# Concept for Assessing the Value and Benefits of Manufacturing Data in the Context of Platform-based Business Models

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Manuscript received March 12, 2024; revised April 7, 2024; accepted May 2, 2024; published August 8, 2024.

***Abstract*—Data has the potential to become a key economic resource in the future value creation process of companies and is increasing in importance as data assets. In this context, platform-based business models that coordinate the provision and exchange of data between different players in an ecosystem play a central role. Today, machine and process data is already being collected at the operational level, shared across companies and used by the players in the ecosystem to optimize their own manufacturing processes in terms of resource efficiency and sustainability. However, a central challenge of platform-based business models is that the value and concrete benefits of data shared across companies are in many cases unknown and thus the willingness to share data within an ecosystem decreases. Based on this, a concept of an approach for assessing the value and benefits of manufacturing data in the context of platform-based business models was developed, with a focus on potential users in medium-sized and small manufacturing companies. For this purpose, current requirements for an approach to determine data values were collected and transferred into a 3-step concept of a method. Finally, the concept was validated using a reference use case from the machining industry in order to test the basic applicability of the concept and to identify further development potential.**

***Keywords*—platform-based business models, data value, data ecosystem, data marketplace, machining industry**

## I. Introduction

The importance of data for business models and their economic success has grown steadily in recent years, as the contribution of data to the value creation of companies has also increased. Data is becoming increasingly relevant in all sectors of the economy, starting with the digitalization of industrial production and the ever-increasing use of the internet of things. An example of this are data-driven companies such as Google and Amazon, which have quickly become the most valuable companies in the world, as their value creation is predominantly based on data monetization (Krotova *et al.*, 2019). Nevertheless, manufacturing companies in particular and especially small and medium sized ones are often still at the beginning of structural value creation with data. Although the use of data from value production processes exists as a decision-making basis for optimization projects to generate cost and time savings, the monetary value of the data plays a subordinate role (Demary *et al.*, 2019; Trauth *et al.*, 2021). The management of data not only offers advantages to companies with predominantly digital business models, but also to companies with classic business models that focus on physical products. A necessary building block for efficient data management also across company boundaries is the sharing of data and the associated data valuation to generate a value out of the sharing with partners in an ecosystem. Nevertheless, there is still no valuation procedure for data that has proven to be universally applicable in both business practice and science. The lack of clarity about how an adequate data valuation must be designed leads to companies being overwhelmed in dealing with data and only hesitantly dealing with data management (Krotova *et al.*, 2019). The uncertainty is exacerbated by the fact that existing approaches to data evaluation often cannot be fully transferred to the manufacturing industry, since aspects such as a lack of infrastructure and know-how, but also the issues of data security and loss of knowledge in your core business, are weighted differently. It can be stated that due to a lack of standardized assessment procedures, data assessment in particular is a challenge for most companies an especially small and medium ones in the manufacturing industry (Demary *et al.*, 2019; Heckman *et al.*, 2015). The present research work addresses this need for action for the value and benefit valuation of manufacturing data. Since data exchange across companies is mostly shared via platforms, regardless of the number of actors on the platform and to what extent it is an open or closed platform, the use of such an infrastructure forms the basis for further work.

In the following section, some thematic basics are given at the beginning before the research methodology is discussed. Subsequently the research need is derived before the concept of the approach is presented. At the end, the approach is validated in the last section using a use case from the manufacturing and specific machining industry.

## II. Fundamentals and Research Approach

In the following, brief insights into the basics of platform-based business models and data valuation are given before the research methodology is discussed.

### *A. Platforms*

Platforms, in the business model context, are referred to as two-sided or multi-sided markets, as they intervene as intermediaries of transactions between two or more groups of users (Bundeskartellamt (BKartA), 2019). A platform creates value by facilitating interaction between the different groups (Osterwalder and Pigneur, 2010). The rapid growth of innovative Information and Communication Technologies (ICT) such as the internet and the internet-of-things has

doi:10.18178/joebm.2024.12.3.808

fundamentally transformed platforms by reducing or eliminating the need to own physical infrastructure and assets. In this way, innovative ICTs are helping to build digital platforms that are easily scalable and enable simple participation via the internet, increasing participation on both sides of the user group, which in turn reinforces the positive network effects (Alstyne *et al.*, 2016).

Demary and Rusche (2018) define a digital platform as an enterprise that uses the internet to facilitate economically beneficial interactions between two or more independent groups of users. According to this definition, digital platforms pursue the goal of mediating transactions or interactions between their users, which only could have been found with great effort without the mediation of the platform.

Even if B2C platforms dominate the public perception, platforms in the manufacturing industry are mostly B2B platforms between manufacturing companies (Boehm *et al.*, 2019). These can be understood as marketplaces or data marketplaces, among other things. Specifically, a digital platform can be used within a data ecosystem to enable the exchange of data and trade in data products across company boundaries.

Moore (2006) defines therefore business ecosystems as an economic community of interrelated organisations and people. The ecosystem represents the organisms of the business world. When data plays a central role in an ecosystem, it is also referred to as data ecology.

### *B. Business Model*

Digital platforms and their ecosystems are often based on a platform-based business model. Here, business models of digital platforms differ significantly from traditional product-oriented business models. The latter pursue the strategy of creating competitive advantages by controlling limited material and immaterial resources, optimising all internal business processes and maximising the value of products and services. In contrast, platform-based business models create competitive advantages by orchestrating the resources brought in by the ecosystem and by generating interactions between provider and consumer (Pflaum and Klötzer, 2019).

Digital business models can be described as a business model field category. Guggenberger *et al.* (2020) divide digital business models into data-driven business models and platform-based business models, which are hierarchically subordinate to the digital business models. Hybrid business models are a combination that is frequently encountered in the industry.

The focus of value creation in hybrid but above all databased business models is on the consideration of data as a key resource. The Fraunhofer Institute for Software and Systems Engineering (ISST) (2022) has developed a systematic structure for data-driven business models that addresses the levels of strategy, process and system. At the process level, data evaluation is a decisive building block for the implementation of a data-driven business model. The concept of a method developed below is aimed at precisely this data evaluation in the context of the manufacturing industry.

### *C. Data Valuation*

Data takes on value through its use for specific purposes, in the context of data-driven business models. In this way, it becomes an economic good and intangible asset (The Fraunhofer Institute for Software and Systems Engineering (ISST) (2022). Due to the continuous shift from an industrial-based to an information- and knowledge-based economy, the importance of intangible assets has increased significantly. This is because the competitiveness and existence of companies are no longer defined only by tangible assets such as production facilities and buildings, but also by intangible assets such as customer and supplier relationships, market positions and process and product-related knowledge.

In general, the term value is often unconsciously associated with financial values, but the term value means an assessment made, i.e., a statement as to whether something is good or bad according to a generally accepted standard. Furthermore, value represents a suitable decision criterion for making a choice from a range of alternatives. A distinction can be made between a subjective and an objective measure of value. The subjective value measure takes into account the personal attitude of the person making the assessment as well as his or her expectation of benefit. The objective value measure is independent of the personal attitude of the assessor and does not take into account the assessor’s utility expectations. The value of data is determined by many factors such as time, the amount of data and the ability to integrate it into systems, but also the data quality (Krotova *et al.*, 2019). The latter generally describes the characteristics of a data stock that make it suitable for fulfilling predefined and presupposed requirements. As a value measure, financial variables play a role in data valuation, too. The terms price, costs and benefits are usually used as value measures in this context.

The benefit reflects the amount that will accrue to the owner of the valuation object in the future through its use. This amount is strongly dependent on the subjective management of the valuation object (Zechmann, 2018). In addition to the price and the costs, the benefit represents a value measure for determining the value of an asset. In this context, the benefit is a reflected amount that will accrue to the owner of the valuation object in the future through its use, provided that the valuation object is subjectively managed. An entity can derive a potential benefit from data if it leads, directly or indirectly, to a possible increase in profit, maintenance of profit, avoidance of loss or reduction of loss (VDI/VDE-Gesellschaft Mess- und Automatisierungstechnik, 2022).

In addition to financial measures of value and valuation methods, data can also be valued non-financially. These include quality-oriented, process-oriented and performance-oriented valuation methods. Due to their qualitative orientation, the non-financial valuation methods do not monetize the data values and instead present the data value in the form of indices and non-financial key figures. During the development of the concept in this research, both the financial and non-financial valuation perspectives should be considered.

### *D. Research Approach*

The approach of the present research is based on the phases of an applied research approach according to Ulrich *et al.* (1984). Characteristic for this procedure is the desired practical and theory-based relevance instead of only a theory-based approach. The research approach provides a basic structure and procedure that should be followed when deriving models and methods in the context of scientific work. The detailed steps and allocation of these to content in this paper are shown in Fig. 1.

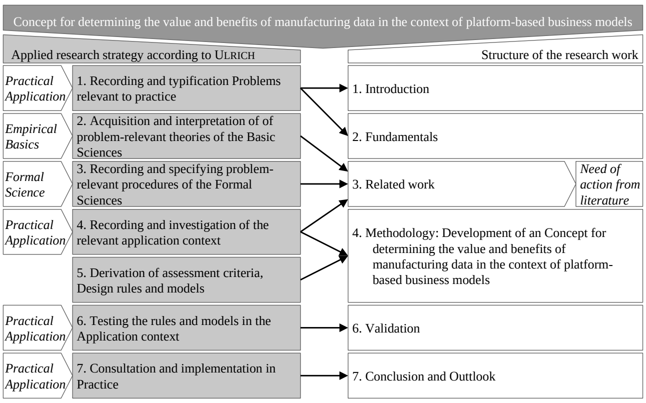

Fig. 1. Research approach according to ULRICH.

## III. RELATED WORK

In this section, related work regarding the valuation of value and benefits of (manufacturing) data in the context of platform-based business models is described and evaluated. By means of an extensive literature search and interviews with researchers from the Internet of Production, a research cluster at RWTH Aachen University, seven requirements for an approach to data evaluation under the conditions assessed in the first section could be derived. These are listed in Fig. 2.

The first requirement "use of data valuation procedures" describes the integration of the financial and non-financial data valuation procedures that are relevant in the context of data valuation in the current literature (Krotova *et al.,* 2019; Hupperz *et al.,* 2022). Further, data quality is one of the most important drivers of the value of data and influences it (Otto, 2015; Stein *et al.,* 2022). The second requirement thus describes the "consideration of data quality" in the data evaluation. The third requirement considers the "identification of data use contexts". Since the value of the identical data can change greatly depending on the context of use (e.g. between analysing data with the goal of increasing productivity or the goal of better working conditions), contexts of use must be defined to ensure comparability between data (VDI/ VDE-Gesellschaft Mess-und Automatisierungstechnik, 2021). The fourth requirement takes into account that an approach and the belonging assessment can handle manufacturing data. In contrast to many other types of data, manufacturing data is often only available in the form of raw data from information technology systems. The fifth requirement demands that, as described in the fundamentals, the data should not only be used for internal optimisation, but that the potential external benefit in terms of monetary value for sharing the data on data marketplaces via platforms should also be taken into account (Trauth *et al.,* 2021). The sixth requirement ensures that the costs of applying a method do not exceed the benefits that can be derived from the valuation. In order for small and medium enterprises to start sharing data across organisations, it is important to ensure that they can assess the value of their data with their limited resources. The last requirement of "objectivity" demands a largely objective value and benefit assessment of production data with objective value measures in order to reduce subjective influences (Stein *et al.,* 2022).

In this research work, various approaches from the literature were analysed and examined. The five-level scale according to LIKERT is used in particular for the evaluation of scientific theoretical approaches in engineering science (Likert, 1932). It is used to uniformly evaluate the suitability of existing approaches in relation to the defined requirements. The visualisation of the evaluation is done with the help of Harvey Balls in Fig. 2.

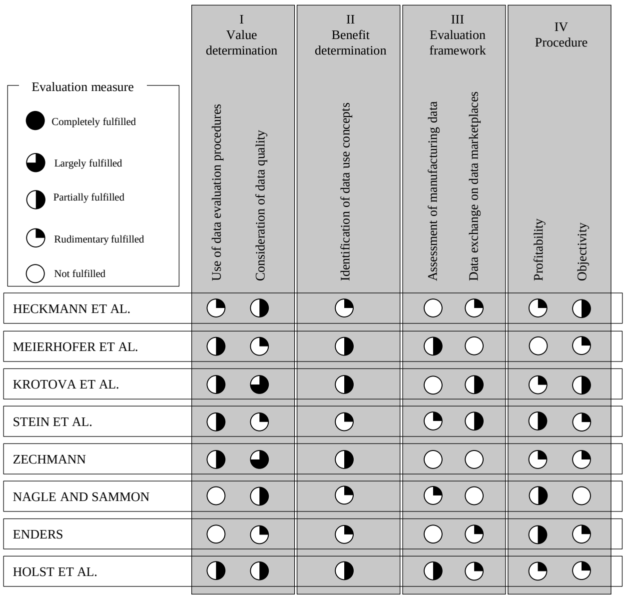

Fig. 2. Evaluation of existing approaches.

Based on a literature search of an initial quick check of currently published approaches, the potentially most promising ones are listed below and evaluated based on previously defined requirements.

The approach according to Heckman *et al.* (2015) outlines a standardized method for valuing data using a linear pricing model. Thereby the approach encounters limitations in the context of the present work, as it requires the development of a classification algorithm for the datasets to be evaluated and subsequent enrichment with training data. Thus, although the approach theoretically has potential for the evaluation of production data as the training data can come from different industrial applications, it remains very complicated and demands extensive preparatory development effort.

The research approach according to Meierhofer *et al.* (2022) investigates the influence of data value in supplier-customer relationships in B2B service ecosystems. The utility value in the form of the return on investment is predominantly used to quantify the data value. The focus of the approach is thus to determine the value of data in the context of data-based services and not to determine the value of stand-alone data products, such as the one-off sale of improved process parameters that generate a benefit for the buyer, as can often occur in the manufacturing industry.

Krotova and Spiekermann (2020) present a data valuation model that is intended to serve as a methodological guide for companies in their data valuation. Although the guide is a promising approach, non-financial data valuation is mainly fulfilled by the quality-oriented valuation procedure. Thus, there is a lack of process- and performance-oriented valuation procedures to assess the internal impact of data on a company. In addition, the reference to production data is missing.

Stein *et al.* (2021) propose a four-step framework for data assessment in the manufacturing industry, which includes the criteria-based, cost-based, report-based and transaction-based data assessment methods. Nevertheless, the approach only provides a framework as a guide for data assessment. The individual steps of the data assessment are not described in detail. Furthermore, the validation of the framework was carried out using Customer Relationship Management (CRM) data, which is why it is open whether the framework is also valid for production data.

Zechmann (2018) develops a usage-based valuation concept to determine the value of a data valuation object on the basis of the future financial benefit generated in the context of data usage in a specifically considered business process and directly attributable to the data valuation object. Since the valuation approach is intended to serve as a supporting management tool, e.g. in corporate controlling, the motive of data valuation is not external data valuation, such as the sharing of data across company boundaries, but internal data monetisation, which means that some aspects of external data monetisation are not fully taken into account.

The approach by Nagle and Sammon (2017) provides a framework that facilitates the development of an organisation-wide understanding of data initiatives. However, the approach does not apply specific data valuation techniques and does not specify a quantitative or qualitative determination of data value. Furthermore, the framework only describes the internal added values of data monetisation; the possibility of data divestment is not given.

Enders' 2018 research approach proposes a four-step research agenda. The approach explores the research question of how organizations can determine the value of their data assets and how this affects data management activities. The proposed agenda aims to drive further research into data value and develop a deeper understanding of the strategic value of data assets to an organization. The exchange of data or the achievement of external added values from data monetization are secondary in the present approach. Further, the approach does not include concrete procedures of data valuation.

The approach according to Holst *et al.* (2020) describes a six-step framework for data evaluation for production companies that offer intelligent Product Service Systems (PSS) in the context of a Business-to-Business (B2B) market. However, production data is only evaluated in combination with product service systems, stand-alone data products are not considered. In addition, the implementation of data valuation for the exchange or trade of data is only mentioned in passing in the context of the developed use cases. Furthermore, data is primarily considered as an asset (data asset) and not as a data product.

As a result of the evaluation of the existing research approaches, it becomes clear that no existing approach succeeds in almost completely fulfilling the criteria defined within the framework of the requirement groups. The following focal points of the research deficits can be identified below:

- The established procedures of data valuation are not found in all existing approaches. Furthermore, mostly only financial data valuation procedures are integrated. The consideration of non-financial data assessment procedures is only fragmentary.
- The existing approaches confirm that the data value is significantly influenced by its data use, but there is no uniform procedure for determining benefit aspects based on data use or generic use cases for reference.
- Some of the approaches evaluated require a high level of resources to determine the value and benefits of data and are therefore unsuitable for small and medium enterprises, where resource availability is limited

Considering the research deficit and following the recommendation of Kubicek (1977), a research question was defined:

*"How must an approach for determining the value and benefits of manufacturing data in the context of platform-based business models be designed?"*

## IV. Methodology

Based on the formal and content-related requirements as well as the objective of this research work, the concept of the method for assessing the value and benefit of manufacturing data in the context of platform-based business models is derived and briefly explained below. In general, the work of Zechmann (2018) which develops a concept for use-based data valuation, serves as the basis for the concept. All in all the conception of this research work is divided into three procedural steps as shown in Fig. 3: definition of the evaluation framework, determination of the benefits of manufacturing data and determination of the value of manufacturing data. The first step of the procedure involves the definition of the system boundaries (framework) and aims at identifying the data valuation objects to be evaluated. In the subsequent second step of the procedure, the benefit of the production data is determined. The data valuation objects identified in step one serve as the basis for determining the benefit of these. The final step of the procedure aims to determine the quantitative value of the production data with the help of data valuation methods in context of each data valuation objects

In order to develop the concept of the approach, it is necessary to delineate the limits of the concept with the help of assumptions to be made:

i. Digital manufacturing data: The data to be evaluated are available in digital format and originates from field-level data sources.
ii. Non-personal manufacturing data: In the context of manufacturing data from production processes, non-personal data is being evaluated.
iii. Data valuation objects: It is assumed that the data valuation objects to be assessed are identifiable, capable of being specified and described, and clearly distinguishable and separable from other data valuation objects.
iv. Automated manufacturing processes: The manufacturing data being valuated originates from automated manufacturing processes that incorporate the data as input and output parameters for manufacturing process use.

As described, the developed approach consists of three successive process steps, whereby each of the three process steps consists of two successive sub-steps, which are explained in more detail below.

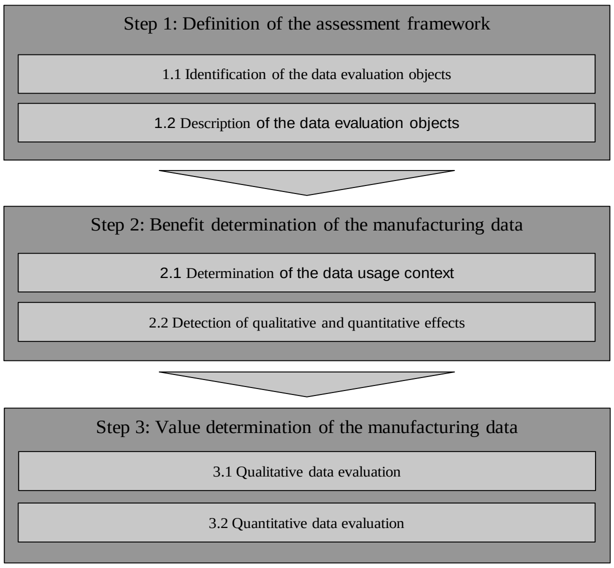


Fig. 3. Overview of the developed approach.

*Step 1.1:*

Manufacturing processes use input and output data to control and program predefined machining operations to ensure safe process execution. In the first sub-step, the focus is on the analysis of the existing manufacturing process with regard to the identification of data valuation objects. Data valuation objects can be in the form of data objects, data records, data tables, digital data documents and databases (Stein *et al.*, 2022).

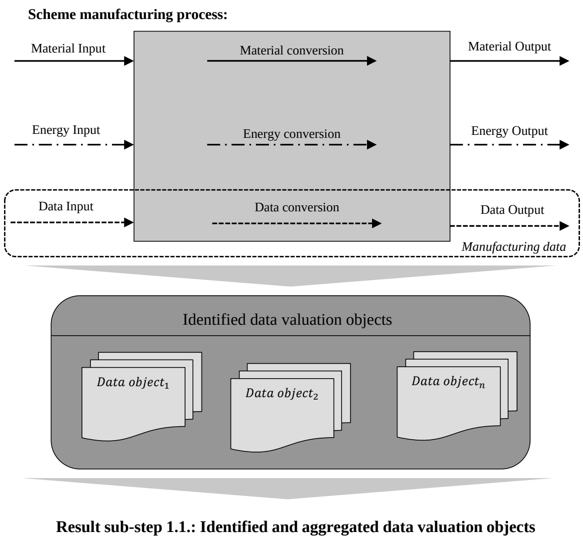


Fig. 4. Sub-step 1.1–Identification of data valuation objects.

Data valuation objects describe data packages that can be subsequently valuated, possibly converted and shared. It must be ensured that the identified data valuation objects are accessible and can be found and extracted with reasonable analysis and research effort, as resources for identification are limited. The identified data objects of the manufacturing process should be independent of each other in order to enable a separate evaluation in the upcoming value and benefit assessment. For this, it is necessary that the data valuation objects are clearly distinguishable and separable from other data (Krotova *et al.*, 2019). In addition, the data valuation objects must be clearly identifiable and characterisable so that they can be interpreted outside the specific manufacturing process environment and are suitable for cross-company data exchange (Kühnl and Sander, 2019). The result of the first step is thus the identified, aggregated and documented data valuation objects.

*Step 1.2:*

After the identification of data evaluation objects in the first sub-step, the second sub-step is about the description of the identified and aggregated data valuation objects. A flow chart was developed to characterise the data evaluation objects. This is shown in aggregated form in Fig. 5.

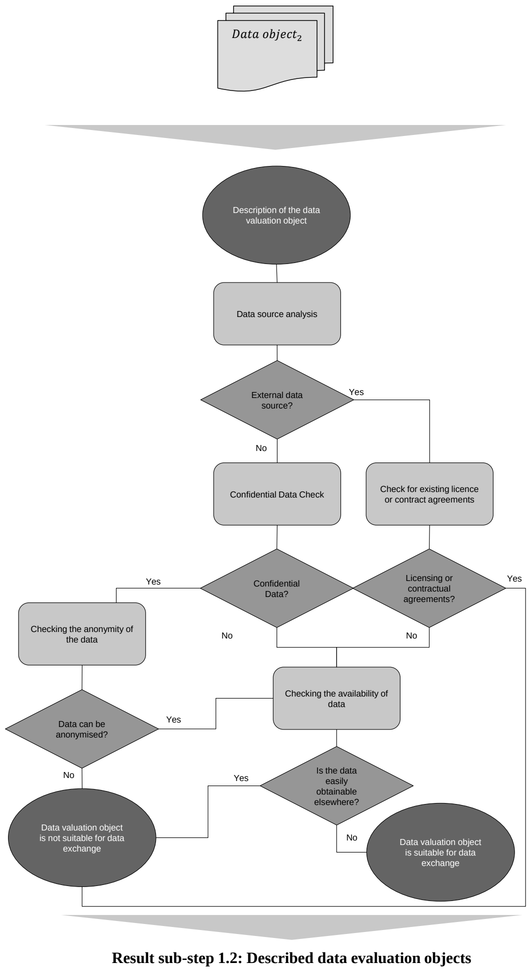


Fig. 5. Sub-step 1.2 – Characterisation of data evaluation objects.

The aim of the characterisation is to examine the identified data evaluation objects for their suitability for cross-company data exchange. First, the data source of the data evaluation object is analysed. If data evaluation objects have an external data source, such as supplier data, customer data or data from platforms, this data must be checked for existing licence or contract agreements, as existing licence or contract agreements may prohibit data exchange in the context of data use. In addition, the confidentiality of the data must be checked. Confidential data is data that represents an essential part of the company's data worthy of protection, such as trade secrets and business model data, and may not be published without further ado. In addition, the degree of availability should be checked. This involves examining whether the data evaluation object can be obtained elsewhere without great effort or cost, e.g. via open data, and thus does not make sense to share from an economic point of view. The result of the second sub-step is the description of suitable data valuation objects that have been checked for their suitability for cross-company data exchange.

*Step 2.1:*

After completing the two sub-steps of the first step, the second one focuses on assessing the benefit of manufacturing data.

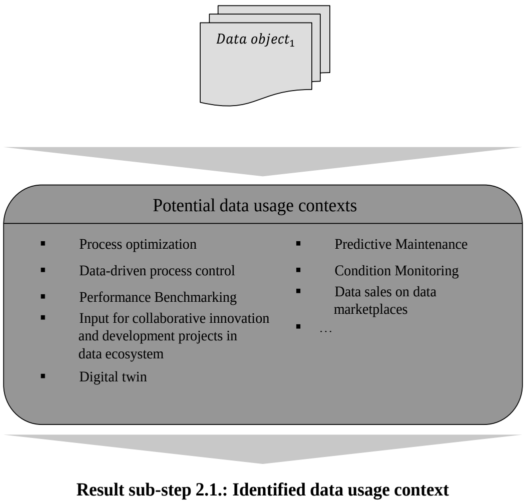


Fig. 6. Sub-step 2.1 – Determination of the data usage contex.

In the first sub-step of the second step, potential data usage contexts are identified for the data valuation objects. The kind of data usage determines the financial value of the data valuation objects through their benefit. The necessity of defining data usage acknowledges the fact that unused data does not generate value in the form of benefit for the company but only incur costs within data management. Therefore, unused data are not only worthless but also a cost source for the company (Stein *et al.*, 2021; Rohde *et al.*, 2022). Data usage contexts describe therefore activities within a manufacturing process that utilize manufacturing data for the purpose of data processing, including data creation, modification, management, retrieval, processing, and distribution. In summary, data usage contexts describe how the data is used to generate a benefit, e.g. through process optimisation. Similar to the identification of data valuation objects from the first procedural step, existing documentation on data flows, data models, and data architectures of manufacturing processes can also be used as tools for identifying data usage contexts. Furthermore, the experiential knowledge of experts gathered through interviews and workshops should be captured and included in the identification of data usage contexts. A potential selection of data usage contexts can be found in Fig. 6.

*Step 2.2:*

Following the identification of potential data usage contexts, the second sub-step involves capturing the qualitative and quantitative effects resulting from the use of manufacturing data. The detected qualitative and quantitative effects in Step 2.2 have resulted from a literature review and the analysis of different best practice approaches from industry. These could be extended context-specifically when the concept is applied.

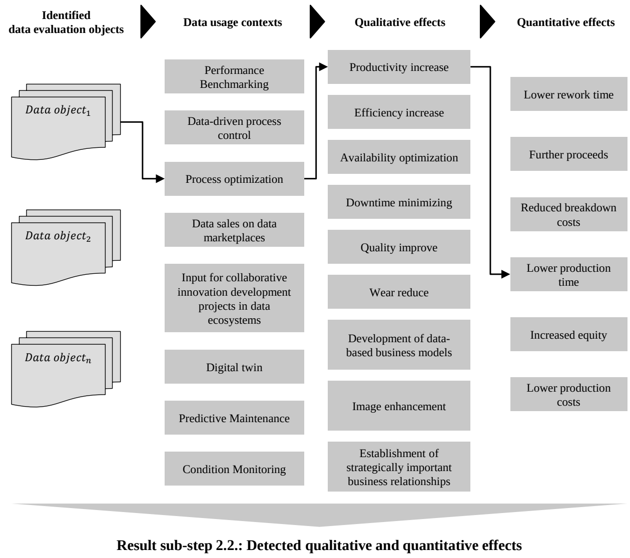


Fig. 7. Sub-step 2.2 – Detection of qualitative and quantitative effects.

The second sub-step is based on a dependency network, represented as a four-column model which is shown in Fig. 7, to capture the qualitative and quantitative effects of data usage contexts. The first column consists of the identified data valuation objects from the first procedural step, which are the manufacturing data to be assessed. The second column lists the potential data usage contexts identified in the previous sub-step, which are associated with the data valuation objects. Finally, the third and fourth columns represent the qualitative and quantitative effects of the data valuation objects resulting from the data usage contexts.

As a first step, it is necessary to assess the potential qualitative impact of data valuation objects in relation to the data usage contexts, which is often feasible by companies on a qualitative basis and is systematised by this sub-step (Meierhofer *et al.*, 2022). It should be noted that a data valuation object is often qualitatively related to many data usage contexts. The combinatorial linkage of data valuation objects and data usage contexts requires extensive knowledge in the form of expert knowledge. The expert must examine the combinatorial possibilities of both variables and evaluate them in terms of technical feasibility and, if necessary, reject them as combinatorial options.

Subsequently, the qualitative effects should be converted into quantitative effects in the next step (column four). The primary focus here is on measures such as time, costs, and revenue or sales. At this stage, the quantitative effect does not need to be precisely measured e.g. through a concrete time value but should be associated with the qualitative effect. In conclusion, the benefit determination resulting from this second procedural step describes the determination of the benefits of manufacturing data based on data usage contexts and the captured qualitative and quantitative effects.

*Step 3.1:*

The third and final procedural step in the approach to assessing the value and benefit of manufacturing data addresses the valuation of the selected data valuation objects in numbers. After previously defining the qualitative and quantitative effects of the data valuation objects, the first sub-step in step three encompasses a seven-step process (seen below) for the specific qualitative measurable valuation of the objects to be assessed.

**Seven steps of qualitative data evaluation:**

1. Selection of data valuation objects suitable for the same data usage contexts and producing qualitatively comparable effects.
2. Identification a representative data quality metric.
3. Assessing the data quality of the selected data valuation objects based on the representative data quality metric.
4. Determining a representative process KPI for measuring the qualitative effect.
5. Conducting the use case.
6. Determining the process KPI for both alternatives of the use case.
7. Calculating the resulting difference in process KPIs between the two alternatives.

In the course of qualitative measurable valuation, the first step is to select those data valuation objects that are suitable for the same data usage contexts and generate comparable qualitative effects through their use. At least two contextually equal data valuation objects must be selected that show a deviation in their data quality compared to each other, i.e., there must be a measurable data quality deficit. For example, two different process parameters such as the feed rate during machining, so that manufacturing can be done more productively on the basis of one process data.

A representative data quality metric is then identified for the assessment of data. Whereupon the existing manufacturing process will be analysed in terms of an existing data quality metric as part of an inventory. The data quality metric describes the degree of fulfilment of the data valuation object in relation to the process-specific requirements of the usage context set by the company's data management and data strategy. Therefore, the data quality metric represents a highly context- and process-specific measure that must be captured based on the respective data usage context. In other words, the data quality metric is a key figure that describes the reliability and accuracy of the data. If an existing representative data quality metric is available for the current data usage context of the manufacturing process, it can be applied to assess the data quality of the data evaluation objects. If no data quality metric is available, the data evaluation objects to be assessed must be analysed in terms of an alternative data quality measurement.

Examples of an alternative data quality measurement are the completeness check of data evaluation objects, the analysis of logical data errors and the filtering of data duplicates. Expert opinions on estimates and forecasts of the frequency of errors in the manufacturing process caused by deficiencies in data quality can also be used. Also the costs incurred by process errors due to data quality deficiencies have shown to be used as a suitable indicator for assessing data quality.

The third step describes the subsequent determination of the data quality of the data valuation objects using the data quality metric determined in the previous step. In the fourth step of the procedure, a representative process KPI should be identified to measure the qualitative value. Depending on the manufacturing process, various process indicators are available for this purpose (e.g. process cycle time). In the fifth step, a simulation of the manufacturing process using the data form the data valuation objects is carried out. In this case, the integration of the data into the production or the simulation is carried out with both the data valuation objects of supposedly lower and higher quality as described in step one. The resulting process KPI is calculated in the sixth step. The calculation of the resulting difference of the process KPIs of the two alternatives of objects with lower and higher quality represents the seventh and last step of the procedure. The calculated difference of the process KPIs ultimately represents the significant increase in qualitative impact that can be attributed to the data quality deficit of the data evaluation objects under consideration.

As a result of the first sub-step for valuing manufacturing data, the captured qualitative data value based on the determined difference in process KPIs is captured.

*Step 3.2:*

The final sub-step of the third step involves the quantitative measurable data valuation (monetary) based on the qualitative measurable value determined in the preceding step of the data valuation objects. The determination of the quantitative data value consists of a six-step procedure. First, a measurement model is to be established in the application context. The measurement model forms the basis for the financial evaluation of the qualitative effects from the preceding step. Thus, the measurement model establishes a relationship between the qualitative data value determined using the process KPI and the quantitative or financial effect. Thus, the financial measurement model is able to derive a data-related cash flow from the qualitative effects identified. In the application context the financial measurement model can be, for example, the machine hourly rate approach evaluated in controlling, which makes time-related process parameters financially assessable. Based on the first step, suitable model assumptions are defined in the second step of the procedure and the characteristic values of the measurement model are determined. In relation to the example, this means that the calculation variables for the machine hourly rate are determined uniformly and coherently and the machine hourly rate are calculated. The third step of the procedure includes the calculation of the quantitative data value using the Net Present Value method. This method represents the conceptually best approach to determining data value and is preferable to market price-oriented and cost-oriented methods (Zechmann, 2018; Meierhofer *et al.*, 2022). This is because the market price-oriented method requires active data markets and the cost-oriented methods determine data value based on past costs without considering current and future benefits (Stein *et al.*, 2022). The calculation of the quantitative data value using the Net Present Value consists of three sub-steps shown below. These sub-steps are the determination of the evaluation period, the determination of the interest rate, and the conversion of the qualitative effects into a data-related cash flow using the established measurement model.

**Determination of the quantitative data:**

1. Establishment of measurement models in the application context.
2. Definition of model assumptions for quantifying qualitative effects.
3. Calculation of the quantitative data value using the present value method.
   i. Determination of the evaluation period and

definition of time periods.

ii. Determination of the discount rate *i*.

iii. Conversion of identified qualitative values into quantitative values using data-related cash flows.

The determination of the evaluation period describes the time periods depicted by the model assumptions. These time periods should have a direct connection to the data usage context and should be able to chronologically represent the difference in Process KPIs obtained from the usage contexts. For this purpose, the time periods of the Net Present Value calculation are to be standardized to the duration of the utilization of the manufacturing process.

Building upon this, the second sub-step of determining the internal interest rate or discount rate within the framework of the Net Present Value calculation should be carried out. A good orientation for this can be provided by the internal discount rates used by the company in investment calculations. It is assumed that this discount rate is risk-free and thus remains constant across all time periods.

Following the determination of the evaluation period and the discount rate, the conversion of the qualitative values derived from the difference in Process KPIs into a databased cash flow can take place. The net present value therefore consists of the sum of the cash flows of the respective periods referenced to the current year. The cash flow includes inflows from revenue increases, cost savings, and efficiency gains that are to be determined for the respective time periods using the established measurement model. For example, identified cost savings should be included as inflows in the cash flow, calculated from the qualitative effects. Additionally, realizations of efficiency gains resulting from increased data quality should also be considered as inflows.

Finally, the determined Net Present Value, based on the established measurement model, represents the quantitative data value of the data evaluation object being assessed.

## V. Validation

### A. Exemplary Use-case in Machining

To illustrate the described methodology, the authors present an exemplary use case from the manufacturing industry: Milling applications in industry are characterized by the use of a large number of different milling tools, each with different machining strategies and process parameters (e.g., cutting speed, feed rate or geometric engagement conditions), which have to be set specifically for the workpiece. Currently, the design of the process with respect to the machining strategy as well as the process parameters depends on the expertise of the programmer and the execution of this process depends on the knowledge of the machine operator. Utilizing real-time production process data allows for the retention of expert knowledge, improvement of process design, speed up the ramp-up of new processes, and enhance both the productivity and quality of existing processes.

With modern CNC machine tools, it is possible to access data such as the axes positions or the turning speed of the tool from machine internal sensors to calculate the above mentioned process parameters parallel to the actual machining. In addition, by processing this internal data with an online material removal simulation more context information regarding the geometric engagement conditions can be derived (Brecher *et al.,* 2021).

In the practice of milling, process parameters like feed rate, which directly correlates with manufacturing time and, consequently, machining productivity, are determined while considering the geometric engagement conditions. Simplified, these engagements conditions consist of two features: cutting depth and cutting width. Depending on the cutting width and depth, the tool manufacturer suggests an optimal feed for one tool, which is often derived from analogy processes but not from real machining processes.

By employing the data foundation described, consisting of process parameters and geometric engagement conditions, valid combinations for process parameters such as the feed and the geometric conditions can be derived directly from the actual production process. These sets of feeds and geometric engagements from real production data describe possible and already productive machining conditions of the considered tool without including user-specific knowledge such as the tool path. Sharing these data sets result into faster process ramp-ups as well as productivity optimization of machining processes (Fig. 8) (Brecher *et al.,* 2023). To implement this approach in production effectively, a substantial database, contributed by diverse stakeholders in the machining industry who use machine tools and tools, is essential. Sharing this data can be facilitated through a platform-based business model. Nevertheless, it is crucial to persuade users of the benefits. One initial aspect to explore this value proposition is to assess the data's value using the methodology described.

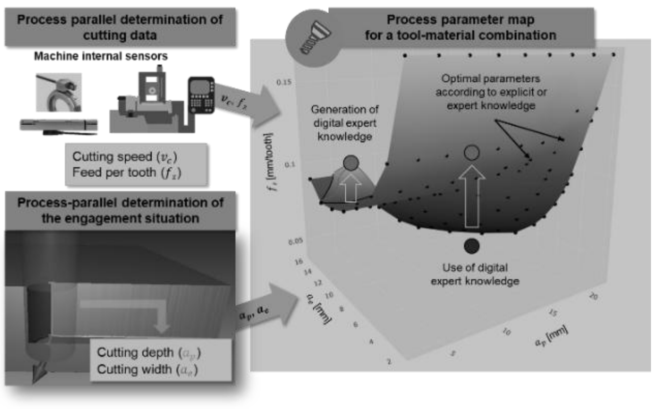


Fig. 8. Process parameter map for process optimization.

### B. Validation

In the following, the developed concept of a method will be validated in a first test based on the presented use case. The basic aim is to ensure the feasibility of the method.

In the first sub-step 1.1 of the methodology, **"the identification of the data valuation objects"**, the following data objects of the manufacturing process could be identified. These are the "manufacturer's data catalogue", "the data model", the "tool data" and the "machine data". The manufacturer's data catalogue includes the information on the tooth feed and the cutting speed. The data model is based on the three defined variables of working engagement, depth of cut and tooth feed. The tool data contains the number of teeth, the diameter and the data on the material such as the hardness. The machine data includes the spindle speed, the feed rate and the geometric engagement conditions derived from the material removal simulation.

In the second sub-step 1.2 **“description of the data valuation objects”**, the description of the identified and aggregated data assessment objects follows.

These are to be checked with regard to their suitability for data exchange on a data marketplace. For this purpose, each identified data valuation object was characterised by experts of the use case with the help of the described flow chart. The assessment showed that firstly none of the described data objects need to be checked for existing licensing or contractual agreements, as they are primarily internal data sources (e.g., digitised expert knowledge) or freely available data (e.g., machine data).

Secondly, it is not data that is confidential and contains trade secrets or data that can generate potential economic damage. The data to share in the provided context does not contain any information on the manufactured workpiece itself. At this point, it should be emphasised that improved process parameters in manufacturing can also be understood as a competitive advantage. However, if the effects are properly evaluated in terms of data valuation with the descripted method, the price of the data sold should consider this effect.

Thirdly and finally, the data availability was evaluated. Accordingly, it had to be examined whether the data model is easily obtainable elsewhere and can thus be obtained by potential buyers without major effort or free of charge. Since the data model in particular is not open data and is offered as a data product, it can be assumed that the data model is not easily available elsewhere.

The evaluation has shown that the data objects are suitable for data exchange. However, for the further procedure of determining the benefits and value of the production data, the data evaluation objects “data catalogue” and “tool data” are not to be considered further, as these are partly provided by tool manufacturers in published form and do not promise any added value.

In the first sub-step 2.1 of the second step of the method **“determination of data usage context”**, the identified data valuation objects are first assigned to data usage contexts. The primary focus here is on the data valuation object “data model”. In this context, “process optimisation” represents an identified potential data usage context. Subsequently, qualitative effects and quantitative effects are assigned to the determined data usage contexts in the second sub-step 2.2 of the benefit determination **“detection of qualitative and quantitative effects”**. This, as well as the determination of the data use context, was achieved based on qualitative interviews with the corresponding use case managers using interview guidelines. The qualitative effect of “increasing efficiency” resulted from the process optimisation for the data model. This is followed by the quantitative effect of “reduced production time” in terms of process processing time.

Thus, the results of the second step describe the expected benefit that potential buyers can generate with the data.

In the first sub-step 3.1 of the value determination **“qualitative data evaluation”**, the qualitative data evaluation was carried out with the help of the seven-step procedure. For this purpose, the data valuation object “data model” was selected, which is compared with the data catalogues and the cutting value recommendations of the tool manufacturers. With the help of an expert assessment, the timeliness and credibility of the process parameters in the data model, i.e., whether the data are reliable, could be identified as a representative data quality indicator. A quality deficit was assumed for the data to be compared, as the “data model” presents higher quality data compared to the “manufacturer’s data catalogue”. The next step was to determine a representative process KPI to measure the qualitative effect of the data. For this use case, the “productivity increase” in terms of the “process processing time” could be determined both with the “manufacturer’s data” and with the described “data model”. In this context, we can accomplish the second step of value determination through **“quantitative data evaluation”**. We select a valid quantitative KPI, which is the reduction in the time required for the evaluated manufacturing process when utilizing optimal parameters from the shared data model. For each process, we derive the material engagement time and the feed per tooth used for all tools. Subsequently, we compare the engagement conditions applied in the process with those in the shared data model containing optimized parameters. In cases where the engagement conditions frequently change in the real process data, we determine the corresponding feed per tooth by selecting the maximum tool engagement. Since the material path remains unchanged, we can directly calculate the process time reduction based on the ratio between the new feed and the old feed. With this time information and the machine hour rate as a quantitative measure, we can calculate a cost estimate for the value of the data in this specific use case.

In this context, the second step of the value determination, the “quantitative data evaluation” could be carried out. The valid quantitative KPI selected was the “reduction in time” required for the evaluated manufacturing process using the optimal parameters from the common data model. For each process, the material engagement time and the feed per tooth were derived for all tools used. The engagement conditions applied in the process were then compared with those in the common data model containing the optimised parameters. In cases where the engagement conditions change frequently in the real process data, the corresponding feed per tooth was determined by selecting the maximum tool engagement. Since the material path remains unchanged, the process time reduction could be calculated directly from the ratio between the new and the old feed. With this time information and the machine hour rate as a quantitative measure, a first cost estimate for the value of the data in this particular usage context could be calculated.

## VI. Conclusion and Summary

Manufacturing companies are often still in the early stages of structurally creating value with data. Data valuation is a prerequisite for data exchange and a necessary building block for efficient data management in the context of platform-based business models on which data is shared. The aim of this research was to meet the challenges of data evaluation for manufacturing data and to develop a solution approach. For this purpose, the research question could be supported as to how a suitable concept for a procedure for determining the value and benefit of manufacturing data in the context of platform-based business models must be designed. This was achieved by developing a concept for determining value and benefits that builds on the current state of research and was adapted to the challenges of small and medium-sized enterprises in the manufacturing industry. The method was validated using a use case from the machining industry.

In general, it has been shown that the described procedure is suitable for carrying out the valuation of data objects with relatively little effort and reducing it to a financial measurement value. Thus, an estimate can be made of how much the shared data is worth to potential buyers. However, it should be noted that data valuation could only be carried out based on internal knowledge. In order to be able to determine the value generated for the potential buyer in more detail, the data would have to be evaluated in cooperation with the buyer, whereby this is rather unrealistic due to the associated data transfer before the sale. There is also a need for further research on the evaluation of data quality and its influence on the data value. Above all, to reduce and compensate for the subjective influence of alternative valuation methods such as expert assessments. In addition, it has been shown that in order to effectively apply the described approach in an industrial machining context in detailed life, further challenges have to be overcome. Firstly, the data model in this example must be enhanced with additional contextual information, such as the application type (e.g., roughing or finishing), desired quality standards, or information about tool wear. While this data can be incorporated into the data model, it necessitates a reevaluation of the steps outlined in the method.

Secondly, the accuracy and validity of the shared data itself must be thoroughly validated and assessed. One potential solution could involve establishing a trusted entity, such as the tool manufacturer, to serve as a custodian or verifier of the data's integrity and reliability.

## Conflict of Interest

The authors declare no conflict of interest.

## Author Contributions

Michael Riesener and Maximilian Kuhn reviewed and edited; Matthias Sebastian Mertens was mainly responsible for method development, conceptualization, and the project management (supervision) of the research project, and wrote the paper original draft; Vincent Lohrmann worked realisation of use-case validation; Arthur Giser worked development of method; Günther Schuh reviewed & edited and provided resources; Christian Brecher worked realisation of use-case validation and provided resources; all authors had approved the final version.

## Funding

Funded by the Deutsche Forschungsgemeinschaft (DFG, German Research Foundation) under Germany's Excellence Strategy–EXC-2023 Internet of Production–390621612.

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