BARRIERS TO THE USE OF ARTIFICIAL INTELLIGENCE IN THE PRODUCT DEVELOPMENT – A SURVEY OF DIMENSIONS INVOLVED

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ABSTRACT

Artificial intelligence (AI) is seen as a great opportunity to secure future competitiveness in many corporate sectors. Potential for its use also exists in product development (PD) activities due to the amount of data generated and processed. Nevertheless, there are problems in applying the technology. This paper addresses current challenges based on a literature review, considering three disciplines that are necessary for the scope of this paper as a minimum: AI itself, information technology infrastructures (ITI) in context of digital transformation (DT), and PD as an application area. Building on the basic considerations of the state of the art, a link between the domains is established by outlining a possible reference framework towards the utilization of AI applications in PD. This enables an expanded interdisciplinary understanding. Key obstacles appear specifically to be difficult collaboration conditions between the disciplines of PD and AI applications development due to communication problems. Reasons for this include:

- Meta models of PD do not provide a sufficient information base
- Lack of standardized process models for the deployment of AI

Keywords: Artificial intelligence, Design methodology, Machine learning, Multi- / Cross- / Trans-disciplinary processes, Small and medium-sized enterprises

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1 INTRODUCTION

Companies today find themselves operating in a dynamic environment and constantly have to react to changes within it. In this context, the success of companies depends to a large extent on anticipating market trends and thus reacting quickly to changing customer needs (Becker *et al.*, 2012). This can affect all areas of a company. Specifically, product development (PD), which plays a decisive role in the long-term success of a company, is subject to constant realignment due to pressure from the environment. This pressure comes from global competition, shortened product life cycles, increased quality demands and standards, product complexity and the need for diversification within markets. Companies must therefore strategically align themselves in such a way that future competitiveness can be ensured. The use of artificial intelligence (AI) is repeatedly mentioned as one way of achieving this goal. If the competencies of humans and intelligent systems are bundled with the goal of maximizing customer value relative to the competition, competitive advantages can be realized (North and Maier, 2018). However, AI can only be deployed where digital infrastructures exist and enable its use. Therefore, efforts to develop AI applications cannot be made without considering discussions of the topic of digital transformation (DT). Today, business activities can no longer be considered separate from information technologies, as these often enable business tasks to be achieved in the first place (Azarov and Leokhin, 2020). It is therefore imperative to consider business activities and digital technologies through the same lens, which will be of even greater importance in the future. By 2028, machines will already be responsible for 20% of the global workforce and 40% of economic productivity (Gartner, 2022). In this context, mastering organizational ambidextry will play a key role in corporate competitiveness. The concept of organizational ambidextry describes the ability of companies to both exploratively implement new strategic ventures while exploitatively relying on existing core competencies from existing business as a competitive advantage (Back *et al.*, 2022). When it comes to the use of AI, this balancing act has not yet been achieved across the board. Although AI is seen as an important topic in senior management, applications are rarely actually used (Ulrich and Bachlechner, 2020). Due to the important role of product development in a company, the use of AI systems seems to be particularly target-oriented in this case. According to representative surveys by the German Digital Association "Bitkom e.V.", 56% of the companies surveyed that do not currently use AI can see themselves using it in product development. However, only 1% of the companies that already use AI applications use them in PD (Streim, 2020). Furthermore, the use of AI depends on the size of the company. Only 5% of companies with 20 to 99 employees use AI (18% in companies with 100 to 499 employees) (Streim and Uhl, 2022). Companies that want to use AI to support their activities operate in a dynamic field of tension that requires the consideration of several disciplines. In this context, at least three dimensions must be considered: The AI technology itself, the application field (e.g. processes in PD), and the information technology infrastructure (ITI) that provides a technical framework for possible applications.

This initial situation forms the starting point for this paper. The research presented here examines the framework conditions for the use of AI in PD on the basis of the minimum necessary consideration dimensions of AI, ITI in the context of DT, and PD as an application area. On this basis, we examine obstacles that currently impede the use of AI. The objective is to consider the disciplines from a basic perspective and to relate them to each other in order to identify interfaces and advance interdisciplinary understanding. The result of this work will provide a qualitative framework for further research. The central research question within the scope of the paper is: Which factors influence the fact that AI applications are hardly used in the PD today?

Based on a literature review, the current state of science in the disciplines considered is first presented (Chapter 2). The basics of AI are covered in Chapter 2.1. DT addresses the changes brought about by digital technologies in the enterprise and is therefore considered a necessary interface discipline for the use of AI in PD in Chapter 2.2. Here, specific reference is made to ITI and its role as an enabler for AI, but also for tasks in PD. The character of PD itself as a target application area of AI is addressed in Chapter 2.3 using existing scientific methodologies. By outlining a possible reference framework towards the use of AI in PD Processes (PDP), Chapter 3 maps the interfaces of the disciplines under consideration. Based on this, current problems and obstacles are listed and discussed in Chapter 4. The contribution of this paper ends with a conclusion and specification of research needs.

2 STATE OF SCIENCE

The fundamental, multidisciplinary field of tension in the context of the use of AI-based applications has a dynamic character. In order to be able to utilize applications in companies, the interdisciplinary involved persons need to work together and bring their respective expertise into the communication. The following section describes the current state of the art in the disciplines of AI, DT (including ITI) and PD as the field of application considered in this paper.

2.1 Artificial intelligence (AI)

A generally accepted definition of artificial intelligence (AI) does not yet exist. However, AI can be further classified into three categories: artificial narrow intelligence (ANI) which allows the performance of individual domain-specific tasks, artificial general intelligence (AGI) which represents a more advanced state of AI where general intellectual tasks can be performed, and artificial super intelligence (ASI) representing a currently still hypothetical state where AI is superior to human intelligence (Wang *et al.*, 2021).

The spectrum of AI performance is broad. An overview in the field of ANI is given by Wang et al. who further divide ANI into three subcategories: Behaviour (e.g. smart robot), perception (natural language processing (NLP) and computer vision), and cognition and learning (e.g. knowledge representation and machine learning with the subcategories supervised learning, unsupervised learning, deep learning, reinforcement learning and transfer learning) (Wang *et al.*, 2021).

In order to be able to use an AI algorithm (e.g. decision tree for the classification of data as a subarea of supervised learning) for the fulfilment of tasks in processes, various step sequences must be processed. Figure 1 shows a model of a holistic machine learning (ML) lifecycle, which describes the preparatory phases of development, the model deployment itself and phases during utilization.

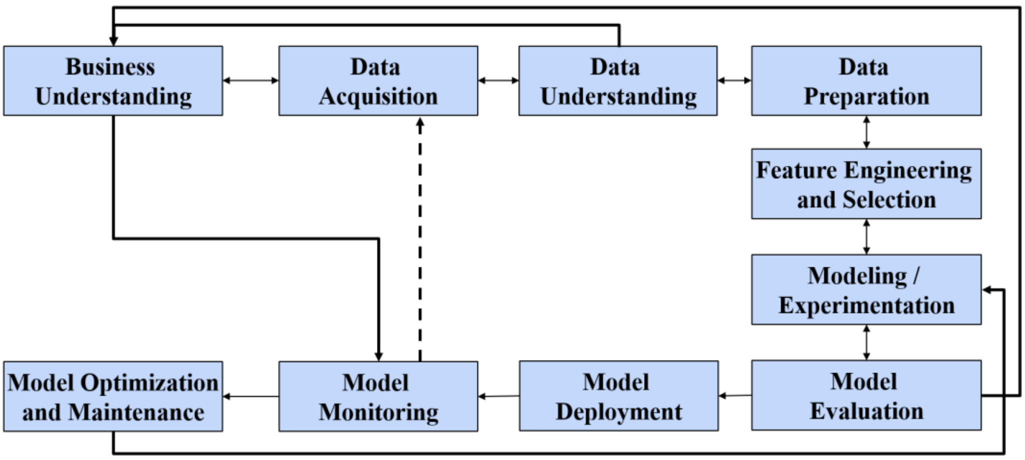

Figure 1. Machine learning-lifecycle (Kessler and Gómez, 2020)

If one processes the step sequences of the ML lifecycle, an AI system exists within the framework of the model deployment phase, which acts in the corporate environment (e.g. fulfils a task in a process, has interfaces to the ITI). In order to develop an end-to-end AI system, several areas that interact with one another have to be considered. In essence, an AI system consists of the areas of data collection, data conditioning, algorithms, and human-machine teaming, which together fulfill a certain value. All of the areas are related to technology aspects (computing , i.e. the fundamental ITI) and robust AI (Gadepally et al., 2019). The concept is shown in graphic form in Figure 2 (Chapter 3). All of the aforementioned areas play a critical role in the success or failure of end-to-end AI systems (Gadepally et al., 2019). The area of human-machine teaming is discussed in more detail here. The goal is to optimize the collaboration between humans and machines. Both humans and machines have complementary strengths. Human intelligence is intuitive and has advantages in flexibility and transfer, empathy and creativity, whereas machine intelligence has advantages in consistency, speed, efficiency, and pattern recognition (Dellermann et al., 2019). Human intelligence as such is also more reliable and robust against catastrophic errors (Holzinger and Müller, 2020). In terms of the perfect composition of system intelligence in specific business processes, there are no sound scientific results. Further research is needed in this field. Another area of particular importance in the literature is that of

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data. Data is of great importance to companies and can be decisive for competition, which is why data management has such an essential role. Kessler and Gómez define eight main indicators for data management to make machine learning (ML) deployment successful: centralized management of data, data sources, appropriate data models, data processing support, data quality monitoring, versioning, usage references, transparency and traceability (Kessler and Gómez, 2020).

In AI system development, there are fundamental differences to traditional software development. Projects that follow the traditional software development approach typically provide a software application which is produced by writing a source code, with the software development process typically following one of the established process models, such as the V-model (van Giffen et al., 2020). AI processes, on the other hand, involve having to train neural networks and processing a large amount of data. The training process is a highly automated and computationally intensive process that requires extreme computing power to develop the AI models (van Giffen et al., 2020). The integration of AI-based applications into products, services, processes, and business models requires both the backing of and anchoring in senior management, and comprehensive AI knowledge in the organization (Kreutzer and Sirrenberg, 2019). Ulrich and Bachlechner also note that IT departments generally have a major influence on the use of AI (Ulrich and Bachlechner, 2020). The level of AI skills required is strongly dependent on the degree of technical implementation effort. If the company purchases enterprise-ready solutions, less in-house competence is required compared to the case of in-house programming and implementation. OpenAI's chatGPT, Microsoft 365 Copilot and others have recently shown how little AI expertise is required to use AI applications.

In summary, it can be stated: For the development of an end-to-end AI system, competencies must be available in all areas. For example, there is a need for precise knowledge about which data can be utilized. And under which technical conditions (ITI) the data can be obtained and processed. The close relationship to the disciplines involved can be described using the ML Lifecycle (cf. Figure 1). The objective of the use of AI must also be precisely coordinated. Due to the peculiarities of AI systems development, collaboration between the disciplines involved (business, in the context of the paper PD, and IT) is necessary. This can be strengthened by mutual competence building through knowledge transfer.

2.2 Digital transformation (DT) and information technology infrastructures (ITI)

Digital transformation (DT) "[…] describes the changes brought about by digital technologies and the digital innovations based on these technologies, with fundamental importance for the company. It emphasizes the introduction of a professional solution (e.g., a new sales control concept), but also emphasizes the leading role of new digital technologies" (Hess, 2022). DT thus brings about changes in many parts of a company, so a holistic approach is required. The development and implementation of digital innovations leads to changes in value creation. The management of a company must ensure that the conditions for successful transformation are in place. This includes (digital) infrastructure that matches the goals, changes in the (digital) corporate culture, and IT competence development.

The associated management roles are discussed in detail in the literature (Hess and Sciuk, 2022; Back *et al.*, 2022). The CEO's task here is to develop a vision for DT (strategic orientation). This involves regular discussion with the CDO, who is responsible for the operational implementation of digitalization projects (Hess and Sciuk, 2022). The role of the CDO is to explore (Back *et al.*, 2022). The role of the CIO, on the other hand, has exploitation characteristics, such as efficiency, control, and a high level of IT competence (Back *et al.*, 2022). According to the organizational ambidextry described in the introduction, both roles are of great importance for the success of DT.

The need for digital competence is a critical factor for success (Azizan *et al.*, 2021; Hess, 2022), however, not everyone involved in the DT processes needs to have the same competencies (Hess, 2022). Good collaboration between stakeholders, on the other hand, is critical to the success of DT projects (Bourdeau *et al.*, 2022). In terms of infrastructure, information technology infrastructures (ITI) play a central role (Bourdeau *et al.*, 2022). "Regarding technological shifts, the main challenge for organizations is to have an ITI that matches both the actual and future organizational needs, i.e., an ITI reliable for today's operations, and open for tomorrow's changes" (Bourdeau *et al.*, 2022). Establishing sustainable ITIs often involves addressing a high level of IT complexity resulting from a large number of historically grown information systems (Hoffmann and Heimes, 2018). Small and medium-sized enterprises (SME´s) in particular are characterized by historically grown structures, which often results in fragmented software landscapes (Stoffers *et al.*, 2022). Interoperability between systems must be mastered in order to exploit the potential associated with the use of digital technologies in corporate processes. The introduction of new digital solutions must follow a systematic process (Hess, 2022).

If the management of DT in the company is mastered well, and the infrastructures are built up to be sustainable, a basis is given for the deployment of AI applications. The performance and availability of ITI play a critical role in the effectiveness and efficiency of AI applications. Organizations need to ensure that their ITI is optimized for AI workloads, including computing, storage, network connectivity, security, and integration requirements.

In conclusion, it can be stated that DT must be considered on a company-wide basis and all levels in the company must be involved. Both strategic questions and questions relating to operational implementation must be answered. The use of artificial intelligence is also highly dependent by the results of the transformation process, as applications are highly dependent on the ITI. This dependency is one of the significant obstacles to the effective use of AI in PDP. The relationship to PD and the IT tools used there can also be described in the same way.

2.3 Product development (PD)

The importance of product development (PD) in a company with regard to ensuring long-term competitiveness has already been described in the introduction. Due to the changed conditions, e.g. increased product complexity and the need for diversification within markets (cf. Chapter 1), the integration of different disciplines in PD is becoming increasingly important. Related to this, there is a growing need for closer collaboration between different disciplines. The focus of this study is on collaboration between product developers and experts in AI development. Since the collaboration between several disciplines requires a common basis for communication (Eisenbart et al., 2011), the character of PD is described below by focusing on scientific design support. This is intended to build understanding of the discipline of PD on the part of AI experts.

Gericke et al. explain how design support involves five generic types of support, namely design methodology, design process, design method, guideline and tool (Gericke et al., 2017). Other publications go into more detail and contrast and discuss established approaches within generic design support types from the literature to show the different manifestations of the discipline (Ammersdörfer and Inkermann, 2022; Costa et al., 2015; Gericke and Blessing, 2012; Qureshi et al., 2014). Some of the manifestations are described subsequently.

Process models are used to describe process elements. Such elements can be information flow, responsibilities, tasks, milestones, and artifacts (Ammersdörfer and Inkermann, 2022). Wilmsen et al. provide an overview of different process types. Meta models describe product development processes (PDP) in a generic way, in order to represent a wide range of applications. They serve as a basis for company-specific reference processes. Examples of meta models are stage-gate-based approaches, waterfall models, the V-model (VDI 2206), and VDI 2221 (Wilmsen et al., 2020). Company-specific reference processes describe the typical sequences of process elements (e.g., milestones, activities, methods). Project-specific target processes are derived from the reference processes, considering specific requirements and framework conditions. They serve as a time and content orientation point for all the participants in the development process. Project-specific actual processes document the actual course of the project and typically deviate from the target processes (Wilmsen et al., 2020). The concept is depicted in graphic form in Figure 2 representing the PD dimension (Chapter 3). The different meta models all have a special focus covering different phases (design states) (Costa et al., 2015). A further distinction can be made between the design models on the basis of their level of detail. The depth of detail means that certain meta information, such as roles, required knowledge, information, and artifacts, are represented (Costa et al., 2015; Wilmsen et al., 2020). The description of the procedures in the PD through detailed PDP is essential for the development and implementation of AI applications (cf. Figure 1: Phases of business understanding and data understanding). In addition, there are different degrees of flexibility, which are important for company-specific implementation. Costa et al. consider a range of flexibilization from "One fixed version" to "Rules for instantiation / customization" (Costa et al., 2015). Information is described according to the level of detail of the process models. A supplementary consideration goes even deeper and concerns the data in PD. Chiarello et al. have conducted an extensive literature review on this topic. The results show, among other things, that among all the papers studied, the most cited data sources are human interactions (23.18%), simulation (16.79%) and web (7.07%). On the other hand, machine learning (ML) as a data source is addressed by only 0.14% of the papers (Chiarello et al., 2021). Concrete

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possibilities of how AI can be used in PDP can be found in the literature, whereby the focus of the consideration is often on the functionality per se and not on the questions regarding technical implementation and compatibility. Examples are provided by Caputo and Cardin (2021), Briard et al. (2021), and Chong *et al.* (2022). Wang et al. also deal with concrete use cases in product design (Wang *et al.*, 2021).
There are many different models, all of which serve a specific purpose and thus have different characteristics based on the specific purpose. To ensure a company uses the appropriate model for its individual focus, the criteria of detail, flexibility, linked methods and tools, and the general characteristics of the models have to be carefully matched with the company's requirements. If the company is aiming to use AI to support development activities, it is essential to capture the process elements in as much detail as possible. For example, collaboration with AI experts can only work well when the data basis of the design activities can be accurately captured, as this is fundamental for AI applications.

3 INTERDEPENDENCIES BETWEEN THE CONSIDERED FOCUS AREAS

Chapter 2 provided basic descriptions of the dimensions considered here. The aim of this chapter is to show the interfaces between PD, the application area of AI (represented by a representation expanded to include process knowledge, information and data following Wilmsen et al. (2020)), the AI itself (represented by the end-to-end AI system following Gadepally et al. (2019)) and the ITI (represented by a generic 3-level model). Since all areas of consideration involve data, its processing into information and the knowledge that can be extracted from it, the knowledge staircase according to North and Maier (2018) is used to provide a basic structure in the context of knowledge-intensive work. Figure 2 describes the qualitative relationship between the dimensions and at the same time provides a theoretical framework that enables the identification of fields of action and the contextualization of the roles/disciplines involved.

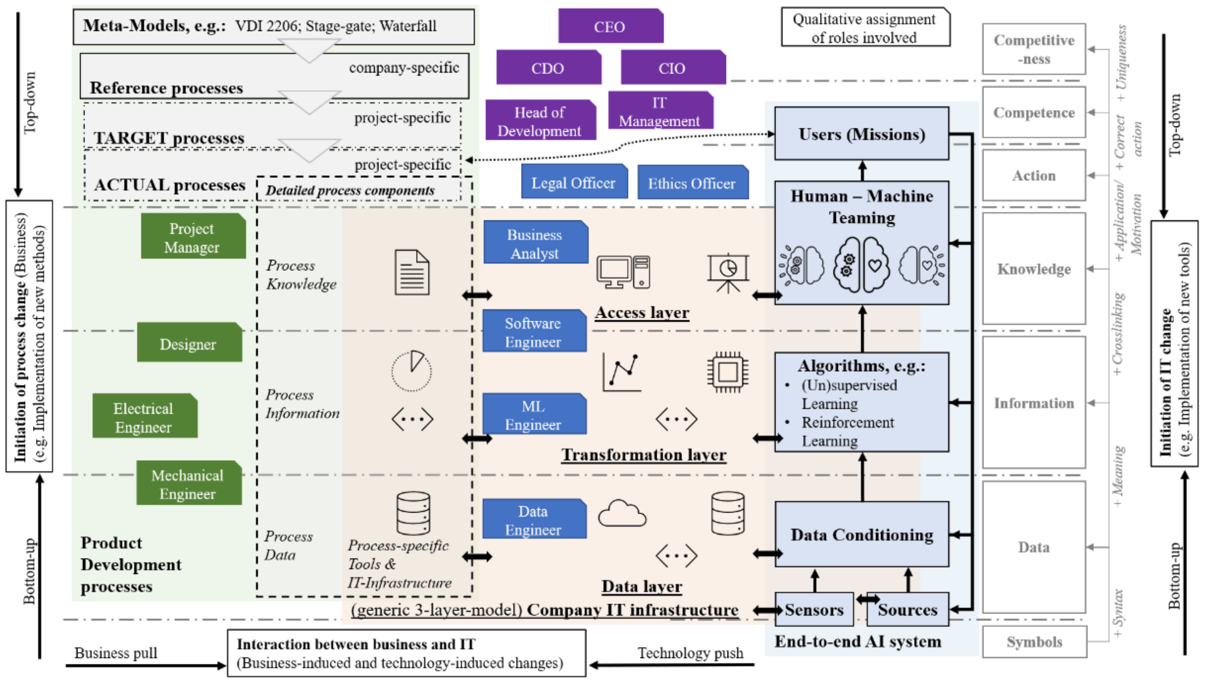

Figure 2. Systematic mapping of the correlations between the considered domains based on Wilmsen et al. (2020); North and Maier (2018); Gadepally et al. (2019)

The left part of the figure shows the relationship between meta models and company-specific reference processes as well as project-specific target and actual processes according to Wilmsen et al. (2020) (cf. Chapter 2.1). The diagram is enriched by another level of detail, the detailed process components which represent the required level of detail for the development of AI applications. These depict the knowledge required for the process as well as the necessary information and data; the available ITI and tools are also noted. The process-specific ITI and tools are linked to the general ITI of the company, which is indicated in the middle section of the figure by a generic 3-level model.

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Similarly, the enterprise's general ITI provides the technical foundation (modern computing) for AI systems. The end-to-end AI system according to Gadepally et al. (2019) (cf. Chapter 2.3) is shown in the right-hand area of the figure. It is striking here that the characteristics of AI related to the knowledge stairway also occupy the levels above the pure representation of knowledge by the technical system. The field of human-machine teaming thus offers new possibilities in the project process and in the design of working methods in the development processes. Further management functions are also noted in the diagram, each of which has responsibility for the respective areas and their development. By naming the management functions, it also becomes clear which roles and perspectives are involved as part of using AI in PD. The need for sharing, collaboration, and purposeful communication as part of introducing and using AI becomes evident. Changes in the depicted system can be initiated top-down (e.g., changes in PDP, change in ITI due to new tools); initiation based on identification of needs or potential (bottom-up) represents another perspective. Furthermore, business-induced changes can occur as a result of the need for certain technologies in the processes (business pull). However, developments in the area of IT can also result in enabler functions of IT for the processes in the opposite direction (technology push). For the utilization of AI applications for tasks in PDPs, this means specifically that if the task is known, it is then possible to look specifically for potential solutions through AI (cf. Chapter 2.1: ANI subgroups). On the other hand, technological advances in the field of AI can also be monitored, which means that, for example, additional tasks (e.g. analyses) can be added to the PDP.

4 PROBLEM DEDUCTION AND DISCUSSION

The use of AI in PDP is based on a complex, dynamic environment. Figure 2 systematically depicts this environment. The use of intelligent applications involves various stakeholder groups from different disciplines with different knowledge in the respective other disciplines. In the following, reference is again made to the respective areas considered in this contribution in order to identify fundamental problems and obstacles. The obstacles listed do not claim to be exhaustive, as the focus of this work is only on some of the many business areas involved.

In the discipline of PD, the characteristics of (process) models were described in Chapter 2.3. Gericke and Blessing (2012) report criticism of current design methodologies and process models. Technology push-initiated development projects are currently not adequately considered (Gericke and Blessing, 2012). The models are therefore rarely capable of systematically initiating projects based on AI technology. Furthermore, Gericke and Blessing (2012) report, that the current approaches do not generally offer a combined view of the aspects design and management. Another point of criticism is that the approaches tend to include assertions about what to do, but not how to perform the activities. In addition, the approaches have shortcomings in their consideration of transdisciplinary collaboration (Gericke and Blessing, 2012), for example through different terminology and ways of modelling (Eisenbart *et al.*, 2011). Some of the models are also outdated and do not represent current requirements. The interfaces between process activities and supporting ITI are not sufficiently described. Building on this, another difficulty is in accurately matching the reference processes with the requirements and behaviors of the actual process users and other relevant framework conditions and restrictions (Wilmsen *et al.*, 2020). In this regard, Gericke *et al.*, 2021 describe the missing link between academia and industry: knowledge transfer. When using artificial intelligence in product development, in which many disciplines are involved (cf. Chapter 2.3), a certain level of information detail in the activity descriptions (through processes and models) is mandatory for communication. Collaboration between many disciplines can result in approaches to interpreting data being biased, but even in the area of data collection there can be fundamentally different priorities based on personal experience (Briard *et al.*, 2021). When it comes to data in engineering design, there is generally great potential in the use of several different data sources. However, Chiarello *et al.* (2021) identify gaps that point to problems at the interface between research and industrial practice, in the relationship with other disciplines, and in the relationship with related business functions. In summary, the following barriers can be noted:

- The scientific meta models do not provide a sufficient information base for the development of AI applications due to their low level of detail (cf. detailed process components in Figure 2).
- There is no standardized method that enables companies to collect and describe the available data in the context of their development activities.

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Regarding AI, Chapter 2.1 already explains its distinction from traditional software projects. A rethinking of the use of AI technology in companies is necessary (van Giffen *et al.*, 2020). The companies surveyed as part of the representative Bitkom survey also cite a lack of personnel resources and data (62% each) and a lack of technical expertise (48%) as barriers to deployment. Around one in five (22%) companies lack use cases for the deployment of AI (Streim and Uhl, 2022).
The fact that knowledge is a key factor in AI projects is made even clearer by the survey results from (Rädler and Rigger, 2022): 63% of the companies surveyed answered the question about how ML algorithms are pre-selected for applications and projects with expert knowledge. Only 13% mentioned "method" and only 3% "fixed toolchain" (Rädler and Rigger, 2022), which is not surprising because there is currently no fully established standard process for the ML lifecycle (Kessler and Gómez, 2020). There is also the question of how distinct the competencies need to be, considering the developments at the beginning of 2023 around OpenAI and enterprise-ready AI (e.g. through Microsoft 365 Copilot).
In the context of DT, which is linked to AI applications through ITI, management tools (cf. Initiation of IT changes in Figure 2) that have structured paths of action – particularly in the initial phases – and describe the interaction between the roles (of senior management), are also required (Back *et al.*, 2022). Examples of currently known models and methods can be found in the literature. van Giffen *et al.* (2020) present the St. Gallen Management Model for the operational use of AI. Kreutzer and Sirrenberg (2019) present a canvas for AI deployment that can facilitate AI deployment by asking questions in seven domains. Among the domains, economic aspects are also covered. Hofmann *et al.* (2020) describe a method for identifying AI use cases. However, the aforementioned approaches lack an orientation framework and a level of detail for use in a company with little or no IT or AI expertise.
If one considers the topics of data management and ITI, both of which are important for the use of AI, it would be advisable to use several models, each with a high depth of detail. However, support in the form of methods and models or guidelines should not only consider the top-down perspective. Hess (2022) highlights that IT experts are often too far removed from the actual products and business models. Also, of great importance is domain knowledge to be able to identify the potential of applications and use cases, and thus initiate bottom-up AI projects. People without much IT expertise should also be involved in the systematic processes to identify application opportunities (Aranda-Muñoz *et al.*, 2022). At this point, care must be taken not to create a missing link between top-down and bottom-up perspectives in scientific literature. AI use will broadly affect a wide range of business areas and functions (van Giffen *et al.*, 2020). Initial approaches involving individuals without broad AI expertise in the development of AI applications use AI Cards as an ad hoc means of mitigating the lack of knowledge (Aranda-Muñoz *et al.*, 2022). The lack of detailed standardised models of AI development makes it difficult to communicate with non-IT engineers. Based on the current lack of best practices in the field of AI, it is also practically impossible today to determine the economic profitability of investments in artificial intelligence processes (Ulrich and Bachlechner, 2020). This aspect also prevents companies from starting initial projects. SMEs have limited resources available due to their company size (Stoffers *et al.*, 2022). Furthermore, as explained earlier, there is often a fragmented software landscape (ITI), which complicates the conditions for the utilization of AI. Finding economically viable usage scenarios is a major challenge (Ulrich and Bachlechner, 2020), and is made more difficult by the existing ITI, as redesigning them to the extent that they meet the requirements of the intended AI applications involves costs. Thus, it is important that the specifics of SMEs are considered when dealing with developments and research on guidelines and methodologies for the application of AI in practice. In summary, the following main barriers to the use of AI can be noted:

- Lack of human resources with AI competence
- Lack of use cases and best practices
- Lack of standardized process models for the implementation of AI,
  - considering SME specifics and different perspectives (top-down, bottom-up)
  - respecting a depth of detail with concrete instructions for action

5 CONCLUSION

The complex and dynamic problem area with regard to the use of AI in PD cannot be unlocked by a single solution. Competence building and improved collaboration between disciplines form the basis for the potential overcoming of the current obstacles. As PDP deviate from existing scientific meta

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models on a company-specific basis, and a high level of detail in terms of process information (exact activities, IT tools used in the company, existing ITI, existing data and its quality) is required to make assertions about the development of AI systems, it is essential to look at individual cases. Discussion with the industry is therefore crucial. Especially when it comes to solutions for the use of AI in SMEs, conducting an SME-specific assessment of the initial situation is crucial. Among other things, it is essential to determine which roles with which competencies exist at all, to what extent there is an understanding of data availability and quality, and what the situation is with regard to cultural aspects (e.g., acceptance of AI). The identification of actual, frequently occurring work steps in product development can be seen as the basis for systematically developing AI solutions and scaling their use both internally and externally. It would be useful to conduct further research on methodologies that describe AI application development within the PDP in sufficient level of detail. Methodologies need to be validated in the context of prototype applications. This will also provide best practice examples that will help the involved parties recognise the potential of, develop, implement, use, and work on the continuous further development of AI-based applications. Further research is also needed in the area of validation, as the reproducibility of results is hampered by company-specific data availability. An approach via open data could be promising for validation. Based on the current lack of competence in the area of digital technologies, AI, and the high costs associated with the introduction of applications, research into low-code and low-cost applications would be useful. In this regard, the results of this paper can provide a framework for future research. By opposing the disciplines, a qualitative framework is created that can contribute to an advanced interdisciplinary understanding, allowing for the possibility of bridging the different understandings of AI.

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