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AI Management Model for Production

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***Abstract* – Artificial Intelligence (AI) projects in production often end in proof-of-concepts with AI solutions not being continuously maintained along their life cycle. Only by managing multiple AI use cases simultaneously and systematically, companies can achieve an industrial level of usage in their production environment and fully benefit from the technology's potential. For that purpose, an AI management model is proposed that serves as a framework to capture, design, and optimize AI activities to continuously improve the quality of the AI solutions and the satisfaction of involved stakeholders. Relevant related concepts from quality management (QM) are employed during the creation of the management model distinguishing three categories of processes: management, core, and support. For each category, corresponding processes and sub-processes are provided and explained for orientation in the implementation in specific scenarios. The proposed management model is validated with AI, QM, and production domain experts on a conceptual level. Furthermore, it is applied operationally in the implementation of real-life use cases from production.**

Keywords – Artificial Intelligence, Management Model, Quality Management, Production.

I. INTRODUCTION

Artificial Intelligence (AI) and its sub-domain Machine Learning (ML) become more and more relevant for production and have been applied in numerous use cases in production [1–3]. A full and successful integration of AI into enterprise operations promises measurable results and benefits, including increased productivity, better product quality, and improved resource management [4]. Ongoing development of new standards and norms regarding AI and ML, such as the European Data Act or the ISO/IEC 42001, underlines the importance of the topic [5,6].

However, many projects end with the creation of proof-of-concept solutions without a continuous management of the solution over a longer period of time [7–9]. In particular, the further development of project prototypes into a fully usable and integrable solution poses challenges for many companies [10]. Successfully handling multiple use cases simultaneously describes the goal for the long-haul approach to AI that has only been mastered by a small percentage of companies, with most being at lower levels of maturity [11].

Fulfilling expectations and standards increase the complexity and difficulty of already existing challenges, which cannot be addressed without a systematic approach to manage these solutions in the context of the processes in the company. By using standardized processes in AI and analytics, competitive disadvantages can be avoided [12].

In this paper, the goal is to establish a framework for managing all AI activities with focus on the production industry in order to achieve the AI goals. Through expert interviews and hands-on implementation, the AI management model is validated to ensure its purpose: enabling the holistic management of AI in a company and preparing the installation of an AI management system as one element of an integrated management system.

The remainder of the paper is structured as follows. Based on the analysis of the state of the art in section 2, the methodology to compose the AI management model is derived in section 3. After that, section 4 describes the results, i.e., the management model and its components, in detail. The discussion and validation of results is presented in section 5, before section 6 concludes and provides an outlook.

II. RELATED RESULTS IN THE LITERATURE

Given the increase in importance of AI and ML in the literature, various concepts have emerged that originate from different fields of investigation and that focus on different aspects of managing AI. In the following, relevant existing approaches regarding the management of AI and ML with both terms being used interchangeably.

1. MLOps and ModelOps

"MLOps (Machine Learning Operations) is a paradigm, including aspects like best practices, sets of concepts, as well as a development culture when it comes to the end-to-end conceptualization, implementation, monitoring, deployment, and scalability of machine learning products" [13]. It focuses on rapid experimentation and deployment of ML models during the data science process to bridge the gap between development and operations. ModelOps includes these features and is defined as "a collection of tools, technologies, and best practices to deploy, monitor and manage machine learning models" [14]. It describes an enterprise capability for the governance and operations of models in production. Both approaches, however, are a mere accumulation of concepts, with no unified and clear structure provided to coordinate AI activities in a systematic way.

2. AI Management Models and Systems

Biegel et al. [15] introduce an *AI Management Model for the Manufacturing Industry* to address the limitations of existing AI project approaches, such as the *CRISP-DM* (Cross-Industry Standard Process for Data Mining) [16], when realized in the manufacturing industry. Therefore, they propose "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." The authors focus on the core activities in an AI project including aspects such as risk management, but no integration into the overall context of the companies' activities is achieved.

In the study *Management System Support for Trustworthy Artificial Intelligence*, researchers at the Fraunhofer Institute for Intelligent Analysis and Information Systems IAIS [17] review the previous draft of ISO/IEC 42001 [6] and compare it with the current requirements in order to derive recommendations for trustworthy AI. Similarly, in the study *Speeding Up Industrial AI And Trustworthiness*, the Franco-German consortium [18] aiming at the development of trustworthy industrial AI applications introduces a comprehensive industrial and trustworthy AI framework providing a high-level overview of necessary elements. Both approaches cover the general elements to manage AI but do not provide any guidance and structure for the setup of an AI management system.

3. AI Quality and AI Quality Management

Santhanam [19] covers QM of ML systems by presenting "a view of a holistic QM framework for ML applications" with the goal to achieve a more trustworthy AI. AI is understood just as software that needs to fulfill software quality criteria. *Heck* [20,21] introduces a quality model for trustworthy AI systems. It extends the ISO 25000 (SQuaRE) Quality Model for AI Systems by providing quality criteria representing characteristics that need to be considered by all three types of artefacts of AI systems: software, datasets, and models. TÜV SÜD [22] has developed the *AI Quality Management Framework* which offers a transparent and objective framework to identify and manage risks associated with AI technologies." The QM approach focuses on a set of AI quality characteristics and encompasses the steps of (1) identification of scope and goals, (2) specification of targets and processes and (3) monitoring and review. These three approaches have in common that they focus on creating and measuring quality criteria without managing AI as a whole.

The German Federal Ministry for Economic Affairs and Climate Action published the *Leitfaden für das Qualitätsmanagement bei der Entwicklung von KI-Lösungen und -anwendungen*, a guideline for the QM during the development of AI solutions and applications [23]. The guideline is broken down into phases, criteria, indicators, and solution support. As an example, for the operations phase, the criterion of performance monitoring encompasses the indicator that raises the question if the performance of the system in operation is captured and documented continuously respectively in periodic intervals. As solution support, the authors refer to existing standards, established tools, or research results. Thus, the guideline covers the emerging questions but does not provide a structured model to interconnect the elements and embed them into one management system.

4. Quality Management

Looking at approaches from non-AI QM, there are many examples for models, standards, and methods [24]. A QM model "is a structured framework or methodology that guides organizations in managing and improving the quality of their products, services, or processes. These models provide a systematic approach to QM by defining principles, practices, and guidelines to ensure consistent and reliable outcomes". Examples include Total Quality Management (TQM) [25], Six Sigma [26], and The Aachen Quality Management Model (ACQMM) [27]. The ACQMM provides comprehensive guidelines for QM, integrating concepts such as process maturity, risk management, and customer satisfaction. These models ensure effective management and improve process quality with regard to the DIN EN ISO 9001 [28]. While providing a holistic framework divided into management, core processes and support to plan and execute actions, the ACQMM however does not establish a link to AI.

5. Interim Conclusion

Existing approaches cover different perspectives of AI, e. g., software development, governance, project management, AI life cycle and AI quality. However, no approach covers the administration of AI from a holistic viewpoint, rather the focus is on a certain phase in the life cycle or a set of quality aspects. Furthermore, current approaches lack applicability for production companies as they either provide high-level generic guidance or operational, data science-focused activities. Principles from QM offer the potential to improve AI management with regard to responsible, efficient, and high-quality development and utilization of AI systems. So far, a comprehensive and unified approach that integrates all these aspects seamlessly, addressing the unique requirements and challenges faced by organizations in managing AI effectively is lacking.

III. DESCRIPTION OF THE METHOD

In this paper, an *AI Management Model for Production* is proposed, which provides a framework for an organization's AI activities with focus on the production industry. The goal of the management model is to be able to holistically structure and design AI-related tasks and their incorporation into the company-wide management systems. It is intended to be used in a descriptive way describing the current state as well as in a formative manner to design improvements along the AI life cycle. In doing so, the model provides multiple perspectives with which various aspects and challenges in a company can be considered and addressed.

As AI management is understood as a comprehensive cross-sectional task that has a lasting impact on the organization's success, concepts from QM – especially from ACQMM – have been incorporated in the construction of the AI management model. First, all relevant processes along the AI life cycle are identified in accordance with existing approaches. Second, the identified processes are clustered and arranged. The classification into management, core, and support processes as well as continuous improvement are derived from QM. Third, each process is defined with its respective sub-processes in order to have clear delimitation and distinction between the processes. Fourth, the processes within a cluster are brought into order and interlinked between processes is established. Fifth, the developed solution is validated with experts from research and industry.

IV. RESULTS

Figure 1 shows the proposed model in form of an AI process landscape with management, core, and support processes. It includes all value-adding processes along the AI life cycle as core processes. Necessary management and support processes to enable the AI life cycle are also included. In the following, the aspects of the model are explained in detail.

1. Management Services

Management services are responsible for alignment of the AI processes with overall context of company. They contain the AI strategy, AI policy and organizational structure. There is a close interlinkage to overall corporate strategy, policies, and structure.

An AI strategy (1.1) refers to a systematic and comprehensive plan that outlines how an organization intends to integrate and utilize AI technologies to enhance the quality of its products, services, and processes. This strategy aims to leverage AI's capabilities to optimize various aspects of quality control, assurance, and improvement within an organization. It includes the definition of an AI vision and mission, clear AI objectives and setting up change management measures.

The AI policy (1.2) comprises guidelines, principles, and regulations established by governments, organizations, or institutions to govern the AI life cycle. AI policies aim to address various concerns related to AI, including ethics, accountability, transparency, privacy, fairness, and security. AI policies are crucial for shaping the ethical, legal, and social dimensions of AI deployment and ensuring that AI technologies are developed and used in a manner that aligns with societal values and priorities. They provide a framework for guiding AI innovation while mitigating potential risks and ensuring that the benefits of AI are realized by individuals and society. It includes internal policies as well as external standards and norms.

Organizational structure (1.3) refers to the way an

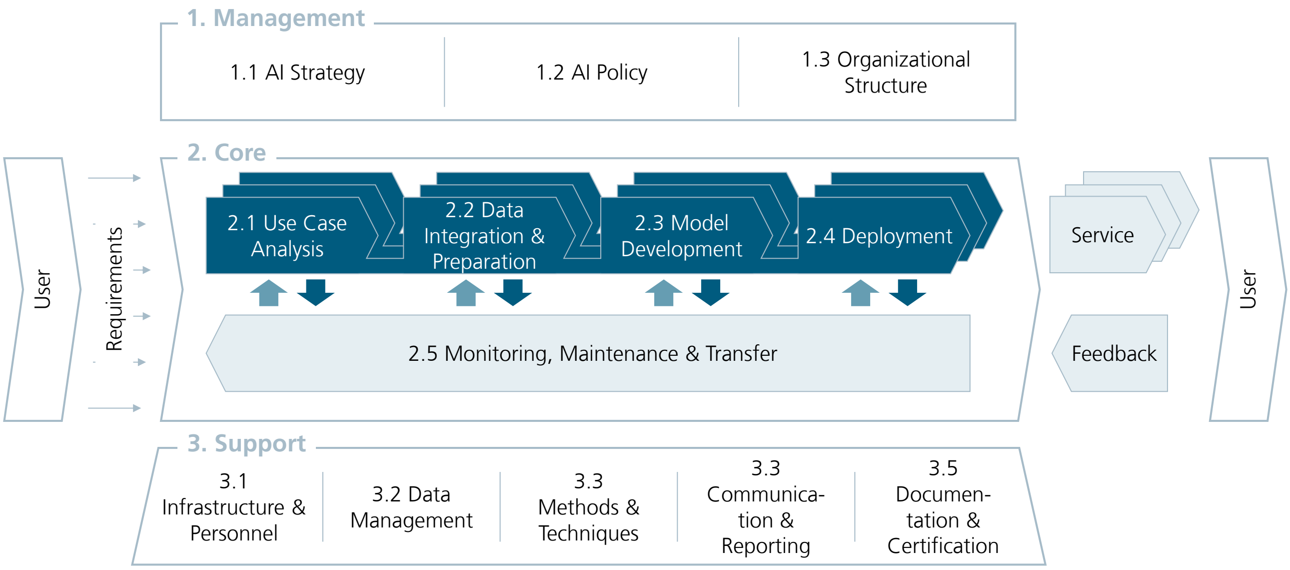

Figure 1: AI Management Model for Production

organization is designed and how its functions, responsibilities, and authorities are defined and organized. It serves to establish a clear hierarchy, define roles as well as responsibilities, and document the relationships as well as interactions between different functions, departments, or positions within the organization. It includes an organizational chart, role descriptions, and stakeholder management.

2. *Core Processes*

Directly value-adding activities along the AI life cycle are bundled in core processes. Managing multiple use cases at the same time is realized through the realization of these core processes, for which user requirements and their quality criteria play an important role. Users interact with and utilize AI technologies to achieve specific goals, solve problems, and extract value from the capabilities offered by these systems. Core processes are set up globally and then come into application on a use case specific level.

Use case analysis (2.1) is the process of thoroughly evaluating a specific scenario or situation to determine its feasibility, potential benefits, risks, and alignment with organizational goals. This assessment helps organizations make informed decisions about whether to pursue a particular use case or initiative. Furthermore, it involves a strategic and iterative approach, where organizations continuously assess, refine, and expand their use of AI technologies to drive business value and achieve their objectives. It requires collaboration between business stakeholders, data scientists, IT teams, and other relevant functions to ensure alignment, successful implementation, and ongoing optimization of AI use cases. It includes the use case definition as well as a continuous assessment of risk, impact, and objectives.

Data integration (2.2) involves combining data from multiple sources into a unified and coherent dataset. It addresses the challenge of merging heterogeneous data sources, which may have different formats, structures, or data representations. The goal of data integration is to create a consolidated dataset that provides a comprehensive view of the data and enables analysis across various sources. Data preparation focuses on getting the data into a suitable format for analysis or modeling. It involves cleaning, transforming, and organizing raw data to ensure its quality, consistency, and usability for further analysis. Data preparation is essential for removing noise, addressing missing values, handling outliers, and transforming variables to facilitate effective analysis or modeling. Data integration and preparation includes the sub-processes of IT-system analysis, the establishment of data models, schema, and relationship, the realization of data integration, data preprocessing and feature engineering.

The model development phase (2.3) is a crucial stage in the life cycle, where the ML model is conceptualized, designed, trained, and refined to fulfill a specific task or solve a particular problem. This phase involves several iterative steps that lead to the creation of a high-performing and accurate model. The phase includes algorithm selection, hyperparameter tuning, training and diagnosis.

Deployment (2.4) refers to the process of taking a trained ML model and making it available for use in a real-world environment. It involves integrating the model into an application, system, or service where it can receive input data, process it, and provide predictions, classifications, or other relevant outputs. The deployment phase includes the deployment design as well as the productionizing & testing.

Monitoring, maintenance, and transfer (2.5) refer to important aspects that come into play after a model has been deployed and is actively used in real-world applications. Monitoring involves continuously observing and analyzing the performance of a deployed ML model in real-world scenarios. This process helps to identify any anomalies, degradation in performance, or unexpected behavior. Maintenance involves ongoing activities to keep the deployed model in a healthy state, maintain its accuracy, and adapt to changing conditions. Transfer refers to the process of moving a model from one environment or application to another, e.g., by adapting the model to new contexts. The phase includes sub-processes regarding monitoring & user feedback, maintenance & retraining as well as transfer & lessons learned.

3. *Support Services*

Support services enable the AI life cycle from an operational perspective. They are not directly value-adding but build the basis for the successful realization of any AI application.

Infrastructure and personnel processes (3.1) comprise sub-processes like resource management or personnel management and staffing. That includes tasks for managing hardware, software, or licenses for building and running AI models as well as including environment settings for supporting the core processes of the AI management system. Resources like machines, energy, or material, which are necessary to create input to feed and run the core processes, will be defined in these processes. Hardware like machines and sensors as well as different interfaces for an environment-friendly integration are typical examples of resources. Furthermore, personnel management includes processes such as the recruitment and hiring of qualified personnel for specific tasks. Moreover, it is crucial to establish and implement performance management processes to ensure that personnel are meeting quality requirements.

Data management (3.2) is defined as a support process, which consists out of different sub-processes related to categories like data governance, data quality, or labeling of data. By effectively managing data, organizations can ensure that they have access to high-quality, reliable data that can support their business objectives. The data governance processes refer to the overall management of the availability, usability, integrity, and security of data used in an organization. It is particularly important because AI models are only as good as the data they are trained on. Poor quality, biased, or incomplete data can lead to inaccurate or unfair AI predictions and decisions. To ensure data quality, it is necessary to defined standards and rules.

Methods and techniques (3.3) include various sub-processes in the context of management AI in an industrial environment and refer to the specific procedures used to implement and maintain an AI management system and especially the core processes. The sub-processes can be divided into categories like project management, best practices, reference architecture, seminars and training, knowledge management as well as automatization.

Communication and reporting (3.4) processes in an AI management system involve effectively communicating information and reporting on AI-quality-related matters. This includes tasks such as developing a communication plan, ensuring clear and timely communication with relevant stakeholders, providing updates on quality performance, reporting quality data, and using appropriate channels and formats. The aim is to ensure transparent and efficient communication, facilitate decision-making, and maintain compliance with quality standards and requirements. It includes tasks such as stakeholder communication regarding decision-making, managing relationships, and continuously monitoring their satisfaction and feedback. The goal is to ensure that stakeholders are engaged, their requirements are met, and their support is gained to improve the AI management system.

Processes for documentation and certification (3.5) involve ensuring that all relevant information regarding the AI system is properly documented and certified. This includes documenting the development process, algorithms used, data sources, model training, validation, and testing as well as maintaining and monitoring procedures. It also involves obtaining certifications or compliance with relevant standards or regulations specific to system, process, and product. The goal is to create a transparent and auditable record of the AI system's development and operation, and to demonstrate its compliance with quality and regulatory requirements.

V. DISCUSSION AND VALIDATION

Added value of the proposed AI management model in production is generated by handling and keeping track of multiple use cases in production over an extended period of time. It helps to create transparency about the origin of the AI performance, identifies needs for action, and improvements of AI quality to support their implementation. Thus, the model represents a possibility to document and evaluate the status quo as a basis for planning and improvement to create a complete, sustainable, and long-term AI integration under consideration of key processes and companies' vision. Furthermore, it provides a structure for knowledge management.

When creating an instance of an AI management model for a specific organization, an AI Management System is brought to existence. Together with other management systems, such as QM or energy management, an integrated management system is composed. AI management has a strong connection to QM. From a management perspective, the strategic AI vision has to be aligned with the overall company goals. Through the creation and maintenance of AI services for use cases following the core processes, the overall production quality is aimed to be improved. Lastly, necessary supporting resources, e.g., from IT, to run AI systems need to be coordinated with resources that support the business processes of the organization.

To ensure the proposed model's substantiality, it was validated through expert interviews as well as hands-on implementation. Experts and use cases originate from the consortium of a publicly funded project as well as the International Center for Networked and Adaptive Production (ICNAP), in which three Aachen-based Fraunhofer Institutes and renowned industrial partners are developing solutions for production systems and value chains aimed at Industry 4.0. On one hand, interviews with AI, QM, and production domain experts were conducted to ensure completeness, consistency, and usability of the model. On the other, three exemplary AI use cases – one for predictive quality and two for predictive maintenance – were implemented by means of the AI management model based on the real-life requirements provided by the industry partners. In the validation it was shown that the AI management model can be applied covering different use cases, different production domains, and different perspectives.

VI. CONCLUSIONS AND OUTLOOK

A concept for an AI Management Model was created, which enables effective and sustainable management of activities along the AI life cycle in production companies. This systematic model will guide companies during the integration and holistic management of AI in their production environment in order to achieve an industrial level of usage of AI within the organization. It builds the base for AI product as well as AI management system certification. As limitation, the model only provides a framework. For a given context, a detailed description of the steps, task and roles which are involved in each processes need to be defined individually. Further lines of investigation include the development of an implementation guideline for AI management systems based on the proposed model. Moreover, the developed AI management model can be applied to further use cases and production scenarios.

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