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Comparison of AI-Based Business Models in Manufacturing: Case Studies on Predictive Maintenance

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Abstract

Recent advances in Artificial Intelligence extend the boundaries of what machines can do in all industries and business sectors. The economic potential to apply AI in manufacturing results in an increasing number of companies striving to gain a competitive advantage through AI and move into new markets. In this context, particular importance is given to the predictive maintenance of machines. Predictive maintenance promises the possibility of avoiding unexpected machine downtimes and thus increasing the availability of production lines. However, only a few machine manufacturers have a marketable offering of AI-based products or services in their portfolio. Even if technical feasibility is proven, companies lack an understanding of how to integrate AI solutions into new Business Models. This paper thus presents three case studies and their Business Models as examples. Practical considerations and recommendations on the strategical adoption of predictive maintenance technologies are derived.

Keywords

Predictive Maintenance; Artificial Intelligence; Business Models; Machine Tools

1. Introduction

The application of Artificial Intelligence (AI) in production offers great potential for companies along the entire value chain. As a result, global GDP is expected to undergo an increase of up to 14 % or $15.7 trillion by 2030 through the use of this technology [1]. This paper considers the so-called weak (or narrow) AI, which can solve concrete problems [2], for example, by using machine learning algorithms. AI can in this context be described as "intelligent systems created to use data, analysis and observations to perform certain tasks without needing to be programmed to do so" [3]. Predictive Maintenance (PdM) is an example of a task that can be performed using AI technologies. PdM promises the possibility of avoiding unexpected machine downtimes and thus increasing the availability of production plants. The economic potential to apply PdM making use of AI technologies in manufacturing results in an increasing number of companies striving to gain a competitive advantage and/or move into new markets. However, even if technical feasibility is proven, companies lack an orientation to integrate AI solutions into business models [4]. In this paper, the development of AI-driven Business Models (BM) is proposed as the first step to strategical integration. The BM canvas is used as a tool for defining the elements that compose the BM. This work contributes to the existing literature with three example case studies and elucidates common aspects of AI-driven BM for PdM. The focus lies, therefore, on the integration of three AI solutions into the companies' BM.

This paper is structured as follows, Section 2 provides the state of the art in the fields of PdM and AI-based BM. In Section 3, the case studies are presented. The first case study is from a machine manufacturer that intends to market its PdM solution as an additional service. The second is from a supplier for machine tools who expects to add value to its existing product by implementing a PdM solution through retrofit. Finally, the third case study is a machine tool manufacturer that plans to offer maintenance services inside its load-based leasing model. Section 4 provides a discussion and compares the proposed BMs. Section 5 summarizes the paper and delineates future research directions.

2. State of the Art

This section presents the main concepts and recent developments related to both PdM and AI-based BM. First, the topic of PdM is introduced, highlighting the role of AI, more specifically of machine learning (ML), in the solutions development. Second, BM and BM Innovation (BMI) as well as recent developments of AI-based BM are elucidated.

2.1 Predictive Maintenance

Maintenance is the technical, administrative, and management measures throughout the part's lifecycle to restore or maintain its functional state. Maintenance measures are divided into service and repair. Service measures are for the delay or reduction of the machine's or machine component's wear, while the repair is for restoring the target condition [5]. At present, the maintenance of machines and plants in production is often carried out reactively. Signs of wear are therefore usually not detected until they already restrict the functionality. At this point, however, there is a high probability that delicate machine parts have already been damaged. This form of reactive maintenance often leads to costly repairs and more extended unplanned downtimes. To avoid this, companies carry out maintenance as a preventive measure according to defined intervals (e.g., defined number of cycles, operating hours of the machine). Maintenance in pre-defined time intervals has, however, the disadvantage that, e.g., machine parts that are often still functional and could still be used for a more extended period are replaced prematurely. The use of Predictive Maintenance (PdM) promises to resolve this conflict of objectives [6]. PdM uses the component's condition monitoring data to forecast its state and identify when maintenance is needed, preventing breakdowns and time losses due to unplanned maintenance interventions [7].

PdM approaches are divided into physical model-based, data-driven or hybrid (a mix between these two approaches) [8]. Physical model-based approaches use physical relationships and mathematical representations of the system's failure mechanisms to simulate future states and determine the remaining valid lifetime. These solutions require a profound understanding of the system's characteristics and become unviable for complex systems in which the failure modes and behaviour under adverse operating conditions is unknown. Data-driven approaches use historical and real-time data to forecast the system's state or identify patterns and estimate the remaining valid lifetime [8]. Data-driven approaches use data (time-series, images, and videos) and data analysis techniques, such as statistical methods like exponential smoothing and autoregressive moving average (ARMA) [9], machine learning algorithms like random forest [10], support vector regressor [11] and neural networks [12] [13] to make predictions and estimate when maintenance is necessary.

2.2 AI-based Business Models

A BM is defined as the mechanism that captures value and generates profitable outcomes through the application of a certain technology, it is thus the mediating construct between technology and economic value [14]. A BM is composed of the three dimensions of value proposition, revenue structure and value chain [15] [16]. The value proposition describes what benefits a company promises its customers with a particular product or service. Further, the revenue structure describes how the cost structure and revenue mechanisms in the company are composed so that value is generated from the business. With the value chain dimension, the central processes and competencies required for the implementation of the BM are captured so that the performance or the value proposition can be fulfilled [17]. An AI-based BM is then a business model developed to capture value from AI technologies and applications. In this regard, at least one of the three dimensions of the business model is influenced by the use of AI-methods [18]. On the one hand, existing business models of a company can be transformed through the use of the technology. On the other hand, due to its high disruptive potential, AI offers opportunities to develop completely new business models [19].

Business Model Innovation (BMI) describes the process of developing and continuously improving a company's business model with potential to refine and expand the product and service portfolio [20]. The integration into the corporate strategy and the development of corresponding competencies in dealing with AI topics at all organizational levels is the necessary basis for the development of sustainable benefits from BMI activities in a company [21]. Despite partially divergent objectives and target domains, the corresponding approaches are mostly iterative and range from an initial conception phase to the final deployment of a solution [22] [23]. To carry out each phase of the BMI process, a variety of tools can be used. One of the most widely used tools for the visualization of the BM is the Business Model Canvas (BMC) developed by Osterwalder and Pigneur [24]. The BMC is a framework for visualizing and structuring business models. It is predominantly used at the beginning of the BMI process to analyze the initial situation and to generate initial ideas, as well as providing a holistic overview of the BM components. Based on the three 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 [22]. One drawback of the model for application to AI-based business models is the high degree of generality. Metelskaia et al. address this shortcoming in their extension of the BMC [4]. Based on a comparison of existing approaches to combining BM and AI, they specify the possible content of the individual elements of the canvas. For example, the key partners are extended to include leading IT companies and the revenue streams are extended to include Software-as-a-Service [2].

3. Methodology

The case studies originate from research projects developed with industry partners within the last two years. These research projects were selected because they resulted in proofs-of-concept and initial developments towards an AI-driven PdM solution. The applications, therefore, are not yet being marketed as products. However, the hypothetical BM developments allow comparing the different case studies and serve as guidelines for future implementations. Researchers that worked on the projects completed the BMC from the manufacturer's perspective based on project stakeholders' workshops or project documentation, e.g., project reports. The BMC was chosen because it enables a structured visual representation for the comparison and is familiar with BM developments of other technologies, facilitating the understanding outside of the AI field, as it is industry and BM independent [26]. The fourth section briefly introduces the case studies and presents the BMC.

4. Predictive Maintenance Case Studies

In the following section, three PdM case studies are presented as examples of how to integrate an AI solution into a BM. These case studies illustrate three different types of PdM solutions: the first as an additional maintenance service, the second incorporates not only the developed software but also the necessary retrofitting sensors to enable a PdM solution, the third as an additional service inside a load-based leasing model.

4.1 Machine Manufacturer – Case Study 1

The first case study is from a project developed with an industry partner that manufactures machines for industrial applications. The developed PdM application forecasts a feature representative of a component's health-state and determines when it must be exchanged, allowing planned maintenance interventions at the end of the component's useful lifetime. This application should replace the former reactive maintenance procedure carried out in predefined time intervals.

Figure 1 depicts the technical architecture of the PdM solution. Historical time series data from sensors pre-installed in the machines are used and processed in batches for running this application. The data is transmitted via the OPC UA server to the forecasting application. The forecasting application, hosted in the cloud, receives and pre-processes the data before saving it in a relational database. The regressor retrieves data from the database daily and outputs a 30-day forecast of the target variable. The program verifies whether the forecasted values exceed a pre-defined operation threshold. When the threshold is surpassed, the component must be replaced. The human-machine interface then displays a warning informing the machine operator when maintenance should be performed within the forecasted 30 days.

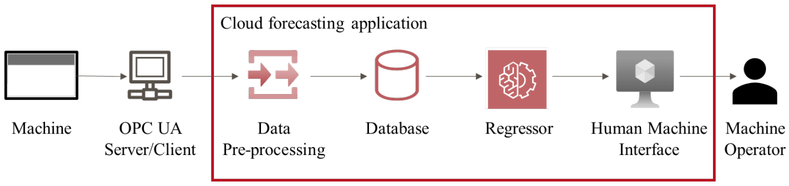

Figure 1. Technical architecture – case study 1

The PdM application is meant to be marketed as an additional service to better plan the necessary maintenance interventions and use the machine components until the end of its useful lifetime. The customer uses the PdM application hosted by the manufacturer, instead of installing the software on its own machines, and accesses the application through the internet. Figure 2 presents the BMC for the first case study.

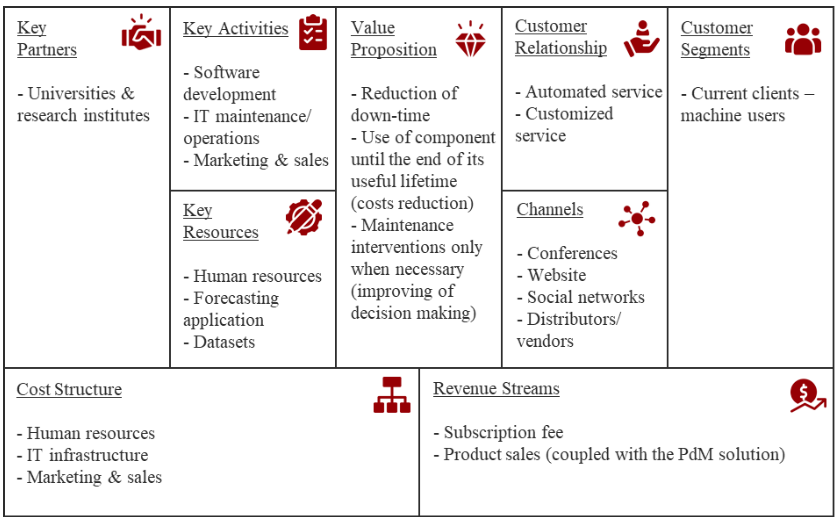

Figure 2. Business model canvas for PdM solution - case study 1

4.2 Supplier for Machine Tools – Case Study 2

The second use case originates from a recently completed research project, which was carried out together with an industrial partner from the supplier sector who manufactures protective covers for machine tools. The project also resulted in a proof of concept as well as an executable functional model on which a later product development can be based. In addition to the development of the technical solution and an AI approach, considerations were also made as to how an initial business model can be designed that is compatible with the prerequisites in the company [27].

As part of the developed PdM approach, sensors record force and acceleration signals at the protective cover during operation of the machine tool. With the help of the recorded data, a feature can be determined that allows conclusions to be drawn about the remaining service life of the component. Based on this, a prediction of the time of failure can be made, enabling maintenance measures to be optimized in terms of time and cost. The solution promises to solve the conflict in industrial practice of a protective cover being replaced too late (reactive maintenance) or too early (preventive maintenance).

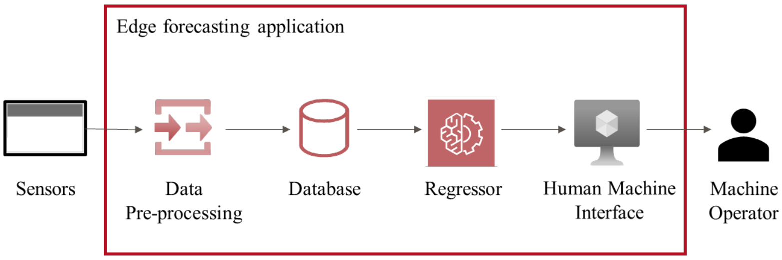

Figure 3. Technical architecture – case study 2

The technical architecture of the PdM solution, as illustrated in Figure 3, is as follows: For the operation of the application, time series data from the installed sensors are collected and pre-processed. This step, as well as making the prediction, is done on an edge device. The regressor continuously receives data and allows conclusions to be drawn about the current wear state at any time. As soon as a defined threshold value for the state value is undercut, the user is notified that the component requires replacement.

In the initial BM, the product is to be marketed as a supplier product directly to machine tool manufacturers via existing sales channels. The company does not plan to provide its own digital PdM service to machine users. This considers two circumstances within the company: Due to the company's origins, there is no expertise in electronics and software development to date. Additionally, it is difficult and time-consuming to build up the necessary expertise because of a persistent shortage of skilled workers. On the other hand, many machine tool manufacturers themselves already have advanced service platforms. The marketing of an own service application without integration into the ecosystem of a manufacturer is not promising. Figure 3 presents the AI BM canvas for the second case study.

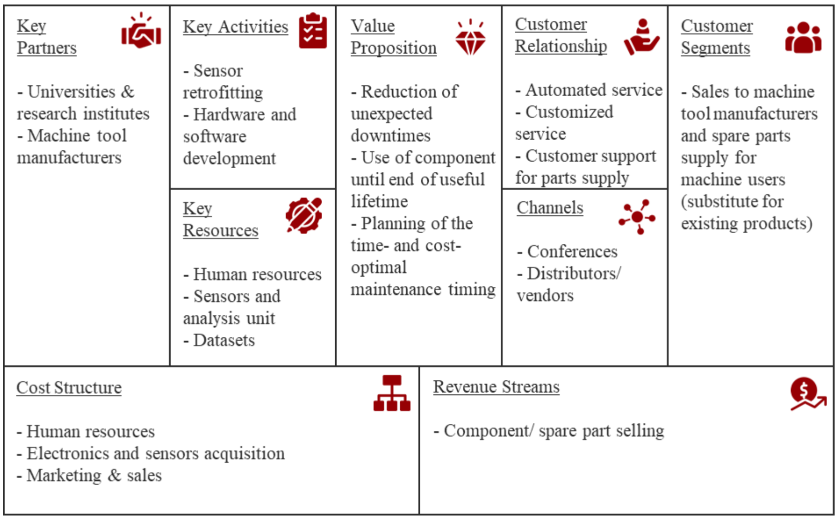

Figure 4. Business model canvas for PdM solution - case study 2

4.3 Machine Tool Manufacturer – Case Study 3

The third case study is derived from an ongoing research project conducted with industry partners. In the project a stress-oriented, data-based payment model for machine tools called "Pay-per-Stress" is developed. Figure 5 provides an overview of the technical architecture. The machine user leases the machine from a lessor who acquires the machine from the machine manufacturer. The payment model has two main components: a monitoring system, which measures the stress linked to the machine and calculates the remaining useful lifetime (RuL), and an incentives system, which sanctions harmful and rewards regular usage, in order to align incentives [28]. The goal of the model is to link stress and actual machine wear and use it as a leasing indicator, mitigating the information asymmetries and inefficiencies from classical leasing and pay-per-x models.

The architecture of the model is visualized in Figure 5 and designed as follows: Sensors installed in the machine are used to record process data during operation and then encoded on the customer's site. The data is then forwarded via blockchain to the machine manufacturer, who processes the data on its own premises. In the case of maintenance services, the results of the evaluation are forwarded to the customer. This makes it possible to provide the customer with recommendations on how to operate the machines in a load-optimized way and when maintenance measures need to be carried out. The BM in this paper is considered from the perspective of the machine tool manufacturer and is restricted to the PdM service that can be provided based on the RuL estimation.

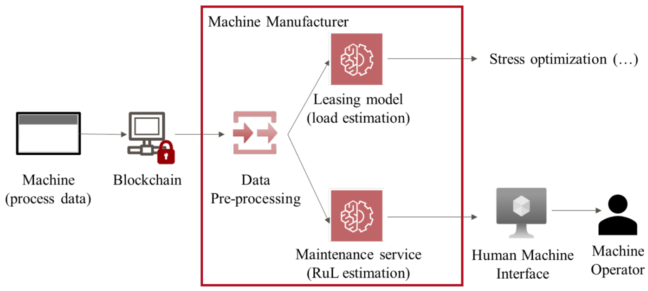

Figure 5. Leasing business model architecture

AI is used as the data-driven technique for calculating the RuL based on process data. On the one hand, the insights gained are used to operate the payment model. On the other hand, it can also be used for the further development of the company's own products and for the operation of maintenance services at the customer's site. Figure 6 presents the BMC for the third case study. The presented BM complements the leasing model BM with additional maintenance services.

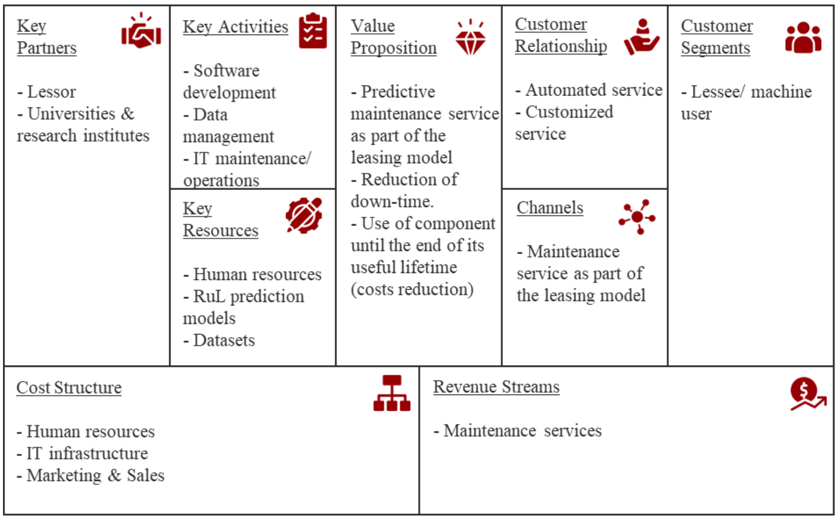

Figure 6. Business model canvas for PdM solution - case study 3

5. Discussion

This section discusses similarities and differences of the presented BMs and highlights opportunities for the strategical adoption of PdM. Table 1 compares the three BMs. Next, insights concerning common aspects to the case studies are presented.

Table 1. Comparison of Business Models

Aspect	Similarities	Differences
Key Partners	- Universities and research institutes.	- Additional key partners for case 2 and 3, since they depend on other partners (machine manufacturers and lessors, respectively) to market the AI solutions.
Key Activities	- Software development. Development of the PdM application.	- Case 2 additionally encompasses the retrofitting of hardware for data collection. Cases 1 and 2 make use of sensors pre-installed in the machines. - Cases 1 and 3 have the IT maintenance and operations. Case 2 uses existing platforms from the machine manufacturer to operate the AI solution.
Key Resources	- Human resources which include the data scientists, software engineers and other members of the AI team [29]. - Datasets/ data. Generated from the machines and production processes and necessary to estimate the components RuL. - AI applications. Including ML algorithms and pipeline.	- Case 2 additionally encompasses the electronics and sensors for retrofitting.
Value Proposition	- PdM objectives: reduction of unexpected downtimes, use of component until the end of its useful lifetime (cost reduction), planning of time- and cost-optimal maintenance measures.	
Customer Relationship	- Automated and customized service. Automated and customized because the customers interact with human-machine interfaces to specify and customize the PdM services. Customer support is necessary to accompany the installation and correct functioning of the application.	- Case 2 foresees customer support for direct sales and part supply. This support is necessary in case of retrofitting of previously acquired machines.
Channels		- In cases 1 and 2 conferences, distributors, and vendors. Channels which are already used in the current BM. - Case 1 additionally foresees advertisement through its website and social network.

		- Case 3 uses as channel the leasing model and offers the PdM solution as an additional service.
Customer Segments	- The new BMs mainly aim at existing customer segments (respectively machine users in case 1 and 3 as well as machine tool manufacturers in use case 2).	- Case 2 foresees an additional opportunity opportunity for direct sales to machine tool users that want to retrofit their machines and allow PdM for the protective covers.
Cost Structure	- Human resources. - Marketing & Sales.	- Cases 1 and 3 also include the IT infrastructure to operate the PdM application. - Case 2 has additional costs for the retrofitting equipment acquisition and does not have additional IT infrastructure costs, since the application would run in the machine manufacturer's platform.
Revenue Streams		- Case 1 through subscription fees and coupled sales with the current products (machines). - Case 2 through sales of the retrofitting equipment for PdM as components/spare parts. - Case 3 through maintenance sales.

It is worth mentioning that the three case studies originate from projects conducted in partnership with research institutes in publicly funded research projects, meaning that it is not a coincidence that for the three use cases, universities and research institutes are identified as key partners in the canvases. This form of collaboration is often used as the first step in creating a technical proof of concept for the content of AI-based BMs. Advantages arise here from the broad expertise of research institutions in innovative technologies, as they deal with these at an early stage. Companies also appreciate the fact that there are often no competing economic interests despite cross-industry collaborations. In addition, cooperation with research institutions is often a necessary prerequisite for gaining access to public funding [30].

Particularly in Germany, where the case studies were carried out, the government offers public funding programs and initiatives aimed at developing AI-based solutions in manufacturing. In addition to the expenses for the personnel required to carry out the project work, expenses for material resources and subcontracts can also be financially supported. Contrary to use cases 1 and 2, not only bilateral consortia are possible, but also consortia consisting of different university and industrial institutions as in use case 3. Public funding allows companies to engage in pre-competitive ventures at a reduced financial risk.

A common aspect to the presented case studies is the central and enabling role of AI technology in the BM (evident in the *Key Resources* field of the BMC). As reinforced by other studies, AI initiatives need to be core to a company's business strategy to create meaningful value and scale [31]. It is argued that the development of a BM for the PdM solutions is the first step for its strategic adoption. Also the *Cost Structure* and *Revenue Streams* need to be aligned with the company's long-term goals in terms of hiring skilled personnel and/or providing training to build an in-house AI team [32]. There is a difference between adopting AI for improving existing business processes, e.g., in manufacturing and in marketing, and adopting AI for developing and enabling new products and new services from which the company can capture value. The second is where the true potential of AI as a competitive advantage lies, and can only be realized when the AI initiatives are developed in-house and are part of the company's strategy [31].

The customer, considered in the fields *Customer Relationship* and *Customer Segments*, is central in the BM development [20]. AI-driven solutions not only have the potential to fulfil customer needs (such as PdM), but also enables new marketing possibilities (described in *Channels*) and image gains, bringing an innovative aspect to the company's portfolio.

6. Summary and Outlook

This paper presents three case studies from the manufacturing industry that have developed AI-based BMs to capture value from PdM solutions. The first case study is from a machine manufacturer that intends to market its solution as an additional service to its machines. The second use case is from a supplier for machine tools who expects to add value to its existing product by implementing a PdM solution through retrofit. Finally, the third case study is a machine tool manufacturer that plans to offer maintenance services inside its load-based leasing model. The business model canvases are presented to identify the main aspects of each case. The discussion section provides a comparison between the case studies, highlighting the similarities and differences and showing that there is not only one option for marketing PdM solutions. AI is perceived here as the enabling technology that allows the development of new BM. Pre-requisites for the AI solutions presented here include not only skilled personnel but also data, in the presented use cases either generated by sensors pre-installed in the machines or through retrofit efforts. This work contributes to the existing literature with three example case studies and elucidates common aspects of AI-driven BM for PdM. Future research includes investigating the actual implementation of the developed BM and identifying the success factors.

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