# From Qualitative to Quantitative Data Valuation in Manufacturing Companies

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**Abstract.** Since data becomes more and more important in industrial context, the question arises on how data-driven added value can be measured consistently and comprehensively by manufacturing companies. Currently, attempts on data valuation are primarily taking place on internal company level and qualitative scale. This leads to inconclusive results and unused opportunities in data monetization. Existing approaches in theory to determine quantitative data value are seldom used and less sophisticated. Although quantitative valuation frameworks could enable entities to transfer data valuation from an internal to an external level to take account of progress in digital transformation into external reporting. This paper contributes to data value assessment by presenting a four-part valuation framework that specifies how to transfer internal, qualitative to external, quantitative data valuation. The proposed framework builds on insights derived from practice-oriented action research. The framework is finally tested with a machine tool manufacturer using a single case study approach. Placing value on data will contribute to management's capability to manage data as well as to realize data-driven benefits and revenue.

**Keywords:** Data value · Data valuation framework · Industry 4.0 · Intangible assets · Case study research

## 1 Introduction

Through transformation by Industry 4.0, manufacturing companies become data-intense environments, supporting transmission, sharing, and analysis of data [1]. Using and analyzing these data becomes a necessity for economic survival [2]. Manufacturing companies improve processes and decision making, offer new services and business models based on data, e.g., through selling machine process data on top of the machine itself [3–5]. Although data seems a valuable asset, numerous challenges are related to discovering data value. Existing metrics and measurement tools struggle to value data consistent and comprehensible [6]. Therefore, data are seldom reported in balance sheets


Published by Springer Nature Switzerland AG 2021
A. Dolgui et al. (Eds.): APMS 2021, IFIP AICT 631, pp. 172–180, 2021.
https://doi.org/10.1007/978-3-030-85902-2_19

or management reports [7]. Furthermore, most data valuation approaches are of qualitative nature, i.e., they do not result in a quantitative, monetary value. Transferring external accounting valuation approaches to data, i.e., cost- income-, or market-based, failed until today. Due to absence of markets, data are rather valued company-internally based on quality, usage or costs. Internal valuation means that company-internal stored data are valued without exchanging results with third parties, i.e., no cash flows are generated. External data valuation implies that valuations are exchanged with third parties or value and cash flows are generated through selling data themselves. In this paper, we present a framework that specifies the process from internal, qualitative to external, quantitative valuation in order to strengthen potential data monetization. Based on extensive literature review and action research, we develop a theoretical four-step valuation framework. It includes criteria-, cost-, reporting- and transaction-based data valuation methods. Framework evaluation is performed through a theory-testing single case study together with a large machine tool manufacturer [8]. We wrap up the paper with a conclusion and future work description. Thus, we provide manufacturing companies with tools and knowledge for valuing and monetizing data as an asset.

## 2 State of the Art

Data value can basically be determined by deriving either a non-financial, i.e., qualitative, or financial, i.e., quantitative, value. An initial overview of the distinction between qualitative and quantitative approaches and their different objective dimensions is provided by the Gartner framework [9].

### 2.1 Qualitative Data Valuation Approaches

The result of case study research by Otto implies qualitative measurements to be suitable in drawing more attention to data as a resource and to uncover cause-effect relationships between data and business value [10]. Laney takes up this point and defines three qualitative value measures: intrinsic, business and performance. Intrinsic value evaluates data sets in terms of predefined data quality dimensions. Business value describes the fulfillment of usage requirements of the considered dataset that arise from relevant business processes. Finally, performance value provides information about contributions of considered datasets to achievement of business goals [9].

### 2.2 Quantitative Data Valuation Approaches

In order to determine monetary value of data in business context, Moody and Walsh examined the three major asset paradigms in accounting theory as approaches for quantitative data valuation methods: Cost (Historical Cost), Market (Current Cash Equivalent) and Utility (Present Value) approaches [11]. These were also included in the Gartner framework [9]. While describing pros and cons of the paradigms in context of data valuation and developing general principles and ideas for valuing data, they do not provide a complete methodology [11]. More sophisticated approaches, e.g., by Zechmann (Usage based) or Heckman (Market based), build upon the qualitative analysis of data sets with regard to impact correlations and data attributes [12, 13]. They incorporate costs, quality criteria or specific usage aims for data sets within their approaches. Next, we present a framework to sensitize potential users to the topic of data evaluation and the dependence of qualitative and quantitative evaluation methods. The framework illustrates the procedure of a data valuation process.

As result of the literature review, we compare existing approaches with our proposed data valuation framework (cf. Sect. 3). Criteria include (1) deployment of method in manufacturing context, (2) integration of several valuation methods into one framework and (3) whether the methods are applied practically. Thereby we rate, whether a criterion is fulfilled (x), partly fulfilled (o) or not fulfilled (-). We summarize this within Table 1.

**Table 1.** Comparison of Literature to Envisioned Framework.

| Publication | Manufacturing context | Integration of valuation methods | Method application |
|---|---|---|---|
| Otto (2015) [10] | o | - | - |
| Laney (2017) [9] | - | x | o |
| Moody & Walsh (1999) [11] | - | - | - |
| Zechmann (2018) [12] | o | o | x |
| Heckman (2015) [13] | o | - | - |
| This study | x | x | x |

## 3 Proposed Framework

We propose a four-step data valuation framework for manufacturing industry based on extensive literature research and practice-oriented action research [14]. The data valuation process is described as follows: First, data are valued by ranking criteria of usage and quality for datasets. The second step values data quantitatively by deriving a monetary value based on costs, incorporating usage and quality from step one. Furthermore, sharing an enhanced criteria-based data valuation within a management report enables a reporting-based, external valuation of data. The fourth step represents transaction-based data valuation, i.e., a quantitative data value is derived externally through selling data, e.g., solely or as part of a new business model. We categorize the four steps in Table 2, assigning them to internal or external, respectively qualitative or quantitative valuation context. In general, we recommend to apply the full integrated valuation framework iteratively from (1)–(4). Still, independent application of the single approaches is possible. Within the next sections, we describe the detailed framework steps for data valuation in manufacturing.

**Table 2.** Categorization of data valuation approaches

| | Qualitative valuation | Quantitative valuation |
|---|---|---|
| Internal valuation | (1) Criteria-based | (2) Cost-based |
| External valuation | (3) Reporting-based | (4) Transaction-based |

**Criteria-based Data Valuation.** Use of data is one of its essential value drivers [11]. If data remain unused, they are valueless to the company, but cause costs that arise in the course of data value chain [15], e.g., for collection, processing and storage. Aim is to identify data-driven business processes that generate highest added-value through data use. Related work in manufacturing context addresses the issue of qualitative data ranking when starting data valuation activities [16]. Especially steps one to three of the six-phase assessment are of particular importance for a qualitative ranking of relevant data sets. Step one serves to initially determine most valuable data sets for the considered system or company segment in the form of a data catalog. To accomplish step two, a catalog of relevant use cases for the data sets based on step one is defined. Subsequently data attributes (e.g., data quality, data sourcing, data processing and analysis) and threshold values are established in step three as every use case has different intrinsic requirements regarding aforementioned attributes [16]. Data quality represents one of the most important data attributes. Defining quality level of data gives an impression on the fit of data to usage targets. Assessing data quality is broadly covered in literature [17–19]. For valuing data internally on a specific valuation date in manufacturing context, the following quality criteria for acquisition and storage of data could be included: completeness, conciseness, relevance, correctness, reliability, accuracy, precision, granularity, currency and timeliness [20].

**Cost-based Data Valuation.** After criteria-based valuation, internal accounting approaches for cost-based valuation are adapted. This enhances understanding of data cost structure, enables better data planning, controlling, coordinating and decision making. Furthermore, it prepares the determination of minimum data value for future data monetization (cf. step (4)). Within cost accounting, costs for material, production and maintenance are summarized. Regarding data, costs arise for collecting, storing, pre-processing and maintaining [21]. In manufacturing context, collection costs can be captured by sensor costs. Assuming 0.42 € per sensor attached to a machine, collection costs for resulting data sets equal 0.42 €. Storage costs depend on companies' infrastructure. While Amazon Web Services offer 1GB storage for 0.019€ per month, a local storage infrastructure might be more costly. Pre-processing costs are linked to data structure and quality. Neatly collected, structured data need no pre-processing before using them, whereas semi- or unstructured data with lacking quality will probably produce more costs. Maintenance costs include overhead costs per data set for hardware (e.g. PCs), software (e.g. ERP-system), personnel (e.g. Chief Data Officer) and IT-security (e.g. security system). By applying adapted cost accounting techniques for data, interrelated costs should be collected, summed up and documented. They result in a quantitative, financial data value [21]. Furthermore, level of usage and data quality are considered and yield to value impairment or enhancement. E.g., a quality level of 98% enhances data value, while quality levels below 50% decrease data value by a percentage of 5%. An application example will be presented in Sect. 4.

**Reporting-based Data Valuation.** Building on a broader understanding for potential usage and value of existing data, developing qualitative data reporting for external data valuation is the next step. Within annual financial statements, companies report on their financial situation and success in a complete, reliable and concise manner. Aim of these statements is documentation, profit determination and information. It should represent all value-relevant information. For example, if revenue streams and business models build on data, they should be included in the statement. Still, data are seldom reported in annual statements [7]. Therefore, we propose to report on data in terms of an integrated data reporting within the annual financial statement, in the style of sustainability reporting. CSR is also added to the management report, which is part of the financial statement [22]. The data report includes for example descriptions of data strategy, i.e., data use, and quality (cf. step 1), data governance, data finance (cf. step (2)) as well as technical aspects and data security. Within this report, potentials and risks of data are presented. Through publication of the annual statement, including management and data reporting, the significance of data for the company is noticed by third parties, e.g., competitors or potential collaborators. This can lead to cooperation with third parties, e.g., by developing new business models together or through monetizing data by enhancing data trading, as presented in the next step of our framework.

**Transaction-based Data Valuation.** The framework concludes with the transaction-based data valuation through direct data monetization. In its simplest form, data can be sold directly to a customer or possibly be traded on marketplaces. Existing business models, such as those of SCHUFA [23] or IOTA market places [24], are based on this form of data monetization. Nevertheless, many companies, especially in the manufacturing sector, hesitate to sell data directly or offer it on marketplaces as they do not know how much of their own existential know-how is represented in the data and what the value of their data is [25]. However, new data-based business models, such as the as-a-Service or subscription-based business model, enable direct data monetization through a participatory business approach for manufacturers [26]. Due to the fact that these new business models are not viable without data from the customer operation phase of products [27, 28] such as the rotation of a spindle for usage-based billing, it is reasonable to assume that the value of this specific data corresponds to the value of the recurring revenues from this business relationship [29]. With the customer lifetime value (CLV), there is an existing approach to calculate the recurring revenues from subscription business models over the entire lifetime of a customer relationship [30, 31]. With a total of all calculated CLVs within the customer or subscriber base, the data within these new business models can be endowed with an exact monetary value.

# 4 Case Study

## 4.1 Methodology

We derived the valuation framework based on existing literature and the practice-oriented action research approach. Quantitative data valuation for manufacturing companies is explorative in its nature, calling for an open, explorative research approach. Therefore, we adopted deductive application of case study research [32, 33]. We applied the proposed valuation framework together with a large German machine tool manufacturer from Nov 2020–Feb 2021. Within the company, we conducted interviews and performed the four parts of the valuation framework with Head of Process Management, Head of Corporate Master Data Management and Head of Subscription. During the case study, further departments, such as controlling, accounting, information technology department or higher management level have been included. The following section describes our results.

## 4.2 Case Study Results

Applying the criteria-based valuation method, we set up a data catalog together with the case study partner. The data catalog consists of 11 customer-related data sets, e.g., historic purchase data, machine runtimes or historic service errors. In a first step, the data sets were ranked regarding certain criteria, such as their frequency of use or their timeliness. Together with an interdisciplinary team of experts within the company, a use case catalog was developed as well, consisting of 17 use cases, e.g., potential for sales of new machinery, potential for additional service business or potential for increasing service efficiency. Afterwards, the data sets were linked to the use cases to identify and rank the data sets with the highest potential of further monetary relevance. In a last step, the findings from the criteria-based rankings were compared, indicating that the machine-related data sets, which have a high potential value, are qualitatively not sufficient for broad use, especially in terms of timeliness. In this context, specific requirements for the real-time capability of data acquisition have already been formulated.

Criteria-based valuation indicates high value for machine-related data. In a next step, cost-based valuation is applied to machine usage data, stored in the CRM system of the company. More accurately, we valued a sample of 100 customers in automotive context. Collection, storage, pre-processing and maintenance costs are evaluated. Machines delivered to customers are already equipped with measurement sensors and settled via customer payments, i.e., they do not produce collection costs in the first place. For the storage costs, controlling calculated 0.01 € of overhead per customer and month. Pre-processing is unnecessary, as data delivered by customers are already structured. Hardware, network, and security costs that are necessary for data maintenance within the company equal 0.34 € per customer per month. Our partners state that three sales employees, responsible for these customers, need 2% of their working hours to maintain the data. This equals personnel costs of 480 € for all customers per month. Due to current sufficient quality and usage, (cf. criteria-based valuation), there is no value impairment due to these factors. On the valuation date, the cost-based value of the data set equals 6.180 €. Setting up this calculation is uncomplicated from the partner's point of view, as controlling could easily calculate the necessary overheads, and the sales department could give required information on the workload for maintenance.

Conducting integrated data reporting together with the company required answering several questions in context of general data use, quality, corporate digitalization, data governance and finance, data security and legal aspects, as well as technical data management. Answering these questions required discussions with several company-internal departments such as IT-departments, management, accounting. Furthermore, questions on whether data cooperation with third parties take place were not answered due to security concerns. Questions on the overall importance of data for business activities were difficult to answer, as the company does not yet possess a unified data strategy. In general, the machine tool manufacturer representatives appreciated the idea of data reporting, as (1) they needed to deal more intensely with the topic of data, which could lead to a better awareness of data relevance, and (2) sharing the report within the management report could lead to strategic data alliances with third parties in the future.

Starting the transaction-based valuation approach, the case study partner expressed concerns about whether data from the production context would ever be sold. Currently no data is sold directly to customers or traded on marketplaces. However, the company is in the middle of setting up a new subscription business to offer customers a flexible business model tailored to their needs. In this context, three machine-related data sets were defined, all of which are critical to the success of monetization in the subscription business. Since the subscription business cannot function without these data sets, they are compared with the calculated CLV of the potential subscription customers. Therefore, we calculated the value of each individual data set equivalent to the overall CLV of the prospect yearly customer base. In general, the company representatives stated to have achieved a better understanding which data sets provide potential data value, which usage possibilities are there and that profit opportunities based on data exist. Furthermore, they got a better idea of how to initially estimate and calculate data value.

## 5 Conclusion and Future Research

Our work presents a data valuation framework that considers internal and external as well as qualitative and quantitative valuation perspectives. The framework was applied and validated through a single case study approach together with a large machine tool manufacturer. Results show that the framework provides support for enhancing the understanding of existing corporate data quality and usage, value calculations and potential revenues for future data transactions or data-based business models.

Due to the exploratory nature of this work, several limitations need to be overcome by future research. First, we evaluated the framework with a single company and focused on CRM data in the manufacturing context. Additional studies with multiple companies in different domains could enhance the gathered knowledge and could support generalization of the results. Further, more data sets could be considered in order to develop data valuation of the entire data collection of companies. Second, the company's feedback on reporting-based valuation revealed that adaptations are necessary so they are better able to answer the data reporting questions widely. Therefore, we will further develop data reporting together with a management consultancy and iteratively validate the report structure with companies. The framework will furthermore be transferred to a technical prototype, leading companies through the application process, based on future study results.

**Acknowledgement.** This work is part of the research project "Future Data Assets" (grant number: 01MD19010C), funded by the German Federal Ministry for Economic Affairs and Energy (BMWi) within the scope of the "Smart Data Economy" technology program, managed by the DLR project management agency. The authors are responsible for the content of this publication.

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