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## Data-driven productivity improvement in machinery supply chains

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**Abstract:** Modern manufacturing machines are equipped with numerous sensors that collect a large amount of various data. This data can be used to improve the machines' productivity. Both the users and suppliers of machines could benefit from such opportunities. However, because machine users risk the loss of intellectual property, they are often reluctant to share their data. This represents a major inhibitor of data sharing in machinery supply chains. This paper proposes a five-step method for initialising data sharing between machine users and their machine suppliers. The method was tested and validated in a case company, and the potential benefits for machine users were quantified.

**Keywords:** data sharing; digital services; smart machining systems.

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## 1 Introduction

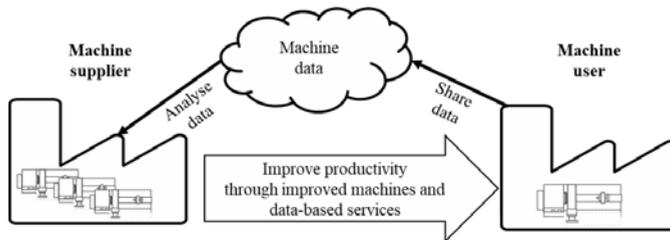
Machine users can uncover new ways to increase productivity by analysing the manufacturing data that come from digitised machines (Brynjolfsson and McAfee, 2016; Kagermann, 2015; Monostori et al., 2016). Machine suppliers can use the same data to improve the design, quality and service offerings related to their machines. Here, a typical use case is predictive maintenance, where machine suppliers offer their customers the service of monitoring and maintaining the components of their machines before these parts fail. This potentially reduces the machine downtime for the user, and the supplier can monetise this benefit through a service contract. Although the benefits for both parties are tangible, it is not easy to establish data sharing in machinery supply chains.

Machine users fear revealing critical knowledge if they share manufacturing data, the result of which could negate a company's competitive advantage. However, companies rarely conduct an objective risk assessment to establish which data are actually critical and which are not. Instead, many machine users simply follow a 'better safe than sorry' strategy and thus miss out on opportunities that data-driven productivity improvements can provide. Non-critical data can usually be shared with few associated risks and can still be valuable for productivity improvement. To address this issue, (Massimino et al., 2018) called for research that establishes which digital assets should be shared with whom. To respond to this call, the current paper proposes a novel and generic method for getting started with data-driven productivity improvements in machinery supply chains.

Following the data-information-knowledge-wisdom (DIKW) pyramid of Rowley (2007), contextualised data can be turned into information, which in turn can reveal knowledge before leading to wisdom. This transformation collectively shapes a

knowledge base that is used for decisions (Aamodt and Nygård, 1995; Knauer, 2015). Accordingly, the flow of contextualised data from a machine user to a machine supplier could enable fact-based decisions. Hence, a structured approach to the exchange of data in machinery supply chains can help increase productivity. To harness productivity gains, manufacturers need to comprehensively analyse and improve the management of data within their machinery supply chain to stay competitive. Figure 1 illustrates this paper's research idea.

**Figure 1** Data-driven productivity improvement in machinery supply chains



The focus of the current paper is the dyad between a machine supplier and a machine user. In contrast to the previous literature (e.g., Mori and Fujishima, 2013), the proposed method starts with the perspective of the machine user. Accordingly, the machine user initiates the sharing of manufacturing data, and the machine user's objective is productivity improvement. The supplier's motivation is to capture more value from the product-service offerings and improve the products. It is anticipated that the machine supplier will offer data analysis for its customers. This is a reasonable assumption because the machine supplier can achieve benefits of scale by learning from the data generated from offering similar services to other machine customers (Schöning and Dorchain, 2014). The proposed collaborative method identifies data of interest for the machine supplier that the machine user deems non-critical.

## 2 Theoretical background

To develop the proposed method, three main streams of related literature were consulted: digitisation, supply chain collaboration and business models.

### 2.1 Digitisation

The emergence of cyber-physical production systems based on digitisation has been noted as a way to significantly shape the future of manufacturing (Kagermann, 2015; Monostori et al., 2016). Because they are characterised by an increasing number of networked entities (Scholz-Reiter et al., 2014; van Brussel, 2013), cyber-physical production systems relate to prior research in the field of autonomous and decentralised systems (e.g., holonic manufacturing systems). Machine users – who connect physical machines and materials with business software over the internet – are able to remotely access manufacturing data in real time. Hence, digitisation enables the real-time (and

historical) analysis of a machine's condition and performance, which was hitherto difficult or impossible to conduct. The results can be used to control and improve machining processes and the machines' productivity.

In cyber-physical production systems, connected machines 'communicate' with each other. This is known as the 'industrial internet of things' (IIoT) (Boyes et al., 2018; Wegener et al., 2016). IIoT data can be stored in the cloud and shared with partners and collaborators, further facilitating the development of data-driven services around physical products (Anderl and Fleischer, 2015). Traditionally, manufacturing firms have sold products to their customers and received payments in return. Today, the importance of 'servitisation' is on the rise. In this context, servitisation means that a firm adds services to its products or replaces products with services (Kaihara et al., 2018). A common example of embedding a product in a service offer is Rolls Royce's 'power by the hour' pricing strategy for their jet engines. Because machines are equipped with more sensors that collect more data, the use cases for leveraging data-driven services are growing. However, a challenge of servitisation is that it is new to many machine suppliers whose core competencies are developing physical machines. Therefore, it is not easy for machine suppliers to identify opportunities for servitisation. Nevertheless, developing additional services pertaining to machines has become a real opportunity (Baines et al., 2009) because it incorporates advantages for the machine user and for the machine supplier.

## 2.2 *Supply chain collaboration*

Traditionally, improvements in manufacturing processes have been mostly firm-internal activities; however, with the emergence of global production networks and digitisation, more vertical and horizontal integration is needed (Kagermann, 2015). Vertical integration refers to intra-firm connectedness and horizontal integration refers to inter-firm networking along the end-to-end supply chain. Soosay and Hyland (2015) suggested that successful supply chain collaboration requires that there are benefits for all the participating partners and an appropriate level of trust among them. Data- and information exchange can take many forms (Tapscott, 1997), and be operationalised by, for instance, vendor-managed inventory, collaborative forecasting planning and replenishment, tracking technologies such as radio frequency identification, or file exchange using standards such as electronic data interchange (EDI) (Soosay and Hyland, 2015).

When firms allow data, information and knowledge to flow openly across organisational boundaries, they can increase the speed of process improvement (von Krogh et al., 2018). 'Openness', in this context, refers to the ability of a firm to let knowledge float to and from sources outside the company (Chesbrough, 2003). Research has shown that companies that open up their process innovation activities with suppliers are more innovative than those whose activities remain closed (Demont and Paulus-Rohmer, 2017; Wagner and Bode, 2014). Because digitisation enables the sharing of manufacturing data to machine suppliers, data-driven open process innovation is likely to become more prominent in the future.

If machine suppliers can access point-of-use data from their users' machines, they can mine data to learn how to improve their product-service offerings (Abramovici and Lindner, 2011), thereby finding ways to provide additional services around their products, such as predictive maintenance (Lim et al., 2018). To realise these new

opportunities, machine suppliers and machine users need to engage with each other in 'data value chains', in which the customer provides data regarding the machine use, and the machine supplier analyses it to offer additional service value to the customer (Lim et al., 2018). An example of this could be a machine supplier's web platform where customers can book specific services related to their machine tools, such as monitoring the conditions and wear of critical machine components or scheduling maintenance and replacements.

The major challenge, however, relates to two dimensions of data security: the potential loss of critical knowledge and the need for the mutual benefits of data-based business models. Although there are numerous expected benefits of supply chain collaboration, there are few documented cases of open flow of machine data across firms.

### *2.3 Business models in machinery supply chains*

Scholars from different disciplines have researched the business model concept for more than two decades (Burkhart et al., 2011). This has led to a multitude of different methods being developed in parallel by several scholars (Schallmo et al., 2017), and companies have heavily adopted some of these methods. For instance, the 'business model canvas' (Osterwalder and Pigneur, 2011) and the 'business model navigator' (Gassmann et al., 2013) are among the most popular ones. Although their generic and universal applicability is one of the main advantages of these methods (Demont and Paulus-Rohmer, 2017), it makes them sometimes too generic for specific contexts. For instance, in the field of digital business models for machinery supply chains, scholars have developed specific business model methods addressing the specific challenges.

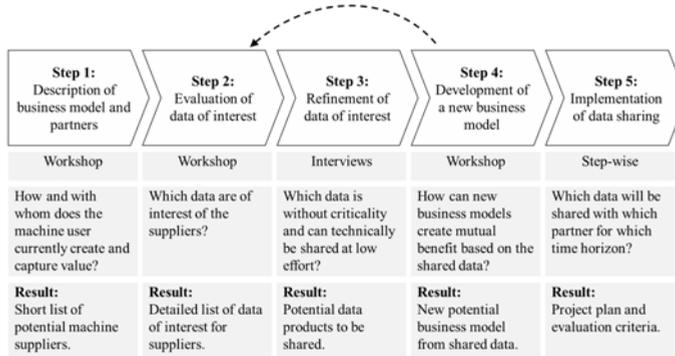
There are at least three requirements for a method in the area of data sharing in machinery supply chains. First, the methods need to address supply chain collaboration because an exchange between the machine supplier and machine user is needed. Second, the methods need to consider how to deal with intellectual property rights and risks. Finally, the methods need to provide an executable procedure that managers can use. Although nearly all existing business model methods offer an executable procedure and consider supply chain collaboration, none explicitly consider know-how protection and how to deal with it (cf. Barbian et al., 2016; Deflorin et al., 2017; Kaufmann, 2015; Osterwalder and Pigneur, 2011). The existing methods also tend to take the perspective of the machine supplier, which provides limited guidance for the machine user. This is surprising considering that the relevant data emerge from the user, not the supplier, and the risks of knowledge drain are almost exclusively with machine users.

## **3 Proposed method**

Figure 2 proposes a novel five-step method for getting started with data-driven productivity improvements in machinery supply chains.

Unlike the existing methods, this method was developed as a means for machine users to engage in discussions with their machine suppliers on how to take advantage of digitisation. It allows for the identification of non-critical manufacturing data that can be shared by machine users and analysed by machine suppliers. The five steps are explained in the subsequent paragraphs.

**Figure 2** Proposed five-step method for getting started with data sharing



### 3.1 Step 1: Description of the current business model and partners

The first step for the machine user is to understand how firms create and capture value. The machine user can obtain this knowledge through a workshop with the management team. The proposed method thereby lends to the concept of describing a business model using the business model canvas (Osterwalder and Pigneur, 2011) because it is practical and widely applied in the industry. The canvas supports the company in focusing on the essential value propositions the company offers its customers and further has a segment called ‘key partners’, which supports the identification of relevant machine suppliers. The machine user records a long list comprising partners within the current business model. This list includes all of the major machine suppliers of the machine user.

To focus the efforts, the long list is evaluated and ranked. Following Soosay and Hyland (2015), two dimensions are critical for successful supply chain collaboration: trustworthiness and expected benefits. Trustworthiness describes the degree to which the machine user trusts each machine supplier. The attributes of this dimension are power relations, personal ties, the historical relationship, the machine supplier’s maturity in data services and the technology applied. The potential benefit of data sharing describes the degree to which the machine supplier can use data to improve the machine productivity of the user. In the case of multiple machines or critical machines being supplied by one supplier, the potential benefits for sharing manufacturing data with this supplier would grow. By ranking the potential partners on their trustworthiness and the potential financial benefits for the machine user, a shortlist of machine suppliers can be created. Similar to the discussions that arise during the purchasing process, the machine user should start discussions with these specific machine suppliers.

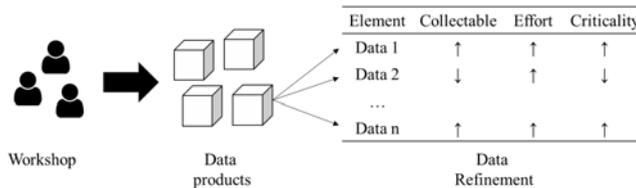
### 3.2 Step 2: Evaluation of the data of interest

In the next step, the machine user identifies – together with the suppliers identified in the previous step – which data of interest should be shared. To do this, the machine user arranges a workshop with the shortlisted machine suppliers; this workshop focuses on determining which manufacturing data could be theoretically interesting for each

machine supplier to access and which use cases the supplier could realise with these data. As a start, a team led by the machine user, consisting of production and technology specialists, establishes a list of the data currently collected on the user's side. The supplier then would contribute a list of data that the particular machines could theoretically collect. However, the workshop would not only focus on existing data, but also allow creativity, hence considering potential data outside the current boundaries. The result of the workshop is the creation of a detailed list of data that are of interest to the machine supplier, with which the machine supplier can create value-adding services for the user.

Here, the term 'data product' is introduced to describe a specific set of data elements shared by the machine user with his machine supplier to create a mutual benefit. Much like a physical product, a data product can be the basis for a business model, such as predictive maintenance, and it can be an aggregate set of multiple data elements. An example of such a data product is water quality. This data product consists of data elements, such as hardness, pH value, purity and others. This relationship is illustrated in Figure 3 and further explained in the next section.

**Figure 3** Deriving data criticality



### 3.3 Step 3: Refinement of the data of interest

In the third step, the machine user evaluates which of the identified data products defined in the preceding step are the most suitable ones for sharing. The evaluation is performed by reflecting on the following three questions for each data element: Is the data collection technically feasible? How much effort will it take to collect and provide the data in the required format? When it comes to sharing, is the data critical or non-critical? For the first two questions, interviews with IT and automation experts of the machine user and machine supplier are conducted. Here, the machine supplier can answer questions about how machine-specific data can be collected.

The answer to the third question regarding criticality, however, requires a more analytical approach. Today, most machine users are unable to judge the criticality of specific manufacturing data. To overcome this issue, the proposed method proposes that the machine users define their 'valuable knowledge' (Lindemann et al., 2012) and combine it with the DIKW pyramid (Rowley, 2007). Examples of valuable knowledge of the machine user can be the optimal combination of raw materials, the process parameters of the machines, and the tools used in the machines. To derive valuable knowledge, the machine user can evaluate and consider the core competencies in manufacturing. Following the DIKW pyramid, this valuable knowledge consists of the required information, which in turn consists of data. Based on the information incorporated in this

valuable knowledge, the technical experts and managers from the machine user evaluate the criticality in a workshop setting. The question asked is whether the disclosure of a certain data element could lead to revealing valuable knowledge or not. Sharing these data should be avoided because it could diminish competitive advantage from a technical and strategic point of view.

Following this approach, the machine user can judge whether a specific data element relates to valuable knowledge. If one data element reveals any predefined valuable knowledge, the subordinate data product is considered critical. If not, the data product can be shared. Hence, the criticality of each individual data product can be evaluated objectively. This step results in a list of data products and their data elements, as illustrated in Figure 3. Therefore, machine users should share the data products that are:

- 1 valuable for the machine supplier (Step 2)
- 2 technically feasible to collect with a low effort for the machine user (Step 3)
- 3 non-critical for the machine user's valuable knowledge (Step 3).

#### 3.4 Step 4: Development of a new business model

After the data products have been defined, a new business model using these data can be deduced. To be successful and sustainable, a business model should benefit both the machine supplier and machine user. For the machine user to benefit, the business model must first only use the data products defined in the previous step. Second, the business model must improve the performance of the machinery supply chain. For instance, if the machine user shares performance data and in return receives parameter optimisation for his machine, the user obtains a tangible benefit.

To let the machine supplier benefit from data sharing, the received data can support product improvement or service enhancement. Taking the example of performance data into account, the machine supplier could use these data to improve the machine in the next generations and for other customers. The supplier thereby benefits from better products and higher-than-expected sales. However, the data can also result in additional services, such as condition monitoring or predictive maintenance. To develop these business models, a subsequent workshop of the machine user and a particular supplier should be organised.

The proposed method uses the business model canvas to describe the new business model. Hence, this step results in a potential new business model capturing how the shared data can benefit both the machine user and supplier, which also includes the technological implementation of how the data are shared.

Along with the value emerging from the new business model, co-created risks need to be considered. This risk constitutes the sharing of faulty data products that emerge from malfunctioning sensors or data collection software, which could result – when undetected – in drawing the wrong conclusions from the data analysis and then making the wrong decisions. In the example of predictive maintenance, this error could result in machine tool failure because the maintenance tasks might be carried out incorrectly. To mitigate these risks, the method recommends both technical and contractual measures to be implemented. As a technical measure, an algorithmic data quality control can be set up to solve common issues such as missing values and deduplication (Ahlemeyer-Stubbe and Coleman, 2018). Here, contractual risk mitigation measures include the formation of

performance-based contracts or outcome-based contracts (Smith, 2013). These agreements are only eligible for certain configurations, where the benefits for machine suppliers and machine users are aligned. An example is a machine supplier aiming to predict and carry out maintenance tasks as an integrated service, along with a machine user aiming to receive such a service. In this case, the machine supplier could then guarantee for the availability of the machine tool (Gassmann et al., 2013).

The fourth step hence results in a description of a new potential business model regarding how the shared data can benefit both the machine user and supplier.

### *3.5 Step 5: Step-wise implementation of sharing data with partners*

The final step is a systematic implementation of the new business model in collaboration with one of the shortlisted machine suppliers. Based on the three dimensions of data refinement discussed in the third step the first data to be shared should be valuable for the supplier, non-critical and easy to collect. After a trial phase of about six months, this method can be used to evaluate the results of the application. Based on this experience, the machine supplier can start proposing and discussing standardised packages of data to be shared with his other machine users. Thereby, the machine supplier can add new solutions to his service portfolio.

## **4 Test and validation in a case company**

The presented procedure enables machine users and suppliers to create and capture more value based on sharing manufacturing data. To test and validate the proposed procedure, this new method was applied in a case company. A suitable machine user would possess the available data on the shop floor and several machines from different machine suppliers.

In this case, the machine user is headquartered in Europe and has more than 30 production sites worldwide. The company develops, produces and sells sanitary products. The factory site at which the method was applied uses more than 70 injection-moulding machines from different machine suppliers. The machines collect a range of different data through integrated software, programmable logic controllers (PLCs) and sensors. Examples of these data include the auger diameter, the humidity of the raw material and the temperatures of the motor, tools and lubricant. For example, the auger diameter is important within the injection moulding process because it indicates the wear and, thus, the performance of the machine.

In the first step of the proposed method, the business model canvas (Osterwalder and Pigneur, 2011) was used to describe the current business model of the machine user in its nine dimensions. Currently, the company is not involved in any business models related to digitisation. Based on the dimension 'key partner' from the current business model, four machine suppliers were identified as potential partners for data sharing.

The second step evaluated possible data of interest. A workshop with the shortlisted machine suppliers was organised, and the machine user presented a list of manufacturing data that had already been collected on the shop floor. Additionally, the machine suppliers presented their potential data of interest and explained how these data would add value to their business models. For example, one machine supplier stated that, 'in

order to improve the dimensioning of individual parts of the machine, it would be important to know the temperature and humidity conditions within the production site throughout the year at the different machines'. In total, 46 potential data products that the machine suppliers would be interested in were identified. These data products have the ability to add value for both the machine users and machine suppliers.

An example here is the 'temperature-humidity data product'. By sharing this with the supplier, the machine user can receive improved machine components that perform better in the on-site temperature conditions, for example, a replacement of a relevant machine component that depends on temperature conditions (e.g., a screw-conveyer). Further, by analysing the data of the specific conditions at the machine user's location, the supplier can model the effect of the environmental conditions into suggestions for parameter settings. In this case, the supplier saw value in understanding the conditions under which its machines are used in the field.

The third step was to refine the data of interest. The 46 data products were evaluated based on their technical feasibility to collect and when it came to their criticality. Five of them, including supply chain coordination and the user's perceptions of the raw material after processing, could not clearly be assigned to a certain type of data to be collected; hence, they were discarded. Thereafter, the remaining 41 data products were evaluated for their criticality to the current business model of the machine user.

The machine user did not have any existing internal definition for the criticality of manufacturing data. Thus, the concept of 'valuable knowledge' was applied and considered against the key activities and key resources defined in the current business model canvas performed in Step 1. Based on this, a workshop with the machine user's senior technical experts was initiated, and a machine-user-specific valuable knowledge definition was developed. The same senior technical experts screened each data product, and this screening process addressed the question of whether the proposed data products can reveal critical information that would uncover some of the machine user's valuable knowledge for external parties. The screening was performed by deducing information that could be derived from each of the data products (e.g., the number of products produced). If that set contains information that can lead to valuable company knowledge, the specific data product would be dropped.

From the initial list of 41 remaining data products after the technical collectability check, only 16 were considered know-how critical. An example of a critical data product is all manufacturing data of the machines processing a raw material named polyvinylidenfluorid (PVDF). The knowledge was classified as critical by the machine user because the manufacturing of high-quality PVDF products requires longstanding experience and is one of the main pillars of the company's current business model. The remaining 25 data products (61%) were not know-how critical and could immediately be shared, according to the machine user. These data products were of interest to the suppliers because they were deemed technically feasible to collect and classified as non-critical to the machine user.

For calculating the possible benefit, the provisional efforts were estimated in the dimensions of data elicitation, data processing and data provision in the categories of low, middle and high. Ten of the 25 data products were easy to share because they had already been collected, which simplified the sharing process even further. Examples of the remaining data products are presented in Table 1. They include the quality of the water used to cool the tools, the torsional torque of the plasticiser unit, the temperature of the screw cylinder and the minimum, average and maximum injection pressures.

**Table 1** Examples of data products

<i>Data product ID</i>	<i>Data product specification</i>	<i>Machine supplier ID</i>
15	Injection moulding tool lifetime	Supplier A
18	Water quality parameters (e.g., hardness)	Supplier B
20	Production site temperature and humidity	Supplier B
28	Torque of plasticiser	Supplier C
29	Injection pressure	Supplier C
33	Temperature of screw cylinder	Supplier C
35	Machine tool start-up cycles (frequency)	Supplier C

In the fourth step, a new business model was developed, as shown in Figure 4. For the design of the new business model, how the machine supplier intended to use each data product and how additional value would be created for the machine user were considered. This resulted in an individual implementation of different data products in the form of a pilot study using a one-to-one machinery supply chain. To mitigate the risk of sharing faulty data products (e.g., because of incorrect data interpretation, both parties agreed that the machine supplier would directly obtain sensor data from the machine and perform data quality control before further processing it). The business model canvas presented in Figure 4 provides a comprehensive description of the new business model because all nine dimensions were successfully identified and described.

**Figure 4** New business model specified in the business model canvas

<b>Key Partners</b> <ul style="list-style-type: none"> <li>IT infrastructure and service provider</li> <li>Supplier for data processing software and hardware</li> <li>Supplier of sensory equipment</li> </ul>	<b>Key Activities</b> <ul style="list-style-type: none"> <li>Elicitation of manufacturing data</li> <li>Processing of manufacturing data</li> <li>Provision of manufacturing data</li> </ul>	<b>Value Proposition</b> <ul style="list-style-type: none"> <li>Individually customized data products, offering detailed insights on how machines are used</li> <li><i>Standardized data products</i></li> </ul>	<b>Customer Relationship</b> <ul style="list-style-type: none"> <li>Direct face-to-face contact</li> <li><i>Anonymous, transactional exchange</i></li> </ul>	<b>Customer segment</b> <ul style="list-style-type: none"> <li>Selected machine suppliers</li> <li><i>Any interested economic entity</i></li> </ul>
	<b>Key Resources</b> <ul style="list-style-type: none"> <li>Manufacturing</li> <li>R&amp;D</li> <li>IT</li> <li>Employees</li> </ul>		<b>Channel</b> <ul style="list-style-type: none"> <li>Direct Virtual Private Network (VPN) transmission</li> <li><i>Data market / platform</i></li> </ul>	
<b>Cost Structure</b> <ul style="list-style-type: none"> <li>IT Infrastructure</li> <li>Sensors</li> <li>Personell cost</li> </ul>			<b>Revenue streams</b> <ul style="list-style-type: none"> <li>Extended services</li> <li><i>Direct monetization</i></li> <li><i>Reciprocal exchange of data products</i></li> </ul>	

Note: Potential, yet unexplored, elements are marked in italics.

Some elements of the new business model were considered promising yet not realisable in this first implementation. These elements, which are marked in italics in Figure 4, are possibilities to extend the business model in the future. These possibilities include the development of standardised data products, which could then be shared with any economic entity through platforms or data markets in a transactional manner; this would also foster new revenue streams, such as the reciprocal exchange of data products and direct monetisation. The example of direct monetisation also illustrates the issues and

challenges related to the quantification of the new business model's revenue streams. In this case, both the machine user and machine supplier considered direct monetisation as option but were not yet able to determine the value of the data. Therefore, direct monetisation, which is common among data-driven business models in many other industries (Ahlemeyer-Stubbe and Coleman, 2018), is seen as a likely prospective revenue stream. In the following section, the issues of direct monetisation are discussed in more detail.

During the collaboration with the selected machine supplier, the machine user shared the data of interest that has the lowest provision efforts and lowest know-how criticality but at the same time had the highest potential benefits for both. This evaluation was based on the results from the workshop in Step 2 and the three categories from Step 3. An example extracted from the case is the data product regarding which interface page of the control panel of the machine tool the machine user is using when and how frequently. This application data can help the machine supplier create a reliable database that describes the behaviour of the operator at the human-machine interface. Hence, the interface and the underlying software can be designed in such a way that they will be more user-friendly. For instance, the pages that are frequented the most often are recommended or even displayed first. User friendliness improves the operator's effectiveness and, thus, the productivity at the machine user's site. Sharing this and other data products shows the yet uncovered potential within the machinery supply chain, as follows:

- 1 The benefits for the machine supplier are high because the results are applicable to all customers and can help provide a better user experience with the machine.
- 2 The benefits for the machine user are high because the results reduce the efforts of a costly machine operator, as well as release additional time for machine usage – not only for new but also existing machines – that are realisable by software updates.
- 3 The data already exist.
- 4 The data are not know-how critical for the machine supplier.

## **5 Evaluation and discussion**

The current paper proposed a structured method that can support machine users in exploiting the potential of sharing data with their machine suppliers. Applying this method to a machine user resulted in a pilot project that experimented with data sharing. In this project, the machine user selected three machines that started to share their manufacturing data with the machine supplier. The machines of the machine user shared 10 predefined types of data products with one of his machine suppliers. The other machines of the same machine supplier continued as before with similar operations but without sharing any manufacturing data. Consequently, the benefits from data sharing were calculated by comparing the performance parameters of machines sharing their data and the machines not sharing any data.

The technical feasibility to access the manufacturing data in terms of data elicitation, processing and provision did not impose difficulties in the application phase with the machine supplier; all the shared data were directly collected from the machine's PLC or other existing machine sensors. Thus, no additional sensors were required. The machines

transmitted the data via a direct virtual private network (VPN) tunnel to the machine supplier that analysed the data. The VPN connection had the advantage of being easy to implement. To assure additional security in the starting phase, the tunnel was only open during predefined time slots to increase the security of the connection. Besides its undisputed importance, neither a secure data transmission nor the topic of data accessibility by third parties is within the scope of this paper. However, innovative solutions, such as secure cloud services (e.g., Siemens MindSphere) and distributed ledger technology systems (e.g., IOTA), are exploring these issues and should be considered in future studies.

Initial benefits for the machine user included improved machine uptime, which stemmed from a reduced mean time-to-repair (MTTR) and an increased mean time before failure (MTBF). The typical case maintenance, relevant to illustrate the benefits of data-sharing, needs the collaboration between the machine user and machine supplier as it is complex to perform. From the machine user's experience, the maintenance process roughly lasts three days. It starts with a phone call from the machine user to the machine supplier (initial day). This is followed by an onsite visit of a technician (first day), plugging in a memory stick and downloading the relevant data from the machine. Afterwards, the technician is returning to the office to analyse the data. Normally, the analysis takes place on the second day. When the error is detected, the technician is visiting the site of the machine user again (third day) to solve the problem (e.g., by updating the firmware). Consequently, and underlined by historical data from the machine user, the duration of a machine's downtime lasts around three days each time.

The automatic sharing of the ten easy-to-share data products significantly improved the collaboration processes; because of the availability of relevant data not only for the machine technician on site, but also for all the relevant specialists of the machine supplier (e.g., software engineers), problems could be solved faster. A faster problem-solving process not only can reduce the machine user's MTTR, but also the cost of the machine supplier for maintenance. When the machine user allowed access to the PLC control, the MTTR was reduced from three days to approximately half a day (i.e., a total savings of 2.5 days per case). This time saving mainly came from cutting out the unnecessary elements of the technician driving to and from the location and the possibility that all the experts could access the data immediately.

For the 70 machines of the machine user, the above-described maintenance process occurs roughly ten times per year. With the costs of a machine hour of USD 200, based on the depreciation of eight years and the prescribed downtime reduction of 2.5 days, this resulted in a total savings of  $10/y \times 2.5 \text{ d} \times 8 \text{ hrs/d} \times \text{USD } 200/\text{hr} = \text{USD } 40,000$  per year for the entire plant. This considerable savings can be captured with little effort. Additionally, these savings only account for the increased availability of the machines, not for the additional savings of the machine supplier. Because the machine supplier covered the costs of implementation, the machine user carried only minor additional set-up costs.

The proposed five-step method not only supported the initialisation phase, but also enabled fact-based discussions about which data to share, depending on the know-how criticality assessment of the machine user. This led to a mindset shift through the continuation of the project: a conscious analysis of know-how criticality to exploit the potentials of sharing manufacturing data in lieu of a 'better safe than sorry' strategy. From a long-term perspective, considering that data sharing will be scaled, both the

machine user and the machine supplier expect the main advantages to be observed in the context of predictive maintenance and improving machine components. Predictive maintenance could possibly be based only on the availability of real-time shop floor data. Additionally, for the machine supplier, the advantage of improved machine components comes from previously inaccessible knowledge of the usage of their machines, as illustrated in the interface example.

Sharing manufacturing data means sharing daily insights regarding the machine user's business. If these data would be given to a competitor, it could eliminate the machine user's current business model along with the company's competitive advantage. Therefore, the following three main drivers to mitigate these risks were identified in the case company:

- 1 Machine users should rely on trusted individual company relations with a strong partnership in the current business model.
- 2 The exchange of manufacturing data should first be performed in one-to-one machine supply chain relations instead of in networks.
- 3 The definition of the data to share helps identify potential knowledge drains. Not all manufacturing data are know-how critical. Hence, the amount – and especially the content of – the shared data can evolve over time, starting with non-critical and easy-to-gather data.

The application confirms the potential of sharing data within machinery supply chains (Herterich et al., 2015; Mori and Fujishima, 2013; Schöning and Dorchain, 2014). Based on the intercompany workshop, the method did not only elaborate on 41 specific data products to be shared, but also proved their mutual value. Moreover, 10 of the 41 data products turned out to be non-critical and were already collected, which reduced the effort to share the data. Consequently, these ten data products reflect examples of a new, data-driven and mutual business model with low entrance barriers. Based on these easy-to-share data, the method shows how productivity can be improved: for the machine user by reducing the downtime and for the machine supplier (and indirectly for the machine user) by reducing maintenance efforts. Notably, other expected benefits exist that could not be measured in the current case study, including improved product and process designs.

Despite the displayed benefits, the application of this method at a specific machinery supply chain revealed that machine users and their suppliers are not yet able to implement new business models fully. One reason is that the core business of machine suppliers (and of the users) is the production of physical goods, not the creation of digital services such as data products. Thus, the market for manufacturing data is less developed than the market for personal data, which is so large that companies have business models based entirely on it (OECD, 2013). Another reason hindering the implementation of this method is the current fear of machine users losing critical know-how.

Moreover, there is a gap in the research and in practice in directly monetising the value of manufacturing data. Within the current application, there are three possible approaches to quantify the value of manufacturing data. The first is through open market mechanisms, though no open markets have been developed yet. The second is through the added value achieved through the machine supplier. However, the supplier cannot precisely estimate this value of the data yet. The third is through the expenses of the

machine user in eliciting, processing and providing the data, hence adding to his general margin in order to achieve an additional incentive to provide the data.

There are also limitations in the proposed method. For instance, this method was only tested in collaboration between one machine user and one machine supplier. Moreover, several soft factors were exhibited in the case study, including the management commitment and the individual interests of different machine suppliers, which are crucial for the success of such a new data-driven business model but that have not been profoundly discussed within the procedure. Furthermore, we do not know if another model would have performed equally good or better than the proposed methods.

## **6 Conclusions**

The current paper presented a novel five-step method for exploiting the potentials of and getting started with sharing manufacturing data between machine users and machine suppliers; this method supports machine users in identifying non-critical data that can be shared with machine suppliers and used to improve machine productivity. Thus, the challenge of knowledge drain from the machine user can be mitigated. In the case study, the method was applied and tested at a company. By following the five-step method, a total savings of USD 40,000 per year for a factory with 70 injection-moulding machines could be identified. Besides the hard financial savings, several soft factors could provide further benefits, for example, in the above-mentioned possibilities for improving the user-friendliness of the machine interfaces by exploiting the typical behaviour of the machine operator or the improved collaboration in the machinery dyad between the machine user and supplier through closer bounds by data sharing. The proposed method builds on the existing literature on business models for digital services. From an academic perspective, the research extends the field by providing the perspective of the machine user, not only the machine supplier. Further, the proposed method fulfils the requirements of ease of use and supply chain collaboration while taking know-how protection into account. For practitioners, the method supports machine users in getting started and familiarised with data sharing in machinery supply chains. A further managerial implication derived from the case study is the importance of identifying the company's valuable knowledge so that the company can evaluate the criticality of its data. The proposed method can be transferred to other machine users in the machinery industry to get them started with data sharing.

Future research can evaluate how a potential market of manufacturing data could be composed, assess important market players and develop approaches to estimate the value of manufacturing data quantitatively.

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