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Integrating Assessment Methods In The Development Of ML-Based Business Models For Manufacturing

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Abstract

The use of machine learning promises great potential along the entire value chain of manufacturing companies. Many companies have already recognized the resulting opportunities for increasing enterprise value and are developing their machine learning applications for the production environment. However, despite these efforts, many of the solutions developed fail in the market. Especially small- and medium-sized enterprises have difficulties developing suitable business models for their technical applications. These difficulties arise because companies do not evaluate their business projects sufficiently during the development phases. As a result, unpromising projects are not recognized until late in the development process and thus cause high sunk costs.

This paper presents an approach for integrating assessment methods into developing machine learning-driven business models for production. Due to the diametric evolution of information availability and uncertainty during the business model development process, various methods and tools can be used for the assessment depending on the current phase. For this purpose, existing assessment methods are evaluated and contrasted regarding their suitability concerning machine learning-based business models for production. Afterwards, three approaches for the different planning phases of business model development (strategic, tactical, operational) are presented in this paper.

Keywords

Artificial Intelligence; Machine Learning; Business Models; Assessment; Manufacturing

1. Introduction

Recent studies reveal various potentials of Machine Learning (ML) for companies along the entire value chain. As a result, global GDP is expected to increase by up to 14 % or $15,7 trillion by 2030 [1]. Today, ML systems are applied across various industries. These help, for instance, to make quality management more efficient or to enable predictive maintenance of machines. Although the feasibility of these applications has already been proven many times at the research level and first marketable products are available, the actual implementation of corresponding applications and offerings lags behind the high expectations [2,3]. One of the main reasons for this discrepancy is that companies are not able to develop economically viable scenarios for their technical solutions [4]. It becomes apparent that especially those companies are successful with ML offerings that emphasize the generation of business value during development. Thus, building a business understanding and evaluating business cases as part of business model (BM) development is a key success factor for implementing competitive ML applications in manufacturing companies [5].

Research on ML-based BMs for manufacturing and the accompanying empowerment of companies is still in its infancy. The following work aims to identify appropriate evaluation methods for the different phases of maturity in the development of ML-based BMs for manufacturing. Using the tools presented, companies can evaluate the current development status of their BM and be supported in their decision-making. The underlying research hypothesis states that an appropriate methodology can be developed by analyzing existing concepts and approaches in the respective technical literature. This work considers ML as a system that "uses data, analysis and observations to perform certain tasks without needing to be programmed to do so" [6]. A BM is ML-driven if at least one relevant dimension is characterized by the use of ML methods [7].

The procedure outlined in the paper is as follows: Section 2 first provides an overview of the development process of ML-based BMs and its three-phase structure. To this end, different process models are discussed and the process is explained using a selected model. Subsequently, phase-specific requirements for the selection of evaluation methods are derived from literature. The resulting evaluation criteria are then used to evaluate existing evaluation methods which were identified in the course of a structured literature analysis. Based on this overview, section 3 proceeds with the presentation of a developed methodology, thereby choosing the most appropriate methods and tools for each planning horizon and adapting these to the area of manufacturing. For validation purposes, the introduced methodology is then applied to an actual use case from the manufacturing industry in section 4. Finally, section 5 ends with the conclusion and potential impulses for further research.

2. Research results

2.1 Development process of ML-based BMs

A successful implementation of ML-based BMs for manufacturing requires a systematic and structured process. This is of particular importance for companies that have only limited experience in the context of developing ML-based applications [3]. To address this problem, numerous process models exist in literature. Many of these approaches originate from the field of data mining, which is the extraction of structures and patterns from large amounts of data using specific analysis techniques [8]. 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) [9]. A deeper analysis of the models in terms of their suitability for the manufacturing industry reveals numerous shortcomings that prevent their practical and holistic application in such a domain. Among the main criticisms is that existing models do not cover the process of selecting a problem and deciding whether to use ML to solve it and do not take into account the specific requirements of production environments [10].

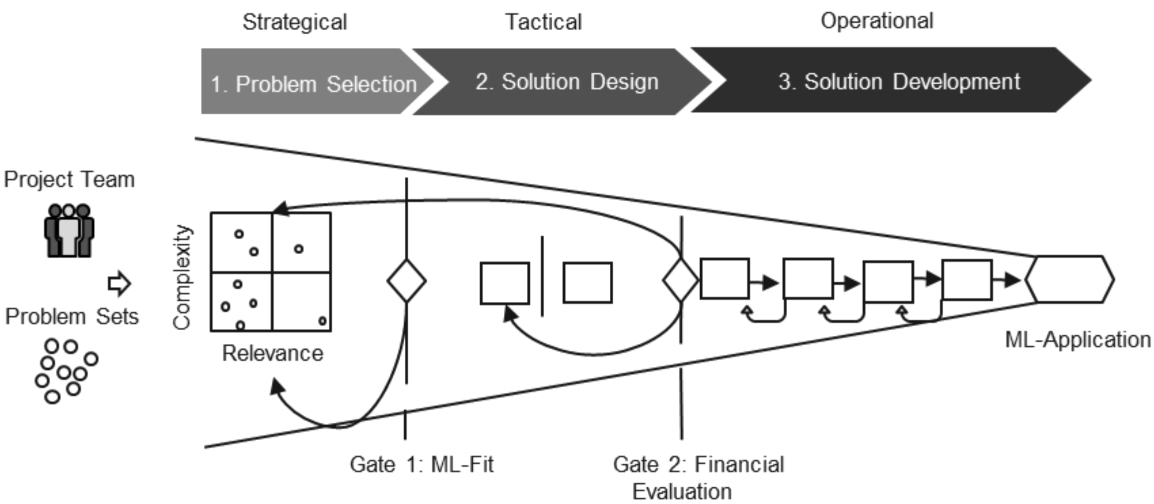

Figure 1: Development Process of ML-based BM according to Biegel et al.

In order to address these shortcomings Biegel et al. [10] introduced their AI Management Model for the Manufacturing Industry (AIMM) (see Figure 1). It is further utilized as a framework for the integration of assessment methods and to emphasize the characteristics of each phase. The process is funneled and starts with potential problems, which are subsequently transformed into an ML application using three phases: problem selection (strategic phase), solution design (tactical phase) and solution development (operational phase). A significant difference between the process phases results from the availability of relevant information and the degree of uncertainty regarding the economic viability. Relevant information includes not only forecasts on technical prospects of success, but also market scenarios and possible legal restrictions. Only a little, primarily qualitative information with a low resolution, is available at the beginning of the process, leading to a high degree of uncertainty. This uncertainty is reduced throughout the process by acquiring new and higher-quality information, gradually enabling a quantitative evaluation of projects [11].

The AIMM is designed to fail quickly in the case of an unpromising endeavor. The model takes into account that, particularly at the beginning of an application development process, the costs 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 [12]. This effect is especially relevant for the domain of production, as physical products - e.g., in the form of machine tools - are frequently linked with digital services in so-called product service systems [13]. In the case of a mere development of digital services, the share of cost emergence in early phases is proportionally higher. In contrast preventing sunk costs in later phases nevertheless has a significant impact [14,15]. Therefore, at the transitions of the phases, the AIMM process enforces to evaluate whether a problem can potentially be solved using AI technology and whether a resulting business case is financially feasible. If an idea is dropped out, the process can be revisited with a different problem, or the solution design can be adjusted accordingly. In this way, the waste of entrepreneurial resources is prevented at an early stage of the use case development [10].

A shortcoming in the AIMM is that the authors only provide a few concrete hints to the phase-specific use of assessment methods. In their approach to technology assessment from 2011, Haag et al. [16] become more specific and propose different assessment methods for the distinct process phases of technology development. However, the approach is highly technology-unspecific and does not incorporate the special requirements that arise when considering ML-based technologies, which will be highlighted throughout this paper. Due to the age of the explanations, many context-specific assessment methods (e.g., from the field of digitalization and Industry 4.0) developed in the meantime are also not included in the approach. In this regard, the method presented in this paper picks up and presents ML-suitable assessment methods in each of the three process phases.

2.2 Phase-specific requirements and evaluation of existing assessment methods

Suitable evaluation criteria must be defined for a comparable and objective evaluation of existing approaches. These result from the requirements of the different process phases and were identified as part of a structured literature review. Next is examined which activities are carried out in each phase and which input and output states are present. In addition, it is included which incoming information is available and which outgoing information must be provided for decision-making (see Figure 2).

In the **strategic phase** of problem selection, the project team first identifies and evaluates relevant problems from the production environment. As incoming information, a selection of possible problem definitions is available, whose potentials and challenges are assessed concerning a possible solution development. The underlying problem set can originate from the documentation of a continuous improvement process or from a dialogue with customers [17]. Since there can be larger problem sets, it is necessary to identify and prioritize the most promising ones. In their model, Biegel et al. propose a qualitative evaluation of problems in the two overarching dimensions of relevance and complexity using a portfolio matrix. While the number of actors and objects involved and their relationships to each other and the required interdisciplinarity is a major influencing factor for complexity, the influence on a company's key performance indicators (e.g., Overall Equipment Effectiveness) is decisive for relevance. After prioritizing the alternatives, the selected problems cross the first gate where the ML fit is examined. In this process, it is checked whether the problem under consideration meets the basic requirements for being solved with ML methods [18]. After passing through the strategic phase, quantitatively evaluated, prioritized, and ML-suitable problems remain for further pursuit in the tactical phase.

Following the results of a structured literature review, the first requirement is that suitable methods for the strategical phase are capable of enabling a comprehensible and systematic ranking of alternatives [19]. Furthermore, especially in this initial phase, it is necessary that the alternatives to be evaluated allow a *holistic assessment*, despite the low level of information [20]. In this context, it should also be possible to conduct *risk assessments* and to make *prognoses* by considering volatilities in technical, financial and organizational conditions [21]. Finally, regarding the *usability* in the strategic phase, it should be ensured that the models are generalizable to enable the evaluation of a wide range of possible problems. In addition, they should be able to determine reproducible results that are comprehensible in terms of *transparency*, even in spite of fluctuating information quality [22].

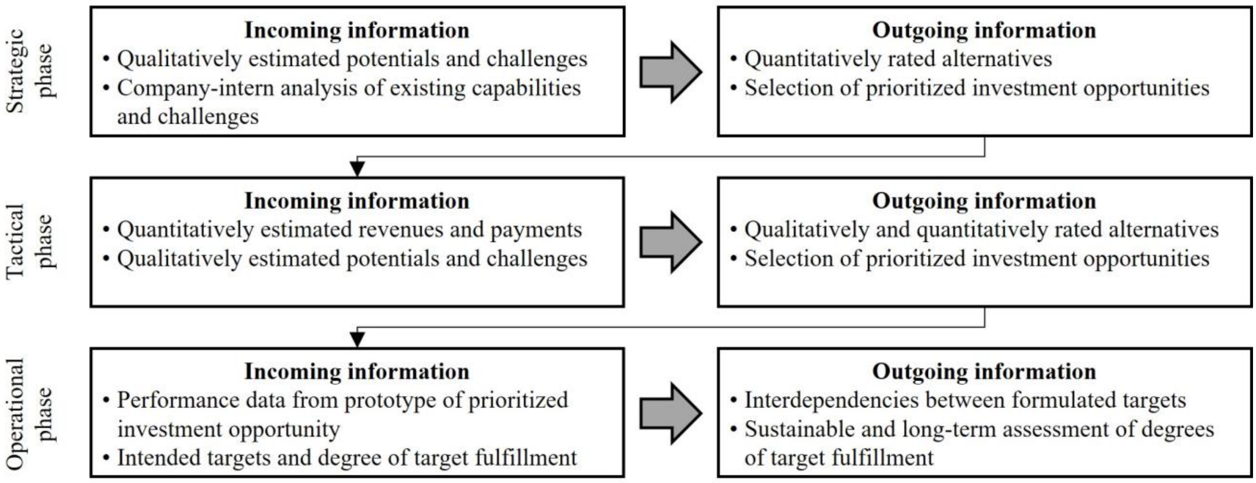

Figure 2: Overview of incoming and outgoing information in the process phases [10]

In the **tactical phase**, a selected problem is examined in more detail and developed into a draft solution in the form of a possible BM. In addition to the qualitative information already available, initial quantitative information is also available as input variables. In-depth examination of the selected problems allows estimations for possible expenses and income streams connected to implementing the respective BM. Among other things, this data can be retrieved from historical data, e.g., from service or sales or from past projects [17]. In their approach, Biegel et al. propose a financial evaluation of the project as a final gate before the solution development phase. However, in view of the extensive planning activities and the increasing availability of information, it is reasonable to further include qualitative aspects. The tactical phase thus represents a transition between the strategic phase, which is driven by qualitative information, and the numbers-driven operational phase. Therefore, suitable models for this phase must be able to merge *qualitative and quantitative aspects* and combine them in a reproducible result. However, in contrast to the previous phase, the tactical phase does not evaluate a broad problem set but various options for the BM design. This includes decisions regarding the scope of the BM (e.g., detection of errors vs. prediction of failures) or the acquisition of competencies (e.g., build up in-house vs. buy in externally) [23]. In order to weigh between these design options, the possibility of *ranking of alternatives* remains relevant in this phase.

Table 1: Evaluation of existing methods

Evaluation scale: ○ not fulfilled; ◐ partially fulfilled; ● completely fulfilled		Data			Methodology			Practical application		
Overall systematics / focus	Evaluation model	Holistic assessment	Realistic depiction	Qualitative and quantitative aspects	Prognosis	Risk assessment	Ranking of alternatives	Usability	Transparency	Compatibility with digital BMs
		A1	A2	A3	B1	B2	B3	C1	C2	C3
Strategic	Balanced scorecard [24]	●	◐		◐	◐	○	●	●	◐
Strategic	Guideline for industry 4.0 [25]	●	●		◐	○	◐	●	●	●
Strategic	Canvas scoreboard [22]	◐	◐		◐	◐	○	●	●	◐
Strategic	Scenario analysis [26]	●	●		●	●	◐	◐	●	●
Strategic	Company culture portfolio [27]	○	●		○	○	◐	●	●	◐
Strategic	Competency portfolio [28]	○	●		◐	○	◐	●	●	◐
Strategic	Technology portfolio [29]	○	●		○	○	◐	●	●	◐
Strategic	Growth-share matrix [30]	○	●		○	○	◐	●	●	◐
Strategic	Utility analysis [31]	●	●		◐	◐	●	●	◐	●
Strategic	Analytic hierarchy process (AHP) [32]	●	●		◐	◐	●	◐	●	●
Strategic	Assessment model by Pokorni et al. [33]	●	●		○	◐	●	◐	●	●
Strategic	Gap analysis [34]	◐	●		●	○	○	◐	◐	◐
Tactical	Digitalization scorecard [35]	●	◐	●	◐	◐	○	◐	●	●
Tactical	Potential analysis [36]	◐	●	●	◐	○	◐	●	●	◐
Tactical	Assessment model by Schuh et al. [37]	●	●	●	◐	◐	●	●	●	●
Operational	Static payback method [38]	○	◐		◐	○		●	●	●
Operational	Net present value method [39]	○	●		◐	○		●	●	●
Operational	Dynamic payback method [38,39]	○	●		◐	○		◐	●	●
Operational	Indicator system [24]	●	●		○	○		●	●	●
Operational	Value driver tree [40]	◐	●		●	◐		◐	●	●
Operational	Industry 4.0 maturity index [41]	●	●		◐	○		◐	●	●

The previously designed BM is developed and implemented as an iterative development project in the final **operational phase**. The input information in this phase consists of target values selected in the planning process, their degree of fulfilment and ML-specific performance data. The latter result from prototypical setups and testing within the development process. Thus, the use of quantitative evaluation methods is particularly indicated in the context of solution development. In their model, Biegel et al. do not specify an approach for the evaluation of the project in this phase. Nevertheless, a continuous evaluation of the project is of particular importance, especially in this resource-intensive phase [14,15]. Due to the highly dynamic nature of the iterative development process, special *usability* requirements arise in this phase. Therefore, suitable methods must enable the integration of knowledge gained from the development process in the short term. Furthermore, the results of the applied evaluation methods must be comprehensible for all stakeholders involved in the project in terms of *transparency*. Finally, especially in the solution development phase, there is a high demand for the evaluation methods regarding their *compatibility with digital business models*. ML-specific figures must be considered to a greater extent, especially regarding possible optimizations by the underlying application. For example, the expected prediction accuracy of the model is decisive for the profitability of an ML use case.

Table 1 shows the results of an assessment of existing evaluation methods using the derived evaluation criteria. The evaluation methods were identified through systematic literature analysis. The methods are divided according to the three process phases: strategic, tactical, and operational. The evaluation criteria are divided into three areas: data, methodology and practical application. The data area includes the criteria *holistic assessment*, inclusion of *qualitative and quantitative aspects* as well as *realistic depiction*. The criterion "realistic depiction", which has not been mentioned so far, refers to the fact that the recording and preparation of all necessary technical and business contexts is necessary for a well-founded evaluation. It is thus relevant for all process phases [42].

3. Description of the assessment methodology

In the following, the developed methodology is introduced. The selection and combination of methods is based on the evaluation of existing approaches which was presented in chapter 2. An overview of the methodology is shown in Figure 3.

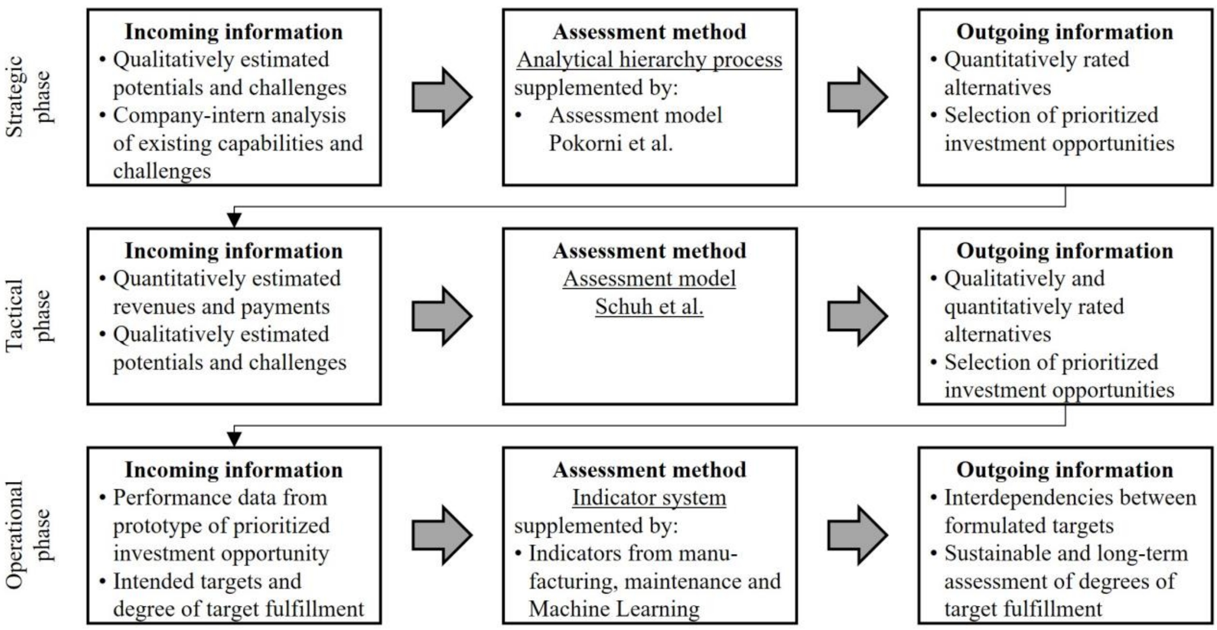

Figure 3: Three-levelled assessment methodology

For the **strategic phase**, the analytic hierarchy process provides the main structure and is supplemented by aspects from the assessment model according to Pokorni et al. In this phase, it is important that a holistic evaluation of the problem set can take place and subsequently a ranking of alternatives is made possible. Among the approaches examined, the utility analysis, the analytic hierarchy process (AHP) and the assessment model by Pokorni et al. fulfil these requirements at the best. Comparing the utility analysis and the AHP, there is a decisive difference: the AHP has an iterative structure and provides a consistency check to avoid logic errors. On the one hand, this makes the AHP more transparent than the utility analysis due to the systematic assurance of consistency. On the other hand, the usability deteriorates due to the increased effort required to perform the analysis. However, this additional effort in the AHP is reduced by a computer-aided execution of the procedure [38]. Nevertheless, due to the high degree of generalizability of the AHP, it makes sense to enrich the procedure with elements from the industry- and context-specific approach of Pokorni et al. In this model, positive effects of the use of ML are interpreted as potentials (e.g., increase in efficiency, increase in productivity) and negative effects as challenges (e.g., implementation costs, compliance challenges).

Due to its holistic approach and good performance overall, the assessment model according to Schuh et al. [37] is selected and adapted for the **tactical phase**. The hybrid model focuses on an assessment of effort and benefit, considering challenges and fields of action of ML-driven BMs. As the digitization scorecard and the potential analysis, this method is suitable for the required use of qualitative and quantitative data. Compared to other approaches, the method of Schuh et al. stands out due to its possibility of ranking alternatives. Within the model, the evaluation of qualitative input information merges with the results of quantitative evaluations in a portfolio matrix. By using and adapting an indifference curve within the model, it is also possible to include user-specific preferences. The position to the indifference curve is used to decide whether a solution design is perceived as an investment decision and transferred to the effort-intensive operational phase. Accordingly, adjustments can be made or an use case is discarded completely [37].

Finally, for the **operational phase**, an indicator system is introduced. It combines domain-specific key figures from the field of manufacturing with ML-based key figures. Thereby, it aims at enabling a sustainable assessment and control of the BM during operation. Compared to methods of investment calculation (static/dynamic payback method; net present value method), an indicator system is more suitable for a holistic assessment. Thus, in addition to purely financial key figures, ML-specific (e.g., precision, accuracy) and production-specific key figures (e.g., utilization rate, productivity) can be included. Compared to the value driver tree, the indicator system distinguishes itself by better usability. Accordingly, it is possible to draw on metrics already known and used by the various stakeholders in the interdisciplinary development project. Finally, the effort of the project team to create the system consists of identifying dependencies between individual key figures and linking them. The remaining Industry 4.0 maturity index is also partially based on a system of key performance indicators. Therefore, the evaluation method of the operational phase also takes up aspects from the model's key figure system.

4. Application and validation

To validate the presented approach, the procedure introduced in this paper was applied to an exemplary use case. It originates from the industry-centric research project "Sensorische Schutzabdeckung" which was funded by the LOEWE – State offensive in Hessen, Germany. The basic idea of this project was to develop a predictive maintenance application for protective covers in machine tools which was realized by applying ML to gathered retro-fit sensor data [43]. In the following, the application of the approach presented in chapter 4 is applied to the use case.

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 assessment method from the strategic phase and to start with the application of the methodology from the tactical phase. It was possible to consider both the potentials of an ML-based use case compared to the previous status quo in the maintenance of protective covers and the challenges that exist along the way. The challenges were incorporated into the evaluation process as qualitative aspects. The biggest challenge identified was that the company itself had little experience in the field of data analysis and that the sensor technology required for data acquisition in the ML application had not existed as a ready-made solution. In this way, important key partners for future development activities could be identified and acquired. At the same time, it was possible to use extensive quantitative input. Thus, a potential cost saving for the avoidance of too early or too late repair measures as well as a customer's willingness to pay and possible unit number ranges for a marketable solution could be determined and included in the evaluation. In doing so, the application of the evaluation method resulted in a positive prognosis for a decision to invest in the development of the ML-based product-service system.

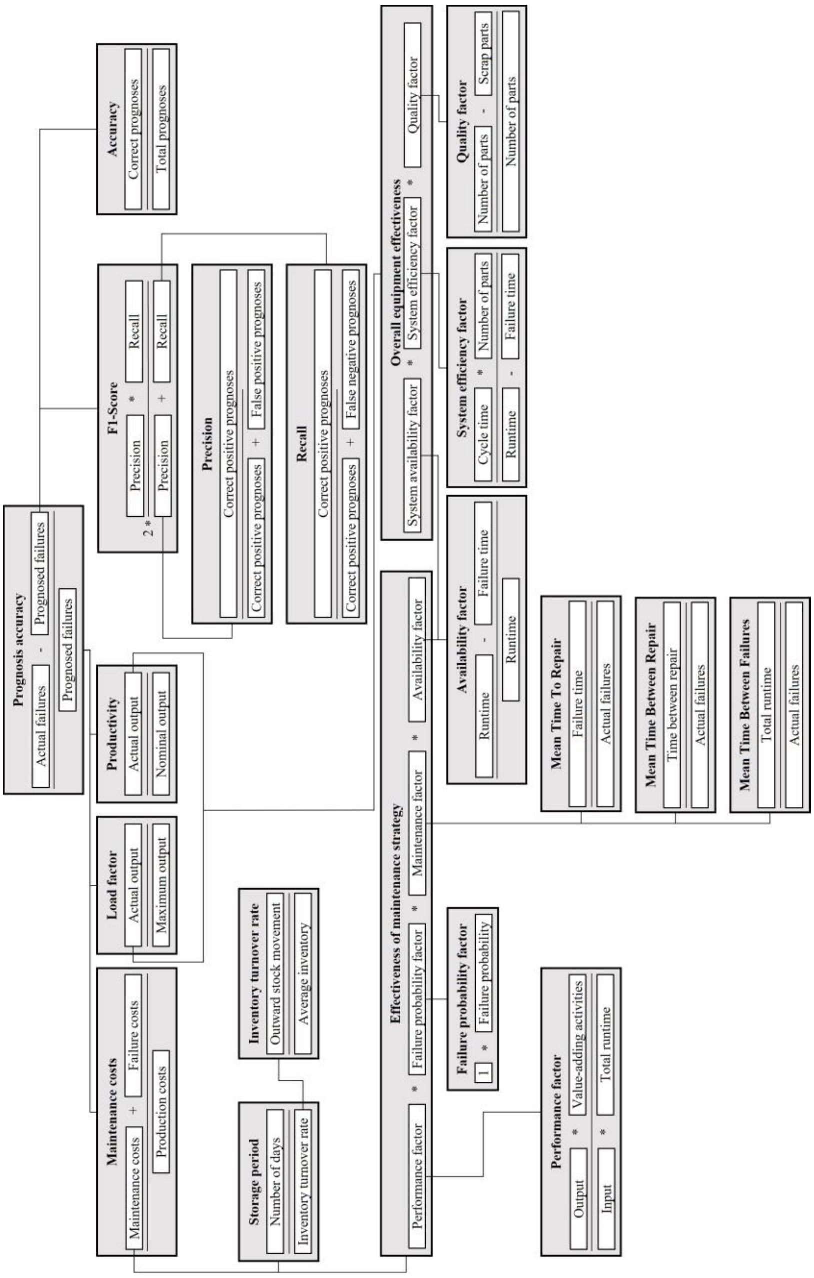

Figure 4: Indicator system for operational phase in the project “Sensorische Schutzabdeckung”

In the subsequent phases, the evaluation method for the operational phase was applied (see Figure 4). Within the resulting indicator system, various context-related key figures are related to each other via mathematical and logical connections. The key figures are taken from both the business management and ML area. In addition, specific key figures from the field of maintenance are included, such as the mean time to repair or the failure probability factor. During the development of the indicator system, the stakeholders involved - namely the management, the company’s domain experts, sensor and electronics developers and data scientists - were thus able to incorporate their relevant indicators. This confirmed a good usability of the approach within the framework of an interdisciplinary project team. By establishing and tracking the indicators, important levers for achieving an economically viable scenario were identified during the course of the project. As a result, it was possible, among other things, to substitute electronic components with less expensive variants and to reduce the amount of data processed.

Within the model shown in Figure 4, mathematical relationships are highlighted by operators, whereas logical relationships are indicated by connecting lines. The data used in the project originated from different sources. Business- and maintenance-specific data was already available through previous research from the company's sales and service departments. ML-specific data was collected as part of the development project and the tracked metrics in the model were subject to significant changes. During development, various sensor and ML concepts were designed and investigated, prototypes were built and experiments were conducted. This enabled more precise figures to be derived for possible model qualities and estimates to be made of the hardware required for implementation. Here, the indicator system confirmed its advantage of incorporating new findings within a short-cycle development process. Since the research project did not comprise a complete product development but ended as an extended feasibility study, reliable figures were not yet available for all aspects at this time. Nevertheless, offers from external contractors and a more in-market analysis were acquired at the end of the project. Thus, it was possible to use the assessment methodology to draw up possible scenarios a continuation of development efforts within the company.

5. Conclusion and future research

Given the increasing availability of data, the importance of ML and its integration into companies’ use cases and BMs is higher than ever before. Assessment methods are meant to evaluate the profitability and viability of BMs during their development, therefore intending to reduce sunk costs by prioritizing promising alternatives in the early stages of development. However, due to the variety of methods and novel potentials as well as challenges coming with ML-based BMs, companies still struggle to find appropriate ways of assessing their BMs. In this paper, a three-levelled methodology for assessing ML-based BMs has been introduced. Considering the strategic, tactical, and operational planning horizons, various assessment methods have been assigned, rated, combined and adapted into a holistic assessment methodology for ML-based BMs. Following the depicted gates within the AIMM from Biegel et al., the developed methodology allows less promising alternatives to drop out and thus to reduce sunk costs. Furthermore, the indicator system, containing of business-, application- and ML-related indicators, enables continuous tracking of BMs after being implemented in practice.

The introduced methodology has been validated using an actual use case from the manufacturing industry. However, given the novelty of the approach, further validations, especially within the strategical phase of the methodology, are necessary – some have already been initiated. Furthermore, in the context of this paper, a broad overview of the selected methods was provided based on their theoretical evaluation. In the future, it is necessary to describe the developed methodology and especially its associated methods in more detail and give further instructions for the practical implementation and application.

6. Acknowledgements

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