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Developing a maturity-based workflow for the implementation of ML-applications using the example of a demand forecast

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Abstract

The aim of the article is to present a guideline that has been developed in the form of a workflow to identify the capability of an organisation to implement machine learning (ML) applications on the one hand and, on the other hand, to describe a maturity-dependent procedure for the development of an ML application based on this knowledge. With the help of the guideline, application-specific requirements can be identified based on the phases of the development process of an ML application adapted to the corporate environment. The article begins with the motivation for using machine learning methods and presents the challenges in implementing these methods. Based on a literature review, a maturity-based approach is designed and the developed and adapted development phases from the literature are described in a more detailed way. The individual characteristics of certain phases are specified based on the maturity level. As well, the weighting of certain maturity dimensions of the respective phase is highlighted. The article ends with an outlook on the further development of the created guideline.

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Keywords: artificial intelligenz, maturity-based workflow, challenges AI

1. Introduction

Through the use of adaptive artificial intelligence (AI) systems, increasingly large amounts of available data can be used for a variety of operational activities [1]. Furthermore, the growth in the amount of data has led to an enormous variety of data that cannot be processed efficiently with conventional management tools [2].

Especially in value chains of supply networks, the high complexity creates challenges. Company and production locations are strongly globally distributed [1]. In addition, production life cycles are becoming shorter and shorter, while highly fluctuating demand must be met [3]. For this reason, AI methods are highly relevant for supply chain management [4].

The described challenges also complicate demand forecasting which is a particularly important baseis for efficient planning in the logistics chain. The goal of good demand forecasting is to meet customer and market demands with ideal capacities and minimum inventories [5]. As a subfield of AI, ML methods ought to be a very useful tool for determining future demand [6]. Other papers also see ML as a promising alternative to traditional forecasting methods (e.g., [4, 7, 8]).

In order to reap the benefits of ML applications, certain obstacles must be taken into account that make the implementation of ML applications difficult or even impossible. Against this background, it is advisable to realistically assess the state of a company in terms of its ML capability using a maturity model before introducing an ML application [9].

Such a maturity model examines the general requirements for the introduction of ML applications. However, application-specific requirements and internal company challenges for ML

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deployment and development are not considered. Process models, in contrast, address these prerequisites and requirements in more detail. At the level of the concrete ML application, there are process models and workflows that describe the individual development phases of an ML model up to implementation. Since ML models and their internal process states cannot be traced and expressed at any time, other development steps than those of a deterministic algorithm must be followed [10].

Therefore, the central research question of this article is how the company-specific environment can be taken into account in the development and implementation of an ML application by managers in practice. To achieve this goal, a guideline in the form of a workflow is developed that both identifies an organisation's ability to implement ML and suggests a maturity-dependent procedure for developing an ML application. With the help of the model, the user is able to identify application-specific prerequisites based on the phases of the development process of an ML application that are adapted to the corporate environment.

The paper is structured as follows: The first section deals with the fundamentals and challenges of using AI and ML in particular. Subsequently, related work and the methodology of the process model are presented (sections 4 and 5). Furthermore, the sub-models belonging to the developed workflow are first presented (chapter 6), before the workflow is described in more detail and maturity-dependent differences are discussed (chapter 7). The article ends with an outlook on current challenges and next steps.

2. Background

Before there were ML methods for extracting information and generating knowledge, classical analysis methods such as data mining (DM) were used [10]. Statistical analysis methods are used to identify trends, structures and patterns in existing data sets. DM focuses on exploratory analysis of structured data and is often found in the context of the so-called knowledge discovery process [11].

As described, ML methods can adapt to changing environmental conditions and generate new information for iterative optimisation of the system [11]. The measurement of the deviation between desired and actual behaviour and the resulting adaptation are referred to as the actual machine learning [12]. Difficulties that can arise in the application of ML methods are various and can often be traced back to the existing data basis - e.g. missing data due to the introduction of new products or short life cycles. In the following section, the challenges in implementing ML are explained in more detail in order to give a systematic overview of them.

3. Challenges in the use of AI

The performance of an ML system is highly dependent on data from the business environment. This in mind, ML systems differ significantly from conventional software engineering: in order to solve certain tasks, ML applications partially replace their source code with self-learning algorithms that are controlled and optimised by data [13]. In conventional software engineering, the functions of the system are embedded in the source code through manual implementation. Compared to ML models, the source code is transparent, interpretable and verifiable by standard procedures [14].

3.1. Non-technical and technical challenges

The challenges of using AI, but ML in particular, can be divided into technical and non-technical challenges: Baier et al [15] group the difficulties identified in a literature review based on the CRISP-DM model into challenges that affect development before and during deployment. In addition, the authors list non-technical challenges that can be grouped into the clusters "strategy", "human aspects", "transparency" and "governance" [15].

The category "strategy" includes fundamental business challenges and requirements for the establishment of an AI strategy before and during the use of an AI and thus also ML technology. In this context, an AI strategy aims at defining the objectives of the AI or ML deployment [16]. The issues related to the human aspects mainly include challenges related to the knowledge, skills and competences of the employees. The cluster "transparency" addresses the challenges of the already described low transparency of ML systems. Within the "Governance" cluster, the obstacles related to the legal framework conditions in the development and commissioning of an AI application are discussed.

The technical challenges can be categorised into the areas of data and infrastructure. The accuracy of an ML model is highly dependent on the training data [9, 15, 17]. Incomplete data, erroneous inputs, noisy features and unbalanced as well as biased data lead to poor data quality and hence poor model quality [15]. The measurement of data quality is highly application-dependent and thus context-dependent [13]. Other challenges in ML development can be found in the infrastructure of the companies [18].

Baier et al [15] see the lack of standardised solutions for ML infrastructures as a challenge, so that an individual infrastructure has to be built for almost every project. If the infrastructure is unsuitable or missing components, the success of the project can be risked [15, 18].

4. Related Work

The concept of a maturity-based implementation to be developed is based on the results of two systematic literature reviews. Following the much acclaimed procedure of Cooper [19], the five steps of (1) problem formulation, (2) literature search, (3) literature evaluation, (4) analysis and interpretation and (5) presentation of the results were used to achieve a broad basis of literature information.

In total 34 publications were identified as relevant to the content of development approaches for AI and ML-based applications. In addition, 16 publications were found that deal with maturity models with a focus on AI, ML or Industry 4.0 (as one of the drivers of AI and therefore ML). For this purpose, two different literature databases (SCOPUS and IEEE Explore) were searched using the search combinations stated in Tab. 1.

Table 1. Selected search combinations.

Development of an AI/ML-based application	Maturity model with AI/ML or Industry 4.0 relation
("artificial intelligence" OR "machine learning" OR "deep learning") AND ("workflow" OR "process model" OR "lifecycle" OR "software engineering process")	("artificial intelligence" OR "machine learning" OR "deep learning") AND ("maturity model" OR "maturity level" OR "maturity framework")Maturity level

The found publications from the two different thematic areas have been compared and analysed on the basis of general and ML-specific characteristics. The characteristics are based on the presented challenges unsing ML as well as on theoretical findings [20, 21, 22, 23]. Tab. 2 shows the comparison criteria that were used in the development of the research status regarding an ML workflow.

Table 2. General or ML-specific characteristics.

	AI/ML workflows	AI/ML Maturity Model
General characteristics	Domain, process control, phase arrangement, form of representation, degree of abstraction, adaptability, user participation, tool recommendation	Development background, number of maturity levels, number of assessment criteria, assessment method, means, weighting, assessment effort, use case, empirical findings
ML-specific characteristics	Verification of data quality & quantity, effort estimation, meta-data, feature engineering, categorial & aggregated data, data leckage, perfect fit, version management	Verification of strategy, degree of digitalization, knowhow of employees, data security, infrastructure

Due to the focus on the process model, we will refrain from a closer look at the papers found and their classification in the comparative characteristics, but only describe the essential findings from the two literature reviews.

During the first literature research, it has been identified that ML applications are developed and deployed through an iterative approach. The presented phases are mainly based on the CRISP-DM (Cross Industry Standard Process for Data Mining) which is a standard process model in DM. However, its steps are extended by additional activities. For a better overview and delimitability, a 9-phase division is used in the further course. These phases are based on the phases established by Kessler & Gómez [10], but are also extended by the activities identified in the literature research.Furthermore, it has been found that few (developmental) technical challenges have been considered in the identified procedures. In addition, the development process is described in many sources, but only inadequately. One reason why data quality and quantity are discussed in very few publications may be the strong dependence on the particular use case of these features. The available literature sources assume that ML applications - for example in demand forecasting - can generate fundamental advantages over conventional methods from statistics, but that these advantages can only be achieved if sufficient attention is paid to the analysis and pre-processing of the collected data.

In the second literature review on maturity models in the field of AI, ML and Industrie 4.0, it was found that many approaches are only poorly documented. Furthermore, it has been recognized that the research activities regarding AI-oriented maturity models range only in a small scope. Additionaly, the majority of identified maturity models consider multilevel, qualitative-descriptive scales. Moreover, many of the maturity models found did not consider the infrastructure, the level of digitization of the enterprise, or the employee skills.

Maturity-dependent differences in ML application development have been identified and described only to a very limited extent by the literature. In the cases where these differences have been considered (e.g., [24, 25]), a holistic approach from the maturity determination to the generation of the sequence and making challenges visible is missing.

For this reason, the development project at hand pursues the creation of a process model that - in addition to determining an AI maturity level and depicting the workflow - also shows maturity-dependent differences and challenges in the individual development phases.

5. Methodology

The workflow for the maturity-based implementation of an ML application was created using an approach based on the methodology presented by Fettke [26]. The methodology is used because it has been successfully applied in the past (e.g., [27]) and only a lack of alternative usuable schemes for the development of process models could be identified.

Fettke [26] presents an inductive approach for creating a reference model based on seven steps. First, requirements and model conventions are formulated (1), before individual models are selected (2), preprocessed (3), and submodels are extracted (4). Furthermore, the submodels are combined and then first evaluated (6) and then maintained and further developed during the use (7). Within this paper, steps 2-4 and steps 6 and 7 have been combined for practicality reasons [26].

The model language BPMN is chosen as the model formalization. Reasons for this are the advantages identified by Kelemen et al [28] in the areas of comprehensibility, coverage of process elements, and the ability to express workflow patterns [28]. In addition, functional and structural requirements for the process model were formulated. They are based on the findings from the literature review and determine the structure and content of the submodels.

The structural requirements for the development workflow are composed of successive phase arrangement, activity-oriented process control, and incremental progressive problem solving. The maturity model, on the other hand, must have a staggered structure and have to consist of a certain number of stages and dimensions with maturity-dependent assessment criteria. The functional requirements for the workflow element ensure that certain activities are performed in each development and implementation phase (e.g., initial phase as project start and formulation of the problem solution). In the context to the AI maturity model, the necessary contents of the different dimensions (e.g. How is the AI knowhow of the employees?) are considered by the functional requirements.

In contrast to Fettke's [26] description, two sub-models - a process model for ML application development and an AI-related maturity model - were developed and combined into a maturity-based approach.

Following Fettke [26] the model is evaluated after its completion and extended by corrections and additions. In the present development project, the model was tested and evaluated by its use in an industrial application.

In the following, the process model for the maturity-based implementation of an ML application and its elements are presented.

6. Elements of the workflow for maturity-based implementation

The workflow for maturity-based implementation consists of two elements that build on each other. Firstly, the maturity model is used to determine the maturity level with regard to the AI capability of a company, and secondly, a procedure for the development and implementation of an ML application is presented. Before presenting the newly developed workflow for visualizing maturity-based challenges and differences along the development and implementation process, the two elements required for this are first considered separately.

6.1. Maturity-based element

Based on the publications identified from the state of research, a model for determining the maturity of a company's AI capability was created following the methodology for developing a maturity model by Becker et al. [29] The model consists of four maturity levels and five different dimensions that are intended to provide a holistic overview of the AI-specific ability of the enterprise. In Table 3, the dimensions are exemplified with the respective requirement to achieve a certain maturity level as an excerpt of the entire model. Although ML applications are the focus of the paper, the AI maturity model can help identify its maturity in the AI field before the start of a project so that it can be used prior to ML projects. Thus, it can also be used within the maturity-based workflow for implementing ML applications.

For each of the given evaluation criteria, four characteristic values allow an assignment to a certain maturity level. Each evaluation criterion is assigned several points depending on the respective maturity level, which are determined on the basis of a questionnaire and assigned according to an exponential scale (AI-new: 0 points; AI-experienced: 1 point; AI-experienced: 3 points; AI-extended: 9 points). The exponential distribution of the scores ensures that the requirements for achieving the next higher maturity level are realistically mapped.

6.2. Workflow element

Based on the literature research and especially on the selected publications, a nine-phase generic workflow was developed according to the requirements. The contents and the processes of the phases are based on the work of [10, 12, 24, 30, 31, 32]. Fig. 2 presents an overview of the different phases within the workflow created in BPMN. Due to the level of granularity and the lack of space, detailed phase representations are not provided.

Within the business understanding, the necessary domain knowledge is established and the project team is put together. The problem to be solved is specified and the purpose formulated in the Business Understanding phase [10]. Data Collection consists of identifying suitable internal and external data sources in order to obtain the highest quality database possible [10, 30].

During Data Understanding, the collected data is analyzed and checked for structure. Clusters and correlations are also

Table 3. Overview of maturity levels.

	AI-new	AI-enabled	AI-experienced	AI-advanced
Strategy	• no AI strategy • no AI budgets • no identified AI use cases	• short-term strategy, but no dedicated AI budget yet • Use Cases are in a pilot project status	• medium-term AI strategy and dedicated AI budgets • only use cases at specific business levels	• long-term AI strategy • dedicated AI budgets • enterprise-wide AI use cases identified
Orga. & staff	• no data analytic skills or AI expertise available	• common data analytic skills (e.g., Excel) • basic understanding of AI workflows available	• ability to perform sophisticated data analyses • in-depth AI- understanding	• ability to perform complex analyses • trained in AI use and development
Tech-nology	• no data management system or/and ERP-system available	• decentralized data management system and/or ERP system with few functions	• centralized data management system and/or devision-specific ERP system	• Data warehouse and/or cross-divisional ERP system
Data	• One-sided and non-historical sample size • Difficult to transfer and unstructured data	• Capture of essential features, but small sample • Limited transferable and semi-structured formats	• Coverage of relevant features, large sample with unequally distributed classes, directly transferable and mixed-scaled formats	• Capture of all relevant features, large sample, overlapping and standardized format, structured and metric-scaled format
Process	• No AI best practices identified	• AI best practices identified but not applied	• Identified AI best practices applies	• AI best practices are applied in a standardized matter

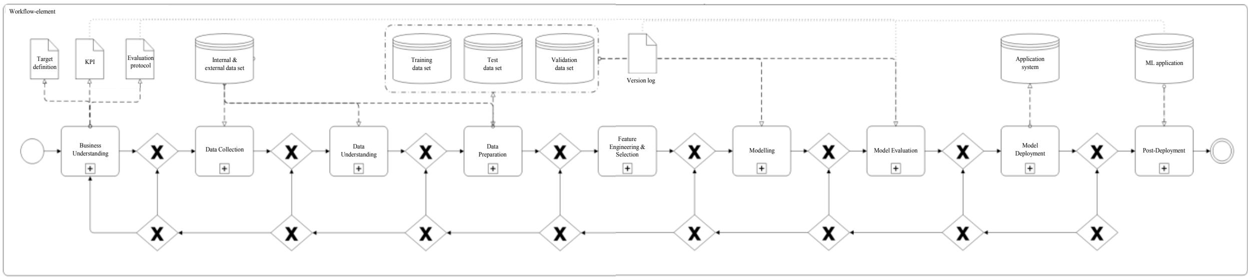

Fig. 1. Workflow element in BPMN.

identified. During Data Preparation, the analyzed data is prepared for use by an ML process. This includes steps such as merging data sources, cleaning errors, and transforming and validating the data. One task of Data Preparation is adding labels or annotations to the data sets (data labeling) [10]. After Data Preparation, the data set is divided into subsets that are used to train, test, and validate the created model [33]. Another step before the actual model creation is feature engineering and feature selection. This involves extracting the data points or features that have the highest information content. It may be necessary to first construct the features by combining different data [30].

The following modeling can be divided into the following sub-steps: Model development, Model training and Parameterization. Model construction implies a procedure that is selected depending on the size of the available data set and typical characteristics of the use case. During model training, the selected models are trained and tuned using the preprocessed data [30]. During the training process, decisions are made on the use of different hyperparameters to achieve better results [24]. The optimal parameterization depends on the particular applications. Between modeling and model evaluation, there are iterative loops to test a created model and adjust and improve it if necessary. Testing the model involves asking whether a model has statistical significance and is performant enough for the application [12]. Once sufficient model configuration has been achieved, the final model can be trained with all available data.

After the ML model has been deployed for operational use and implemented in the processes, the system must also be monitored using post-deployment activities. In addition, the focus is on optimizing the model. This can be achieved by using user input to augment the data sets and re-training the model [31].

While the previous sections of this paper and the included models have been developed based on literature sources, the following section presents the maturity-related differences and challenges that need to be considered in each of the described phases depending on the ML maturity of the enterprise.

7. Maturity-based workflow (using the example of a ML-based demand forecast)

By comparing and taking a closer look at the challenges, the evaluation dimensions and and the phase contents, it was possible to determine that some phase contents are dependent on the dimension-specific maturity level achieved in each case. It is stated there may be maturity-dependent challenges in the phases. The developed two-part workflow takes this finding into account.

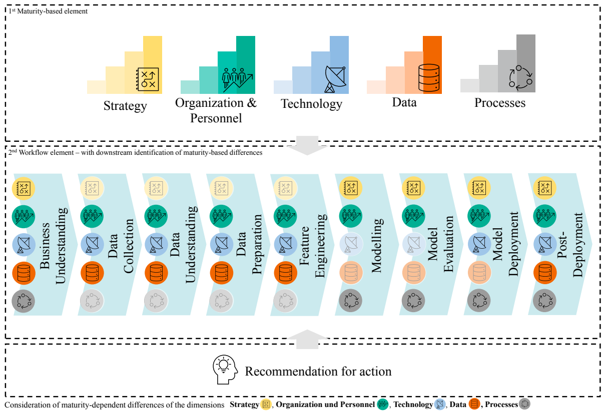

Fig. 2. Two-part, maturity-based workflow.

As roughly shown in Fig. 2, the maturity-based workflow starts by determining the maturity level per dimension. Based on this, the procedure described in section 6.2. is adapted with regard to the maturity level achieved. Furthermore, the maturity-based differences and challenges in each phase are pointed out and possible recommendations for action are presented. This workflow allows the user to determine the effort required before the start of the project on the basis of the challenges that can be expected at the respective maturity level. For reasons of clarity, the BPMN representations are omitted. The maturity-based challenges and differences per phase are shown below.

In the phase **Business Understanding**, an understanding of the ML deployment is created. Companies that describe themselves as AI-experienced or AI-advanced can perform this activity more effectively. Once ML applications are implemented or best practices are identified, the problem is tangible and the solution to the problem can be specified. For example, the definition of the goals regarding implementing a ML-based demand forecast can be easier, if there are already ML applications. AI-new and AI-enabled organizations, on the other hand, will have challenges in data analytic understanding due to lack of staff experience. The same is applicable to building the project team: this business understanding activity is fundamentally determined by the maturity level a company has reached, especially in terms of organization and personnel. Companies with a high level of strategic and process maturity will also have advantages over less mature companies when it comes to establishing performance indicators and evaluation protocols, as they can build on existing use cases or best practices.

When identifying and reviewing internal and external data sources (**data collection**), the contents of the dimensions technology and data take on a superordinate role. It can also be stated that the maturity level of the technology and the maturity level of the data are directly related. In addition, it can be assumed that if the level of maturity of the technology is high - with the presence of an ERP or a data management system - the data will also have a relatively high level of maturity. For this reason, AI-experienced and AI-advanced companies will not have any major problems or challenges, as the information systems often specify standardized data structures and the origin of the data can be determined relatively easily. Looking at the example of the ML-based demand forecast, there is a good initial situation for data collection with a wide data coverage of the processes and circumstances within (e.g., historic sales data) and outside the company (e.g., promotion data of customers). AI-new and AI-enabled companies will have problems with data collection because there are no information systems and therefore data collection is manual or data is stored on paper. If only very basic information systems are in place, the data may be in unstructured form or difficult to track, inconsistent, and difficult to verify.

A similar relationship applies to **data understanding**. AI-new and AI-enabled companies may have difficulty in data exploration or in identifying clusters and correlations, as this places certain demands on existing information systems. AI-experienced and AI-advanced companies will have information systems with more advanced analytics and visualization capabilities that can be used for this phase. For example, during developing a ML-based demand forecast, the correlations between certain data sets (e.g., above mentioned internal and external data) have to be analysed before using in a ML model. In the case of low data maturity, the first step before testing is to get the data into an analyzable form. This can be a very time-consuming step.

Since **data preparation** is primarily about creating processable data, companies that demonstrate a high level of data and technology maturity are likely to be more effective at preprocessing data and adding labels and comments. For example, good data maturity is characterized by complete data and a low number of logical inconsistencies, so it can be assumed that the steps will be a relatively low effort for these companies. For a ML-based demand forecast historic purchasing data without gaps are needed in any case to create a reliable ML model. AI-experienced and AI-advanced enterprises will most likely have this data sets and therefore little effort in this phase. Feature engineering and feature selection is supported by high maturity in the dimensions of technology, data organization and personnel. Existing ERP or data management systems can be used for feature comparison. In general, a good level of data maturity provides a better basis for this step. Of particular interest in this context is a company's maturity level in terms of data completeness and traceability. Sufficient information about the context of use is also particularly helpful in this context, as features that have a positive influence on the model result can often be identified on this basis. AI-experienced and AI-advanced companies are usually in a better starting position for this, as their practitioners and employees have data analytic and AI knowledge and can consequently gather information on this. A set feature regarding a ML-based demand forecast is of cource the number of sales in the last, considered time period.

Since an adequate data situation already exists in the **modeling** phase due to the implementation of the activities of the previous phases, the data dimension tends to move into the background. Companies that have a high strategic maturity level can use experience from AI or ML projects for the development and training of the model. Likewise, processes of model training are known or knowledge of domain-related parameterizations can be used within this phase to achieve a high-quality model. In this context, on the one hand, the AI skills of the employees or stakeholders and thus the maturity level of the organization and personnel dimension are certainly important. On the other hand, identified and deployed best practices and thus the maturity assignment of the process dimension must be taken into account, as this provides knowledge about e.g. suitable model architectures or necessary model components. AI-new and AI-enabled companies will have corresponding difficulties in this respect, but can still develop simple models.

Existing use cases and best practices can also be used to guide the **model evaluation**. Metrics already used to measure performance can also be incorporated into the evaluation, as a guideline or basis for comparison. A point not to be neglected is error analysis, if the error values determined are too high. Here, data analytic and AI skills are essential. Therefore, it can be stated that AI-experienced and AI-advanced companies have a better basis for more effective model evaluation. Thus, AI-new and AI-enabled companies can expect challenges if the level of staffing, strategy, or process maturity is too low.

The technology dimension has an important role to play in **model deployment**. Companies that belong to the AI-experienced and AI-advanced maturity group in this dimension have a good basis for easy implementation of the AI application due to the AI technology or information systems already in use. For these companies, the opportunity arises that the review of company resources and the associated implementation of the adjustments are not necessary.

The identification of optimization potentials can be supported in the **post-deployment** phase by already implemented use cases and identified best practices by using them as a guide. Similarly, existing use cases and best practices can be used to monitor model performance. For example, drifts of concept from already implemented ML applications can be identified and proactive countermeasures can be initiated and adjustments made. For example, in the course of a ML-based demand forecast, seasonal changes of product time series are of a special interest. In this case, the model needs to update with different parameters to ensure a good data quality.

Model performance monitoring can also be supported by appropriate data maturity. In this case, shifts can be better identified and adjustments can be made earlier. For this reason, AI-experienced and AI-advanced organizations typically have better capabilities to address extensible model performance. To be able to recognize concept shifts, employees or practitioners must have the necessary knowledge.

8. Conclusion

The central research question was how the company-specific environment can be taken into account in the development and implementation of an ML application. For this purpose, a workflow has been developed as a guideline that supports the user in identifying his AI maturity and, based on this, presents maturity-based differences and challenges in addition to a 9-phase procedure.

The elaboration of maturity-based differences and challenges represent a novelty to the publications identified in two literature searches. In the found papers, commonalities in terms of design and structure have been identified, but nevertheless maturity-based differences of certain activities and challenges during the development and implementation of an ML model have been described only to a very small extent. The workflow created attempts to improve these shortcomings.

Through the present work, further investigations can be initiated. Further model deployments can be used to identify additional previously unaddressed challenges and to develop the proposed model accordingly. Additional research can verify the accuracy and relevance of the evaluation criteria. Since the criteria described in this paper have been formulated and assigned to dimensions on a theoretical basis, additional case studies can be used to analyse and make any necessary adjustments to the model. Through an evaluation - not described in this paper - in a company from the food industry, the developed approach could be successfully tested in the potential implementation of ML-based forecasting.

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