concept of Data Valuation Methods.

4.2.   Role of Data Quality as Value Indicator

As of prior results, data quality is required to be incorporated in data valuation methods. This aligns with literature reviewed in section 2. Poor data quality reduces the value of data assets in an enterprise if their utility is low [12]. To gather information on the relationship between data quality and value, the experts were asked to consider the influence of data quality on data value. The overall influence from data quality on data value was rated high to very high (mean = 4.5, std. dev. = 0.45) by all of the experts on a 5-point-Likert scale ranging from very low influence (1) to neutral (3) to very high influence (5). It is considered as one of the central dimensions for determination of data value. E2 – E5 state, the percentage height of data quality will depend on the target of use. E5 points to the fact, that "a higher data quality for one use case and a lower data quality for the other use case" might be sufficient. But low data quality in general leads to higher personnel costs according to E5: "80 % of work in customer projects is data preparation and not data analysis". E3 states that in real world, enterprise "data is not always where and how you want it to be. They are redundant, they are outdated, they do not fit together. So this will play a big role for deriving data value in future." E6 expresses the role of quality criteria in terms of cashflow prediction: "With a scale of data quality, it is difficult for me to evaluate the monetary aspect, but it is a matter of knitting cashflows or some kind of planning calculations around it, and the better my data quality is, the lower the risk that my cashflows or future profit contributions are slumbering somewhere, accordingly it is certainly easier to forecast the future profit contributions and this

would then be reflected." In addition, E4 considers "the influence of data quality on the value of data to be very high. But one has to differentiate between individual data quality criteria. Because there is a very large number of different characteristics that can be taken into account. And here I think that some have more influence than others."

In a next step, the experts rated influence strength from eight specific data quality criteria on data value on a 5-point-Likert scale. According quality criteria were derived in section 2.2. The mean of single quality criteria influence ranges from 4.00 to 4.50 except for usage degree (mean = 2.83, std. dev. = 1.47). Accessibility and completeness represent criteria with the highest influence on data value. The experts described their view on the influence of quality criteria and why it is important to fulfil the criteria. These explanations were aggregated within coding and are presented in the following.

- Accuracy: Inaccurate or false data leads to high costs or total value loss for data. (mean = 4, std. dev. = 0.63)

- Completeness: Incomplete data leads to (1) processing costs for adding missing values, (2) mistakes through distorted decision bases. (mean = 4.17, std. dev. = 0.75)

- Accessibility: Having less or inaccessible data will lead to less data value, e.g., through rising costs when searching for data. (mean = 4.5, std. dev. = 0.55)

- Consistency: Inconsistencies can lead to: (1)

processing costs, (2) mistakes through distorted decision bases. (mean = 4, std. dev. = 0.89)

- Timeliness: Degree of timeliness depends on usage aim, but there is more tendency towards current data enhancing data value. (mean = 4, std. dev. = 1.09)

- Relevancy: Using non-relevant data will lead to more time consumption and higher costs. (mean = 4.33, std. dev. = 0.82)

- Usage degree: The usage degree can but does not necessarily influence data value. (mean = 2.83, std. dev. = 1.47)

- Portability: Using one dataset in different contexts can lead to more savings or income. (mean = 4, std. dev. = 0.63)

As usage degree was rated as neutral to rather low influence, it is excluded as value-influencing factor. The seven remaining quality criteria are considered as value-influencing and should be incorporated in future quantitative data valuation methods.

4.3. Challenges in Data Valuation

We divided challenges formulated in the expert interviews into accounting-, legal- and IS-related and present them in the following.

Current standards in accounting are outdated when it comes to valuing data (E1, E2, E5, E6). Data valuation and resulting data-driven business models are considered highly relevant for investment decisions in digital transformation and for realistic representation of company value. Still there exist no consistent quantitative data valuation methods. Data are ineligible for recognition in balance sheets if they are not traded (E6). In contrast, all experts state that data still are highly valuable without being traded, e.g., in terms of optimization, cost reduction or similar. In future, accounting standards need to be adapted in order to picture company values in a realistic way. E2 and E5 mention valuation differences between digital companies and old economy companies, as their core resources differ: digital companies' success mainly builds on intangible assets and old economy companies' success on tangible assets. Accounting needs to elaborate, whether companies mainly producing physical products are allowed to balance data and how or whether this will differ from valuation of digital companies. In addition, it needs to be discussed, whether old economy companies developing new data-driven business models need to

be treated differently, due to different core business and company structure. This means, accounting needs to elaborate valuation rules for data assets, in order to picture the complete value of a company through financial statements.

In addition, these new valuation rules need to be validated through legal entities by refreshing rules and standards for accounting, such as IAS. Furthermore, due to European General Data Protection Regulation (GDPR), storing data is aggravated for companies, which could prevent from a comprehensive data valuation. Customer data could be omitted in this case. In addition, data usage restrictions are not covered by Copyright Act §31. In case of data trading, this could lead to misuse or double valuation (E2, E3, E6). Therefore, adapting copyright and usage laws is necessary.

IS challenges are related to data security, data governance and automation of valuation approaches. E2 and E6 state that making relevant data available and identifying them in terms of data governance will be crucial when starting to adopt data valuation methods. IS needs to provide methods for cost-efficient recognition of relevant data. Furthermore, automatizing identification and data valuation techniques for reducing costs and efforts in data valuation will be essential (E4, E5). If data values are stated in financial statements in future, data security in IS needs to be increased, due to the fact that valuable data could attract more cyber criminals (E2, E3).

5. Discussion and Outlook

Goal of this work was to specify requirements for data valuation methods. Value-influencing data quality criteria and challenges in data valuation were examined. Building on empirical results from expert interviews, we derived eleven requirements for data valuation methods. These partly align with existing literature (cf. table 1) and extends it further. Dimensions for valuing IS success comprise quality, usage and benefit [35]. Within the requirements, recognition of quality and usage are incorporated. Furthermore, the aspect of costs reflects the financial perspective of benefit. In addition, seven further publications incorporate costs and four incorporate usage facets into their valuation methods (cf. table 1). The literature review on valuation methods in table 1 revealed that multi-dimensional approaches for data valuation, incorporating several aspects seem promising. This fact was confirmed by the empirical results. Requirements of multi-dimensionality, traceability or objectifiability align with IAS. We defined value-influencing quality

criteria building on literature and validated them within expert interviews. Furthermore, we describe how these quality criteria might influence data value according to the experts. Future challenges in data valuation move in the accounting, legal and IS-related context. These require renovation of accounting standards, legal regulations as well as increasing data management, data security and automation in IS. This further tackles IS research in terms of transferring and enhancing known and extended concepts to companies' IS.

This paper is subject to several limitations which need to be overcome by future work. First, we performed qualitative interviews with six qualified experts. Additional quantitative studies could enhance knowledge on influence of data quality on data value and evaluate the requirements derived. Second, the results indicate a strong relationship between data value, usage and quality. The investigation of this relationship and especially the role of usage could be enhanced in future work, e.g., by defining minimum data quality level requirements for specific data usage concepts. Third, the measurement of quality criteria was only recognized within elaboration of value-influencing quality criteria. In future research, objective and automated measurement of data quality and data value could be examined in order to meet the interviewees mentioned challenges on automation of valuation. Fourth, this work rather focused on company-internal valuation of operational data. With upcoming data ecosystems such as the European GAIA-X initiative, a shift towards market-based data valuation is expected. Nevertheless, the requirements derived for valuation methods will be applicable as they reflect general relevant requirements. Still, the expansion of data ecosystems could further support data valuation as aspects such as willingness to pay by market participants could be included into data valuation approaches.

The contribution of this work is threefold. First, requirements will support researchers in developing data valuation methods that build on literature and empirical results. Second, we elaborated seven value-influencing quality criteria, evaluated by experts and with a description of their influence on data value, suitable for application in valuation methods. Third, future challenges for data valuation are determined to direct accountants, lawyers, information systems and computer science researchers to prepare and develop cross-domain data valuation methods.

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