An AI Management Model for the Manufacturing Industry - AIMM

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Abstract

The use of artificial intelligence in manufacturing holds a multitude of potentials for improving the performance of a company in the dimensions time, quality, and cost. Many companies have recognized these possibilities, but only a few have already integrated this technology into their production. A major reason for this discrepancy is a lack of knowledge about necessary steps to conduct an AI project in order to solve an existing manufacturing problem. In literature, several models exist that provide structure and standards for the process of data mining in industrial applications (e.g. CRISP-DM, SEMMA, KDD). However, these process models have several shortcomings that prevent the effective usage in the manufacturing industry.

The following paper addresses these shortcomings and proposes a holistic process model that shall serve as a standard management model for manufacturing companies to successfully introduce and apply AI as a production-related problem-solving tool. All three levels of the process model are presented, namely the strategic, tactical, and operational level. On the strategic level, an existing set of production problems is evaluated and prioritized concerning their feasibility and suitability for the application of AI. In the tactical part of the model, a solution for a selected problem is designed. Therefore, the problem understanding is deepened, infrastructural requirements are identified, and a financial evaluation of the developed solution is performed. The final, operational level focuses on the implementation of the developed solution to a finished AI application by a project team.

Keywords: Artificial Intelligence, Process Model, Manufacturing, Management, AI project

1. Introduction

Recent advances in artificial intelligence (AI) are pushing the boundaries of what machines can do in all industries and business sectors [1]. Industrial nations around the world form strategic plans and mobilize huge budgets to be at the forefront of AI. The United States of America as the global leader of AI developed their first AI strategy in 2016 [2] and invested $973.5 million in fiscal year 2020 with further increases planned throughout the following years [3]. China issued a three step plan that shall be completed by 2030 with the objective to become world leader in AI with an industry worth 130 billion Euro [2, 4]. In 2018 the German government presented the strategy “AI made in Germany” with the objective to invest 3 billion Euro until 2025 to become a leading global player [5]. Especially the application of AI in manufacturing is becoming increasingly relevant. Within the last decade, the number of scientific articles that address the application of AI in manufacturing increased sharply. Figure 1 illustrates the number of published articles, proceedings and reviews that were retrieved by a search conducted in Web of Science[1].

[1] www.webofknowledge.com

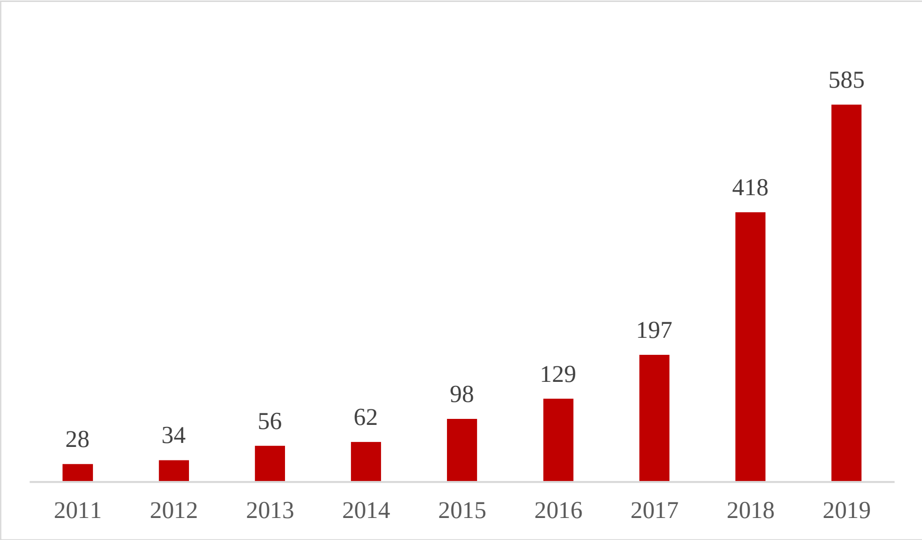


Figure 1. Number of papers related to AI in manufacturing (2011-2020)

The economic potential to apply AI in manufacturing results in an increasing number of companies that are trying to use AI in order to gain a competitive advantage or move into new businesses [6]. However, a global study conducted by the Boston Consulting Group (BCG) with 1,096 executives, production and technology managers revealed that although 87% of the participants plan to implement AI in production within the next three years, only 28% do have an implementation plan whereas, among the remaining 72% that lack actual implementation plans, merely 32% are testing selected use cases [7]. This indicates that despite recent advances the adoption of AI in production is still in its development phase and far away from being a standard tool for companies. Applying AI in production poses plenty of questions and challenges that a company must face, such as:

- Which problems can be solved using AI?
- What data should be used?
- Where does the data come from?
- What algorithms should be used for which problem?
- What are the required roles in an AI project?

To give an answer to these questions, several researchers focussed on the development of process models that provide general guidelines and shall support the conduction of AI projects. Existing process models such as the widely known CRISP-DM [8] have the advantage that they can be applied independent of the respective industry, which is why they in turn lack problem specific tools and guidelines and hence are difficult to apply in areas in which the problems show characteristics that are unique for the respective field. Due to this shortcoming, several process models have been introduced to provide a more problem-specific approach. However, even though some of the presented process models in Section 2 focus more on the respective field of application, they are still very high level and do not provide proper tools that can be used within a project to provide assistance in conducting AI projects successfully.

Most of the process models presented in our research work use the term "Data Mining" instead of "AI". Data Mining can be considered as the extraction of structures and patterns from large amounts of data using specific algorithms [9]. Following the definition of Fayyad et al. [10] we consider Data Mining as being a part of the Knowledge Discovery in Databases (KDD) process. Literature is inconsistent in terms of the terminology of Data Mining and its relationship to the KDD process. In the work of Gunopulos et al. [11] and Mannila [12] as well as in the context of the CRISP-DM process model [8], Data Mining is used as a synonym for the KDD process rather than being an element of it. Whereas authors such as Buczak and Guven [13] explicitly emphasize that Data Mining is part of the KDD process and that methods used in Data Mining and AI have a significant overlap. In fact, the most influential algorithms in Data Mining are actually AI algorithms [14, 15]. Therefore, we follow the definition of Mannila [12] and consider AI and its methods as the tools that are used to fulfil the objective of Data Mining.

The goal of this paper is to present a new process model that overcomes the shortcomings of existing ones and shall serve as a standard procedure for manufacturing companies to successfully introduce and apply AI as a production-related problem-solving tool. More precisely, it shall be established as the baseline of an AI project and provide a holistic step by step guideline that will eventually result in a working AI solution. The contributions of this paper are as follows:

- Identification of the operational, tactical, and strategical elements in the development and implementation of AI projects in manufacturing companies
- Definition of a new holistic, standardized, and structured process model for the introduction of AI in manufacturing, starting with the selection of an existing production problem up to the integration of the developed solution
- Development of tools and support for the implementation of AI projects in production in the areas of problem selection, solution development and implementation

The remainder of the paper is structured as follows: Section 2 provides a literature review of the most common process models that are used to conduct AI projects. In Section 3 the **AI M**anagement Model for the **M**anufacturing Industry (AIMM) is introduced and derived based on the identified shortcomings of existing AI process models. The conclusion and future research agenda are combined in Section 4.

2. Literature Review

In literature, several models exist that provide structure and standards for Data Mining in industrial applications. In general, these models divide the Data Mining process into sequential steps that guide the user through parts of the Data Mining application lifecycle. This section provides an overview of the most popular models. A 2014 poll [16] showed KDD, SEMMA and CRISP-DM to be the most used models for conducting Data Mining projects. We additionally reference ASUM-DM and DMME as they are specific extensions to CRISP-DM that are of relevance to our proposed model.

The Knowledge Discovery in Databases (KDD) process was developed by Fayyad et al. at Microsoft Research in 1996 and describes methods to assist in extracting knowledge from the growing repositories of data available in organizations. The KDD process has five sequential stages: Selection, Preprocessing, Transformation, Data Mining, and Interpretation/Evaluation [10]. KDD is less of a framework as it is an overview and systematic snapshot of the state-of-the-art in Data Mining. In contrast to explicit frameworks such as CRISP-DM, KDD offers technical explanations and examples of various algorithms as well as common challenges and problems when dealing with Data Mining problems. CRISP-DM, SEMMA, [17] ASUM-DM as well as DMME can be seen as framework implementations of KDD.

Sample, Explore, Modify, Model, Assess (SEMMA) is a process model for the implementation of Data Mining applications [17] which consists of the five steps that form the acronym. SEMMA was developed by the SAS Institute and forms the basis of their proprietary Data Mining tool "SAS Enterprise Miner" but is often considered to be a general Data Mining methodology [18]. As SEMMA is designed to guide the Data Mining process using the tools offered by SAS, it does not cover business/strategic aspects of Data Mining projects [19].

The Cross Industry Standard Process for Data Mining (CRISP-DM) is an open standard process model for executing Data Mining projects. The CRISP-DM process model was presented in 1999 by a consortium of ISL, Teradata, Daimler AG, NCR and OHRA as the result of a funding initiative of the European Union. CRISP-DM splits the lifecycle of a Data Mining project into six phases starting with Business Understanding and ending with the Deployment of the model. Within the phases, CRISP-DM provides structure and guidance for implementation. The six phases of CRISP-DM are the highest level of abstraction within the hierarchical process model. Lower levels of abstraction within CRISP-DM define more specific tasks and process instances relating to the phases [8]. While CRISP-DM is often cited as the leading methodology used by Data Mining experts across industries [16], its generality does not come without limitations. As CRISP-DM is not specific to any industry or problem category, the guidance provided is rather abstract even at the lowest, most specific hierarchy level of the model. Besides, CRISP-DM does not provide technical guidance, e.g., in the selection of a suitable algorithm for a given type of problem or the data acquisition phase. Further, CRISP-DM is an operative process model and thus focusses on the implementation of a specific Data Mining project and does not assist in the selection of suitable problems that may be solved by applying Data Mining.

The Analytics Solutions Unified Method for Data Mining (ASUM-DM) is a revision and extension to CRISP-DM and was released by IBM in 2015. ASUM-DM specifically targets IBM Analytics consulting projects but is free and publicly available [20]. ASUM-DM defines five phases that build upon the CRISP-DM process model, with templates and guidelines that are supervised by a project management team. In contrast to CRISP-DM, the phases are partially designed for agile project management with iterative prototyping and development. Further, ASUM-DM adds information and templates for collaborative work, versioning, and compliance.

The Data Mining Methodology for Engineering Applications (DMME) is an extension to the CRISP-DM process model that targets domain specific difficulties of Data Mining projects in the engineering context. DMME extends the original six phases of the CRISP-DM process model by three additional phases: The Technical Understanding phase emphasises a deep understanding of the technical system structure and related physical effects to transform the business goals into measurable technical goals. The Technical Realization phase focuses on planning and executing controlled experiments for data acquisition. Lastly, the hardware and software infrastructure is developed for long-term deployment of the model and corresponding data acquisition system in the Technical Implementation phase. The provided use case examples focus on the manufacturing domain [21].

Analysing the characteristics of existing AI process models, we identify several shortcomings that prevent the effective and holistic usage of these models in the manufacturing industry. First, the described models lack detailed and concrete toolsets. While this feature can also be interpreted as a strength in terms of generalizability, it limits the support gained by using the models since they do not provide specific guidance. Secondly, existing models do not provide holistic support during the complete AI lifecycle as they do not cover the process of selecting a problem and deciding whether a problem should be solved with AI. Lastly, existing models do not consider the specific requirements of manufacturing environments. We address the identified shortcomings in our proposed model which is introduced in Section 3.

3. AI Management Model for the Manufacturing Industry

The proposed AIMM provides a systematic process for the identification and resolution of AI problems in the manufacturing domain. We define an AI problem as a data-based problem within the manufacturing domain which is economically relevant and cannot be solved by a model- or knowledge-based solution. An AI problem may be solved using a mathematical model which is trained on data specific to the problem. The performance of the corresponding model can be quantified. The individual phases and contents of the model are presented in the following section.

3.1 Model Overview

A conceptual overview of the proposed model is shown in Figure 2. The process resembles a funnel, which starts with a project team as well as potential AI problems and consequently outputs an AI solution for a specific problem. It has three main phases: Problem Selection, Solution Design and Solution

Development. Notably, the process model is designed to fail fast: Drop-out gates at the intersection of phases check whether a problem can be solved by using AI technology as well as if it is financially sustainable to do so. If this is the case, the process can be run again with a different problem or the solution design can be adjusted accordingly. Thus, the waste of resources will be prevented early in the process.

According to their chronological arrangement in the model, the three phases can be assigned to the areas of strategic, tactical, and operational management. The strategic phase of the model, which is represented by the Problem Selection, is characterized by a high level of uncertainty and insufficient information availability. During the Solution Design, which is the tactical phase of the model, the existing information deficit is reduced, and certainty is increased. The final, operational phase of the model, which is represented by the Solution Development, is characterized by a high level of information availability with only a low remaining level of uncertainty. The considerations at the beginning of the management process encompass the entire company’s production and show a high level of abstraction, more detailed and complete investigations of specific use cases take place in later phases (see [22, 23]).

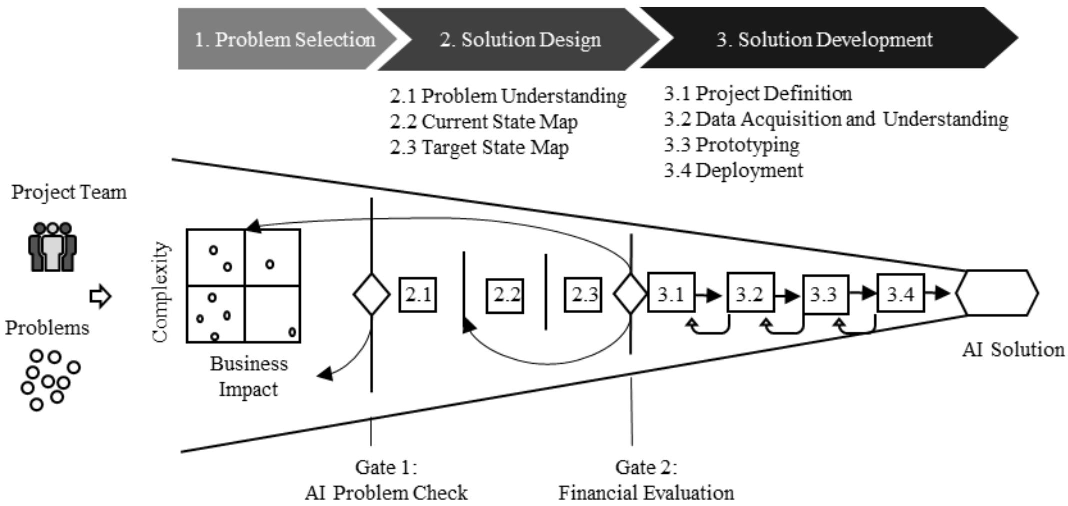


Figure 2. Conceptual overview of the proposed model

The inputs for the model are the AI project team and the manufacturing-related problems. The motivation for defining a project team is the need to identify suitable personnel and to emphasize the responsibilities that each member has in the course of the project [24]. The following roles are distinguished here: The project sponsor, the domain expert, the data scientist, and the software engineer. The project sponsor ensures that the project has sufficient resources and visibility within the organization and ensures that it is in line with the organization's strategy. Because of the expertise and decision-making power required, he should be part of top management [25]. The domain expert is an employee who works close to production and is familiar with the operation, processes, and the use case. He is responsible for explaining the use case and identifying relevant data sources. He also ensures that the data for analysis is reliable and error-free. He can estimate what type of data can be generated and which findings will provide the greatest benefit. Case studies in which domain knowledge was used in the AI project emphasize its importance for validating and improving the results of the analysis [26]. Ultimately, the domain expert brings the hypotheses about relationships between the problem and the process into the project, allowing the data scientist to proceed in a more targeted way. The data scientist can examine data for business decisions and knows data analysis methods and their possible applications. He knows the implementation of algorithms, is up to date with the latest research and can implement ideas from academic publications. The software engineer is familiar with the company's IT infrastructure and is responsible for the operationalization of the AI model. The AI team is present throughout the three phases of the model however in the last phase, i.e., the Solution Development Process, the data scientist and the software engineer have central roles.

3.2 Problem Selection

The *Problem Selection* (PS) represents the strategical part of the model and consists of two phases. It starts with a selection of manufacturing problems that may be solved by AI and consequently filters them to a single problem. In the first stage, the portfolio matrix, the existing production problems are evaluated and ranked in terms of their relationship between complexity and business impact. In the downstream AI problem check it is analysed, whether a selected problem may be solved using AI. The individual stages are explained in detail below.

Portfolio Matrix

In the first step of the PS, a pre-selection of possible problems is made, which could potentially be solved in an AI project. Thus, existing manufacturing-related problems of the company are evaluated and classified according to their complexity and business impact. In the context of our model, complexity is defined as the totality of all possibilities to solve a production problem. Key influencing factors are the number of actors and objects involved and their relationships to each other as well as the required interdisciplinarity [27]. The business impact, on the other hand, is defined as the influence on the key performance indicators of a company (e.g. Overall Equipment Effectiveness (OEE), Yield) that are critical to success. Since only superficial information is available at the time of the evaluation, methods such as the paired comparison or the Analytic Hierarchy Process are particularly suitable for determining the two key figures (see [28, 29]).

When the enumerated problems are evaluated in terms of their complexity and business impact, they are classified in a Portfolio Matrix, see Figure 3. The ordinate of the matrix shows the complexity of the problem, while the abscissa shows the business impact. Based on their placement in the Portfolio Matrix, the problems are prioritized for further assessment. Problems located in the lower right-hand quadrant are described as “AI Stars” and promise a high business impact with low problem complexity and should be selected first. On the other hand, the problems in the upper left quadrant, which are referred to as "AI Wasters", should only be carried out in exceptional cases, as the necessary project expenditure often exceeds the resulting business impact. The selection of other problems depends on the individual preferences and know-how of the company in the decision-making process. Thus, prioritizing problems with high business impact and high complexity (right, upper quadrant) is just as conceivable as the selection of problems with low complexity and low business impact (left, lower quadrant). While the problems in the lower left quadrant known as "AI Starters" should be used as a starting point by companies that have used little or no AI to date, problems in the upper right quadrant known as "AI Excellence" should only be tackled by companies with sufficient previous experience.

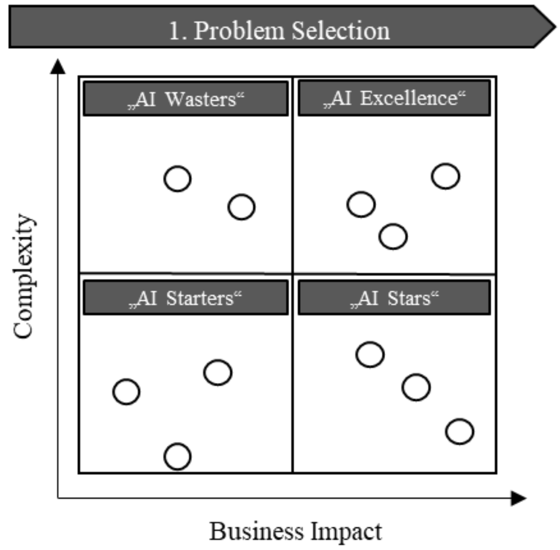


Figure 3. Portfolio Matrix used in the PS

AI Problem Check

The pre-selected problems are consequently evaluated in a Problem Check regarding their suitability for being solved through AI technologies. This evaluation makes use of criteria divided into three categories: problem context, data orientation and alternative solutions that do not involve AI. The problem context category examines whether basic organizational, legal, and statistical requirements are met to successfully apply AI to solve the given problem. The questions on data orientation are used to determine whether the technical and infrastructural requirements for the application of AI are met. The final category, Alternative Solutions, evaluates whether the given problem can be solved using approaches other than AI (e.g., statistical, or organizational). An overview of the AI problem check with exemplary questions is provided in Figure 4.

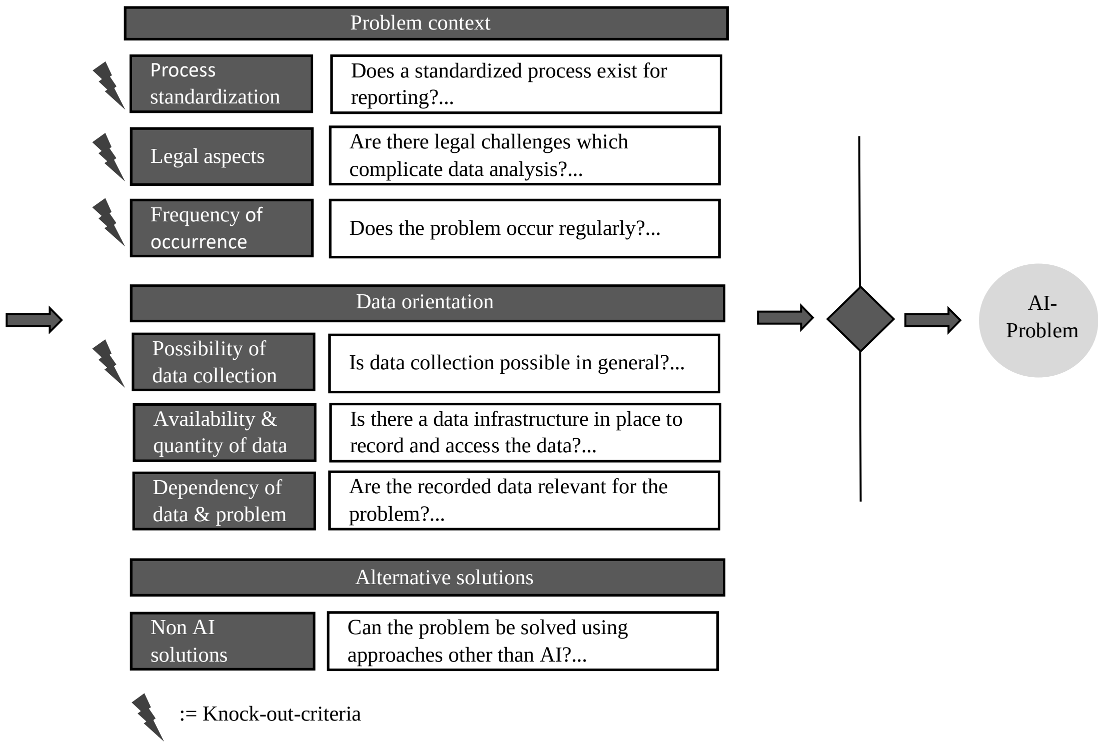


Figure 4. AI Problem Check

- "Process Standardization" is used to verify whether a standardized process for reporting is available and whether a Continuous Improvement Process has been established in the respective business area. In the context of the model, a lack of process standardization is considered a knock-out criterion for the application of AI. Many problems in manufacturing companies can already be remedied by achieving sufficient process standardization. Furthermore, a lack of process standardization makes the sustainable operation of AI applications more difficult.

- The criterion "Legal Aspects" examines whether the existing legal situation has restrictions regarding the use and analysis of data. This aspect depends on the location of the company and possibly other involved parties since the legal situation often differs. It should be noted that knock-out criteria often arise from a legal perspective when using personal data. Due to a lack of legal certainty in dealing with company data, the necessity of contractual agreements must be considered.

- The criterion "Frequency of Occurrence of the Problem" checks how regularly the described problem occurs in the process. If a problem occurs regularly and with a recognizable pattern, there is an increased probability of solving it using AI methods. If it occurs very rarely or even singularly, there is an increased probability that the effort of implementing the AI solution is not in proportion to the expected benefit, for instance due to the lack of required data.

- The criterion "Possibility of data collection" is used to check whether data collection is basically possible in the problem context. Especially in the production environment there are often technical or organizational hurdles that make the use of necessary sensor technology difficult or impossible. In the context of the model, a lack of data collection capability is considered a knock-out criterion for the use of AI, since corresponding models cannot be developed and operated without the necessary input of problem-specific data.

- The criterion "Availability & Quantity of data" is used to check whether and to what extent data is already collected and processed in production. Particular attention is paid to the technical infrastructure for the collection, storage and processing of data arising in the company. In the context of the model, a missing or inadequate digital infrastructure is not considered a knock-out criterion, as corresponding deficits can be compensated by investments. These necessary initial expenditures must be considered in a later financial evaluation of the possible AI project.

- The criterion "Dependency of Data & Problem" is used to check whether there is a connection between data already collected and the problem under consideration. If the data has only a low relevance for the given context, there is a high chance that the resulting model can only make inaccurate statements. If there is a lack of problem-relevant data, it should be checked whether it is possible to collect data at other, more promising parts of the considered process.

- The criterion "Non AI Solutions" is used to check whether a problem can be solved using methods other than AI. In many cases, problems in production can be improved or eliminated by simple technical and organizational adjustments. Likewise, classical and established statistical methods can also lead to sufficient knowledge gains. The existence of alternative solutions is not necessarily a knock-out criterion. A comparison with the application of AI regarding effectiveness and economy should always be considered.

The evaluation during the AI problem check is done using a quantitative model. A possible method here is the evaluation of Likert-scaled response options [30, 31]. Based on the resulting continuous evaluation, it can be decided whether the problem should be pursued further or discarded. While a high score value leads to a high probability that the application of AI will lead to a solution of the problem, this probability decreases with a decreasing score value. Problems that do not exceed a company-specific threshold or violate a knock-out criterion are not pursued further and the process is run through again with a different problem setting.

3.3 Solution Design

Having completed the PS, a problem that can potentially be solved with AI has been identified and can now be further processed within the Solution Design (SD). The SD represents the tactical model and follows a three-step procedure to find the solution requirements systematically. The three steps involved in the SD are Problem Understanding, Current State Map and Target State Map. The problem understanding step involves a deeper analysis of the problem to achieve a more comprehensive understanding. It provides the foundation for the identification of the AI-solution's functional and infrastructural requirements. The Current State Map depicts the status of the underlying process in which the problem is situated in terms of data flow, interfaces, and resources. Based on the Current State Map and the information gathered within the Problem Understanding step, the Target State Map can be developed. It serves as a conceptual visualisation of the future process and mainly addresses the identification of infrastructural requirements. Having elaborated the functional and infrastructural requirements of the solution, the SD ends with a financial evaluation to contrast the expected financial benefit with the expected costs and to decide whether the problem will move on to the next phase. Figure 5 illustrates the SD together with its components. The following paragraphs will provide a more detailed explanation of the three-step procedure.

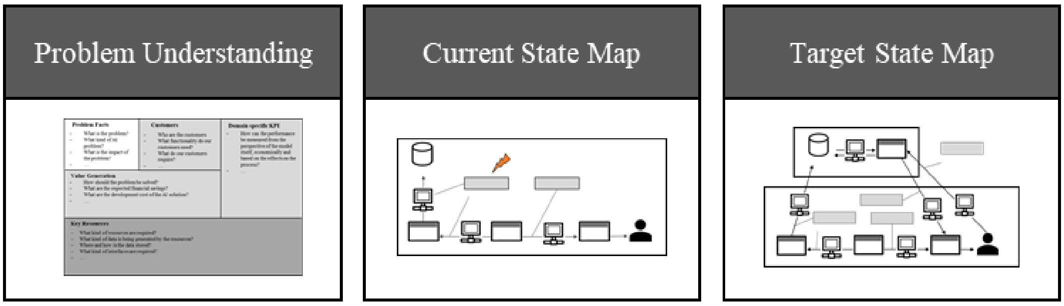


Figure 5. Solution Design

Problem Understanding

The foundation for the identification of the functional and infrastructural requirements are laid in the problem understanding step. In this step, the AI team works through a visualization tool, that has been derived from the Business Model Canvas [32], the so called problem canvas, to structure the problem across several dimensions. The dimensions used in the AIMM are problem facts, customers, domain specific KPI, key resources and value generation. Within each dimension, the AI team answers questions to concretize the solution's requirements. The problem canvas provides a colour coding scheme to help differentiate between functional and infrastructural requirements. Dimensions that address functional requirements are marked in light grey, whereas the key resource dimension is marked dark grey and accounts for infrastructural requirements. The problem facts dimension is marked white as the purpose of this dimension is neither functional nor infrastructural, but rather descriptive in terms of a better problem definition. Figure 6 illustrates the problem canvas of the problem understanding step.

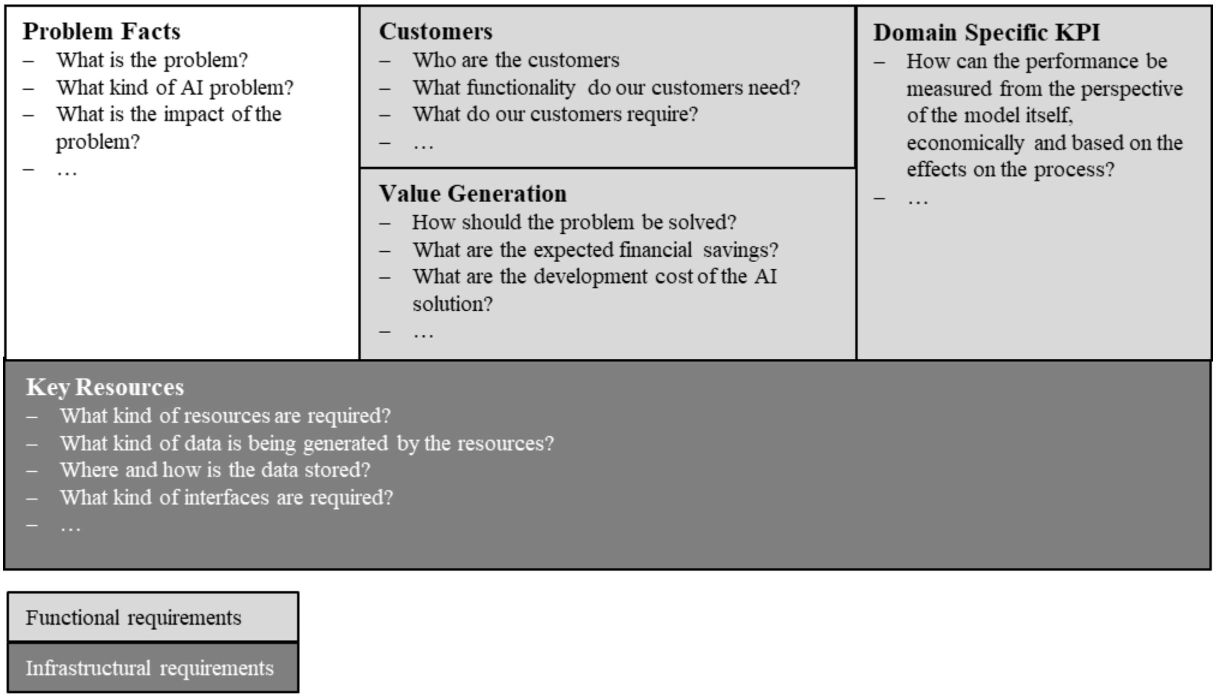


Figure 6. Problem Canvas with exemplary question

The Problem Facts aim at retrieving descriptive information about the problem. In this dimension, questions are used to deepen the understanding of the underlying problem such as: What is the problem? What kind of problem is one confronted with? What is the impact of the problem? When does the problem occur?

The dimension Value Generation addresses the financial impact of a possible AI solution in terms of development costs as well as expected financial benefits. In addition to that, this dimension focusses on functional requirements for the problem's solution. Here, questions should be formulated in the following manner: How should the problem be solved? What are the expected benefits? What are the costs involving the development of a solution?

The next dimension, Customers, is used to determine functional requirements based on the end-users that are supposed to use and work with the solution. Depending on the end-user, the system needs to encompass different functionalities such as enhanced visualization tools, ease of interpretability etc. In this dimension, the AI team should ask questions like: Who are the customers? What functionality is needed? What do our customers require?

The Domain Specific KPI dimension is used to define KPIs that are required to evaluate the solution's effectiveness i.e., whether it fulfils functional and infrastructural requirements in a quantitative manner. This dimension is thus crucial to the Problem Understanding step, since the KPIs that are determined in this dimension serve as a comparison baseline to find the best matching solution among all possible solutions for the problem. There exists many performance metrics in the AI literature that are commonly used to compare AI models. Metrics that can be used as a good starting point include among others: F1-score, classification accuracy, confusion matrix, area under curve (AUC), mean absolute error (MAE) and mean square error (MSE). However, since the solution to the AI problem shall be deployed in a real-life process, not only KPIs that address the performance of the model itself should be defined but also KPIs that focus on the economic aspect of the solution such as return on investment (ROI), net present value etc. Furthermore, production related KPIs such as OEE should be used to project the effects of the solution on the respective process. Thus, a suitable question for this dimension is: How can the model's performance be measured from the perspectives of the model itself, economically and based on the effects on the process?

The last dimension Key Resources addresses the infrastructural requirements. Here, the AI team should answer the following questions: What resources are required? What data are required and should be generated by the resources? How and where are the data stored? What interfaces are required? By answering these questions, the AI team can infer the most basic requirements and gather a better understanding of the overall AI solution.

Depending on the complexity of the underlying process it can be difficult and error prone to derive all the infrastructural and functional requirements upfront without a detailed knowledge about the current infrastructure and available resources. Thus, the problem canvas cannot be filled out entirely within the problem understanding phase of the SD but will be completed throughout the subsequent phases i.e., Current State Map and Target State Map. Hence, the Problem Understanding phase should be considered as a brainstorming phase in which the first thoughts towards a solution of the problem are collected and refined.

Current State Map

The problem understanding step provides the baseline for functional and infrastructural requirements. However, given the possible complexity of the problem and the underlying process a further analysis is needed to determine additional requirements to complete the problem canvas and to proceed to the operative model.

The objective of the Current State Map (CSM) is to create a schematic overview of the process and to get a better understanding of the existing infrastructure. It serves as the foundation for the development of the target state map. The CSM depicts the present workflow of the process and uses a set of standardized symbols to visualize data storage, resources, interfaces, customers, dataflow, and system borders. The standardized symbols to construct the CSM can be found in Figure 7. Initially, the existing resources should be drawn inside the map. We consider a resource to be any physical or virtual instance that generates or processes data. Followed by the resources, existing data storages and customers are drawn in the map. The next step involves adding the data flow by connecting resources, data storage and customer with the respective direction of the data flow. Lastly, the existing interfaces are added to the map. It is important to note that the purpose of the CSM is to increase the awareness of how the process operates from a perspective of solving the problem in order to develop a better understanding for additional requirements. The CSM should provide an illustration that is as simple as possible while simultaneously being as complex as necessary to reveal further requirements for solving the problem. Figure 8 illustrates an example for a CSM.

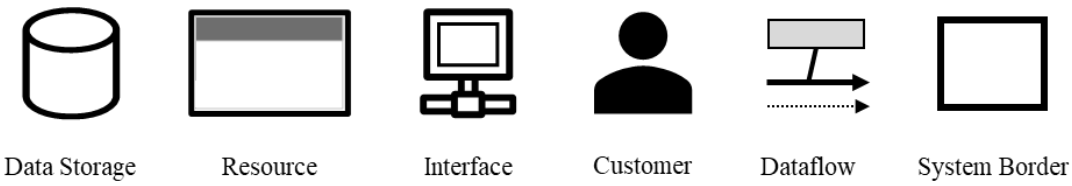


Figure 7. Standardized symbols for State Maps

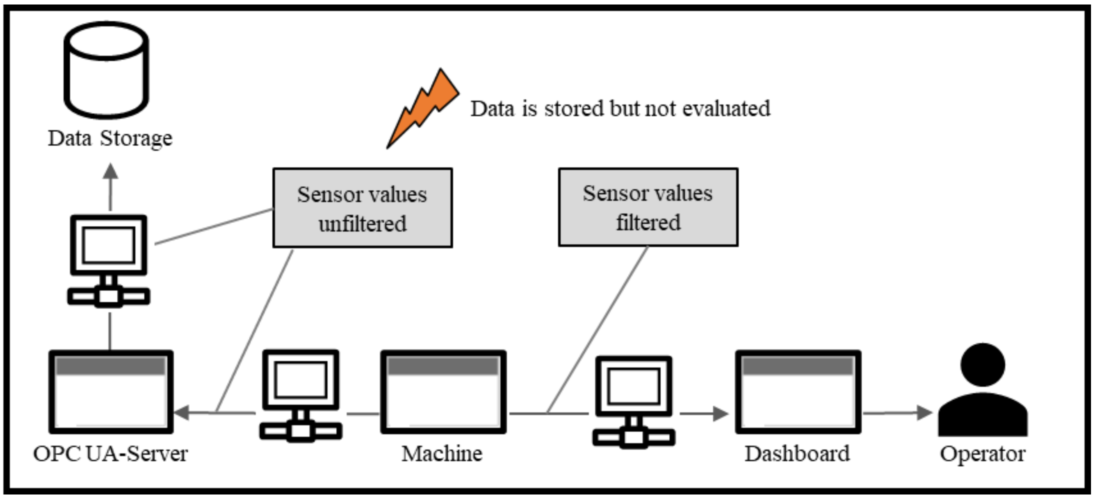


Figure 8. Current State Map – example

Target State Map

Having created the CSM to get a more comprehensive understanding of the process, the next step involves the design of the Target State Map (TSM). The objective in this step is to design the target state for the AI solution based on the CSM and the initial requirements gathered in the Problem Understanding phase. By contrasting the CSM with the TSM, the AI team can infer additional functional and infrastructural requirements that were not visible beforehand and thus complete the Problem Canvas. The design of the TSM follows the same principles as the CSM. The AI team must consider which components are necessary to meet the functional and infrastructural requirements derived in the problem understanding phase. Thus, data storage, resources, interfaces, customers, dataflow, and system borders must be altered, deleted, or added. Figure 9 shows an example of a TSM based on the CSM in the previous section. One can observe the difference between both maps immediately and see what changes are required to transit from the current state to the target state.

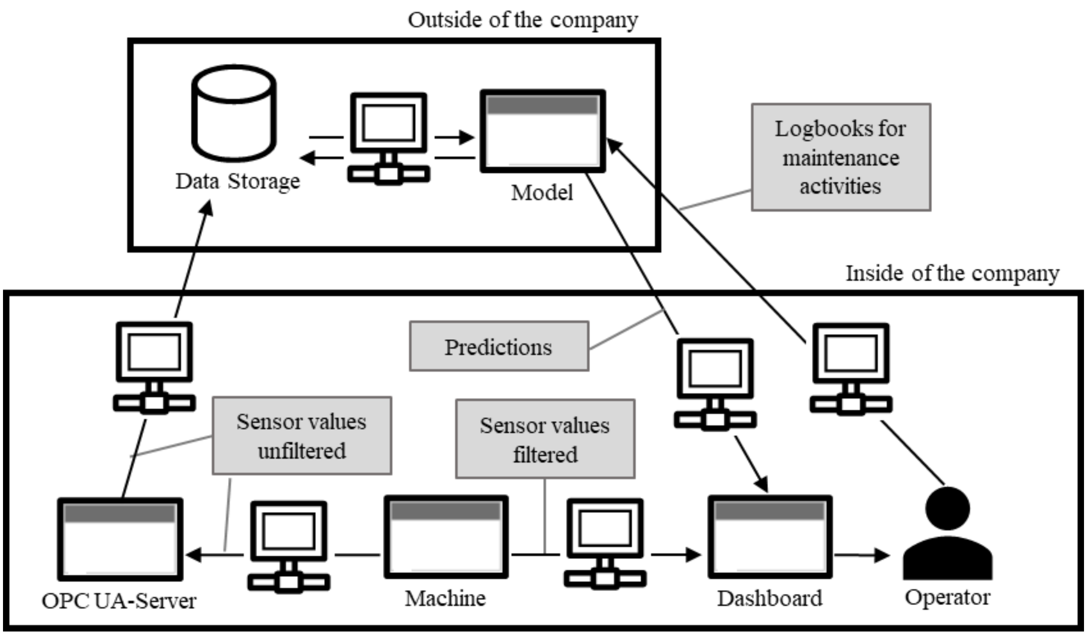


Figure 9. Target State Map - example

The visualization provided by the TSM allows to break down the solution's complexity. Especially when the process at hand is complex and shares resources with other processes, the AI team gets an overview of the extension of the required changes to reach the target state. It should be noted that there could be more than one possible TSM, among which the AI team would have to choose the one that fits best to the problem at hand and the given circumstances. With this information, the problem canvas can be completed and transit to the Financial Evaluation gate.

Financial Evaluation

As mentioned in previous sections, the AIMM is designed to fail fast to minimize the consumption of resources and to increase the probability of a successful project the further it moves down the funnel presented in Figure 2. The Financial Evaluation serves as the second drop-out gate of our model since it is located at the intersection between the tactical and the operative models. The objective of this drop-out gate is to determine whether the problem can be solved in a financially sustainable way. Based on the Problem Canvas and the TSM, the AI team can determine the expected costs as well as the expected benefits of solving the problem. With the help of the KPIs defined in the Problem Canvas, measures such as ROI and net present value are used to get an understanding of whether the investment that is required to develop and implement the solution is reasonable in contrast to the expected benefits. In addition to rather traditional financial metrics, we suggest a new illustration that contrasts cost and benefits of a solution. By providing pessimistic and optimistic estimates for the cost and benefits respectively both the financial cost range and financial benefit range can be visualized as seen in Figure 10.

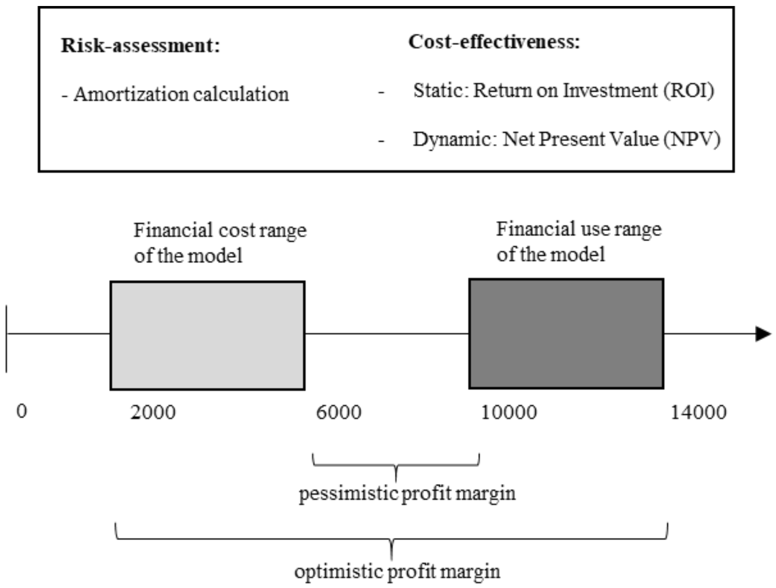


Figure 10. Financial Evaluation

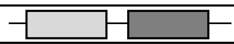
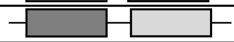
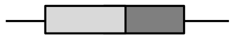
We define two simple metrics, the pessimistic profit margin (ppm) and the optimistic profit margin (opm) that can be used as additional evaluation criteria and visualization of this phase:

ppm := min(benefit) – max(cost)

opm := max(benefit) – min(cost)

By defining these two metrics one can distinguish between three scenarios that can be used as decision support as seen in Table 1.

Table 1. Financial Evaluation Scenarios

	ppm	opm	Visualization
Scenario 1	< 0	≤ 0	
Scenario 2	≥ 0	> 0	
Scenario 3	< 0	> 0	

Scenario 1 and 2 provide a clear tendency in terms of whether the solution will move on to the operative model. If ppm > 0 and opm ≥ 0 the solution can be expected to be profitable given all the available information that could have been retrieved throughout the project. Conversely, if ppm < 0 and opm ≤ 0 the solution should rather be dismissed since one can expect at best zero profit given the available information. However, given Scenario 3 it is difficult to determine whether to keep or to dismiss the project. Here, the AI team must rule out a tendency as to which event is more likely to occur and decide in favour of the most likely event. In case the AI team decides to dismiss a solution there is the possibility to reiterate within the SD and try to adjust the current solution in such a way that it will pass the financial evaluation. If the dismissal is inevitable, the AI team has to return to the PS and choose a new problem based on the portfolio matrix since the initial AI problem cannot be reasonably solved given the current circumstances.

Having conducted the Financial Evaluation, the SD is completed, and the AI team has determined all necessary functional and infrastructural requirements within the problem canvas. When the solution of the problem passes the evaluation, the project will move on to the operational model.

Figure 11 illustrates an example of the problem canvas after the AI team has worked through each individual dimension.

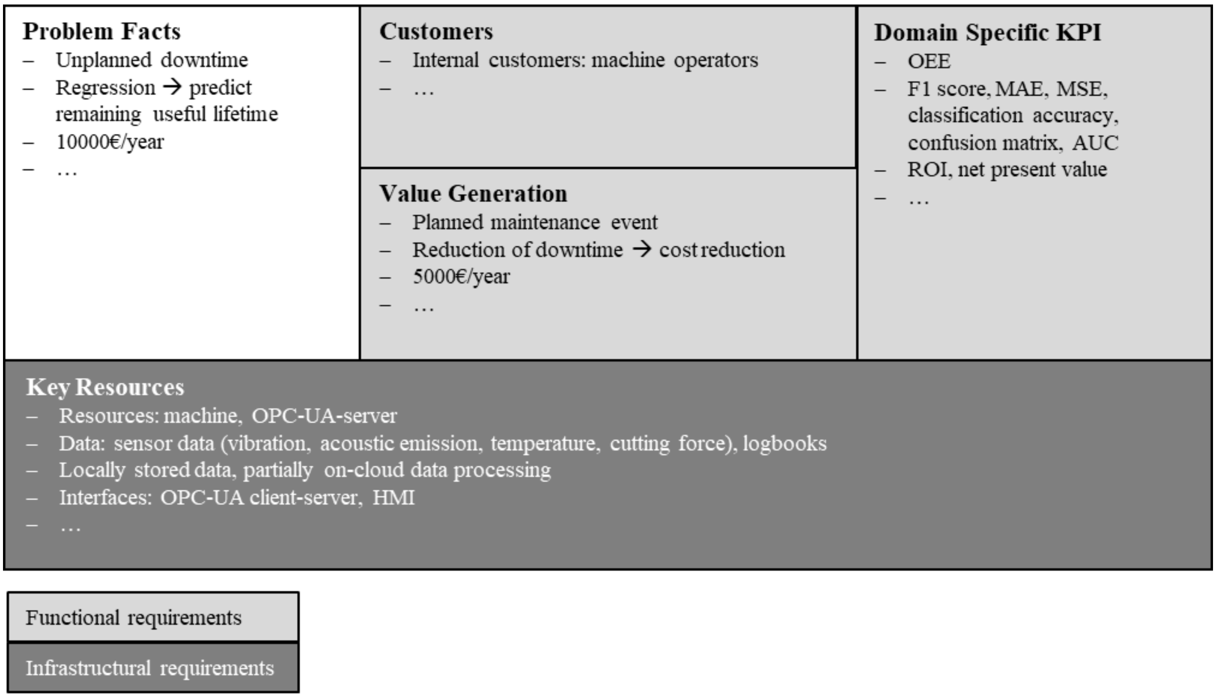


Figure 11. Completed problem canvas after SD

3.4 Solution Development

The Solution Development (DEV) represents the operative model and provides step-by-step guidance to achieve the target state and to fulfil the requirements defined in the SD. The DEV, illustrated in Figure 12, encompasses an initial Project Definition, the Data Acquisition and Understanding, the Prototyping, and the Deployment phases.

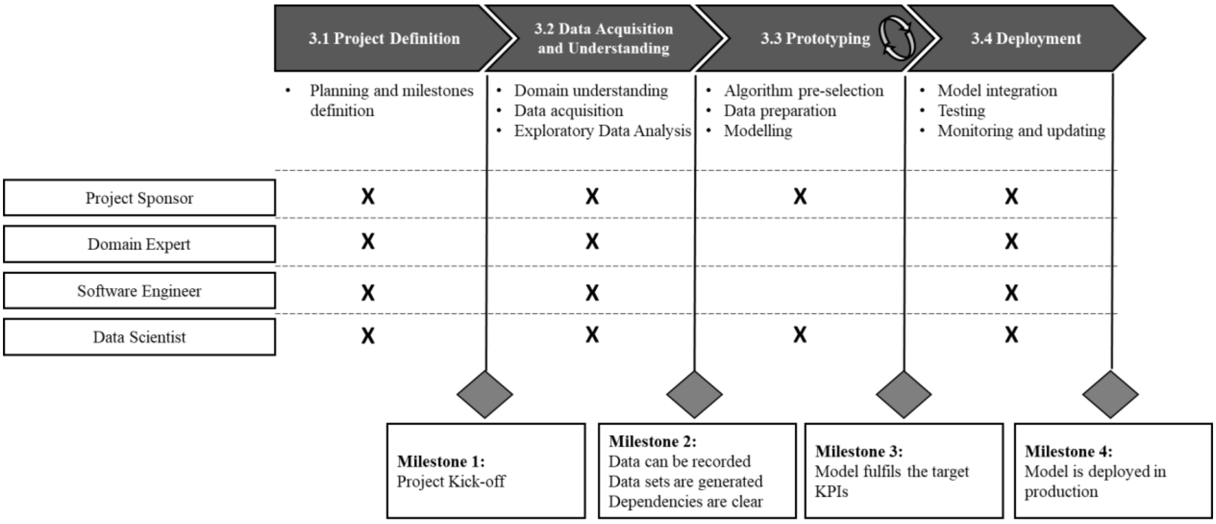


Figure 12. Solution Development

The DEV starts with planning and defining project milestones in the Project Definition phase. The project team, more specifically the domain expert, the software engineer, and the data scientist, assign the requirements based on the problem canvas to the project milestones. The first milestone is the project kick-off. The second milestone is reached when data is acquired, datasets are generated, and process dependencies are clear. The third milestone is reached when the model fulfils the defined KPIs. And finally, the fourth milestone is reached when the model is deployed into production. Figure 13 provides an example of requirements allocated to each project milestone.

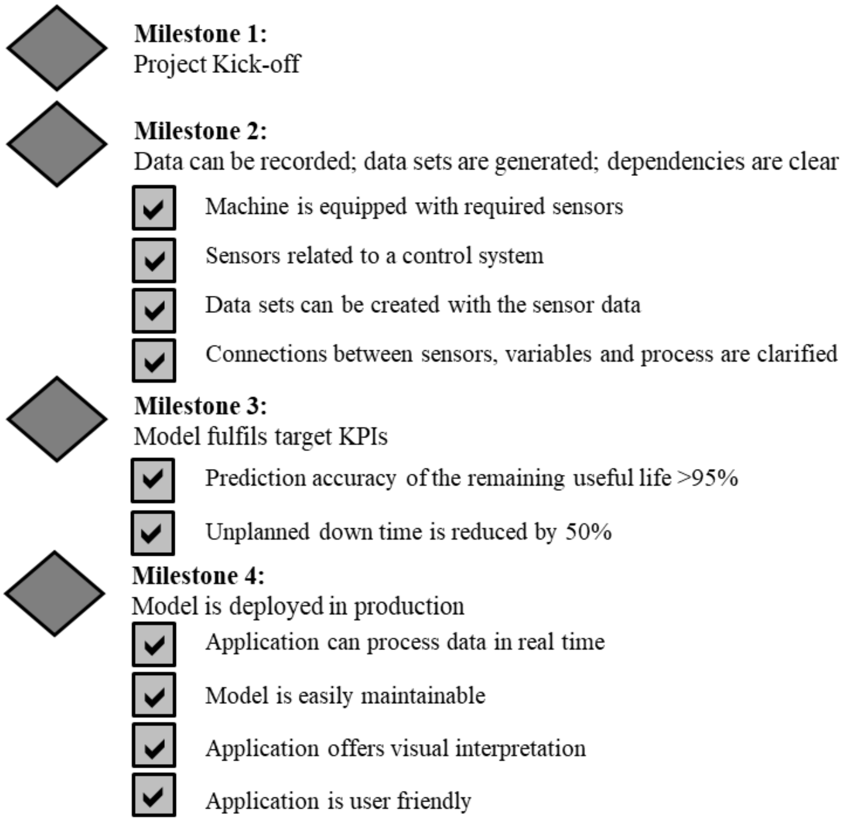


Figure 13. Planning Phase

The Data Acquisition and Understanding phase encompasses the domain understanding, the data collection, and the Explorative Data Analysis (EDA). In the domain understanding, the domain experts explain the process, the data sources, and dependencies to the data scientists. Once the project team defines the data sources and prepares the IT infrastructure, the data collection can take place. The EDA provides the first insights about the data and its quality. The dataset(s) are summarized, the data distribution visualized, outliers identified and treated. At the end of this phase, the project team should have a good understanding of the data and derive the first model characteristics to start the prototyping phase.

The Prototyping phase has as goal the proof of concept, which determines if the available data and developed models are able to solve the problem as desired. First, the data scientist pre-selects algorithms suited for the use case. For example, in case of regression and depending on the amount of available data, a linear regression, a Random Forest, a Support Vector Regression, or a Neural Network can be pre-selected. Each algorithm expects a specific format and features as input. The data preparation is consequently conducted. In the modelling phase, the selected algorithms are tested and evaluated based on the KPIs defined in the SD. It is common to start with a simpler model to establish a baseline for comparison. At the end of the Prototyping phase, the best model is selected according to the evaluation metric and other factors such as computing time and latency. Finally, the model which is developed, trained, tested, and validated in the offline environment is prepared for the Deployment.

The agile project management approach is recommended for the Prototyping phase. This management approach suits the development of an AI product for two main reasons. First, the short iteration cycles and clearly defined deliverables help minimize risks and foresees multiple solution paths. Second, the direct communication with internal partners (such as domain experts) saves time of project documentation and allows the team to adapt quickly to changing requirements [33]. As Figure 14 depicts, the agile project management makes use of frequent iterations or short, defined, repeated periods of time (also called sprints, that usually last two weeks) to break long development projects [34]. The main components of agile project management according to [35] are:

- *Sprint planning meeting*: at the beginning of each new iteration, the team defines the goals and tasks for the sprint.
- *Daily stand-up meetings*: during each iteration, the team meets daily to review what was done, define what should be done in the day and solve problems.
- *Demo*: at the end of each iteration solution increments are demonstrated and validated with stakeholders.
- *Retrospective meeting*: at the end of each iteration, the project team meets to evaluate what was achieved and find improvement potentials.

The project management tools are key resources to the agile methodology. The project backlog, where product features developed in each sprint are listed, is derived from the planning phase, portrayed in Figure 14. The Kanban board is used to organize tasks in three categories: what must be done, what is being done and what was done [35]. The data preparation phase benefits equally from the faster iteration cycles and validation with stakeholders.

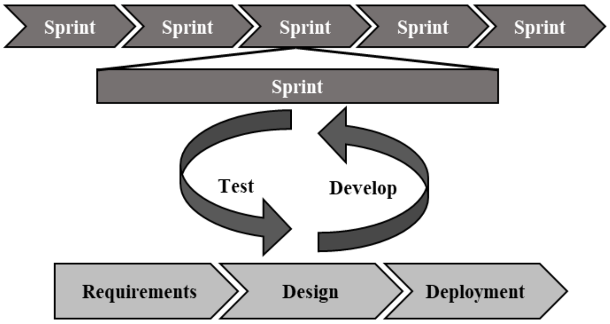


Figure 14. Agile project management in the prototyping phase

The model's Deployment begins with its integration into the IT infrastructure. The integration is solution specific, depending on whether the model will operate for example in a virtual machine on the company's local server or in an embedded microcontroller. The integrated model is tested and run in parallel without being used for decision making. The testing phase is completed when the model receives new, unseen data and its results are as good as the ones produced in the Prototyping phase. Once the model satisfies the requirements, the monitoring and updating starts. Significant changes in the data and unexpected events can potentially render the model unfunctional. The monitoring and updating are tasks that need to be conducted continuously during the productive usage of the model.

4. Conclusion and future research agenda

This paper introduces the AIMM that provides a guideline and tools for the development of an AI solution from problem selection to project execution. The model specifically targets manufacturing enterprises and their production-related use cases. By providing not only a guideline but also the necessary tools to conduct each phase, this model addresses the gap of existing Data Mining methodologies and makes the AI solution development tangible. The project team initially lists the existing problems and evaluates them regarding their business impact and complexity. The problems are organized into the four quadrants of the Portfolio Matrix. Problems which show a low complexity and low business impact are potential problems for pilot projects, while problems with low complexity and high business impact are the most promising. According to the company's preferences, the problems are prioritized and consequently selected to move past the first drop-out gate, the AI Problem Check. In this drop-out gate, a checklist with knock-out criteria is used to evaluate whether the problem can potentially be solved with AI technology. If the problem fulfils the criteria, it passes on to the SD. Here, we provide the tools for further analysis of the problem using the Problem Canvas as well as identifying functional and infrastructural requirements for the AI solution in the CSM and TSM respectively. The second drop-out gate embodies the Financial Evaluation. This evaluation utilizes the information from the TSM and the Problem Canvas to assess the solution's feasibility and potential gains in financial terms. If the solution is proved to be economically advantageous, the project team can start the DEV, which is divided into four sequential phases: Project Definition, Data Acquisition & Understanding, Prototyping and Deployment. Here, we provide guidance and best-practices for the technical aspects of AI development and deployment as well as the organization of the development process using agile principles.

The main contributions of this work are as follows: First, the operational, tactical, and strategical elements in the development and implementation of AI solutions are identified. Second, a new holistic, standardized, and structured process model for the introduction of AI solutions is presented. And third, a set of practical tools to support the realization of AI projects is suggested. Summarizing, the results of this paper provide the means for manufacturing companies to implement AI solutions targeted to solve production-related problems.

The presented model has limitations that need to be addressed by future research. One limitation is the need of a more technical guidance for the monitoring and updating of a completed AI model. The deployment of AI solutions poses big challenges for keeping the model updated and ensuring the results' reliability. In future work this aspect should be taken into consideration and become part of the process model. The same consideration is made for the DEV, where a more detailed guidance is needed when selecting and evaluating algorithms for the AI solution. The future research agenda comprises the model's validation with new use cases from industry partners and potential improvements derived from it. A second publication follows containing more detailed explanation of the presented tools and how the project team should use them.

Declaration of competing interests

The authors declare no competing interests.

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