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Survey of the Role of Domain Experts in Recent AI System Life Cycle Models

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Abstract: Artificial intelligence (AI) is a cross-cutting technology with applications along the entire value chain. The integration of AI systems in product development opens up potential applications as of now. Challenges arise due to different levels of expertise from the involvement of non-AI experts in the development of AI systems. This contribution examines the recent involvement of domain experts in AI system life cycle models from the literature and identifies cross-disciplinary research needs, such as the development of comprehensible methods for the needs-based collection of information.

Keywords: Artificial Intelligence (AI), Multi-/Cross-/Trans-Disciplinary Approaches, Product Development, Change Management

1 Introduction

Artificial intelligence (AI) is becoming increasingly prevalent and has the potential to significantly impact our world in the long term. It has numerous potential applications along the entire value chain. Product development (PD), where large amounts of data are processed to make fundamental decisions that affect downstream processes, is a notable area in which AI can offer significant benefits. Yet despite the well-established potential of AI, it currently sees only limited use in industry. The technology is mainly used by large companies in the domains of marketing and production, and less in the area of research and development (Streim and Uhl, 2022). Current barriers to implementing the technology include lack of staff, technical expertise, and concrete applications (Müller et al., 2023).

When applying AI systems to product development, the computer systems must perform tasks that typically require intelligence, such that the results meet the requirements of the domain. The development and introduction of AI systems is the subject of numerous research projects, primarily in the discipline of information technology (IT). One example is the AI system life cycle, as described by ISO/IEC 22989. This life cycle covers phases from inception through development to the retirement of the systems. However, in spite of the availability of general frameworks for the development and operation of AI in literature, there is a lack of practicable methods and process models that can be applied in an industrial context. Most methods and models rely on expert knowledge (Rädler and Rigger, 2022), which is a critical success factor in AI development projects. Consequently, IT departments have a significant impact on AI implementation, even though AI development is fundamentally interdisciplinary and involves multiple competencies (e.g. domain and AI expertise). Although existing models often incorporate AI technologies (e.g. machine learning (ML) or deep learning (DL)), the interfaces to the application domain (e.g. PD) itself remain little explored. Domain experts (e.g. traditional engineers) often do not have the expertise needed to deploy data-driven solutions, whereas AI experts (e.g. computer scientists) lack the necessary knowledge of engineering systems (Schleiss et al., 2022). This situation makes it difficult to implement initial AI solutions in companies. To address competency gaps in an industrial setting, it may be necessary to compensate for missing skills either through internal acquisition (e.g. by training employees or hiring new employees with AI skills) or external outsourcing of AI system development and implementation. Since the internal development of AI skills is a large field of research, this scope of this contribution will be restricted to the external outsourcing scenario which is often associated with high costs and the availability of expertise only on a temporary basis. Opportunities to improve this situation exist in the scientific context through research on standardized models and methods along the AI system life cycle that consider the specific needs of domain experts to support the internal empowerment to independently address the implementation of AI systems (Müller et al., 2023).

This contribution examines the involvement of domain experts in AI system life cycle models by surveying the recent literature. The questions to be addressed are: At what stages in AI system life cycle models is the role of domain experts considered? What are their specific tasks and resulting information requirements?

To address these issues, Section 2 begins by considering the relevant terminology and presenting an application-focused understanding of AI in the context of this contribution. The current state of science and technology is presented in Section 3 on the basis of a literature review. According to Müller et al. (2023), AI systems in the context of IT infrastructure (ITI) are considered on the levels of data, transformation and access, processes and activities of the application domain, AI system development processes/lifecycle models, involved roles, and competencies. Based on this, Section 4 identifies stages relating to domain experts and describes the role and tasks of domain experts in AI system development. Based on the description and analysis of the tasks and content objectives of the stage, information requirements are derived for the application domain or domain experts. Section 5 summarizes the information requirements based on the previous results. Finally, the results of the analyses are discussed in Section 6. The article concludes with a summary and identification of future research needs in Section 7.

2 Terminology and definitions

The term artificial intelligence (AI) is defined as "<discipline> research and development of mechanisms and applications of AI systems" (ISO/IEC 22989:2022). Table 1 lists additional definitions of terms relevant to this context.

Table 1. Terminology

Term	Definition
AI system	"Engineered system that generates outputs such as content, forecasts, recommendations or decisions for a given set of human-defined objectives" [1]
AI application	"Software application with AI functional characteristics and operates in context with its stakeholders' interrelated activities to deliver an intended result" [2]
Task	"<artificial intelligence> action required to achieve a specific goal" [1]
Process	"Set of interrelated or interacting activities that uses or transforms inputs to deliver a result" [3]
Competence	"Ability to apply knowledge and skills to achieve intended results" [3]
Data	"Re-interpretable representation of information in a formalized manner suitable for communication, interpretation, or processing" [4]
Production data	"Data acquired during the operation phase of an AI system, for which a deployed AI system calculates a predicted output or inference" [1]
Training data	"Data used to train a machine learning model" [1]
Validation data	"Data used to compare the performance of different candidate models" [1]
Test data	"Data used to assess the performance of a final model" [1]
Data quality	"Characteristic of data that the data meet the organization's data requirements for a specified context" [5]
Data quality characteristics	"Category of data quality attributes that bears on data quality" [5]
Quality requirements	"Requirement for quality properties or attributes of an ICT product, data or service that satisfy needs which ensue from the purpose for which that ICT product, data or service is to be used" [5]
Stakeholder	"Any individual, group, or organization that can affect, be affected by or perceive itself to be affected by a decision or activity" [1]

References - Table 1: [1] ISO/IEC 22989:2022; [2] ISO/IEC DIS 5339:2023; [3] ISO/IEC DIS 42001:2023; [4] ISO/IEC DIS 5259-2:2023; [5] ISO/IEC DIS 5259-1:2023

In order to gain a better overview in the context of the application of AI, it is useful to consider AI classifications. Gobble (2019) describes three AI classifications: artificial narrow intelligence (ANI), artificial general intelligence (AGI), and artificial super intelligence (ASI) (Gobble, 2019). "Narrow AI" systems have the ability to perform defined tasks that address a specific problem (ISO/IEC 22989:2022). "General AI" systems can perform multiple tasks satisfactorily (ISO/IEC 22989:2022). Current AI systems can be assigned to ANI, but it is not yet clear whether AGI systems are technically feasible (ISO/IEC 22989:2022). ASI systems are currently regarded as hypothetical; compared to human intelligence, these systems are considered superior (Gobble, 2019). Wang et al. (2021) describe three subgroups of ANI. AI techniques can be assigned to each subgroup, which are shown in brackets as examples in the following list:

- Behavior (smart robot, intelligent application, robot application automation software)
- Perception (e.g. natural language processing (NLP), computer vision)
- Cognition and learning (e.g. logic, knowledge representation, ML)

Another view of the use of AI technology in companies is described by Brem et al. (2023) using the terms "originator" and "facilitator". As an "originator", AI is the starting point for innovation and thus shapes product and process development. As a "facilitator," AI is a starting point for transformation and serves to enhance existing products and processes (Brem et al., 2023). In the context of this contribution, AI is understood according to the definitions described above. Specific AI techniques are not excluded.

3 Related work

The consideration of the dimensions involved in the use of AI in PD according to Müller et al. (2023) provides a framework and presents interfaces between the domains involved. The following sections look at AI systems and their dependencies on the ITI (Section 3.1), fundamentals relating to data (Section 3.2), the description of processes in the application domain (Section 3.3), AI system lifecycle and development process models (Section 3.4), and the stakeholders, roles and relevant competencies involved in AI system development (Section 3.5).

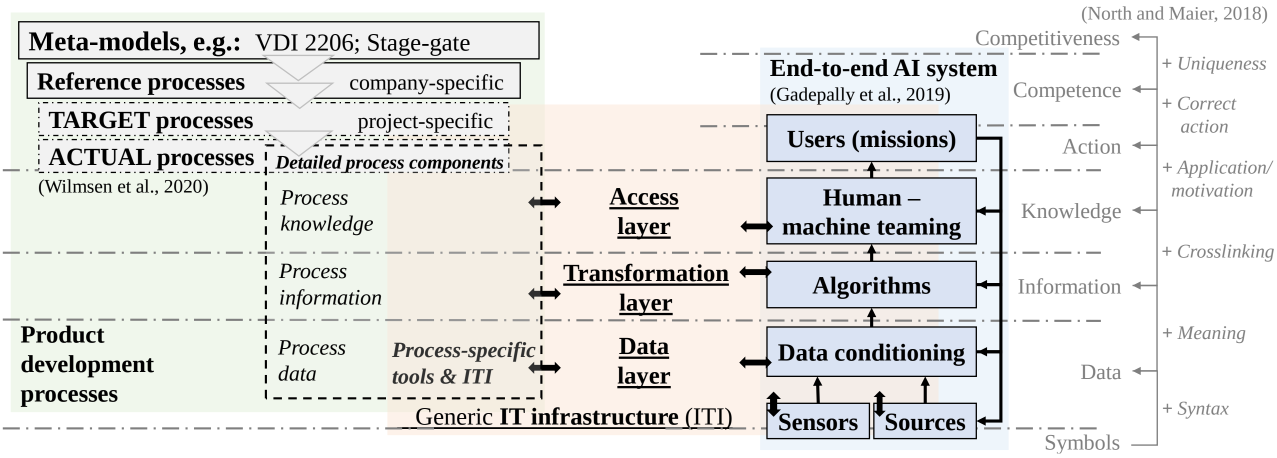


Figure 1. Simplified mapping of the AI system to the applied domain from Müller et al. (2023) based on Wilmsen et al. (2020), Gadepally et al. (2019), North and Maier (2018)

3.1 AI systems in application domains

An AI system works according to a global function path in which information or knowledge is acquired. This can be done either by hardcoding (through engineering) or machine learning, build from learning on training data to generate a model of a domain (ISO/IEC 22989:2022). Figure 1 contains a representation of a generic end-to-end AI system according to Gadepally et al. (2019). This consists of data sources (sensors, sources), data conditioning, algorithms, human-machine teaming, and users (missions) (Gadepally et al., 2019). From the functional point of view of the AI system, inputs are processed by a model to produce outputs. At the input level of the AI system (represented by sensors and sources in Figure 1), data is generated or made available. This data can be big data. The input data may need to be pre-processed before it is made available to the model for processing. The pre-processing is represented by the data conditioning layer. For example, data pre-processing tools and techniques are used to preserve certain characteristics of the data. Data management plays an important role in ensuring the required quality (see Section 3.2). Once the data is pre-processed, it can be sent to the model (algorithms) for processing. A distinction can be made between the training case of an ML system and the use case: The training case contains training data, while the AI use case contains production data. The input can also be information in the domain of engineering models (i.e. hardcoding) (ISO/IEC 22989:2022). AI systems contain a model (cf. algorithms level) that processes inputs according to specifications and generates outputs. In engineering models, the model can be seen as a machine-readable representation of knowledge. Two main types of knowledge can be distinguished: declarative (i.e. what something is) and procedural (i.e. how to do something) (ISO/IEC 22989:2022). At the human-machine teaming level, the integration of human interaction with machine intelligence capabilities produces a result that fulfills a predefined task (users) (ISO/IEC 22989:2022).

During the development and use of the AI system, human design decisions, engineering, and oversight have an impact on the system (ISO/IEC 22989:2022). Large AI systems incorporate a mix of technologies and use several at the same time, such as neural networks and probabilistic reasoning (ISO/IEC 22989:2022). Depending on the system type, each AI system relies on resources from compute, storage, and network domains, thus depending on the ITI application domain (ISO/IEC 22989:2022; Gadepally et al., 2018). In this respect, considerations for cloud and edge computing are limited.

3.2 Data

In AI systems, the availability and quality of data is often related to the quality of the system (ISO/IEC 5259-1:2023). This is particularly the case with ML systems, as they use data (e.g. for training the model) independently of the system characteristics, which can be available in various forms. In some cases, this is big data, which has become important as companies have increased the breadth and depth of data collection. ISO/IEC 22989 defines the term as follows: "Big data is extensive datasets whose characteristics in terms of volume, variety, velocity and variability require specialized technologies and techniques to process and realize value." (ISO/IEC 22989:2022)

In the context of data in AI systems, the data sources, categorization of data in the context of ML, their (pre-)processing, and their quality are highlighted below. The data used in AI systems is derived from a specific source. There is a wide range of possible data sources. ISO/IEC 22989 includes sales and other transactions, statistical studies, sensors, images, audio, documents, and interfacing with systems (ISO/IEC 22989:2022). Regarding the reference of the data, ISO/IEC 22989 distinguishes three cases:

- 1st party collection: data is acquired by the same organization that uses it
- 3rd party collection: data is acquired by 3rd parties, e.g. research organizations who collect and sell or share data with other organizations
- Data is acquired by querying and joining data from different datasets (1st and 3rd party)

Data used in ML systems can be categorized as training data, validation data, test data, and production data (ISO/IEC DIS 5259-1:2023). The term target data is used in the context of data quality measurements. Target data can be raw data or transformed data and can consist of data elements or datasets. A data element consists of an element name, a data value, and a data type that represents a range of values. Examples of data types include strings, text, dates, numbers, images, and sounds. Datasets, in turn, can be divided into four categories: a collection of data items, a collection of data records, a collection of data frames, and a set of datasets that share the same specification, such as structures and semantics. Target data may also be unlabelled or labelled. (ISO/IEC DIS 5259-2:2023)

When processing data, there are many data life cycles with different focuses (e.g. data quality, data governance, development, and use of AI systems). ISO/IEC 8183 provides an overarching framework that describes a basic data lifecycle. The phases of the life cycle are idea conception, business requirements, data planning, data acquisition, data preparation, model building, system deployment, system operation, data retirement, and system decommissioning. Reviewing the phases, it is possible to see similarities with the phases of the AI system lifecycle (see Section 3.4). It should also be noted that the phases do not have to occur in every process run. Due to feedback paths that are not visible in the simplified representation, there may be iterations between the life cycle phases. (ISO/IEC 8183:2023)

Data quality plays a key role when considering the performance of AI systems that use data. Data quality requirements are always related to the purpose of the AI system, which necessitates data quality management (ISO/IEC DIS 5259-1:2023). ISO/IEC DIS 5259-2 addresses the measurement of data quality. It describes data quality characteristics (i.e. accuracy, consistency, accessibility, understandability, timeliness) and measures that can be used to specify and verify the data quality requirements for the desired data. The specific data quality measures used will depend on the context of the AI system (ISO/IEC DIS 5259-2:2023). Moreover, the ISO/IEC DIS 5259 series delineates a data quality management life cycle (ISO/IEC DIS 5259-3), a data quality process framework (ISO/IEC DIS 5259-4), and the topic of data quality governance (ISO/IEC DIS 5259-5).

3.3 Processes and activities in the product development application domain

In product development, the application domain for AI in the context of this contribution, there are numerous process models in scientific literature. The respective models have different focuses in the area of PD as well as different characteristics (Müller et al., 2023). Wilmsen et al. (2020) describe different levels to which process models can be assigned (see Figure 1). Meta-models (e.g. Stage-Gate, Waterfall, V-Model) describe PD processes in a generic way and are scientifically documented. The situation is different with company-specific reference processes, which are often derived on the basis of meta models. They describe the typical sequences of process elements (e.g. milestones, activities, and methods) in the company. Project-specific processes, which are derived from the reference processes and include specific requirements and environmental conditions in the respective project, represent a further level. At this level, target and actual processes can be distinguished, which are important in project management (e.g. for monitoring and controlling projects). (Wilmsen et al., 2020)

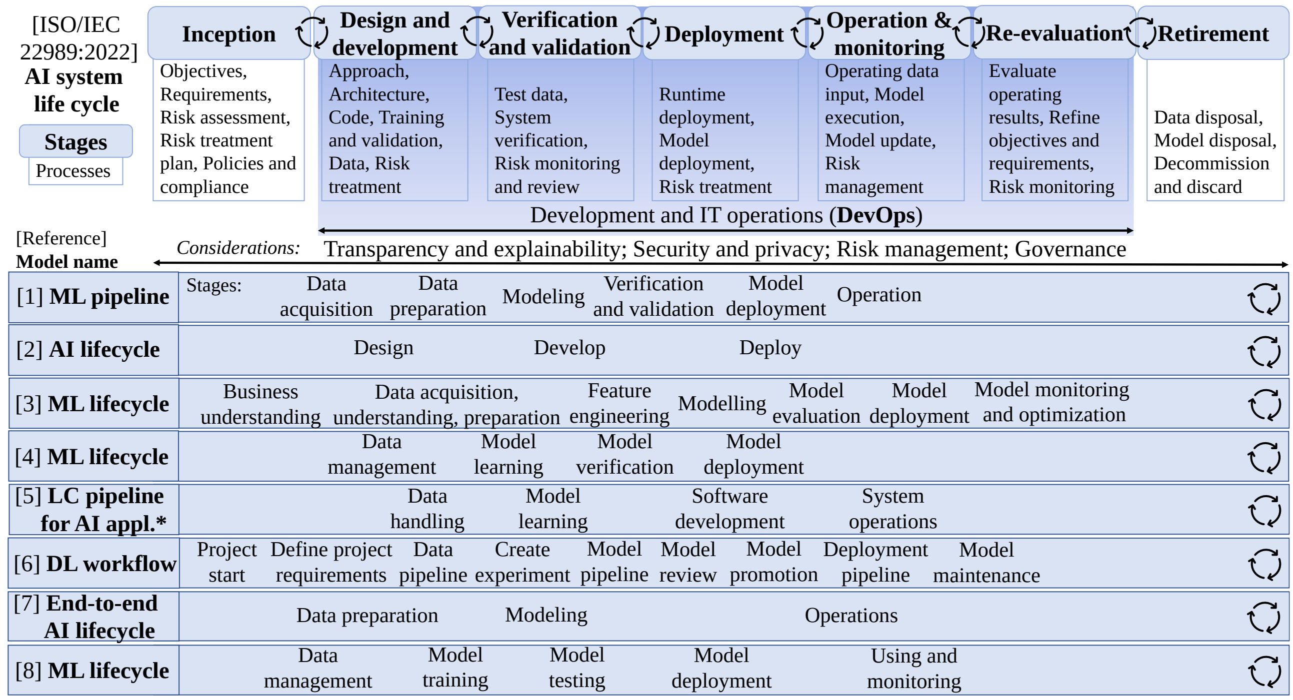
One shortcoming in terms of science is the lack of accessible information about the course of development processes on a company-specific and project-specific level (Müller et al., 2023). Outside industry itself, there is hardly any structured and documented information about the processes involved in the development of AI systems. This makes it difficult to derive industry requirements for AI systems. Because of the dependency of artificial intelligence systems on the underlying data (i.e. the data available to the company and the project), it is essential to capture and document the initial situation in the domain in great detail. In order to develop scientifically sound models and methods along the AI system lifecycle, it is necessary to develop this domain-specific basis.

3.4 AI development processes and lifecycle models

The development of AI systems is well described in literature. There are numerous models that describe typical phases in the life cycle of AI systems. There are also process models that focus on developing and implementing AI systems.

AI systems are fundamentally different from traditional software systems, which has implications for their development. For example, traditional software applications are usually predictable, while AI systems often are not; operational experience and AI system adaptation are typically required to meet goals. In addition, traditional software applications are usually verifiable, whereas it can be challenging to assess and verify the performance of AI systems. There are also differences in data and release management. (ISO/IEC 22989:2022)

An example of an AI system life cycle according to ISO/IEC 22989 is shown in Figure 2 (upper part). The life cycle extends from inception through development, deployment, operation, and retirement. It should be noted that the life cycle is generally iterative as this is not obvious from the simplified diagram. The size of the boxes is not related to the amount of work involved in each phase. The life cycle shown here consists of a number of phases with associated processes that are representative examples, as specific processes depend on the AI system. The figure also shows that there are various considerations that should be considered throughout the life cycle. Examples include governance implications caused by the development or use of AI systems, transparency and accountability aspects, and security threats caused by data-dependent system development (ISO/IEC 22989:2022).



[1] ISO/IEC 23053:2022; [2] De Silva and Alahakoon (2022); [3] Kessler and Gómez (2020); [4] Ashmore et al. (2021); [5] Steidl et al. (2023) - *Continuous lifecycle pipeline for AI applications; [6] Baltensperger et al. (2022); [7] Arnold et al. (2020); [8] Yang et al. (2021)

Figure 2. Simplified representation of AI system life cycle and process models

Other process models focus on specific phases of the AI system life cycle described above and describe these in more detail. Such models often consider specific technologies (e.g. ML or deep learning (DL)). Figure 2 (lower part) provides an overview of other models from the literature by listing the high-level stage designations. The focus here is only on the overarching structure of the models. The original sources describe the stages in more detail, e.g. by assigning typical stage-related processes. It is also worth noting that the general level of detail in the description of the model phases varies, e.g. De Silva and Alahakoon (2022) define only three superordinate phases (design, develop, and deploy), but also list 19 subordinate stages. Similarly, Baltensperger et al. (2022) provide a more detailed description of their model specifically for deep learning, detailing the data pipeline, model pipeline, and deployment pipeline phases. The three-phase model according to Arnold et al. (2020) can also be examined in more detail by subdividing the data preparation phase into data investigation, data fusion and data cleaning. Feature creation and modeling are two subordinate phases of modeling. The operations phase is further split into pre-deploy test, deploy, monitor and improve (Arnold et al., 2020). The models considered all have an iterative character, which is not apparent from the illustration. Figure 2 shows that the models considered have certain similarities. For example, in all models, stages can be identified that relate to data, modelling, deployment, and operation. Some models include stages describing activities upstream of DevOps. Further considerations use a simplified model consisting of the stage’s inception, data, modelling, deployment, operation, and retirement.

3.5 Stakeholders, roles, and competencies

This section describes the numerous stakeholders and roles involved in developing AI systems. ISO/IEC 22989 describes stakeholder roles and associated sub-roles, where an organization or entity may have more than one role. These are: AI provider (sub-roles: AI platform provider, AI service or product provider), AI producer (AI developer), AI customer (AI user), AI partner (AI system integrator, data provider, AI evaluator, AI auditor), AI subject (data subject, other subjects), and relevant authorities (policy makers, regulators) (ISO/IEC 22989:2022). The literature describes roles as a function of AI system life cycles. Typical roles in AI development projects are shown in Figure 3.

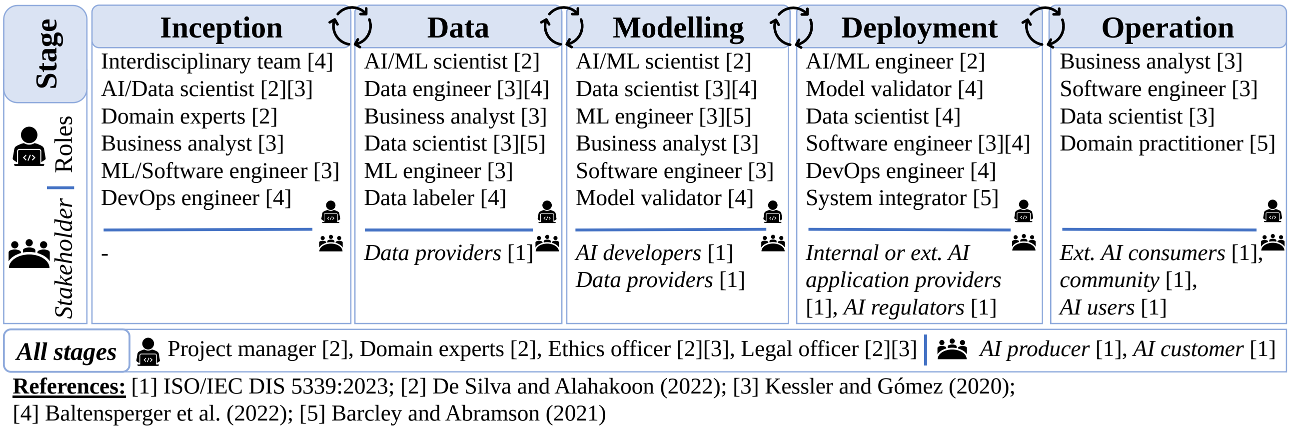


Figure 3. Overview of assigned roles and stakeholders within a simplified AI system life cycle

Roles were identified during the literature review and assigned to simplified AI lifecycle stages (cf. Section 3.4), no role assignment can be identified in stage retirement. Furthermore, the inception phase does not identify any stakeholders as described in the literature. The classification serves as an initial overview and does not claim to be exhaustive. In addition, since the use of different terminology in the literature makes it difficult to determine exactly what the roles are and to assign them to the phases, it is therefore a qualitative consideration. Depending on the role (e.g. data scientist, business analyst), work involving humans and AI requires different skills (competencies). There are contributions in the literature that categorize competencies. Schleiss et al. (2022) describe the categories of technical competencies, methodological competencies, social competencies, and personal competencies. For a further valuable view in the context of AI, Rampelt et al. (2022) specify six levels of competence that can be divided into two layers. At the knowledge layer (basic and domain knowledge), competence levels 1 (remember/know) and 2 (understand) are assigned. The action and problem-solving layer (action competence) includes levels 3 (apply), 4 (analyze), 5 (evaluate), and 6 (create) (Rampelt et al., 2022).

4 Identification of phases and their corresponding activities involving domain experts

The first step is to define what is meant by the need for domain competence. For the purposes of this contribution, domain competence refers to the ability to act (see Section 3.5) in the application domain of the AI system. Roles are characterized as functional characteristics in organizations. Employees who occupy roles in the application domain, e.g. product developers and designers, can possess this competence (e.g. through professional experience). They have knowledge of the processes and contents of PD, e.g. they are familiar with data, methods, and applications that are used in the context of development activities. Thus, they assume the role of a domain expert.

The literature on AI systems identifies the roles of business analyst, domain practitioner, and domain expert, as well as the stakeholder groups of AI customers and AI users (cf. Section 3.5). While the business analyst is described by Kessler and Gómez (2020) as a role that has no technical link to AI, it must clearly and consistently define business processes and problems for the AI team. In addition, this role enables the establishment of AI, e.g. by aligning business structures with the technology in the long term (Kessler and Gómez, 2020). Barcley and Abramson (2021) also describe the dependencies of the domain practitioner (DP) role, which is the end user of the AI system, on the AI development team (e.g. data scientists, ML engineers, and system integrators). The DP is responsible for ensuring that the AI system meets the requirements of the domain and that the data used is appropriate for use. Furthermore, the DP is often attributed a lack of AI expertise. (Barcley and Abramson, 2021)

ISO/IEC 22989 defines the AI customer stakeholder group as the organization or entity that directly uses an AI product or service or provides it to AI users. Organizations or entities that use AI products or services are assigned to the AI users stakeholder group. (ISO/IEC 22989:2022)

When compared with the results in Section 3.5, the roles can in principle be involved throughout the entire AI system life cycle with regard to domain competence. However, it is possible to identify focal points in the early stages (inception/ business understanding), in the use of AI systems (operation), and in evaluations distributed over the life cycle (i.e. data validation, model evaluation, system evaluation, and model monitoring).

Further considerations are limited to the early stages, as these are initially relevant in the context of an external assignment. In addition, the use and assessment phases depend on the purpose and design of the AI system, which cannot be considered in a comprehensive way due to the variety of possibilities. Further considerations assume that externally engaged companies proceed on the basis of the contents of the AI life cycle as part of the engagement.

The content of the early phases of the AI system life cycle is examined in more detail in order to identify the requirements for domain experts. The inception stage is described in ISO/IEC 22989 and begins when stakeholders decide to transform an idea into a tangible system. This phase can include different processes. It should be noted that there is also a dependency on the AI system (i.e. information requirements regarding data related to the AI system (cf. Kessler and Gómez, 2020)) to be developed (see Section 3.4). Issues to consider include goals, requirements, risk management, transparency and accountability, cost and funding, resources, and feasibility (ISO/IEC 22989:2022). Figure 4 provides an overview of the possible characteristics. If new information comes to light in later phases (e.g. if the system cannot be technically implemented in the manner originally planned), the inception phase may be repeated. The phase concludes with the decision to implement the AI system, at which point the design and development phase begins (ISO/IEC 22989:2022). Figure 4 also contains compilations of the early phase contents from Kessler and Gómez (2020) and Da Silva and Alahakoon (2022).

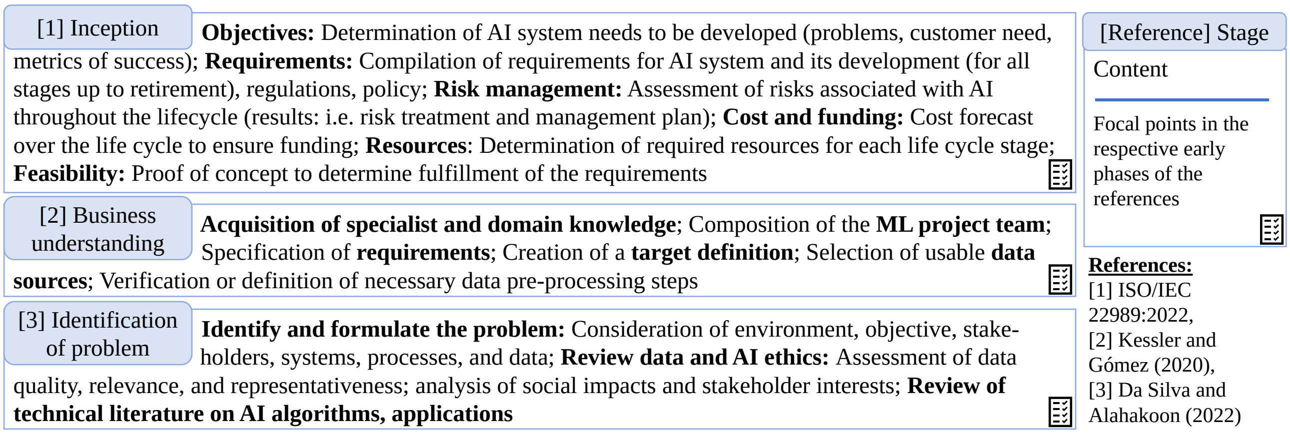


Figure 4. Contents of the early phases in AI life cycle and development process models

It can be stated that the purpose and objectives to be fulfilled by the system to be developed are considered in the early phases of AI system development. The composition of the roles involved is interdisciplinary in order to capture the initial situation (Da Silva and Alahakoon, 2022). It is important to examine the application area within a domain as precisely as possible. This is to avoid possible iterations of the early phases being based on insufficient information from the first iteration. Starting from the AI system itself, the technical implementation phases need to describe precise initial information in the areas of data, ITI, and existing processes and activities (not yet AI-enabled). However, the model phases lack sufficient detail on the methods to be used for the respective contents of the analysis.

5 Composition of information requirements for domain experts in the initial stages

As mentioned in Section 4, specific initial stage information relating to processes, activities, data, ITI, roles, and competencies is captured in the early phases of AI system development. This includes a description of the initial situation in the target application domain of the AI system to be developed, together with information about the goal of the application. Section 3.3 shows that there are no scientific models for capturing detailed process information in PD.

In order to schematically represent the information requirements for domain experts, a meta-process model according to Hollingsworth (1995) is used and supplemented with AI-specific components. The basic process definition meta-model comprises the object types of "workflow type definition," "activity," "role," "workflow relevant data," "involved application," and "transition conditions" (Hollingsworth, 1995). In the context of AI systems, an additional object type named "AI system requirements" is added to map AI system-related information. Since the development of AI systems depends on governance and AI-related management, the object type "governance and management" is also added. The scheme is shown in Figure 5. Based on the results of the previous section, initial requirements can already be derived from the phase activities and objects under consideration. Further requirements were identified through literature research, the figure refers to relevant sections of this contribution. Although complete and detailed mapping is not possible under the given restrictions, an overview is nevertheless provided in Figure 5. In order to facilitate the understanding of the information requirements, examples of individual categories are also presented. This does not claim to be exhaustive.

Process and **activity description** (cf. Section 3.3)

<u>Initial description of actual processes:</u> Use of meta models; documented **company-specific** development process; characteristics of the development process (i.e. agile, stage-gate); **project-specific** development processes; centralized or decentralized process management <u>Description of the activity to be AI enabled:</u> **Activity without AI** (input, processing, output); quantification; dependencies on up- or downstream activities; **problem** to be addressed by AI; **objectives and desired outcome**

Example: *Product development process is conducted in accordance with a stage-gate methodology. AI will be utilized in one stage to assist in the patent search process. The results of the search should be cross-checked by experienced employees. Further steps will be discussed in the subsequent stage.*

Roles and **competencies** (cf. Section 3.5)

<u>Initial description of the roles involved in the AI application domain:</u> Roles involved, **identifiable stakeholders**; existing **digital and AI competencies**; intended role of domain experts in AI system development; description of **future AI users** and their requirements

While experienced product developers (domain expertise) and IT operations personnel are in place, a lack of AI expertise is apparent. The company has never deployed an AI system.

Involved Applications, **ITI** (cf. Section 3.1)

<u>Initial description of the accessible ITI and applications used:</u> structure of current ITI; available **resource pools** (compute, storage, network, cloud and edge computing); activity related applications (i.e. CAD, PDM); company-wide applications (i.e. PLM); **AI systems in use**

Access to online patent database (platform), availability of int. computing resources is limited

AI system requirements (cf. Section 3.1)

<u>Initial description of the **target AI system**</u> (i.e. AI platforms, enterprise-ready AI); originator or facilitator function; **requirements for human-machine teaming**; ethical and legal aspects; stakeholder requirements; requirements regarding the problem solution

AI systems to facilitate optimization of analysis activities in PD, significant importance of traceable results and customized search by users, application implemented as web application, user interface in a way that no coding is required

Governance and **Management** (cf. Section 3.4)

<u>Initial description of the existing management:</u> Existence of a basic **AI strategy**; processes regarding AI governance, transparency and explainability, security and privacy, risk management; **resource and data management** for ITI and AI; competence development strategy

Data (cf. Section 3.2)

<u>Initial description of the data basis:</u> **Specification of available data** – data source; reference of data sourcing (1st party collection, 3rd party collection, 1st and 3rd party); characteristics of the data (raw data, transformed data, data types, labeled or unlabeled); is it big data (volume, variety, velocity, variability, value); **Data quality** – definition of characteristics (i.e. accuracy, consistency, accessibility) and measures; **Data handling** – specification of existing processes (i.e. access control, version control); **Data requirements** – definition depending on the intended use, relevance and representativeness

Large amount of structured text data from patent database (3rd party collection) in PDF format, different languages, continuously updated, full access to database existing, external data (pre-) processing by database operator

Transition conditions (cf. Section 3.4)

<u>Initial description of flow or execution conditions:</u> **Limiting environmental effects**; use of the AI system tied to a time-limited development project or one-time activity; known factors that can hinder regulated project execution; time or financial restrictions; known deficits

Max. budget: 25,000 euros, system ready for use in July, AI competence deficits → outsourcing, Compliance with applicable data security standards

Figure 5. Overview of information requirements for domain experts

6 Discussion

The previous sections address the role of domain experts in the AI system life cycle. One aim of the examinations was to identify the phase-related involvement of domain experts in AI system life cycle models. As a result of the observations, involvement is recognizable throughout the entire life cycle, but focal points are in the early phase (inception), in the use phase (operation), and particularly in tasks related to the evaluation of (partial) results (cf. Section 4).

The models considered here are concerned with roles that have little or no AI expertise but do feature domain expertise. Although the roles are named differently in the different models, the general involvement in the AI system life cycle with regard to the domain can be derived. Assigning the identified domain roles to the phases of the ML life cycle can be done qualitatively, despite the different phase names used in the considered literature. In addition, no specific information is provided about the characteristics of an application domain, which therefore only allows a limited view of the role of the domain experts. Furthermore, no conclusions can be drawn about specific competence profiles from the domain-related roles identified in the literature. However, it was only possible to take a superficial look at the links between roles and competence profiles for the purposes of this study. Further research is required. A further aim of the considerations involved working out specific tasks and the resulting information requirements. Analysis of the phase-related processes, tasks, and objectives enabled the identification of information requirements for the domain experts. Using a basic process definition meta-model and AI-specific extensions, these requirements could be mapped into eight information requirement areas with exemplary contents in each case.

Since the exact content of the early phases is dependent on the later selection of the AI technology, it is difficult to determine the exact information requirements. This is also due to the iterative nature of AI system development models. This causes a deficit with regard to the completeness and depth of detail of the identifiable information requirements. Also challenging is that the AI development and lifecycle models are derived from the discipline of IT and do not provide a direct reference to the requirements of specific application domains. In addition, the models considered differ in the level of detail in the description of their stages and represent the overall AI system life cycle without referring to a specific combination of a target AI system (including specific AI models) and specific use cases. This also results in a lack of clarity in the findings, which requires more detailed analysis. Upon examining the initial stages of the models under consideration, it is evident that not all models address the preliminary phases in the technical development of AI systems. Models that consider phase activities often describe them superficially and neutrally in terms of a specific AI technology (see ISO/IEC 22989:2022, De Silva and Alahakoon (2022), Kessler and Gómez (2020), Baltensperger et al. (2022)). However, the derived information requirements are still applicable to PD, as they are formulated in general terms, but it appears useful to look at the application domain more closely. The completeness of the information requirements should therefore be expanded both in terms of breadth and depth of detail. With regard to the general industrial applicability of the current representation of information requirements, especially by non-AI experts, this is to be regarded as limited since there is no structured methodology. Numerous areas are to be considered, which in turn require multidisciplinary domain experts, and there are also many aspects to be considered. On top of this, the identified requirements contain a lot of terms that may not be familiar to the non-AI experts. This makes communication between non-AI experts and AI experts a key factor. There is still a dependency on expert knowledge both in the area of specialized AI skills and in the implementation of AI development projects. Additionally, the models in the literature always assume that the problems in the application domain are to be solved by AI. In the current state of AI in industry, which is characterized by a strong need for standardization and a lack of transparency, the question arises if there is still a missing stage in the lifecycle of AI systems. This stage could describe the process of weighing up technologies and also include instructions on how to prepare for developing AI projects.

7 Conclusion and future works

This contribution has considered the role of domain experts in AI system life cycles. By considering AI life cycle models, it has been possible to identify and describe phases of typical AI development projects. By examining the characteristics of roles and stakeholder groups and assigning them to the AI system life cycle stages, the involvement of domain experts could be identified on a stage-specific basis. In addition to an involvement that can be determined over the entire life cycle of an AI system, focal points in the early phases, in the use of AI systems (operation), and in evaluations distributed over the life cycle were identified. By taking a closer look at the early phases, it became possible to derive information requirements for domain experts by working out specific tasks and their objectives. These can be qualitatively summarized in 7 areas by extending a basic process meta-model to AI application cases. However, further research seems necessary in order to incorporate the application domain perspective into the AI process models originating from the IT discipline. Recommendations for future research are summarized as follows:

- More detailed analyses need to be conducted: Consideration of industrial use cases in the field of AI system development in order to examine collaboration between non-AI experts and AI experts in the industrial environment in more detail, to better understand their roles and to ascertain respective requirements for collaboration.

- Based on the fact that existing development processes for AI systems have been researched within the discipline of IT, surveys regarding the requirements of the application domain are necessary. These can provide important information for transforming the models in terms of their broad comprehensibility and industrial applicability.

- In-depth consideration and description of the activities in the early phases of the AI system life cycle models, considering the application domain. Building on this, development of methods that are understandable and applicable across disciplines for the standardized recording of initial domain states and goals of the AI system being developed.

- Research into the integration of existing methods and models may be promising with respect to applicability. For example, maturity models for analyzing the initial situation in the domain can support a structured approach in the areas of information requirements, i.e. digital transformation, data, or AI in general.

- Further research seems necessary in order to expand the depth and breadth of the information needs on the one hand, and to improve the type of presentation in the context of applicability on the other.

- Research into the relationship between required competence profiles depending on specific AI systems (those systems that contain one or more specific AI technology and whose ecosystem is widely defined) and their role assignment in the AI system life cycle.

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