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Developing Gaia-X Business Models For Production

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Abstract

The manufacturing industry is in the midst of a digital transformation. As part of the increasing internal and external integration of manufacturing companies, ever more significant volumes of data are being exchanged in order to meet the challenges of a globalized production world. The European initiative Gaia-X aims to establish a federal data infrastructure based on European law to ensure data sovereignty in the resulting digital value creation ecosystems. Under the conditions thus created, it will be possible for manufacturing companies to develop entirely new business models. Within the scope of these business models, the benefit of data sharing in the sense of added value will come into focus.

The following paper presents opportunities for the development of disruptive digital business models for manufacturing companies in the context of Gaia-X. The paper focuses on how data sharing can be used to create value. Furthermore, it highlights how the transition from technological use case to monetizable value creation can be made with data-based, digital business models in the context of Gaia-X. Finally, the state of work in business model development in the Gaia-X project EuProGigant is presented for discussion and exemplified by two use cases.

Keywords

Digitization; Business Models; Gaia-X; Production Technology

1. Introduction

The industrial sector is currently in the midst of a fundamental digital transformation. In the last 12 years, the amount of data generated worldwide almost increased by fifty, and progressive growth is expected in the coming years as well [1]. Manufacturing companies support this increase by constantly driving forward the digitization of their products and processes. Due to the advancing use of sensors and increasing connectivity of machines and systems, information availability continues to rise [2]. In this context, digital, data-based business models represent an essential foundation for generating benefits from the data acquired. A platform-based exchange of data across locations and company boundaries becomes increasingly important as a key benefit driver [3]. However, the spread of such platform-based business models is very limited. Many potential players are not willing to participate out of fear of losing their data sovereignty [4]. The European initiative Gaia-X, launched in 2019, addresses this challenge by establishing a federated data infrastructure to ensure data sovereignty based on the European legal situation. Gaia-X's decentralized approach aims to aggregate the heterogeneous infrastructures of different actors into a homogeneous system. Those systems are named ecosystems or data space and are characterized by technology, business and legal [5]. In this context, the idea of open source is of high priority. Especially smaller companies can also benefit from the development. Trust is established through transparency of code, contract and verifiable identities and credentials. Furthermore, various instances are networked via open interfaces and standards to optimize the linkage of data sources and sinks. This intends to increase the sovereignty of customers of platform-based business models and the scalability, interlinkage and competitive position of their providers [6].

Research on platform-based business models in industrial production and the accompanying empowerment of companies is still in its infancy [3]. The same applies to the development efforts on building data infrastructure in the Gaia-X context. Among other things, parties involved are intensively working on designing the underlying architecture in numerous working groups. Accordingly, the overall requirements for corresponding data-based business models continue to change. The following remarks reveal future possibilities of platform-based business models within Gaia-X. First of all, this paper addresses the concept of platform-based business models. Subsequently, it presents a possible procedure for the structured development of decentralized, multi-platform-based business models in the context of Gaia-X. Thus, the current work on developing use cases and business models in the EuProGigant project is addressed and exemplified by two use cases. Due to the early stage of the project and the limited scope of the paper, the application is focused on the initial area of solution development.

2. State of the Art

A business model captures value and generates profitable outcomes through applying a particular technology. A business model is a connecting link between technology and its economic value characterized by the three complementary dimensions of value generation, value proposition and revenue structure [7]. The value proposition dimension depicts the benefits a company offers its customers with a particular product or service. The value generation dimension captures central processes and competencies required to implement the business model and fulfil the value proposition. Finally, the revenue structure dimension describes the composition of cost and revenue mechanisms and the resulting value generated from the business [8].

Data-driven, digital business models represent a specific form and have a customer-oriented, service-driven value generation based on data and a full digitalized implementation [9]. Concerning value generation, a data value chain significantly shapes the interactions in such a business model's ecosystem [10]. The data thus utilized can be obtained from various internal and external data sources [11]. In the manufacturing field, data often originates from using products such as machine tools. This is not least due to the ongoing transition from physical products to product-service systems and software-as-a-service models, as the significance of dematerialized value increases continuously [12]. There is also an adjustment in the profile of the players involved in a data-driven business model — the three essential roles of data user, data supplier and data enabler—the three essential roles of data user, data supplier and data enabler [13]. The data user utilizes the data resources available to him in order to create and realize value. The value creation can focus on internal and external value creation (optimization of internal process vs sale of products). The data supplier or data enabler supports the data user in his activities. A data provider ensures a supply of context-specific, relevant data. In contrast, a data enabler provides supporting data services or data infrastructure solutions [13,14]. The interaction of these players is not characterized by one-off or sporadic interactions but by reoccurring and regular ones. Accordingly, there is also a change in the revenue structure to reflect this transformation of service exchange. Thus, the trend is toward repetitive transactions in data-based service bundles. This trend includes subscriptions, key figure-oriented billing (e.g., payment per component produced) or profit-sharing (e.g., participation in savings achieved through using a product). Likewise, compensation models are conceivable in which payment is made through the provision of data [15].

Platform-based business models pick up on this aspect of a transformation in exchanging goods and services and drive it further. Their goal is to reach a more significant number of different participants and facilitate interactions between them [16]. In the business-to-consumer sector, such digital platforms are already widespread. A fundamental distinction can be made between three types of platforms: aggregation, social and mobilization platforms. Aggregation platforms merge a wide range of relevant resources. They help a user connect to the resources he needs, making them highly transactional and task-oriented. The most common examples of this form are broker platforms like eBay and Amazon. Aggregation platforms often operate according to the hub-and-spoke principle, in which a platform owner mediates all transactions. Social platforms aggregate users and support engagement among those with common interests. The most common examples of this form are social media platforms like Facebook or Twitter. Social platforms mainly foster networks without the involvement of an organiser or owner.

Lastly, mobilization platforms get users to collaborate to achieve common goals. Long-term relationships are targeted instead of completing short-term transactions or tasks. Mobilization platforms connect users in extended business processes, such as delivery networks or sales operations. Well-known examples of this are the global supply chain platform Li & Fung or Linux and Apache software platforms [17]. In the context of production, aggregation and mobilization platforms are in focus. In terms of data processing, these two concepts enable capturing financial value from data assets. The data provider and the platform provider can achieve a corresponding monetization. Thus, such platforms position themselves as a central interface between data user, data supplier and data enabler within a cross-process value network [4]. Although the spread of platform-based B2B business models in production is still in its infancy, the first corresponding offerings are already on the market [4]. However, these are essentially proprietary applications from machine manufacturers for company- or lifecycle-phase-specific applications. This contrasts with the openness and trustworthiness of digital platforms as a decisive success factor, as the Gaia-X initiative aims [18].

3. Methodology

The following section addresses how the transition from technological use case to monetizable value creation can be performed within Gaia-X. To this end, the approach to business model development pursued in the EuProGigant project is depicted. The project is a German-Austrian cooperation, which was selected by the Gaia-X initiative as a lighthouse project in the production environment. The presented approach emerges from process models and methods of business model innovation and data science (see Figure 1).

Successful implementation of data-based business models for production requires a systematic and structured process [19]. Concerning the underlying data-based applications, numerous process models exist in the literature. Most of them originate from the field of data mining [20]. Well-known approaches in this field include the Cross-Industry Standard Process for Data Mining (CRISP-DM), the Sample, Explore, Modify, Model, Assess (SEMMA) and the Knowledge Discovery in Databases (KDD) [21]. A deeper analysis of the models in terms of their suitability for the manufacturing industry reveals numerous shortcomings. These prevent a practical and holistic application in such a domain. Among the main criticisms are a lacking possibility of problem selection and a missing consideration of specific requirements from production environments [22].

In order to address these shortcomings, Biegel et al. [22,19] introduced their own Artificial Intelligence Management Model for the Manufacturing Industry (AIMM). Although the model has its bases on artificial intelligence, the approach can also be adapted to the area of platform-based business models. This work then further utilizes the AIMM as a general framework for business model development. In the course of expert workshops in EuProGigant, the model was adapted in broad areas to the already known framework conditions of Gaia-X. This includes, among other things, necessary criteria and building blocks that enable the implementation of business models with Gaia-X.

The process model is funneled and starts with potential problems, subsequently transformed into an application (see Figure 1). The approach has three phases: problem selection, solution design and solution development. In the initial phase of problem selection, the project team first identifies and evaluates relevant problems from the production environment. These are then compared in terms of their complexity as well as relevance and their Gaia-X fit is checked. Promising approaches are selected for further work in the solution design phase. In this phase, the approaches are developed into business models from a holistic perspective. Further, they are evaluated in terms of their technical, organizational and economic feasibility. In the final solution development phase, the elaborated concepts are finally realized, tested and implemented in a development project. A significant difference between the process phases results from the availability of relevant information and the present degree of uncertainty. At the beginning of the process, there is only a low level of information and, at the same time, a high degree of uncertainty. This relationship is reversed as the process progresses [23]. The approach is further designed to fail quickly in the case of an unpromising endeavor. This considers that, particularly at the beginning of an application development process, the efforts incurred are still low. At the same time, a strong influence can be exerted on the future cost-benefit ratio in later phases of development and utilization [24]. Therefore, the process enforces to evaluate if a business case is technically, organizationally, financially and legally – e.g., in terms of data sovereignty – feasible. If an approach drops out, the process can be revisited with a different problem. Otherwise, the solution design can be adjusted accordingly. In this way, the waste of entrepreneurial resources is prevented at an early stage [22].

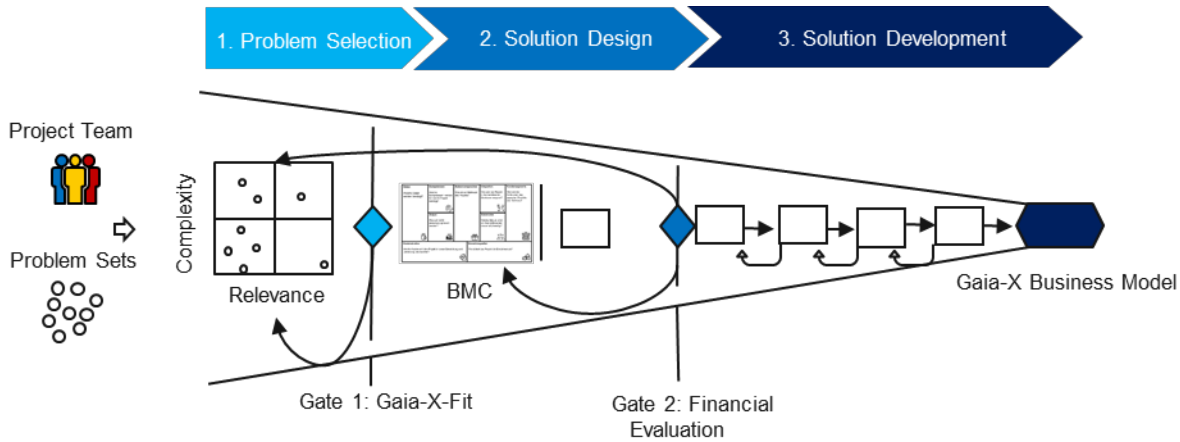

Figure 1: EuProGigant business model development process in accordance with [22,25]

In addition to the evaluation mentioned above within dropout gates, the approach also integrates tools from business model innovation. These are applied in particular in the solution design phase. One of the tools used in this phase of the process model is the Business Model Canvas (BMC) by Osterwalder and Pigneur. The BMC is a framework for visualizing and structuring business models. It is used to generate initial business ideas and creates a holistic overview of business model components. Based on the already presented areas of a business model, the BMC divides them into a total of nine segments, namely: key partners, key activities, key resources, value proposition, customer relation, channels, customer segments, cost structure and revenue streams [25]. The advantage of the BMC is the ability to present a business model in a holistic and clear way and thus to identify possible dependencies. In addition, a uniform understanding of the significance of individual components of the business model can be generated in a project team [26]. One drawback of the model for application to data-based business models is its high degree of generality. Metelskaia et al. [27] address this shortcoming in their extension of the BMC. Based on a comparison of existing approaches to combining business models and data analysis, they specify possible contents of the canvas elements. For example, the key partners are supplemented by IT and data science companies and the revenue streams include novel approaches like Pay-per-X. These specifications make it easier for inexperienced users to create their own approaches with the help of the BMC.

4. Application

In this section, the current work on developing use cases and business models in the EuProGigant project is presented and exemplified in two use cases. Compared to an application in a real industrial environment, there is a significant difference when applied to a research project: Whereas in industry one often must choose between working on different problems arising from one's own company or from customer requirements, the problem in a research project is usually already defined in advance. For this reason, it was decided not to apply the methods from the Problem Selection phase. Furthermore, due to the early stage of the project and the limited scope of the paper, the application is focused on the initial area of solution development. For this purpose, the use case is first described, and then the BMC is applied. The two use cases shown are the ideal component matching and the validation platform. The results presented were developed within interdisciplinary workshops with the project participants. In both cases, domain experts, data scientists, as well as software and electronics developers were among the participants.

4.1 Ideal Component Matching

The assembly of modules (e.g., a shaft-hub connection) combines individual parts from various sources. Typically, some of these components are manufactured in-house by machining companies, and the rest of the parts are sourced from different suppliers. Due to stochastic variations in each company's manufacturing environment, the actual geometries of the components generally deviate slightly from the specifications. Limits are set for combination tolerances of the assembly and allowable deviations of individual parts. Specially manufactured components compensate deviations of a sum tolerance. The solution involves the use of sensory tools and workpiece clamping devices. The data is processed using artificial intelligence methods. In this way, the identification of statistical correlation between component dimensions and processes is enabled. This allows manufacturers to improve the quality of their assemblies and produce targeted matching components as needed.

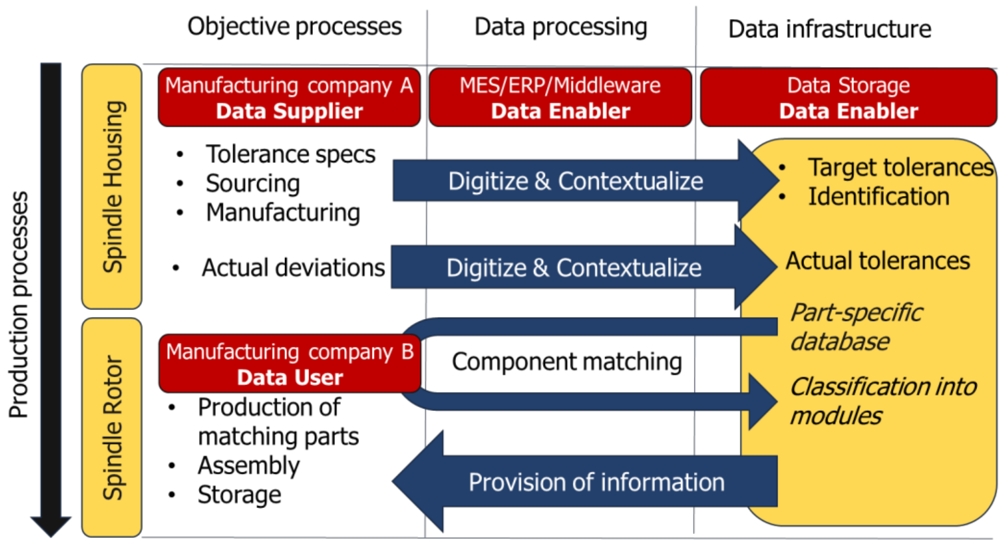

Figure 2: Concept of ideal component matching for a machine tool spindle

In the EuProGigant project, the novel concept is being tested on a machine tool spindle. Two project partners manufacture the two relevant components in the spindle housing and the spindle rotor at different locations. One reason why the machine tool spindle is suitable for the concept is that it is a higher-value component that accounts for a relevant proportion of the total cost of the end product. In addition, the spindle is essential for the manufacturing accuracy and thus for the quality of the components manufactured on a machine tool [28]. Therefore, there are high requirements for the manufacturing accuracies of the housing and the rotor. The same applies to the fitment accuracy and the concentricity of the resulting assembly. The concept of ideal component matching in EuProGigant is shown in Figure 2. The concept is only possible by the close interaction of data supplier, data enabler and data user. In this process, manufacturer A produces the spindle housing according to the tolerance specifications. The captured data - including actual deviations - is then digitized and contextualized via the middleware and stored in the data storage. The stored data are uniquely assigned to each produced component. With the available data, manufacturer B can identify the ideal counterpart to the spindle rotors it manufactures. In this process, the component data for component matching is merged via the middleware and ideal pairs of spindle and rotor are identified. The result in the form of a classification into modules is finally stored in the data storage. Manufacturer B can then plan its component assembly based on this information. Furthermore, manufacturer B can produce a matching spindle rotor based on this data if no corresponding counterpart is available.

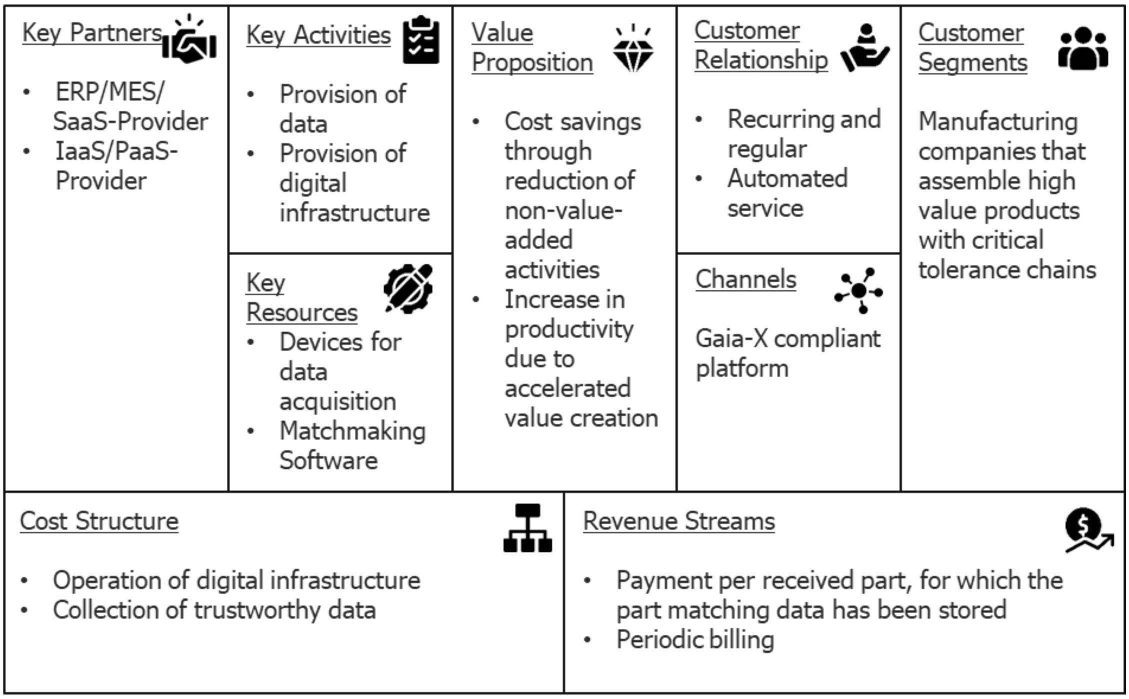

Figure 3: BMC applied on the ideal component matching

Figure 3 shows the application of the BMC. A central value proposition of the ideal component matching is a significant reduction in non-value-adding tasks. Another value proposition is a higher resource efficiency due to fewer rejected parts. This value proposition is made possible through a trustworthy data transfer within Gaia-X. The concept eliminates the need for a direct sequence of final goods inspection at the supplier and incoming goods inspection at the customer. Instead, the customer receives trustworthy component information directly from the supplier's final inspection. Furthermore, it enables creating time flexibility potentials in cross-company value chains. Thus, the sustainable value contribution for the stakeholders of the use case ideal component matching lies primarily in an increased speed of value creation. Through a resulting reduction in assembly time, a possible productivity increase of 10% can be achieved in case of the machine tool spindle. The data provider - in other words, the component supplier - and the data enabler - in other words, the infrastructure provider - can be remunerated for this added benefit to the data user within a revenue model. The pricing can thereby be aligned with the expected cost savings per assembled component. In the use case, the payment is made per purchased component for which the matching data was provided during the handover. In this case, billing can take place at regular intervals. This takes the high number of individual contacts and thus transactions into account. Data providers and enablers thus can cover their costs for operating the digital infrastructure and collecting trusted data. Accordingly, they can obtain a profit opportunity as an incentive to participate in the business model.

4.2 Validation Platform

Predictive maintenance in production promises to reduce maintenance costs and the number of unplanned machine downtimes. On the one hand, this can improve economic efficiency. On the other hand, it can increase the availability of machines and systems [29]. Many companies have already recognized the potential of this technology, but they often fail to implement it practically [30]. Predictive maintenance is based on mathematical models, which often originate from machine learning. These models use as input sensor data from machine components both for its training and operation. Especially models that are supposed to predict the remaining lifetime of components depend on a broad basis of historical data for a reliable output [31]. However, especially in the case of components that bear a high proportion of the cost of a machine – such as a machine tool spindle – it can be assumed that long-term recording of data on several, comparable machines is necessary to provide data records of degradation and wear events in sufficient quantity [32]. In particular, small and medium-sized enterprises have problems with the provision of corresponding data sets. One of the reasons for this is that they often only have access to historical data sets that are not very comprehensive or of insufficient quality [33]. In addition, they often have heterogeneous machine fleets that make collecting data on similar machines and their components even more difficult. The use of a validation platform enables monitoring machines and assemblies for companies without an extensive database. Collaborative and predictive maintenance of machines and their components can thus be enabled due to different companies' shared use of data.

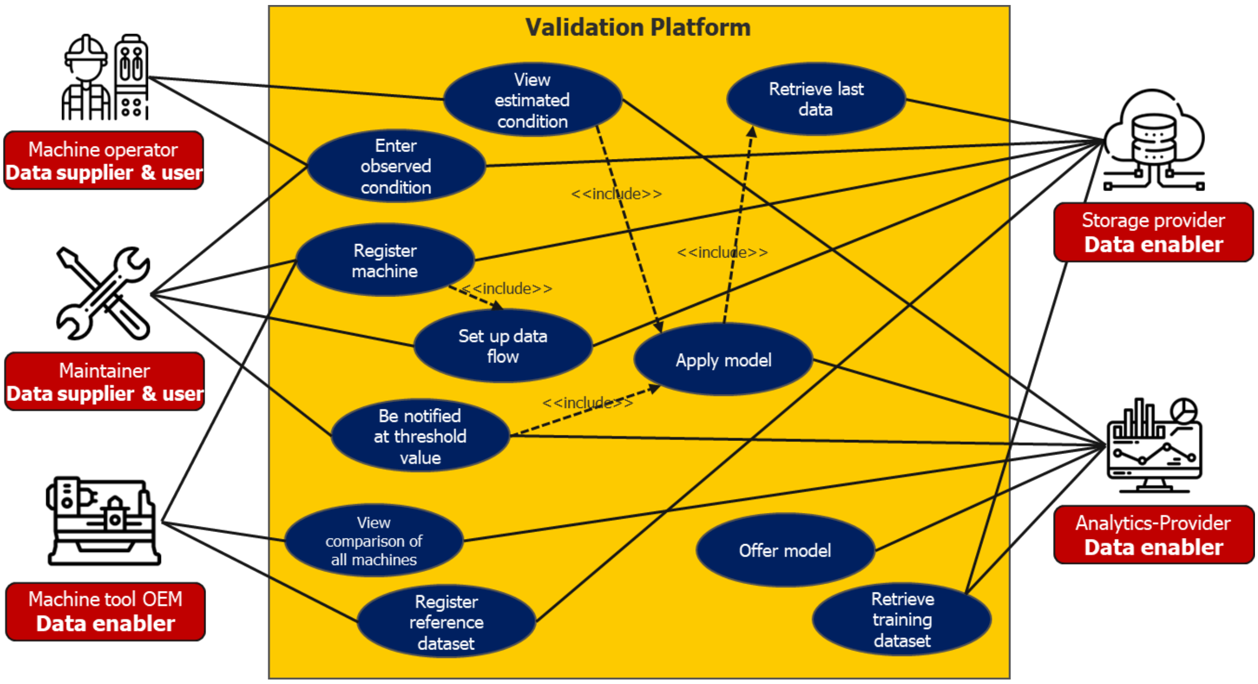

Figure 4: Concept of validation platform for machine tools

The EuProGigant project tests the concept of a validation platform on several similar machine tools. These are located at various sites of different production companies. The concept of the validation platform in EuProGigant can be seen in Figure 4. As in the case of the ideal component matching example, it can be seen here that the approach is only made possible by the close interaction of data suppliers, data enablers and data users. Here, the machine operator and the maintenance engineer simultaneously act as data suppliers and data users. During the operation and maintenance of the machine, both actors generate condition-relevant data, which is stored by the storage provider. The analytics provider can in turn use this data to train and operate its provided condition monitoring model. Thereby the machine tool OEM determines by registration of the machine, which reference data set of similar machine can be used. Based on the results of the condition monitoring model, the machine operator receives an assessment of the machine condition via the platform. Furthermore, the maintainer is informed as soon as the remaining service life of a component falls below a threshold value. Both actors then return feedback regarding the observed condition to the platform. This feedback can in turn be used to improve the condition monitoring model. The machine tool OEM, the storage provider and the analytics provider thus assume the roles of data enablers.

Figure 5 shows the application of the BMC. The validation platform has several complementary value propositions. On the one hand, it enables companies with a heterogeneous machine park to apply predictive maintenance for a more significant part of their machines. Thus, it leverages the potential already presented. Furthermore, it is possible to build up an adequate database more quickly and thus reduce the start-up phases of corresponding solutions. Finally, the prediction accuracy of the models can be improved by a broader data basis with actual process data from machine operation.

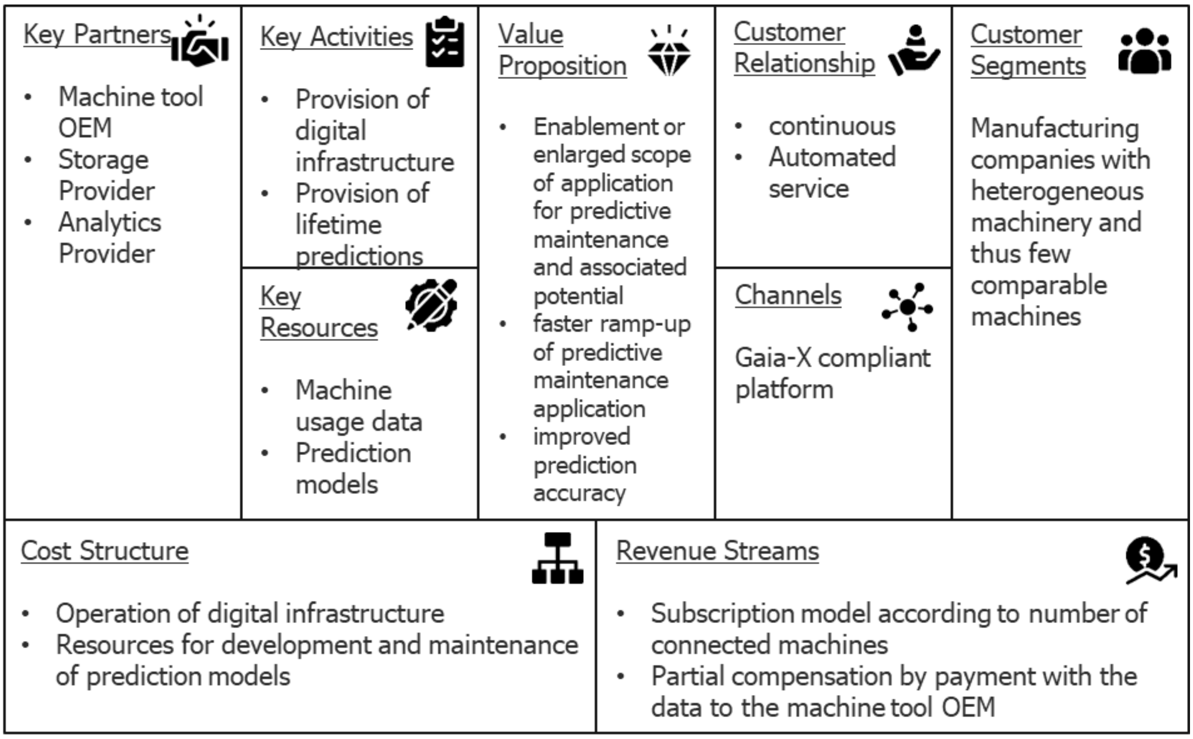

Figure 5: BMC applied on the validation platform

A Gaia-X-compliant platform enables trustworthy data transfer and merges data streams from different companies. This ensures that only authorized players can access the data and that there is no leakage of intellectual property over the data from machine usage. The data enablers - i.e., the machine tool OEM, the storage provider and the analytics provider - can generate new cash flows via an appropriate revenue model in return for the added value of the data user. Due to the continuous provision of services, a subscription model is recommended. In the context of the use case, it is intended that payment will be made per connected machine or component. Tiered pricing is also considered a possible model if several machines are connected. This pricing can be based on the expected cost savings due to an enabled or improved predictive maintenance use.

Furthermore, the machine tool OEM can use the data to optimize its own products and product-service offerings. In return, a part of the payments could be compensated by this benefit. Through the revenue streams thus realized, the data enablers have the opportunity to cover their costs of operating the digital infrastructure and developing and maintaining the predictive models. Ultimately they receive a profit opportunity as an incentive to participate in the business model.

5. Conclusion and Future Research

This paper presents a possible methodological approach for developing digital, platform-based business models in the context of Gaia-X. First, fundamental properties of data-driven, platform-based business models were discussed and then a process model was derived. The presented approach and the tools contained therein are practically applied in the context of the Austrian-German lead project for Gaia-X in the manufacturing industry called EuProGigant. Two of the business models considered in the project were finally presented and captured in a BMC, which was utilized in the solution design phase of the project. A key insight from the presentation of the two use cases is that the utility value of a common data infrastructure does not only lie in the direct selling and buying of data and services. It is instead in the saving of value-destroying sections of process chains. These, in turn, open up time-transparent flexibility potential and thus strengthen resilience in the network.

In the considerations made in the context of this paper, it should be noted that the contents presented provide an initial outlook on the future possibilities of platform-based business models within Gaia-X. The Gaia-X initiative and the lighthouse project EuProGigant, are still in their infancy and are currently characterized by high development dynamics. Once the Gaia-X community has created a robust framework, the business models' technical details can be further refined. Thus, the presented process model shall be regarded as a working status. It will be continuously adapted by the progress of the project and optimized and extended with regard to the knowledge gained. Furthermore, the approaches to business model development must be further tested, and their technical feasibility must be confirmed. In the course of this, the evaluation methods outlined can also be used to assess the economic viability of the business models. Adjustments can be made as part of an iterative improvement process if necessary. Lastly, only one section of the process model, namely solution development with the BMC, was considered in the context of the paper. The aim of further work and publications in the project should be to apply and evaluate the tools of the other phases in practice as well.

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8. Biography

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