

Dissertation to obtain the academic degree of DOKTOR-INGENIEUR (DR.-ING.) on the subject of

DEVELOPMENT AND EVALUATION OF A MORPHOLOGICAL BOX FOR ARTIFICIAL INTELLIGENCE SOLUTION INTEGRATION

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Kurzzusammenfassung

Selbst in der Zeit der generativen künstlichen Intelligenz (KI) schlagen etliche Versuche der KI-Integration in Unternehmen immer noch fehl und Unternehmen tun sich damit schwer, KI-Anwendungen erfolgreich in ihre Businesses zu integrieren [Gar25; EY18; For+23]. Dank des KI-Hypes durch Anwendungen wie OpenAIs ChatGPT oder Microsoft Copilot ist die Anzahl an Unternehmen, die KI nutzen und von ihr profitieren wollen, extrem angestiegen. Allerdings führt das fehlende Wissen über die Komplexität von KI und die Besonderheiten ihrer Integration in Unternehmensprozesse, -strukturen und -anwendungen dazu, dass viele Einführungsprojekte fehlschlagen oder viel teurer werden als ursprünglich geplant. Darüber hinaus haben Gespräche mit Unternehmen sowie eine im Rahmen dieser Arbeit durchgeführte strukturierte Literaturanalyse gezeigt, dass noch kein passendes Artefakt existiert, welches die Aspekte mit dem größten Einfluss auf eine erfolgreiche Einführung von KI in Unternehmen zusammenfasst.

Diese Dissertation nutzt das Design Science Research Paradigma, um ein Artefakt zu entwickeln, welches die verschiedenen Facetten von KI und seiner Integration in Unternehmen zusammenfasst: die morphologische Box für KI-Integration. Das Hauptziel einer morphologischen Box ist es, ein umfangreiches und komplexes Problem in viele kleinere Probleme aufzuteilen, die dann wiederum einfach zu verstehen und zu lösen sind [Zwi69]. Der Autor dieser Dissertation argumentiert, dass diese Strategie auch auf das zuvor beschriebene Problem der Einführung von KI in Unternehmen angewandt werden kann, in dem der Themenkomplex der KI-Integration in seine wichtigsten Eigenschaften ("Features") aufgeteilt wird. Die Box enthält dazu mögliche Ausprägungen ("Values") für die verschiedenen Eigenschaften. Die morphologische Box wurde durch einen iterativen Prozess entworfen, verbessert und evaluiert. Dieser Prozesse beinhaltete fünf Evaluationsepisoden, darunter Experteninterviews und -diskussionen sowie zwei Umfragen, und die Anwendung der Box in verschiedenen unternehmerischen und wissenschaftlichen Use Cases. Die jeweils unterschiedlichen Use Cases demonstrieren zusätzlich die diversen Anwendungsmöglichkeiten und -potenziale des Artefakts sowie die Vorteile seiner Nutzung.

Den Hauptbeitrag dieser Arbeit bildet die ausführlich evaluierte morphologische Box für KI-Integration und die Demonstration ihrer Nutzungsmöglichkeiten und -vorteile in Wirtschaft und Wissenschaft.

Abstract

Even in the area of generative Artificial Intelligence (AI), many AI integration projects still fail, and companies struggle to successfully integrate AI applications in their businesses [Gar25; EY18; For+23]. Due to the hype of AI since the rise of solutions like OpenAI's ChatGPT and Microsoft Copilot, the number of companies wanting to benefit from the technology increased significantly. However, the lack of knowledge about AI and the lack of awareness for the complexity of AI applications and their integration into existing business structures, processes and applications lead to the failure or rising costs of many integration projects. Furthermore, discussions with companies and a Structured Literature Review (SLR) showed the lack of a suitable artifact that provides the most important aspects for successful AI introduction in businesses.

This dissertation uses the Design Science Research paradigm to develop an artifact that summarizes the different facets of AI and of its integration in companies: the Morphological Box (MB) for AI solution integration. The main goal of a MB is to break down a wide and complex problem into many smaller problems that are then easier to understand and to solve [Zwi69]. The author of this dissertation argues that this strategy can be adopted for AI with the goal to break down the overall topic of AI integration in companies into its most important features and provide the user of the artifact with possible values for each feature. The MB was constructed and refined through an iterative process of five evaluation episodes, including expert interviews and discussions and two surveys, as well as by applying it in different business and scientific use cases. Furthermore, the use cases demonstrate the variety of application potentials of the artifact and benefits of using it, besides the support for AI solution integration in companies.

The main contribution of this thesis is the evaluated MB for AI solution integration and the demonstration of its application possibilities and benefits in business and science.

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List of Abbreviations

ACT	Air Conditioning and Clean Room Technologies
AI	Artificial Intelligence
AIaaS	Artificial Intelligence as a Service
COTS	Commercial-of-the-Shelf
DL	Deep Learning
DSR	Design Science Research
DVZ	Data Processing Center (German: Datenverarbeitungszentrum)
EA	Enterprise Architecture
EAM	Enterprise Architecture Management
e.g.	for example
etc.	et cetera
GDPR	General Data Protection Regulation
GPT	Generative Pre-trained Transformer
i.e.	that is
IoT	Internet-of-Things
IPT	Instant Payment Transactions
IS	Information Systems
IT	Information Technology
KMO	Kaiser-Meyer-Olkin

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LLM	Large Language Modell
MB	Morphological Box
ML	Machine Learning
MM	Maturity Model
NLP	Natural Language Processing
RL	Reinforcement Learning
RQ	Research Question
SLR	Structured Literature Review
SME	Small and Medium Sized Enterprise
SVM	Support Vector Machines

Introduction

AI as a research area initially emerged in the early 1900s to the 1950s. However, a new "AI boom" started in the late 2010s and is still ongoing today. This boom originated from a plethora of new developments and advancements in AI technologies, even leading to a spread among the broad masses of the population with generative AI solutions, like OpenAI's ChatGPT, making AI accessible and useable for anybody. The countless usage possibilities and benefits of using AI, like automation or content generation, lead to the fact that many companies want to use AI to optimize processes or even create business opportunities.

However, the integration of AI in business processes and structures still often fails for several different reasons, like a lack of knowledge about AI, its requirements, or even the acceptance by a company's employees. A survey by Gartner [Gar25] discovered that only 54 % of AI projects move from pilot to production. Reasons for this include unrealistic expectations, inadequate funding, and organizational culture.

Research by the Boston Consulting Group claims that even "70 % of digital transformations fall short of their objectives" [For+23]. They emphasize that this is not only due to technology but also human-focused reasons, like the resistance or fear of employees, or the lack of management support.

Another report by Gartner estimated that 85 % of AI projects fail because of data quality issues [RB21], which can then even have negative impacts like financial losses or demoralization of employees.

Especially, such overrunning costs can be a major problem for companies during the introduction of AI. An article by McKinsey & Company [BQS18] reports that AI projects are often costlier than expected, and the costs would keep rising. Significant reasons, therefore, are the need for specialized hardware, the lack of understanding of the complexity of AI and the

process to integrate it, and the lack of trained personnel. Also, to experiment with strategies, technologies, and opportunities of AI, companies have to commit to significant investments.

To cope with the failure of many AI introduction projects and to help businesses with AI integration, this thesis proposes the use of a Morphological Box (MB) for AI solution integration that was developed and evaluated following the Design Science Research (DSR) paradigm. A MB is a technique from product development that helps to break down a problem into several more minor problems that are then easier to solve. In this thesis, AI shall be broken down into the most relevant features for its integration in companies. This initial chapter will further discuss the problem at hand, why it is essential for businesses and research, how this thesis tackles it, and what contributions emerged from this research project.

1.1 Research Problem & Context

Technological advances in the last years have made AI solutions attractive to enterprises in various industry domains. Investigations into the organizational uptake of AI solutions confirm that there is a growing interest in enterprises [Eur22] and public authorities [Mik+23] to use AI for, for example (e.g.), the automation of routine tasks, implementing process innovation, changes in the business model, or entirely new products and services [MMN23], which are commonly attributed advantages of AI solutions. Many researchers consider AI as one of the cornerstones of digital transformation (e.g., [BF19] and [HH17]). Recent studies claim that more than 75 % of all large enterprises and 50 % of enterprises with less than 1000 employees work on AI solutions [IDG23]; in the sector of Small and Medium Sized Enterprises (SMEs), more than 45 % are interested in AI solutions and 21 % consider AI as an essential topic for the future and started to investigate the use of AI in their own business [Vit+22].

However, at the same time, research in organizational readiness for AI solutions [JWW21], innovation management and change processes [UE23] confirms that, in particular, SMEs still have problems grasping the potential of AI [San19] and deciding under what conditions AI is useful, what actual solution to select, and how to introduce solutions [HB21]. AI technologies are different from other Information Technology (IT) technologies due to the capability to perform cognitive functions in a way that resembles a human-like manner and the ability to learn and self-correct [RN16]. Thus, the introduction of AI solutions differs from other IT introduction processes. For instance, it has also been observed during the introduction of AI solutions into organizations that the development processes of AI solutions create different challenges than the development of other, more established kinds of IT or IS. Some of the challenges are related to the current technology hype concerning AI [Pan18], which can "blur the distinction between what the technology can actually do and what potential users imagine" [HG10]. Other challenges relate to the specific needs of AI solutions regarding the availability and quality of large datasets or domain knowledge and workflows to be supported.

Another problem is seen in the variety of different AI approaches and the difficulties in distinguishing the suitability of these approaches for enterprise problems. Machine Learning (ML) [Mah20], Deep Learning (DL) [Pou+19], Support Vector Machines (SVM) [Sut16] or principle component analysis [BS14] to take only some examples, might all apply to the same organizational problem. If one starts from the technical task to be solved, like classification of data, information extraction, or pattern recognition, the same variety of solution potential exists that has to be taken into account in the organizational adoption journey [UE23].

Developing and introducing AI solutions into enterprises or public administrations are considered complex processes [Hol16]. Recommendations by AI competence centers highlight the importance of different perspectives in them [Bra+]:

- How business models, organizational structures, and business processes are affected and have to be adjusted.
- What competencies and competence development of employees and management staff are required.
- How the overall change management process is performed when introducing AI-based innovations.
- Technology, data, and composition of the actual AI solution.

1.2 Problem Relevance

The fact that companies still struggle with AI introduction, as explained in the previous section, shows that currently, no artifact exists that copes with this problem satisfyingly. A Structured Literature Review (SLR), presented in detail in chapter 4.3, showed that existing artifacts and research mainly tackle the problems from only one viewpoint, e.g. they concentrate either on the technological aspects, social acceptance or on processes for training AI models. Also, established literature like Russell & Norvig [RN16] discusses how algorithms and data processing should be implemented, but provides little information on what to observe when designing such applications for an organizational context. The same applies to the periodic system of AI applications by BITKOM that focuses on basic functions and the kind of input data required [Bit18].

This thesis argues that methodical support for the organizational introduction of AI solutions is needed that not only addresses the IT-related aspects but also supports decision-making, scoping, and requirements definition for AI solutions, that is (i.e.), coordination and alignment of business and IT-related aspects. The approach of this thesis is to support understanding and managing the complexity of organizational AI solutions by decomposing this

complexity into aspects that represent the features of AI solutions. More concretely, the author proposes a MB for use in organizational AI solution development. In this context, it is argued that systematizing features of AI solutions might help organizations in their decision processes or even in conducting introduction processes.

During work with enterprises interested in AI solutions, particularly with four SMEs, the author observed that the concept of AI, the different types of AI solutions, and the varying pre-conditions for introducing AI resulted in substantial problems to understanding the concept of AI. In this context, this research project started to compare AI solutions with other software solutions and used analogies to existing products. As this seemed to ease the understanding of what AI is, the conjecture that a MB could be helpful was developed. The four local cases that motivated and initiated this research and showed its business relevance are explained in detail in section 4.1. Based on those four cases, a global problem statement for this thesis was deduced.

A knowledge base analysis conducted via a SLR also showed that literature does currently not provide a tool, method or other artifact that can solve the global problem discovered in the four cases, thus, also proving the scientific relevance of the topic (see section 4.3).

In conclusion, the following research question for this research project was deduced:

- **RQ:** What aspects have to be considered by organizations investigating the use of AI?

This thesis claims that the MB can support AI introduction and help to solve the presented problems in the following ways:

- **Improve Awareness:** The MB provides an easily understandable classification of the different aspects of AI that are relevant for AI introduction, which helps to get a better overall view of the technology.
- **Assist in Decision Making:** The enhanced awareness and gained knowledge from the MB could enable decision-makers to make the right decisions.
- **Prevent Losses:** The MB could help to reveal possible dangers and stumbling blocks in the early stages of the AI solution development process.

1.3 Research Strategy

This thesis applied the DSR paradigm to design the described artifact, the MB for AI solutions. The goal of DSR is to design (IT-)artifacts that solve problems and thereby contribute to the

academic knowledge base [VK04]. Those artifacts should help to effectively and efficiently design, implement, manage, and use ISs [Hev+04]. The goal of this research project was the design of an artifact that fosters the introduction of AI, hence solving a specific problem and helping with ISs. Because of that, the DSR paradigm could be used for this research project.

According to Hevner [Hev07], a DSR project is characterized by three cycles: the design, relevance, and rigor cycle (see Figure 2.3). Those three cycles must be clearly present in a DSR project to be called as such. The heart of a DSR project is the design cycle, which includes building, evaluating, and refining the artifact through several cycles. The relevance cycle concerns the environment of the artifact, including the business problem that the artifact should solve, the requirements derived from it, and testing the artifact in the field. Thereby, this cycle initiates the research with a problem from the application domain and determines how well the artifact performs and if further design cycle iterations are necessary. Finally, the rigor cycle ensures that the knowledge base does not already provide an artifact that fulfills the requirements of the application domain, ultimately leading to an improvement, invention, or exaptation and not just routine design. The research should contribute to the knowledge base with the artifact it creates and the knowledge gained during its design. Furthermore, the researcher should apply appropriate and proven research methods and theories for designing and evaluating the artifact. [Hev07]

The research followed the three cycles by Hevner as well as the seven DSR guidelines (see section 2.1.1.2) by Hevner et al. [Hev+04], that include, amongst others, that the designed artifact must be a construct, model, method or instantiation. It can be argued that a MB for AI solutions as described would be a representation of the reality (*model*) or a concrete implementation of a MB (*instantiation*). However, it could also be argued that it provides a procedure for understanding and exploring the multi-dimensional design space of AI solutions and identifying suitable design alternatives, ultimately supporting the development and integration of AI solutions, which would cement it as a *method*. Regardless of which, for the moment, the most important fact is that the MB qualifies as an DSR artifact.

For the practical implementation of the DSR paradigm, the thesis follows the DSR process by Peffers et al. [Pef+07] (see Figure 2.1). This process proposes seven steps for conducting a DSR project: (1) problem identification and motivation, which is realized by this chapter and a SLR (see sections 4.1 and 4.3), (2) definition of objectives for the solution, which were deduced from the SLR results and problem description and are defined in section 4.4, (3) design, which is presented in chapter 5 and discussed after each evaluation episode, (4) demonstration, which describes using and applying the artifact (see chapter 6), (5) evaluation, which was thoroughly conducted in five evaluation episodes (see chapter 7) and finally (6) communication, which was realized by publishing this research's results at several scientific outlets (see section 1.4).

More information about the research process will be explained in chapter 2.

1.4 Contributions

This section briefly summarizes the contributions produced by this thesis and the published work that emerged during the research project.

1.4.1 Contributions to the Knowledge Base

The main contribution of this thesis is the developed and thoroughly evaluated artifact, the MB for AI solutions. The MB includes deliberately chosen features of AI and presents possible values for them. It is important to note that the features, values, and their names were not just chosen because they are correct, but also because they are relevant for the introduction of AI. The thesis further lines out scientific and business use cases for the artifact and shows three examples of such. Additionally, the research project contributes to the scientific body of knowledge with a SLR that reviewed and analyzed the knowledge base of AI introduction in companies by answering the following research questions:

- **RQ1:** What methodological support for AI introduction in companies exists in the literature?
- **RQ2:** Which relevant factors for introducing AI in companies does the literature specify?
- **RQ3:** What challenges and problems of introducing AI in enterprises does the literature describe?

1.4.2 Published Work in the Context of this Thesis

During this research project, several scientific papers were published that presented results of this thesis, e.g. from evaluation episodes or applications of the MB. The following papers are in this context highly significant to this thesis:

- Jack Daniel Rittelmeyer and Kurt Sandkuhl. "Features of AI Solutions and their Use in AI Context Modeling." Gesellschaft für Informatik e.V, 2022. [RS22]
- Jack Daniel Rittelmeyer and Kurt Sandkuhl. "A Morphological Box for AI Solutions: Evaluation, Refinement and Application Potentials". In: *Advanced Information Systems Engineering Workshops*. Springer International Publishing AG, 2023. [RS23a]
- Jack Daniel Rittelmeyer and Kurt Sandkuhl. "Morphological box for AI solutions: evaluation and refinement with a taxonomy development method". In: *International Conference on Business Informatics Research*. Springer, 2023. [RS23b]
- Jack Daniel Rittelmeyer and Kurt Sandkuhl. "A Survey to Evaluate the Completeness and Correctness of a Morphological Box for AI Solutions". In: *International Conference on Advanced Information Systems Engineering*. Springer, 2024. [RS24]

The aforementioned papers build the basis for this thesis, whereas the following papers emerged in the scope of this thesis by completing preparatory work or applying the artifact of this thesis in different use cases:

- Jack Daniel Rittelmeyer and Kurt Sandkuhl. "Effects of Artificial Intelligence on Enterprise Architectures - A Structured Literature Review". In: *2021 IEEE 25th International Enterprise Distributed Object Computing Workshop (EDOCW)*. IEEE, 2021. [RS21]
- Kurt Sandkuhl and Jack Daniel Rittelmeyer. "Use of EA Models in Organizational AI Solution Development". In: Springer, Cham, 2022. [SR21]
- Leon Griesch, Jack Rittelmeyer, and Kurt Sandkuhl. "Towards AI as a Service for Small and Medium-Sized Enterprises (SME)". In: *IFIP Working Conference on The Practice of Enterprise Modeling*. Springer, 2023. [GRS23]

This thesis cites the presented works in several sections. All citations will be clearly stated in each section or chapter. This introduction chapter cites from [RS23a], [RS22] and [SR21].

1.5 Thesis Structure

The thesis is structured as follows: after this first chapter introduces and motivates the topic, the next chapter will explain the research design of this thesis (section 2), followed by the theoretical background relevant for understanding it (section 3). After that, chapter 4 investigates the problem that the thesis tackles from a business and scientific perspective. Similarities

and differences in four local cases of AI integration projects in SMEs were used to deduce a global problem statement and emphasize the business relevance of the project (section 4.1). A knowledge base analysis realized by conducting a SLR will be presented. The SLR was used to review the research area and identify relevant literature to cement the scientific relevance (section 4.3). The end of this chapter uses the problem investigation to elicit requirements for an artifact that can possibly solve the global problem and discusses why this applies to the MB. Chapter 5 presents the artifact of this thesis, the MB for AI solution integration. It will explain how the first version of the MB was developed and how the final version of it differs. Additionally, possible use cases of the artifact are summarized. Chapter 6 then shows how the MB was applied in three of those use cases and how it could further be used along the IS development process. Chapter 7 thoroughly explains the five evaluation episodes the artifact went through. For each episode, it will be discussed how it affected or changed the MB, showing the development cycles from the initial to the final version and all the different versions in between. Finally, chapter 8 summarizes the steps of this thesis, discusses its contributions, shows threats to validity and limitations, and presents lessons learned and future research possibilities.

Research Design

In this chapter, the research approach of this thesis will be described. First, the overall idea of DSR, the research paradigm this thesis follows, and different DSR approaches will be presented (section 2.1). After that, it will be explained which DSR approaches were used by this thesis and why. The chapter concludes with a description of the research methods applied by this thesis (section 2.2).

2.1 Design Science Research

In general, DSR is a research methodology that concentrates on the design, development, and evaluation of artifacts that should solve specific problems. The results of applying the DSR process not only consist of the created artifact but also include the design knowledge that was necessary for its creation. This knowledge helps to understand how and why the artifact enriches the application content and problem space. Therefore, its results are practical solutions in the form of the artifact as well as theoretical knowledge. Today, DSR is widely used in the area of IS. [VHM20].

However, different principles for conducting the DSR process exist that each focus on different aspects. An overview of the most well-known ones will be presented in the following section.

2.1.1 An Overview of Design Science Principles

This section will briefly summarize the different design science principles by Peffers et al. [Pef+07], Hevner et al. [Hev+04], Johannesson and Perjons [JP14], and Wieringa [Wie14].

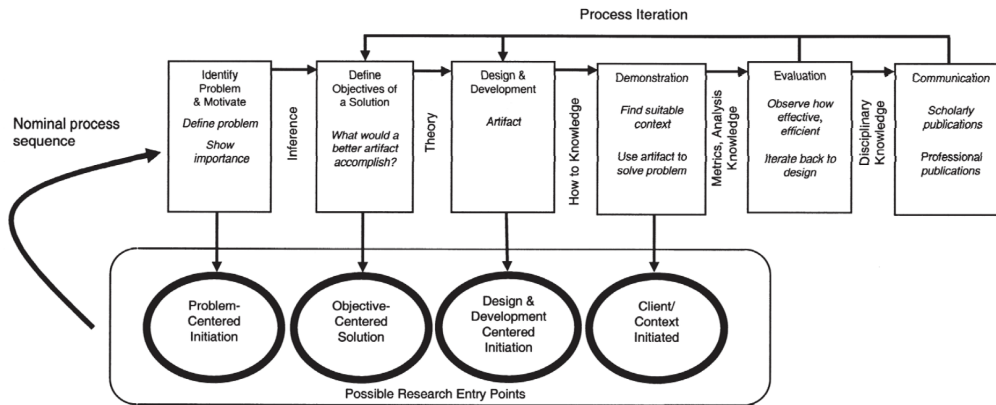


Figure 2.1: DSR process from Peffers et al. [Pef+07]

2.1.1.1 Peffers et al.

Peffers et al. described the need for a procedure for DSR that provides researchers with a "[...] generally accepted process for carrying it out." [Pef+07] Therefore, they created a process model with six steps that can be followed to create an artifact (see Figure 2.1). The first step is the identification of a problem and the motivation for why a solution to this problem is important. In the second step, the objectives of the solution should be defined. Then, the actual design and development of the artifact begins. When the first version of the artifact is created, it should be demonstrated how it can solve the problem (step 4). To evaluate the solution is the fifth step, which can include, amongst others, the evaluation of its effectiveness, efficiency, correctness, and suitability. From this step on, the solution should be made public and communicated with scholars and professionals. From the evaluation and communication, the researcher has the opportunity to go back to one of the earlier steps to refine the objectives and/or the artifact itself. The process should then be iterated several times until a satisfying artifact is developed. [Pef+07]

Additionally, Peffers et al. define four entry points for the process to emphasize that it is also possible and meaningful to use the process when starting from a later stage and not only from the first step of problem identification and motivation. For example, if a solution was already created or specific objectives for a solution are predefined, then the research can start directly from those points. The same goes for the demonstration step, e.g., if a client states new requirements or wishes for changes in a solution after the demonstration step. [Pef+07]

In summary, Peffers et al. provide a reference process for guiding DSR research projects as well as a vocabulary to communicate the research's entry point and phases.

2.1.1.2 Hevner

The DSR model by Hevner et al. [Hev+04], first published in 2004, provides a framework for DSR (see Figure 2.2), guidelines on how to conduct DSR research (see Figure 2.4), and a catalog

of evaluation methods (see Figure 2.5).

The first version of the framework, as shown in Figure 2.2, embeds the behavioral science and design-science paradigms to understand, execute, and evaluate IS research. It performs research in two phases: behavioral science, which develops and justifies theories, and design science, which builds and evaluates artifacts. The framework insists that truth and utility are inseparable. The former belongs to behavioral science, while the latter is attributed to design science. Rigor and validity in research are based on the knowledge base represented by prior research and methodologies. The knowledge base differentiates routine design from design research in terms of novelty and contribution to the knowledge base. DSR deals with "wicked problems" manifested by unstable requirements, complex interactions, flexibility, and reliance on human imagination and collaboration. It supports adaptive and process-oriented guidelines because the framework is aware that the design theories in IS research keep evolving as technology advances. [Hev+04]

Moreover, a refined version of the framework was presented in 2007 (see Figure 2.3) that integrated relevance, rigor, and design as cycles into the framework [Hev07]. The rigor cycle shall guarantee that the research project addresses a relevant problem and that the developed artifact is evaluated in field tests, meaning in a practical and real context. Therefore, it includes steps like problem identification, context understanding, and making sure that the solution is useful and applicable. The rigor cycle, on the other hand, ensures that the research is grounded in established theories and that it adds to the existing knowledge base. The design cycle comprises the actual development of the artifact, including not only the first version but also refinement and evaluation steps to guarantee that it tackles the identified problem. [Hev07]

The guidelines by Hevner et al. state that DSR involves creating purposeful and innovative artifacts to solve specified problems (guidelines 1 and 2). The artifact must be purposeful, which requires thorough evaluation (guideline 3). For this purpose, they summarized typically used evaluation methods that are shown in Figure 2.5. The artifact must provide a novel, new, or more effective solution (guideline 4). It must be rigorously defined and consistent (guideline 5). The creation process should search for an effective solution (guideline 6). Lastly, the results should be communicated effectively to scientific and industry audiences (guideline 7). [Hev+04]

Finally, as DSR always creates an artifact and related knowledge during the development and evaluation, Gregor and Hevner established three levels of contribution maturity of the knowledge developed during the DSR project. The different maturity levels are shown in Figure 2.6. Knowledge of Level 1 would be an instantiation of an artifact, meaning it is very specific and situational, and its knowledge is not very mature. The majority of DSR artifacts, like general approaches, models, or methods, are on Level 2, according to them. Level 3 then includes the most mature and abstract knowledge. [GH13]

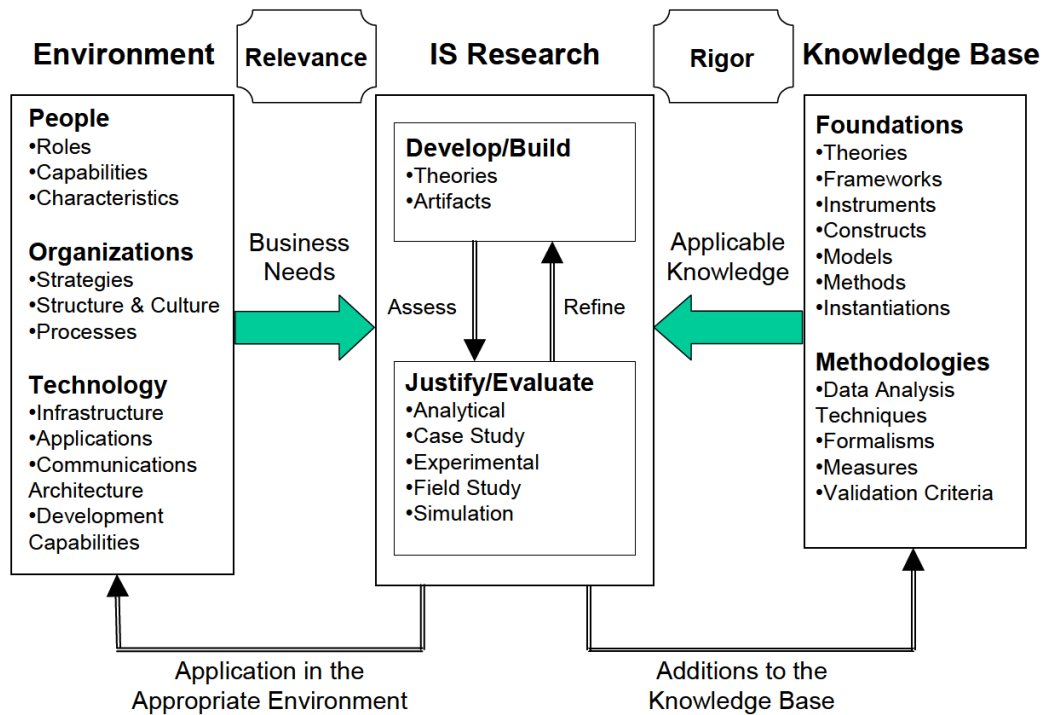


Figure 2.2: DSR framework by Hevner et al. [Hev+04]

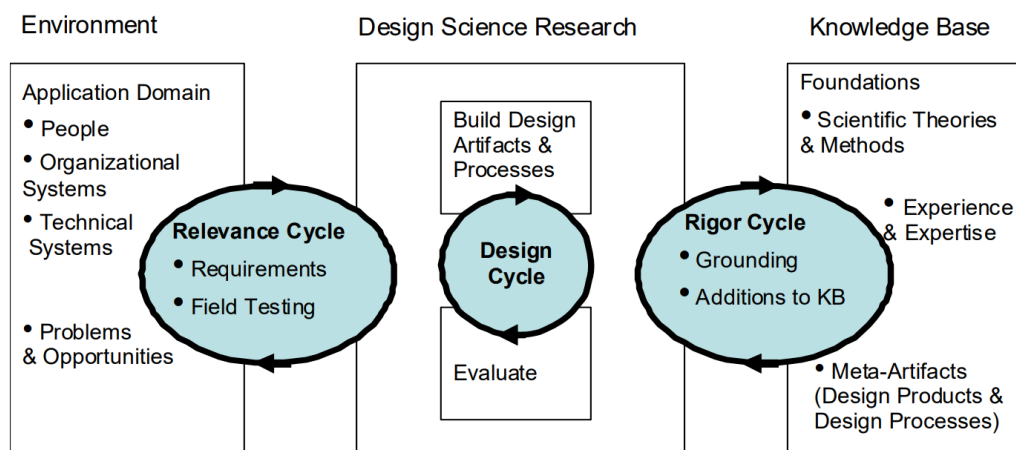


Figure 2.3: Refined DSR framework by Hevner et al. [Hev07]

Guideline	Description
Guideline 1: Design as an Artifact	Design-science research must produce a viable artifact in the form of a construct, a model, a method, or an instantiation.
Guideline 2: Problem Relevance	The objective of design-science research is to develop technology-based solutions to important and relevant business problems.
Guideline 3: Design Evaluation	The utility, quality, and efficacy of a design artifact must be rigorously demonstrated via well-executed evaluation methods.
Guideline 4: Research Contributions	Effective design-science research must provide clear and verifiable contributions in the areas of the design artifact, design foundations, and/or design methodologies.
Guideline 5: Research Rigor	Design-science research relies upon the application of rigorous methods in both the construction and evaluation of the design artifact.
Guideline 6: Design as a Search Process	The search for an effective artifact requires utilizing available means to reach desired ends while satisfying laws in the problem environment.
Guideline 7: Communication of Research	Design-science research must be presented effectively both to technology-oriented as well as management-oriented audiences.

Figure 2.4: DSR guidelines by Hevner et al. [Hev+04]

1. Observational	Case Study: Study artifact in depth in business environment
	Field Study: Monitor use of artifact in multiple projects
2. Analytical	Static Analysis: Examine structure of artifact for static qualities (e.g., complexity)
	Architecture Analysis: Study fit of artifact into technical IS architecture
	Optimization: Demonstrate inherent optimal properties of artifact or provide optimality bounds on artifact behavior
	Dynamic Analysis: Study artifact in use for dynamic qualities (e.g., performance)
3. Experimental	Controlled Experiment: Study artifact in controlled environment for qualities (e.g., usability)
	Simulation – Execute artifact with artificial data
4. Testing	Functional (Black Box) Testing: Execute artifact interfaces to discover failures and identify defects
	Structural (White Box) Testing: Perform coverage testing of some metric (e.g., execution paths) in the artifact implementation
5. Descriptive	Informed Argument: Use information from the knowledge base (e.g., relevant research) to build a convincing argument for the artifact's utility
	Scenarios: Construct detailed scenarios around the artifact to demonstrate its utility

Figure 2.5: A DSR evaluation method catalog by Hevner et al. [Hev+04]

	Contribution Types	Example Artifacts
More abstract, complete, and mature knowledge ↑ ↑ ↑ ↑ More specific, limited, and less mature knowledge	Level 3. Well-developed design theory about embedded phenomena	Design theories (mid-range and grand theories)
	Level 2. Nascent design theory—knowledge as operational principles/architecture	Constructs, methods, models, design principles, technological rules.
	Level 1. Situated implementation of artifact	Instantiations (software products or implemented processes)

Figure 2.6: DSR contribution types by Gregor and Hevner [GH13]

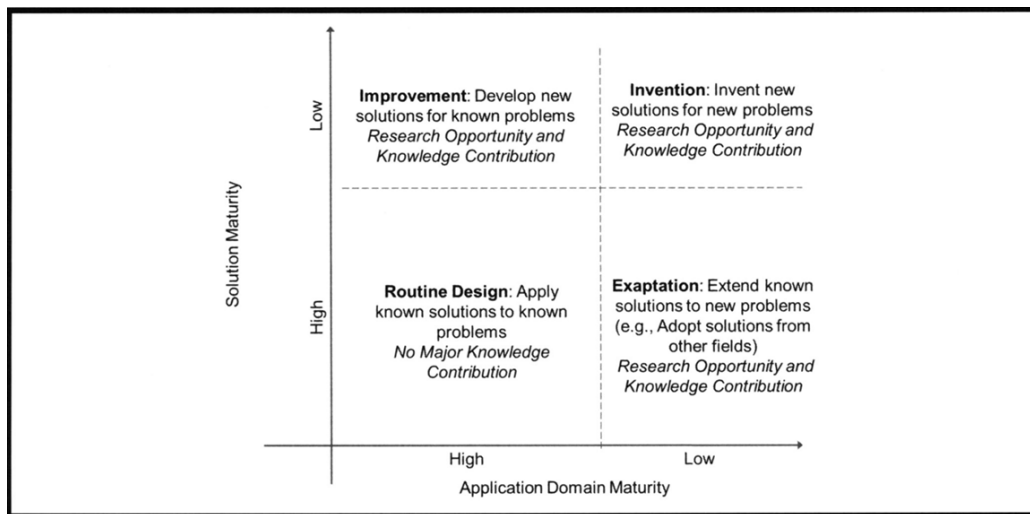


Figure 2.7: DSR contribution matrix by Gregor and Hevner [GH13]

Gregor and Hevner also developed a contribution framework for DSR artifacts in the form of a matrix concerning the research project's context and the DSR contributions. Figure 2.7 shows the four areas of the framework: improvement, invention, exaptation, and routine design. The x-axis represents the maturity of the application domain in which the DSR project takes place, while the y-axis describes the maturity of the existing solutions that could be a starting point for the research project. Hence, a DSR artifact is an invention when the domain and the existing solutions are immature. Gregor and Hevner explain that often, nearly no information about the domain or solutions for it existed, and that such real inventions are, therefore, very rare. Improvements, on the other hand, would be the most common case for DSR objects in IS research. Here, the domain is already well-established and known, but few solutions exist, so new solutions can be created for existing problems. It is the opposite with exaptation. In this case, proven solutions from other domains are applied to new domains. Finally, routine design does not deliver real contributions to the knowledge base because it only applies known solutions to known problems. This framework can help to classify the maturity of a DSR artifact and its knowledge. [GH13]

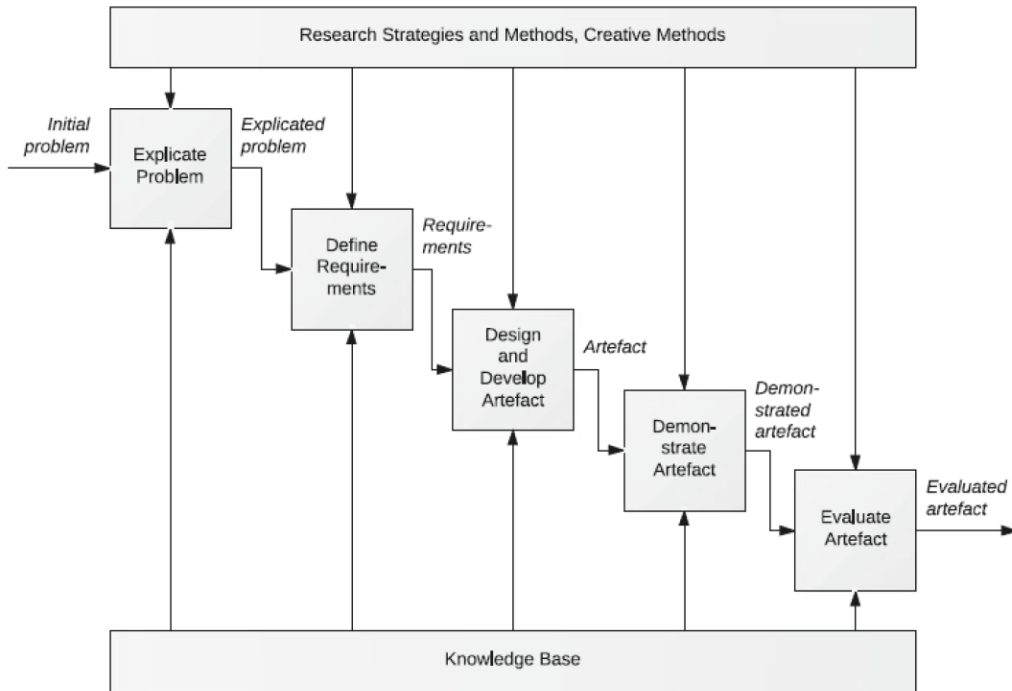


Figure 2.8: DSR framework from Johannesson and Perjons[JP14]

2.1.1.3 Johannesson and Perjons

Similarly to Peffers et al. [Pef+07], Johannesson and Perjons' DSR approach consists of a process model, but it also provides a design science canvas as an overview of DSR activities, and it is written like a textbook, including review questions. Therefore, it also has a strong focus on developing an artifact. The overall process shown in Figure 2.8 consists of five steps. According to Johannesson and Perjons, the initial problem should be explicated first. After that, requirements for the artifact have to be defined, which should be able to solve the explicated problem. This is followed by the design and development of the artifact. When the first version of the artifact is created, its application should be demonstrated, and the artifact itself should be evaluated. The end result of this process is an evaluated artifact. Besides the process steps, Figure 2.8 also depicts the knowledge base, research strategies, methods, and creative methods that should be used to enrich the different development steps. [JP14]

2.1.1.4 Wieringa

Compared to the previous approaches, Wieringa's model does not follow the build, evaluate, and refine pattern. Wieringa chooses a more complex and overarching approach that may better embrace complex research projects. Because of that, he designed several artifacts that can be used in the design science process. Figure 2.9 shows the framework by Wieringa that,

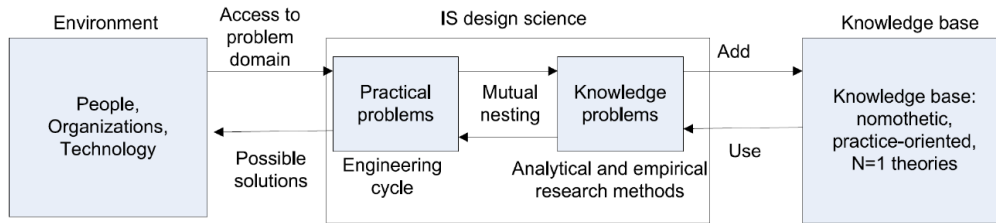


Figure 2.9: DSR framework from Wieringa [Wie09]

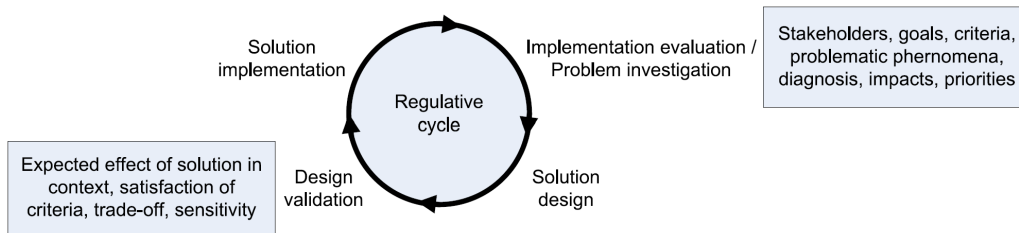


Figure 2.10: Regulative cycle by Wieringa [Wie09]

in summary, focuses on the design and development of solutions for stakeholders by solving nested practical problems as well as knowledge problems while also contributing to the knowledge base. [Wie09]

He further proposes a regulative cycle that determines how work should be conducted (see Figure 2.10). During the problem investigation, the motivation for the research should be determined. However, compared to many other approaches, but similar to Peffers et al. [Pef+07], Wieringa emphasizes the possibility of more diverse motivations than just problem orientation. The research could also be goal-, solution- (e.g., transferring solutions across problems) or impact-driven. The solution design then aims to specify a plan to reach the stakeholder goals by creating a specific artifact that can accomplish that. During the design validation, the validity of the planned design is evaluated regarding its internal and external validity as well as trade-offs. The solution implementation does not so much declare the final development or implementation itself, but rather means to "do something," which includes various activities like executing a process or test designs. The implementation should then be followed by an evaluation of it, concluding and starting the cycle anew [Wie14].

Finally, Wieringa [Wie09] summarizes his most important recommendations that were mostly described earlier in eight guidelines that are shown in Figure 2.11.

2.1.2 Applied DSR Process by this Thesis

In the previous section, different approaches of DSR, including their respective frameworks and guidelines, were summarized. This section shall give an overview of which approach was

[G1] Distinguish practical problems from knowledge questions
[G2] Solve practical problems by the regulative cycle
[G3] Distinguish problem investigation from design validation
[G4] Problem investigation may be problem-driven, solution-driven, goal-driven, or impact-driven
[G5] When designing a solution, maintain the design argument
[G6] When validating a design, consider trade-offs and sensitivity
[G7] When validating a design, aim to incorporate conditions of practice
[G8] When solving a knowledge question in the regulative cycle by means of research, no research method is banned.

Figure 2.11: Guidelines by Wieringa [Wie09]

chosen for this research project, why it was chosen specifically, and how the research process was conducted.

The research project described in this thesis mainly followed the DSR approach of Peffers et al. [Pef+07]. The main reason, therefore, was that their approach offered different entry points for the DSR process, as shown in Figure 2.1. It can be argued which entry point exactly was used for this thesis. On the one side, the initiation of the project was the problems of SMEs with the adoption of AI as explained in chapter 1. On the other side, the first initial version of the artifact, the MB, was developed immediately after the project initiation. This would mean that the starting point of the research was the initial artifact. Arguably, only the process by Peffers et al. [Pef+07] actively supports this starting possibility. The following sections will now explain how this thesis conducted each step of Peffers et al.'s DSR (see Figure 2.1).

2.1.2.1 Step 1: Identify Problem & Motivate

The problem that this thesis tries to tackle arose from the experience of various projects with industry partners as well as from the literature. As described thoroughly in chapters 1 and 4, support with the introduction of AI in companies and even more with understanding AI is needed.

2.1.2.2 Step 2: Define Objectives of a Solution

The objectives of the artifact are described in section 4.4. The initial objectives were derived from industry projects and literature. However, new objectives arose during the demonstration and evaluation of the artifact. The reason for that is that new application potentials were discovered besides the initially planned support of AI introduction in companies.

2.1.2.3 Step 3: Design and Development

The artifact, the MB, was designed by the author of this thesis based on the recommendations by Zwicky [Zwi69], the "developer" of the idea of MBs. The initial version was designed based on the author's knowledge about projects with industry partners and from the literature. The MB was then further refined after each application and evaluation episode. The development and refinement of the artifact are explained in detail in section 5.

2.1.2.4 Step 4: Demonstration

The applicability of the artifact was demonstrated in three use cases presented in chapter 6. In those three cases, the MB was used to enhance another scientific artifact, i.e., an AI context modeling method, to compare AI solution integration approaches, i.e., AI on-premise and Artificial Intelligence as a Service (AIaaS) and to develop an AI use case evaluation tool. Unfortunately, the MB could not be applied in the initially planned use case of a company wanting to integrate a new AI solution because no suitable cooperation with a company could be established for that.

2.1.2.5 Step 5: Evaluation

The artifact was evaluated in five distinct evaluation episodes presented in chapter 7. The evaluation episodes include two surveys, guideline-based expert interviews, expert discussions, and the application of a taxonomy development method. After all evaluation episodes, the MB was adjusted if necessary. Thereby, the artifact went through several iterations of the processes by Peffers et al. [Pef+07] while maturing and developing with each iteration. Hence, several versions of the MB are listed in chapter 5.

2.1.2.6 Step 6: Communication

The results were communicated after the initial development and each evaluation episode, except for the last two episodes. The last two evaluation episodes are presented for the first time in this thesis. All other results were published and presented in various outlets in the papers named in section 1.4:

- Jack Daniel Rittelmeyer and Kurt Sandkuhl. "Features of AI Solutions and their Use in AI Context Modeling." Gesellschaft für Informatik e.V, 2022. [RS22]
- Jack Daniel Rittelmeyer and Kurt Sandkuhl. "A Morphological Box for AI Solutions: Evaluation, Refinement and Application Potentials". In: *Advanced Information Systems Engineering Workshops*. Springer International Publishing AG, 2023. [RS23a]
- Jack Daniel Rittelmeyer and Kurt Sandkuhl. "Morphological box for AI solutions: evaluation and refinement with a taxonomy development method". In: *International Conference on Business Informatics Research*. Springer, 2023. [RS23b]
- Jack Daniel Rittelmeyer and Kurt Sandkuhl. "A Survey to Evaluate the Completeness and Correctness of a Morphological Box for AI Solutions". In: *International Conference on Advanced Information Systems Engineering*. Springer, 2024. [RS24]

The results were presented to and discussed with other researchers at the associated conferences. This also helped to collect further feedback on the MB and thereby can be seen as additional evaluation episodes.

2.2 Research Methods Utilized by this Thesis

As described in the previous section, various different research methods were used during the development of the MB. Precisely, a specific method for taxonomy development and application (section 2.2.1) was applied and a SLR (section 2.2.2), expert interviews and discussions, as well as two surveys were conducted (section 2.2.3). In this section, the theory behind those methods will be explained.

2.2.1 A Method for Taxonomy Development and its Application

This section cites from [RS23a]: Nickerson et al. [NVM13] presented a taxonomy development method for ISs with several process steps (see Figure 2.12) that can be used not only for taxonomies but for similar artifacts [NVM13]. They claim that their method supports the development of useful taxonomies, not necessarily the best or correct ones. The method starts

with the determination of a meta-characteristic, which should be based on the purpose of the taxonomy as well as its potential users, target audience, and projected use. In the second step, the ending conditions for the taxonomy development process should be determined, differentiating between subjective and objective ending conditions. They propose that a useful taxonomy has to be concise, robust, comprehensive, extendible, and explanatory (subjective ending conditions). They further present eight general objective ending conditions, which are not exhaustive [NVM13]:

- All objects or a representative sample of objects have been examined.
- No object was merged with a similar object or split into multiple objects in the last iteration.
- At least one object is classified under every characteristic of every dimension.
- No new dimensions or characteristics were added in the last iteration.
- No dimensions or characteristics were merged or split in the last iteration.
- Every dimension is unique and not repeated (i.e., there is no dimension duplication).
- Every characteristic is unique within its dimension (i.e., there is no characteristic duplication within a dimension)
- Each cell (combination of characteristics) is unique and is not repeated (i.e., there is no cell duplication)

After those two preparation phases, the actual development of the taxonomy starts with the decision of the approach that should be used in the first iteration of the process: empirical-to-conceptual (steps 4e to 6e) or conceptual-to-empirical (steps 4c to 6c). They recommend using the empirical-to-conceptual approach if the researcher has a lot of data but not much knowledge about the domain, and vice versa for the conceptual-to-empirical approach. [NVM13]

The empirical-to-conceptual approach starts with identifying (new) subsets of objects. The researcher should use a set of familiar objects that shall be classified. In the next step, one should search for common characteristics of those objects. The characteristics should be “logical consequences of the meta-characteristic.” [NVM13] However, it is highly important that a characteristic discriminates between the objects, meaning that not all objects should have the exact same value for a specific characteristic. In the last step, the characteristics should be grouped into dimensions to create or revise (for later loops) the taxonomy. [NVM13]

The conceptual-to-empirical approach starts with the conceptualization of (new) characteristics and dimensions of objects based on the researcher’s own knowledge and understanding of the domain. The characteristics of the dimensions should again be “logical consequences

of the meta-characteristic.” After that, the researcher should choose objects to be examined for the conceptualized characteristics and dimensions to evaluate and review them. It is emphasized that “each dimension must contain characteristics that are mutually exclusive and collectively exhaustive.” [NVM13] This results in a first or revised version of the taxonomy, similar to the conceptual-to-empirical approach. [NVM13]

After one of the two approaches is accomplished, the last step is to check if the ending conditions are met or not. Both the objective as well as the subjective ending conditions must be met. If they are met, the process is done, and the taxonomy is finished. If the conditions are not met, the process returns to the third step, and the empirical-to-conceptual or conceptual-to-empirical approach should be applied again. Those loops are run through until the ending conditions are met. In each loop, it is allowed to choose either of the two approaches. [NVM13]

The paper also gives a short outlook on what should be done after the method is finished. The most important aspect is to evaluate the developed taxonomy for its usefulness. One crucial question that should be evaluated is whether the user’s purpose can be accomplished with the taxonomy. To achieve that, interviews or questionnaires could be used to ask potential users if and how they would use the taxonomy. Additionally, the taxonomy could be evaluated while the researchers accompany real use cases where the taxonomy will be used and applied in practice [NVM13].

2.2.2 Structured Literature Review

The Structured Literature Review, as proposed by Kitchenham [Kit04], follows a systematic and methodical way of reviewing the available literature on a particular topic. The essential characteristics include providing a critical and evaluative account of what has been published, summarizing, synthesizing, and analyzing the arguments of others. It describes the existing body of knowledge and thereby also identifies research gaps. The SLR is expected to identify similarities, differences, consistencies, inconsistencies, and controversies from previous studies.

Furthermore, Kitchenham [KC07] provides guidelines for SLRs that can be summarized as a procedural approach about how to conduct a SLR. The process starts with formulating the problem at hand. This involves defining the research questions that guide the review. The second step is the identification of papers. This step includes the actual search for relevant papers through a well-defined search process. In general, this involves the iterative development of a search string, choosing suitable outlets, reviewing the results, and fine-tuning the search query several times.

Once a list of potential papers is collected, the inclusion and exclusion criteria should be applied to select the relevant papers (paper selection). With this step, the researcher can ensure

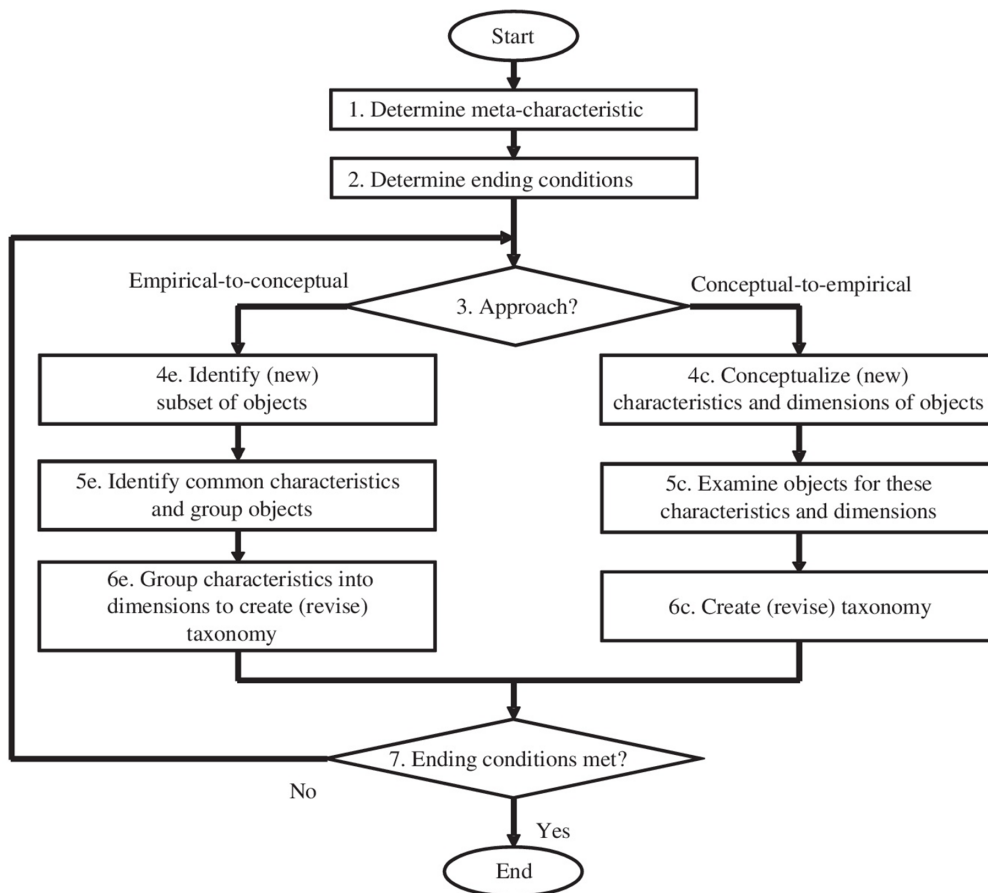


Figure 2.12: Taxonomy development method by Nickerson et al. [NVM13]

that the papers included in the SLR deal directly with the research questions and are relevant to these subjects. It should be documented which papers meet the inclusion and exclusion criteria to increase transparency and repetitiveness of this procedure.

This is followed by the data collection, meaning sources, authors, institutions, main topic areas, research questions, and approaches are identified from the extracted papers.

The fifth step, data analysis and interpretation, is about analyzing the data for trends, patterns, and gaps in existing research as well as interpreting the results, meaning to derive insights and conclusions on the research topic.

Finally, one needs to document the entire process and results of the SLR. Therefore, one should document, in detail, e.g., the keywords, synonyms, and combinations that have been used, the parts of the publications that have been included in the search, the number of papers initially found and selected, and the strategy used for searching and selecting the papers. [KC07]

The SLR conducted for this thesis will be described in chapter 4.3.

2.2.3 Surveys (Interviews, Questionnaires & Document Analysis)

Surveys can be conducted in different ways, suitable for different situations, research questions, and goals. Mainly, there are two directions: qualitative and quantitative research. According to Oates [Oat06], a distinction is made based on the type of data collected. In qualitative research, verbal data is used, while quantitative research relies on numerical data. Interviews are often used for qualitative and questionnaires for quantitative research. [Oat06] Because both interviews and questionnaires were used to evaluate this thesis's artifact, they will both be described in more detail.

2.2.3.1 Qualitative Research

Qualitative interviews are a part of qualitative research. In the book of Bortz and Döring [BD13], verbal data is also referred to as non-numerical data. This involves, amongst others, text, audio, and video data that are used to explore concepts, experiences, or social phenomena. The focus is on understanding the context, meanings, and experiences. Therefore, it is rather exploratory, interpretative, and subjective. Qualitative research is often used in interpretivism or critical research paradigms. [Oat06]

Interviews are structured or semi-structured conversations designed to elicit in-depth information, guided by the researcher's agenda, yet allowing the interviewee freedom within the conversation. There are three main types of interviews: structured, semi-structured, and unstructured interviews.

Structured interviews have standardized questions for all participants and resemble verbal

questionnaires. Semi-structured interviews have predefined themes but allow flexibility in the order of questions. Finally, unstructured interviews are open discussions guided only by a general topic. [Oat06]

The preparation for an interview involves the definition of themes and questions, gathering background information about participants, and conducting practice interviews. For the actual execution, the selection of a suitable location and time, as well as decisions about recording methods, are important. Then, the interview can be conducted. Transcriptions should be made after the interview if not enough notes were taken during the interview. After that, the data should be analyzed using established approaches, like the qualitative content analysis by Mayring [MF19]. Overall, interviewing should be a planned, precisely executed, and analyzed technique that makes it effective in obtaining valuable information about a research topic. [Oat06]

In Naderer and Balzer [Nad+07], it is stated that interviews are among the most common research methods and hold a significant place in market research. Furthermore, they state that the term "qualitative interviews" encompasses a collection of methods that can be arranged along different dimensions. One such dimension is the degree of structuring and standardization of the interview. The term "qualitative" should be avoided if the degree of structuring interferes too much, leaving little room for the interviewee's responses. For these reasons, a narrative interview was chosen for this thesis. According to [Nad+07], the narrative interview was developed by Fritz Schütze in 1970 with the aim of obtaining a very detailed description of a specific topic.

Kirchmair [Kir22] divides the narrative interview into four phases: the opening phase, the narrative phase, the questioning phase, and the summary phase. According to him, these phases are described as follows: The opening phase introduces the participant to the specific interview form and sensitizes them to the upcoming phases. Next is the narrative phase: Here, only the participant speaks about the topic. When the participant finishes, they conclude this part. The interviewer may only prompt for further details on specific points, but not ask other questions. This is followed by the questioning phase, where the interviewer can then ask questions related to important aspects of the narrative phase. The interview concludes with the summary phase. In this phase, the interviewer summarizes the most important statements, and the participant can comment on them. [Kir22]

2.2.3.2 Quantitative Research

This section is based on a section from [RS24]. In quantitative evaluation, responses are converted into numerical data and statistically analyzed using mathematical and statistical methods [JC07].

Quantitative research methods, such as questionnaires or systematic observations, aim to

provide a reliable overview of a defined section of reality by focusing on the quantity of the results as well as on measurements and testing hypotheses. It is objective and relies on statistical evidence. They are mainly applied in positivist research paradigms. [Oat06]

Questionnaires are one of the important tools of quantitative research. By using questionnaires, large datasets can be easily gathered from a group of people. They can be carried out online, by post, by telephone, or in person. The questions can be closed or open, and the responses can be quantitatively or qualitatively analyzed. [JC07]

Open questions allow respondents to express their views freely, while closed questions have predefined response options, such as multiple-choice. Response scales, like the Likert Scale, record the degree of agreement or disagreement, while the Semantic Differential Scale records feelings along bipolar scales, e.g., between good and bad or fast and slow.

To conduct a questionnaire, several steps have to be taken. First, research objectives have to be identified, and content validity has to be ensured. The questionnaire itself and each of its questions should be evaluated through test runs. After the evaluation, the questionnaire has to be distributed via appropriate channels, and consistency in its administration has to be ensured. Finally, the results of the questionnaire must be analyzed, either through coding in the case of open responses or with statistical techniques in the case of closed responses. [Oat06]

Theoretical Foundations

In this chapter, the theoretical background necessary for understanding this thesis will be explained. This includes the field of AI in general, as well as the term AI, how this thesis defines AI, and AI solution development (section 3.1). Secondly, the idea and theory behind the concept of the MB will be described (section 3.2).

3.1 Artificial Intelligence

This section cites from [RS21]: The term AI is used in many areas of business and research. However, the definition of the various fields often differs, as discussed in a variety of articles [HR22; Wan19; Bit18].

Especially, the “intelligence” is a controversial subject. John McCarthy is said to be the inventor of the modern AI term and its conception [McC07]. He defined AI as “the science and engineering of making intelligent machines.” Intelligence is defined as “the computational part of the ability to achieve goals in the world.” McCarthy further divides AI into branches such as pattern recognition, ontologies, or neural networks. The application possibilities are manifold and range from speech recognition to computer vision or expert systems [Vas14; RN16]. More concretely, one of the most cited publications on AI, the textbook by Russell and Norvig [RN16], distinguishes between problem-solving, reasoning, and decision-making, ML, DL, probabilistic programming, and multiagent systems. However, this categorization focuses on technological principles, “inner” architecture, or intended functionality, and elaborates in detail on how algorithms and data processing should be implemented.

Applications for AI are as manifold as its definitions, ranging from speech recognition to understanding natural language, computer vision, expert systems, heuristic classification, or

game playing, to name a few [McC07]. Furthermore, new application possibilities will continue to consistently emerge with the advancement of AI as a technology.

This section will provide an overview of the various definitions of AI. After that, the most important AI approaches, as well as the process and problems of AI solution development, will be described. At the end of this chapter, this thesis's definition of AI will be determined.

3.1.1 Overview of the Term “Artificial Intelligence”

Firstly, a distinction can be made between weak or specialized AI and strong or universal AI. Universal AI is characterized by the fact that the machine or computer can optimally achieve goals in a wide range of different applications [Leg08]. Whether and how universal AI can be achieved, however, is the subject of much debate in research [Leg08; Tho15; Jac18]. In contrast, weak AI can only be used optimally in a limited field of application. In this thesis, the term AI is used synonymously with weak AI.

The term AI refers to the Dartmouth Summer research project in 1955 [Wan19; McC07]. It was initially discussed in the fields of mathematics and computer science. However, the term also gained interest in other research areas, such as psychology, philosophy, neurology, and business administration [HR22; LBM19; RN16]. For now, the author of this thesis defines AI from the perspective of computer science as an object or machine that is capable of reacting safely and effectively to various novel situations [RN16]. Based on this general definition, a thorough classification will be given in the following section based on the categorization by Russell and Norvig [RN16].

3.1.2 Defining Artificial Intelligence

The wealth of definitions of AI that can be found in the literature means that an overview must first be obtained. For this purpose, a subdivision of the possible definitions is provided. This is based on the categorization described by Russell and Norvig [RN16].

The intelligence of AI can be assessed in different ways. While the internal thought process, i.e., the thought, is decisive for some areas of research, the result, i.e., the action, is considered more important for others. On the other hand, a distinction can be made as to which forms of the underlying maxim are used. A distinction can be made here between human and rational thought or action. The four areas generated by the two dimensions of human versus rational and thinking versus acting can be summarized by the definitions by Russell and Norvig shown in Table 3.1 [RN16].

These definitions should give a rough insight into the mindset of the areas. The different areas will be explained in more detail in the following paragraphs.

	Thinking	Acting
Humanly	AI, the exciting new approach of creating thinking computers. Machines with brains, in both the figurative and local sense. [RN16]	The development of calculations, that enable perception, reason and action. [RN16]
Rationally	Our ambivalent attitude to the question whether a machine is really capable of human thought human thinking leads us to regard a functioning system as useful, but not intelligent. [RN16]	Computational intelligence is the study and development of intelligent agents. [RN16]

Table 3.1: Categories of AI Definitions by Russell and Norvig [RN16]

3.1.2.1 Humanly Acting AI

The four scientists responsible for the Dartmouth summer research project were initially instrumental in shaping the term and the field of AI [Wan19]. John McCarthy [McC07] described AI with the following words: “In the present proposal, the problem of AI is understood to be about building a machine that behaves in a way that would be called intelligent if a human were to behave that way” [McC07]. This definition was strongly influenced by actions that should be as human-like as possible. Even before the term gained popularity, Turing proposed a test for the behavior of AI systems in 1950, the so-called Turing test. In this test, the AI must convince an outside observer of its humanity [Tur09]. According to this test, the AI must have natural language comprehension, a representation of knowledge, automated logical thinking, and ML. These are particularly important for computer science [RN16]. This definition is also frequently used in service and consumer research [HR22]. However, one objection to this definition is that, as with human flight, it is not important to imitate the birds but to find one’s own way [RN16].

3.1.2.2 Humanly Thinking AI

An equally important approach to describing AI is to write a program in such a way that it thinks like a human [RN16]. For example, the “General Problem Solver” developed by the researchers Newell and Simon [SN62] was designed for this perspective. It could reproduce the individual steps that led the AI to its result. These steps were then compared with human subjects [SN62]. This definition is strongly related to a mixture of computer modeling and psychology, which converge in the field of cognitive science [RN16]. In this context, AI can be described as synthetic intelligence since true intelligence is to be generated. The comparison between artificial and synthetic diamonds is often used, whereby only synthetic diamonds are real diamonds [Hau89].

3.1.2.3 Rationally Thinking AI

The concept of rationality can be described as an action that chooses the best outcome given the available information [Val95]. However, how thinking can be organized as rationally as possible has been described differently over the last millennia. For Aristotle, a person was rational if he did things that had a positive influence on his life [ResO3]. Based on this, the field of logic was developed, which deals with the objects of the real world and their relationship. As early as 1965, all problems that could be described using logic could, in principle, be solved by a computer. However, many of the phenomena observable in the real world cannot be described by pure logic alone. Randomly occurring actions and systems that are not clearly predictable require a probabilistic approach. This allows decisions to be made even if the information basis is unclear or incomplete. This enables AI to make decisions as rationally as possible, although this is not synonymous with a rationally meaningful action [RN16].

3.1.2.4 Rationally Acting AI

An AI that acts rationally must maximize a rational result measured by its action. In computer science, the term agent is used for this purpose. An agent is simply a person, an object, or a computer that performs an action. A rational agent is an agent that achieves the best possible expected result based on given information. Such an AI must, therefore, be able to infer. It also requires all the abilities already described for human thinking. Such a machine would also be able to pass the Turing test [RN16].

However, not all rational actions can be described using inference. For actions that are particularly time-critical or driven by intuition, AI can only fall back on limited rationality in order to minimize the time required to find a result [RN16]. In this case, AI can be described as computational intelligence, as computational systems are used in the implementation [PGM98]. This description of AI has also become established in research. Accordingly, AI is concerned with “[...] the research and development of agents that act correctly” [RN16].

3.1.3 Artificial Intelligence Approaches

According to Schmidt and Zimmermann, the currently most prominent AI technologies are “symbolic AI, ML and connectionist approaches.” [R S+20] This section will explain the differences between symbolic and subsymbolic AI as well as ML, DL and Large Language Model (LLM)s as the most relevant approaches in more detail.

3.1.3.1 Symbolic vs. Subsymbolic AI

Symbolic AI, often referred to as "classic" AI, is, in general, based on facts and rules and uses inference machines for deductive reasoning. [RS+20] Therefore, it is the branch of AI that utilizes formal logic and symbols to represent knowledge and solve problems. As the reasoning process is generally transparent and traceable, it is easier to interpret and understand. Because of that, symbolic AI is widely used in the areas of knowledge representation, reasoning, and problem-solving as well as Natural Language Processing (NLP). [HQ+17]

Ontologies and expert systems are two examples of symbolic AI applications. Ontologies are formal representations of concepts and their relationships in a specific domain. [Cri05] They help computers to understand information at a semantic level and also make communication between different systems easier, thereby improving interoperability. [GG24] On the other hand, expert systems are computer systems that should emulate the decision-making abilities of human experts. They consist of a knowledge base that includes relevant domain-specific facts and rules about the domain and an inference engine that applies the defined rules to the knowledge base to make decisions. [Tyl07]

Compared to the traceable and understandable symbolic AI, subsymbolic AI tries to reconstruct the functionality of the human brain by resembling a neural network with layers of nodes and weighted connections. With methods like ML or DL, neural networks can be trained with vast amounts of data to recognize patterns and learn from the data. Despite the large potential, it can be problematic that the decisions of such systems are often not traceable or understandable. To solve this problem, the ideas of explainable AI and the combination of symbolic and subsymbolic AI are currently gaining much attention in research. [Ren+24] ML and DL will be explained in more detail in the following section because of their relevance.

3.1.3.2 Machine Learning

ML uses statistical methods on data sets to induce rules, representing an inductive approach. [RS+20] This involves the development of computer programs that learn from experience or their own results in order to make predictions [BS21]. To this end, the algorithms are specifically "trained" with data sets. Each instance in such a "test data set can be described using a series of features identified by the algorithm during the training phase" [KZP+07]. Certain structures can, therefore, be derived from the results of this training. If completely unknown data is then applied to this trained model, the "learned structures can be compared with the unknown data so that predictions can be made for this data" [BW21].

ML can be further classified into supervised and unsupervised learning. If the training data is already "labeled," i.e., the expected output of the program for this data set is already known in advance, this is referred to as supervised learning [KZP+07]. With these learning methods, the

program is given a sufficient quantity of inputs and the appropriate outputs. The algorithm's task is now to find a corresponding function that maps the input to the corresponding output [Fro19].

This contrasts with unsupervised learning. Here, the algorithm is not fed with labeled data and, therefore, does not have the opportunity to find a function for defined target patterns. Rather, unsupervised learning is used to allow the algorithm to find previously unknown, useful patterns independently. [KZP+07]

In addition to these two categories, there is also the reinforcement learning approach. This approach is helpful when it is not necessarily possible to label the data because the instances cannot be clearly evaluated, but the actual goal is known. In addition, assessing whether a result is desirable or not in a particular situation is possible. [Fro19] Overall, it is about solving a problem in a dynamic environment, in which the subject learns from interactions in the environment according to a “trial-and-error scheme” and thus comes closer and closer to the actual goal [KLM96].

ML can be further divided into connectionist and non-connectionist approaches. Connectionist approaches are based on neural networks and include deep learning (see the following section). Non-connectionist approaches, on the other hand, do not rely on connectionist principles like neural networks and include approaches like support vector machines, decision trees, linear regression, and k-means clustering.

3.1.3.3 Deep Learning

Connectionist approaches like DL also use neural networks to simulate the human brain. They often benefit from vast amounts of data to train a network so that it can identify rules. DL is a sub-area of ML and uses more complex neural networks that have several layers. These multi-layer neural networks are, therefore, used in computer vision or NLP. Because the knowledge is acquired during the development of an application, i.e., during the network's training, classic software engineering methods are not always applicable to AI application development. In their cases, to apply them, it is necessary to know the domain knowledge at the beginning of the development [R S+20].

3.1.3.4 Large Language Modell

A LLM is a type of DL model that focuses on NLP. The main focus of LLMs is to process, understand, and generate human-like content. This makes them powerful tools for a wide range of application scenarios. LLMs are trained on vast amounts of data, including books, articles,

and websites, if focused on text. The same is done for image, video, or sound-focused LLMs with respective data. Thereby, LLMs gain the ability to give appropriate answers that fit the context of their prompts. By using extensive training data, they can accomplish ambitious tasks, like translating or summarizing texts. [Bro+20]

The currently probably best-known model is the GPT from OpenAI. GPT stands for generative pre-trained transformer and describes LLMs that uses a so-called transformer architecture that is specialized in processing text efficiently and in understanding connections between words. Their newest model, GPT-4, can, e.g., write emails or detailed reports. Nevertheless, these models are not without fail. Their results can sometimes be unprecise or even include information that is wrong or does not exist, which is called "hallucination." [Gör+24]

A factor that highly influences the quality of the results the user receives from an LLM is the phrasing of the input, usually referred to as "prompt." The field of "prompt engineering" even emerged from that. Prompt engineering deals with the optimization of the phrasing of prompts to receive the most precise, useful, and correct answers from the LLM. [Liu+23]

Examples of the use of LLMs in companies are the generation of clinical notes or deducing possible findings from patient data in clinics, or their use as chatbots for customer service.

3.1.4 Artificial Intelligence Solution Development

This section cites from [RS23b]: Another SLR conducted by the author of this thesis identified procedural approaches for introducing AI solutions into organizations [RS21]. The main finding of this work was that the general phases to be taken are basically identical to the introduction of ISs or software systems, and differences are visible within these general phases. Thus, for the general process of introducing AI solutions, the following phases typically are recommended by IS development methods [AF03] - for the realization phase, refinements from software development methods were included [Som11]:

The first phase is used for decision-making and can include different tasks depending on the starting point. An analysis of the AI potential should take place if no specific AI application has yet been defined, but the possibilities are to be considered in general. Here, examples of AI applications of other companies from their own industry or the analysis of the business model can be relevant. A feasibility analysis is the right step if the purpose of the AI use is already known, but there are technical uncertainties regarding sufficient data quality or accuracy of the AI.

A context analysis is essential when the analysis of potential has identified promising AI applications, but it is not clear which departments, processes, or data would be affected and what would need to be changed. This is basically where the company's readiness for AI implementation is examined. Budget estimation and potential suppliers or development partners

should also be explored in the process. The result of the first phase is the decision for which purpose and where AI should be introduced in the company.

The second phase is the specification of the operational integration and technical features of the AI solution. This also includes how these will be checked (evaluation). Operational integration is sometimes very simple (e.g., installing an AI component in a machine with no impact on processes), but often, it changes processes and places new demands on employees and the entire organization. This must be recognized early on and specified accordingly. The technical specifications for the development (functionality of the AI, specifications for accuracy and speed) should also be defined, especially if the solution is developed or delivered and installed by external parties.

The third phase is then usually the contracting and realization. Few companies will be able to develop the planned AI in-house, so contracting out is necessary. During realization, the company usually gets involved in the project regarding concretizing processes or providing data.

The final phase is acceptance and introduction. The defined properties from the specification phase can then be used to accept the AI solution. Likewise, the operational changes defined there help with their implementation.

3.1.5 The Artificial Intelligence Definition of this Thesis

This dissertation deals with the introduction of weak AI in companies in terms of rational agent theory. Universal AI is not accessible in the near future and may never be achievable [Leg08; Tho15; Jac18]. In addition, there are still no studies and approaches that deal with the introduction and benefits of universal AI in companies. The description of AI as a rational agent is not only used in AI research but is also suitable for describing AI in business. Rational behavior is based on a measurable criterion that can be used to evaluate the results. For use in companies, the measurability and the underlying heuristics can be useful for understanding the decisions made by AI. In business, these properties could ensure transparency and regulability [Arr+20; Doy05]. However, rational behavior can also lead to the emergence of bias, as formal descriptions of rationality are often used [NSR24]. In addition, a definition of AI can only serve as a basis for further descriptions of AI, as this definition only gives a rough insight into what the word AI entails. [Bit18].

3.2 Morphological Box

This section cites from [RS22]: The concept of a “Morphological Box” is based on work by Fritz Zwicky [Zwi69] as a creativity technique for product development. A MB is often used to solve

problems by combining (partial) solutions already available in other areas. The general approach is to logically divide the problem into different aspects that can be seen as parameters or features and to identify potential values for these features. [Zwi69]

The process of building a MB starts by exactly defining the problem or phenomenon under consideration (scoping). This is followed by selecting features that characterize the chosen phenomenon, which in the case of this thesis are the AI solutions currently available. All features must be explicit and should not interfere with or affect one another. The box is mostly depicted as a table. The features are noted down vertically and form the box' first column. At the same time, each feature has a row that captures the values that the feature can adopt. These values for each feature have to first be identified and must be specific and characteristic for the particular feature. All values are represented as columns for the features in their row. The result is a table with a specific number of rows (features) in the first column and a varying number of columns (values). [Zwi69]

Many applications of the MB are known and were the subject of publications. Some examples are the use as a tool for planning market innovations [SN12], identifying new electricity business cases [PL21], support of strategic decision-making [WR07], business model prototyping [SSL14], knowledge transfer in organizations [KG09], or business model creation [LH+11].

Problem Investigation and Requirements

The problem identification and motivation is the first step in the DSR process by Peffers et al. [Pef+07]. This research project also started with this step by investigating four local practices, i.e. AI development and integration projects of the chair for business information systems of the University of Rostock with different enterprises of various industries. As the goal of DSR is to solve a global problem, the problem must occur in more than one of the local practices. Furthermore, it has to be proven that no research exists that can already solve the problem. To investigate that, a knowledge base analysis including a SLR can be used to analyze the current body of knowledge and evaluate and compare existing tools, approaches, and methods.

This chapter investigates four local cases by summarizing and comparing them, identifying their differences and similarities. Thereby, a global problem statement can be derived from these local cases (section 4.1). After that, a SLR will be presented that analyzes the current body of knowledge regarding existing support for AI introduction in companies (section 4.3). This chapter concludes with the elicitation of requirements for an artifact that can tackle the global business problem while filling the research gap uncovered by the knowledge base analysis.

4.1 Investigation of Local Cases

The majority of this section is based on the papers [RS22] and [SR21] and uses direct citations from them:

The four local case studies were industry cooperations of the chair for business information systems of the University of Rostock with companies from different application domains. In these cases, AI solutions were developed and integrated into the companies. Table 4.1 summarizes the four cases, including their domains, for what AI was used and where more information about each case can be found (if available). The following subsections will describe and analyze these use cases in detail.

Case	Domain	AI solution	Literature
A	Clean room and air conditioning	Energy optimization on fleet-level; anomaly detection on facility level	This section
B	Financial industries	Fraud detection for instant payments	[DSM19]
C	Marketing	AI for Object Recognition and Marketing Support	[Rei+21]
D	Garden products	Forecast of transaction development; anomaly detection	[SR21]

Table 4.1: Analyzed industrial case studies

4.1.1 Case Study A

Case study A is an industrial case from Air Conditioning and Clean Room Technologies (ACT). The case study company is a medium-sized enterprise from Germany designing, developing, installing, and operating large ACT facilities. For energy optimization purposes and as a basis for predictive maintenance, additional sensors and control systems had to be integrated into the ACT facilities and connected to a network. This resulted in an Internet-of-Things (IoT) solution that formed the basis for new business services.

The complexity and scope of such systems are increasing more and more in the field of industry and public buildings. Inspections of air handling units in operation often reveal significant deviations from the assessed energy efficiency. In the course of automation as well as IC, the amount of data is increasing strongly. The direct and indirect processes involving air handling units can no longer be operated in an energy-efficient or optimal way without intelligent data processing. The need for system solutions for self-recognition and self-organized learning, and control of the systems is therefore high. AI solutions are capable of supporting this.

The envisioned IoT solution was supposed to implement diagnosis support of possible optimizations in air handling units, as well as for the operational processes of the case study company. In such a solution, it must be possible to process a large amount of data from different sources within the systems. The IoT solution had to be integrated into the case company's operational processes to support new types of services. In an ACT facility, different technical devices are installed that are integrated into a control flow and together provide the desired AC functionality. Examples of such devices are ventilators, recuperators, humidifiers, heating or cooling units, and air filters. Some of these devices were already equipped with sensors for capturing energy consumption, temperature, revolution speed, or other relevant parameters before the project started. Other devices were equipped with additional sensors during the development of the IoT solution. These sensors provide information that is evaluated at the facility level to determine energy consumption, anomalies, or error situations. ACT facilities can be grouped according to their functionality, which often corresponds to the type of buildings they were designed for and are installed in. The ACT groups relevant to the case study company were hospitals, manufacturing buildings, shopping centers, and educational organizations. For all ACT facilities within a group, evaluation of the collected facility-level

No.	Use Case	Required AI solution
1	Maintenance Support	Detection of unusual sensor values and anomalies based on rule set and knowledge base
2	Energetic Inspection	Detection of errors in control systems, errors caused by the operators, energy consumption exceeding usual patterns
3	Contracting	Economic evaluation if repair of facilities and required spare parts are recommendable
4	Dimensioning of new facilities	Evaluation of historic data for categories of ACT facilities to recommend dimensioning of new facilities

Table 4.2: Use Cases and AI Solutions in case A

information is relevant during planning and operations, e.g., for dimension planning, i.e., deciding on the required performance class. The use cases supported by AI solutions are summarized in Table 4.2.

4.1.2 Case Study B

Case study company B is a payment service provider offering various IT-based services for handling payment transactions for small and medium-sized banks. The company was among the first in Germany to process Instant Payment Transactions (IPT). Instant payment solutions usually consist of the scheme layer (end-user solutions for the market), clearing layer (arrangements for clearing of transactions between payment service providers), and settlement layer (arrangements for settlement of transactions). Company B provided clearing layer and settlement layer functions in combination with value-added services, such as fraud detection, sanction screening, and embargo checking. The case emerged when the company decided to explore the possibilities of AI use in IPT handling.

After a requirements analysis, the case study company performed a feasibility study that examined different AI-based solutions for detecting fraudulent transactions [DSM19] and how to integrate them into the existing Enterprise Architecture (EA). In the business architecture, the future roles expected to use the AI solution for instant payment fraud detection were identified. These roles are the ones who need to understand the decisions of the AI solution. The business process steps to be automated by the future AI components also had to be determined, and the related affected tasks of other processes were located, i.e., what process steps deliver input and need to receive output information.

In the information architecture, the focus was on the information required for fraud detection (and what applications or services provide or consume this information) and what information was missing. The required information for fraud detection was spread between different data sources (payment monitoring system, core banking system, customer transaction history). With this distribution onto different data sources, a new integrated data set was mandatory to allow for a high-performance implementation of the AI solution. Integrating

data “on the fly” would have required too much time. In the application and technology architecture, the applications affected by the new AI solution, because they provide or receive data, were identified.

4.1.3 Case Study C

Case study company C is a content-marketing enterprise specializing in the creation and distribution of online videos and in using these videos for marketing purposes. This company aimed at new business models exploiting the possibility to create interaction with the users and new innovative media formats. In particular, free online videos have a high reach in the advertising-relevant target group. Such videos contain several scenes and show mostly fashion-related content applicable to content-related advertising. For example, if a video shows a close-up of a male face wearing sunglasses, advertisements should be placed for these glasses. Therefore, knowing what kind of object is shown in the video is crucial for the service. Traditionally, the objects in videos were identified by manual “tagging” of the videos. This approach is labor-intensive and difficult to scale up due to the need to hire and train the workforce. Automatic image detection technologies can enable more efficient and cost-effective operations.

The case study company started to develop an innovative technological approach by combining a technique from the symbolic and approximate sub-disciplines of AI research [Rei+21]. The aim was to apply knowledge captured in an ontology to improve the object recognition process in videos, which was based on an artificial neural network and a DL approach. The ontology is supposed to capture the relevant knowledge for the application field of discovering fashion items in videos. This knowledge includes, e.g., a taxonomy of fashion items, environments suitable for specific fashion categories (mountain, skiing, outdoor), social contexts relevant to fashion categories (weddings, parties), and more. The ontology is also used to capture combinations of fashion items relevant for defined marketing purposes, e.g., the fashion for a particular target group. Each concept in the ontology has a corresponding classification model in the DL part of the system. This part comprises the DL management software component, providing access to the artificial neural network database containing available models.

From an organizational perspective, both the maintenance of the ontology, the continued training of the DL module, the integration of the automatic tagging into existing processes, and the development of new business services based on this platform had to accompany the implementation of the AI solution described above. From a technical perspective, the key task was the integration with the existing marketing and content distribution engine, which also included customer profiles, campaign management, and advertisements.

4.1.4 Case Study D

The industrial enterprise considered in case study D is a world-leading producer of outdoor power products, including chainsaws, trimmers, robotic lawnmowers, garden tractors, and watering systems. The company was in a transformation process where they saw it as a necessity to transform their business model in order to stay competitive and to deliver improved value to their stakeholders. This transformation basically moved from outdoor power products without communication and interconnectivity features to networked ones, which also involved new features based on AI. This changed the product development and deployment processes, and also the customer care, sales, and marketing departments. Figure 4.1 shows the areas of the EA-model that changed during the digital transformation process in the company.

As a result of the transformation, many products not only have built-in electronics or embedded systems but also features based on networking and communication capabilities. The built-in IT is, in many cases, used for controlling the different mechatronic components of the product and for collecting data when the product is in use, either performance parameters or used product features, or the environment of the product. The networking features are used for communicating usage statistics, license information, or location information (if anti-theft features are activated) to either the product owner or the back office of the manufacturer. The data collected by these new features is supposed to be used for detecting maintenance needs of the devices, new sales opportunities, and anomalies in functionalities indicating defects or optimization potential for internal functions (e.g., for energy consumption) – to name only a few examples. The garden owner can access services for operating, supervising, and planning garden maintenance using mobile devices.

Since many of the products offered similar functionalities regarding networking and communication, the process of digital transformation included the design and implementation of reusable services and components for either the “digitized” product or the back-office infrastructure, which comprises an IT and service architecture for the IT built into the physical product. Furthermore, data management services were implemented, including collections of time-series data and data warehouse-based services. [KSS21]

4.2 Derivation of a Global Problem Statement

All four industrial cases share similarities and differences. First, they show that AI is relevant to all kinds of industries and it can be applied to a plethora of different use cases, ranging from optimization to detection, forecasting, and support, amongst others. The same goes for the types of AI that were applied in the cases, like ontologies, DL, artificial neural networks, et cetera (etc.) The type of data required in each use case depended on the type of AI they applied. Existing data often serves as the basis for the development of the AI solutions. In all

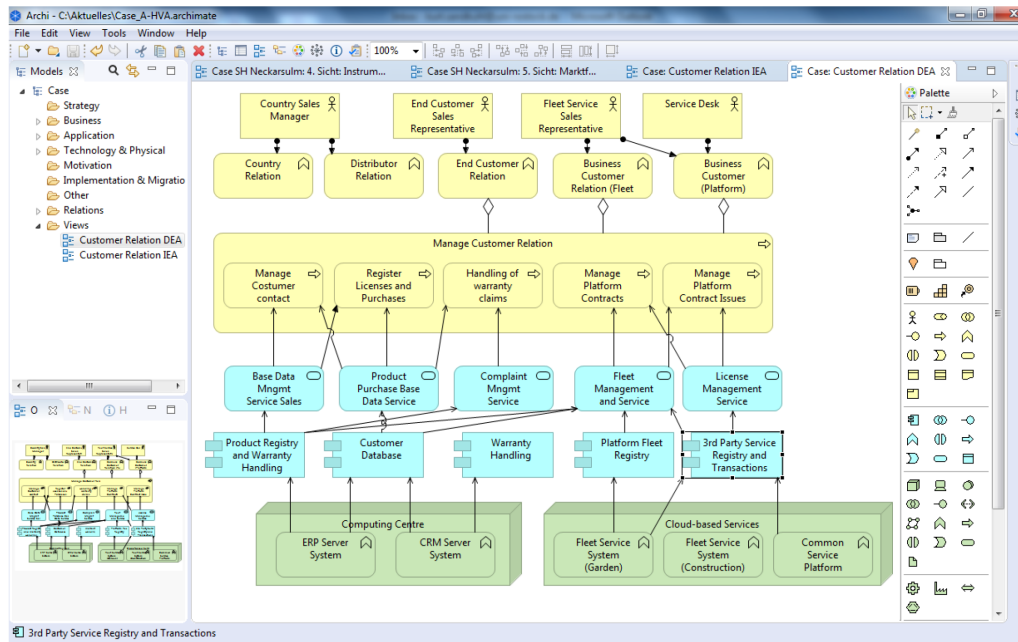


Figure 4.1: "Excerpt from EA-model of case D with focus on parts affected by digital transformation" from Sandkuhl and Rittelmeyer [SR21]

cases, the introduction of AI changed processes in and products/services of the companies. The problems that occurred during the development and integration of AI heavily depended on the specific use case, the situation of the company, the available resources, and the technology of AI that should be used. However, all companies struggled, e.g., with how to start the development and integration, which type of AI they should use, if their data will be enough (quantitative and qualitative), how the solution should be integrated into the company processes while securing the employees acceptance. In general, from the four local cases, the following global problem statement can be derived:

Global Problem Statement of this Thesis:

Companies want and sometimes have to use AI to stay competitive or gain an advantage over their competition. However, the application scenarios of AI vary as much as the goals behind its use (e.g. optimization, forecasting, detection) and the vast number of different AI technologies available. This, in addition to the specific characteristics of AI that differentiate it from classic software solutions, plus the intricacy of introducing new software solutions in companies in general, depicts the high complexity and various facets of AI introduction in companies. For practice, this complexity makes the integration and adoption of AI complicated and often comes with high risks. A reason for that is that practice lacks methodological support that can break down the complexity of AI and thereby support the introduction of AI solutions.

The analysis of the four local cases all showed similar problems, although sometimes in different shapes. From those similarities and differences, the global problem statement of this thesis was derived, marking the starting point of this research and showing its business rele-

vance.

To also ensure the scientific relevance, the next chapter presents a SLR that analyzed the existing knowledge base regarding artifacts that can tackle the global problem by reducing the complexity of AI and supporting its integration in companies.

4.3 Knowledge Base Analysis – A Systematic Literature Review

The goal of this chapter is to investigate the current knowledge base regarding the topic of this research. It is important to thoroughly search for relevant and similar research to ensure that this thesis contributes significantly to the scientific body of knowledge. The knowledge base analysis should further help to differentiate the research project from other research, show the research gap, and motivate its realization. To accomplish this goal, a SLR was conducted following the approach by Kitchenham [KC07] as described in section 2.2.2.

First, the scope, process, and goals of the SLR will be defined, including the RQs that should be answered (section 4.3.1). Section 4.3.2 will describe the iterative development of a search string to answer the RQs, followed by the paper selection process, which includes the definition of inclusion and exclusion criteria (section 4.3.3). The fourth step then covers the extraction and analysis of the data from the selected papers (section 4.3.4). This chapter concludes by defining the research agenda for the development of the MB based on the research gap and requirements identified by the SLR (section 4.3.5).

4.3.1 Step 1: Definition of the SLR Scope

As described before, this SLR aims to find existing scientific literature relevant to this thesis to analyze the current body of knowledge. Therefore, literature should be searched that contributes to the field of integrating AI in companies (RQ1). Especially relevant is research that focuses on methodological support for integrating AI, like frameworks, guidelines, or best practices, as this is the main problem that this thesis addresses. If such approaches can be found, how they compare and what problems or gaps still exist should be analyzed. Furthermore, relevant factors for AI integration that are defined should be collected as they can contribute directly to the development of the MB (RQ2). The same could apply to already existing categorizations of AI and their components. For further motivation of this thesis, it should also be reviewed if the literature includes information about challenges and problems of AI introduction (RQ3). However, this shall not be the main focus of the SLR. In conclusion, the following RQs can be determined:

- **RQ1:** What methodological support for AI introduction in companies exists in the literature?

- **RQ2:** Which relevant factors for introducing AI in companies does the literature specify?
- **RQ3:** What challenges and problems of introducing AI in enterprises does the literature describe?

4.3.2 Step 2: Literature Search

To answer the RQs defined in the previous section, a SLR was conducted in February 2025. First, for developing a suitable search string, the key areas for the search were defined. Then, synonyms for each area were collected. After that, the terms of the key areas were connected, and limitations were added to narrow down the number of results. Scopus was chosen as the database for the search because, according to Norris and Oppenheim, it is the largest scholarly database. [NO07]

As RQ1 and RQ2 are the most essential RQs to motivate this thesis, the focus was on finding as much relevant literature as possible to answer them. Because of that, the selected key areas for the search were "AI" and "company" as they together cover AI in companies. Furthermore, guidelines/frameworks/methods/etc. were added as the third area to cover the need for methodological support for introducing AI. To ensure that this area was connected to the topic of AI in the results, the two areas were connected with a word distance operator, initially allowing a five-word distance between the areas. To make sure that this is a paper's main topic, the search terms should be found in the title, abstract, or keywords and not only in the text. This led to the following initial search string:

TITLE-ABS-KEY (("artificial intelligence" OR "AI" OR "neural network" OR "neural networks" OR "machine learning" OR "ML" OR "deep learning" OR "DL" OR "intelligent system*" OR "large language model*" OR "LLM" OR "support vector machines") **W/5** (introduc* OR method* OR integrat* OR "framework*" OR "model*" OR "guideline*" OR "best practice*" OR "strateg*") **AND** ("company" OR "companies" OR "enterprise"))

Applying this search string to Scopus already delivered 20.045 results. Nevertheless, to be sure not to miss important literature, more synonyms were collected for the three key areas before starting to narrow down the results. As seen in the first search string, wildcards (in the form of the "*" symbol) were applied to the terms to find their different variations. With the added synonyms, the following query resulted in 162.555 papers:

TITLE-ABS-KEY (("artificial intelligence" OR "AI" OR "neural network*" OR "artificial neural network*" OR "machine learning" OR "ML" OR "deep learning" OR "DL" OR "intelligent system*" OR "large language model*" OR "LLM" OR "support vector machine*" OR "cognitive computing" OR "natural language processing" OR "NLP" OR "computer vision" OR "reinforcement learning" OR "expert system*" OR "predictive analytics" OR "data mining" OR "automated reasoning" OR "robotic process automation" OR "RPA") **W/5** (introduc* OR implement* OR adopt* OR deploy* OR integrat* OR "framework*" OR "model*" OR "guideline*" OR "best practice*" OR "strateg*" OR "roadmap*" OR approach* OR process* OR plan* OR method* OR methodolog* OR transition* OR transformation* OR readiness OR assessment* OR advisory) **AND** ("company" OR "companies" OR "enterprise*" OR "business*" OR "organization*" OR "organisation*" OR "firm*" OR "corporat*" OR "industry" OR "industries" OR "SME*" OR "small and medium-sized enterprise*" OR "startup*" OR "start-up*" OR "commercial" OR "private sector" OR "institution*"))

To narrow down the vast number of results, it was decided to only include papers with the search terms in their title and not in the abstract or keywords. This should guarantee that the results' primary focus is on methodological support, like a framework or similar terms. As planned, this drastically reduced the number of search results to 4.919.

To ensure the relevance to the research field and the currentness of data, the search was restricted to the field of computer science and research published after 2009. This year was chosen because the so-called AI boom started in the late 2010s. Thereby, this new search string resulted in 2.610 papers:

TITLE (("artificial intelligence" OR "AI" OR "neural network*" OR "artificial neural network*" OR "machine learning" OR "ML" OR "deep learning" OR "DL" OR "intelligent system*" OR "large language model*" OR "LLM" OR "support vector machine*" OR "cognitive computing" OR "natural language processing" OR "NLP" OR "computer vision" OR "reinforcement learning" OR "expert system*" OR "predictive analytics" OR "data mining" OR "automated reasoning" OR "robotic process automation" OR "RPA") **W/5** (introduc* OR implement* OR adopt* OR deploy* OR integrat* OR "framework*" OR "model*" OR "guideline*" OR "best practice*" OR "strateg*" OR "roadmap*" OR approach* OR process* OR plan* OR method* OR methodolog* OR transition* OR transformation* OR readiness OR assessment* OR advisory) **AND** ("company" OR "companies" OR "enterprise*" OR "business*" OR "organization*" OR "organisation*" OR "firm*" OR "corporat*" OR "industry" OR "industries" OR "SME*" OR "small and medium-sized enterprise*" OR "startup*" OR "start-up*" OR "commercial" OR "private sector" OR "institution*")) **AND** SUBJAREA (comp) **AND** PUBYEAR > 2009

After reviewing some titles and abstracts of the found papers, some search terms were deleted that seemed to produce results that were not relevant to the topic, like "advisory," "private sector," and "commercial." Additionally, the word distance was reduced the four to test how

much this would change the number of search results, leading to the next iteration of the search string:

TITLE (("artificial intelligence" OR "AI" OR "neural network*" OR "artificial neural network*" OR "machine learning" OR "ML" OR "deep learning" OR "DL" OR "intelligent system*" OR "large language model*" OR "LLM" OR "support vector machine*" OR "cognitive computing" OR "natural language processing" OR "NLP" OR "computer vision" OR "reinforcement learning" OR "expert system*") **W/4** (introduc* OR implement* OR adopt* OR deploy* OR integrat* OR "framework*" OR "model*" OR "guideline*" OR "best practice*" OR "strateg*" OR "roadmap*" OR approach* OR process* OR plan* OR method* OR methodolog* OR readiness OR assessment*) **AND** ("company" OR "companies" OR "enterprise*" OR "business*" OR "organization*" OR "organisation*" OR "firm*" OR "corporat*" OR "SME*" OR "small and medium-sized enterprise*" OR "institution*")) **AND** SUBJAREA (comp) **AND** PUBYEAR > 2009

Because many of the results still did not cover general approaches for AI integration, it was decided to split up the area of frameworks/integration into two separate areas: the introduction, integration, implementation, etc., on the one side and the methodology/artifact in the form of a framework, guideline, etc. on the other side. Hence, the following search string was developed:

TITLE (("artificial intelligence" OR "AI" OR "neural network*" OR "artificial neural network*" OR "machine learning" OR "ML" OR "deep learning" OR "DL" OR "intelligent system*" OR "large language model*" OR "LLM" OR "support vector machine*" OR "cognitive computing" OR "natural language processing" OR "NLP" OR "computer vision" OR "reinforcement learning" OR "expert system*") **W/4** (introduc* OR implement* OR adopt* OR deploy* OR integrat* OR readiness OR assessment*) **AND** ("framework*" OR "model*" OR "guideline*" OR "best practice*" OR "strateg*" OR "roadmap*" OR approach* OR process* OR plan* OR method* OR methodolog*) **AND** ("company" OR "companies" OR "enterprise*" OR "business*" OR "organization*" OR "organisation*" OR "firm*" OR "corporat*" OR "SME*" OR "small and medium-sized enterprise*" OR "institution*")) **AND** SUBJAREA (comp) **AND** PUBYEAR > 2009

This final search string delivered 114 results. Because this number was vastly lower than the earlier results, the title and, if necessary, the abstract were checked for each of the 114 papers. Because many of the results were highly relevant, and the majority seemed to be at least somewhat relevant or connected to the topic, this search string was chosen as the final one. The next step was to find the appropriate papers for the different RQs in the result set of papers.

4.3.3 Step 3: Paper Selection

To accurately identify relevant results for each of the different RQs, the following inclusion criteria were chosen:

- Includes an artifact that supports the introduction of AI in companies.
- Investigates the introduction of AI in companies.
- Discovers and explains success factors for introducing AI in companies.
- Discovers and explains problems that companies face with the introduction of AI.
- Examples for implementing AI in companies that describe the integration process and factors that were relevant to it.

Similarly, suitable exclusion criteria were determined:

- Uses AI to develop artifacts that help with specific business functions.
- Develops software that uses AI and does not describe the integration in the business.

With those criteria defined, each paper was read and checked thoroughly. In the end, 24 papers were deemed highly relevant to the topic and helpful to answer the RQs. The remaining papers often dealt with the development of artifacts or software that use AI to support specific processes or goals in companies, which is irrelevant to the RQs.

Because some relevant papers referenced literature not discovered with the search string that also seemed appropriate, an additional backward search was conducted for those papers. Thus, five additional papers were found.

4.3.4 Step 4: Data Extraction & Analysis

This section will answer the RQs by summarizing and analyzing the discovered papers. However, an overview of the discovered literature will be provided first.

Figure 4.2 shows that the amount of research about AI introduction in companies correlates with the so-called AI boom that started in the late 2010s. In 2017 and 2018, the number of published documents climbed for the first time and has continued to climb significantly since 2019. 2025 delivered only one paper because the SLR was conducted at the beginning of 2025. When looking at where the most research in this area happened, Figure 4.3 shows that India, Germany, and China delivered the most documents, followed by the United Kingdom, Malaysia, Sweden, and the United States. From Figure 4.4, it can be seen that more than half of the documents are from computer science and engineering. In contrast, more than six percent each come from mathematics, business and management, decision sciences, and social sciences.

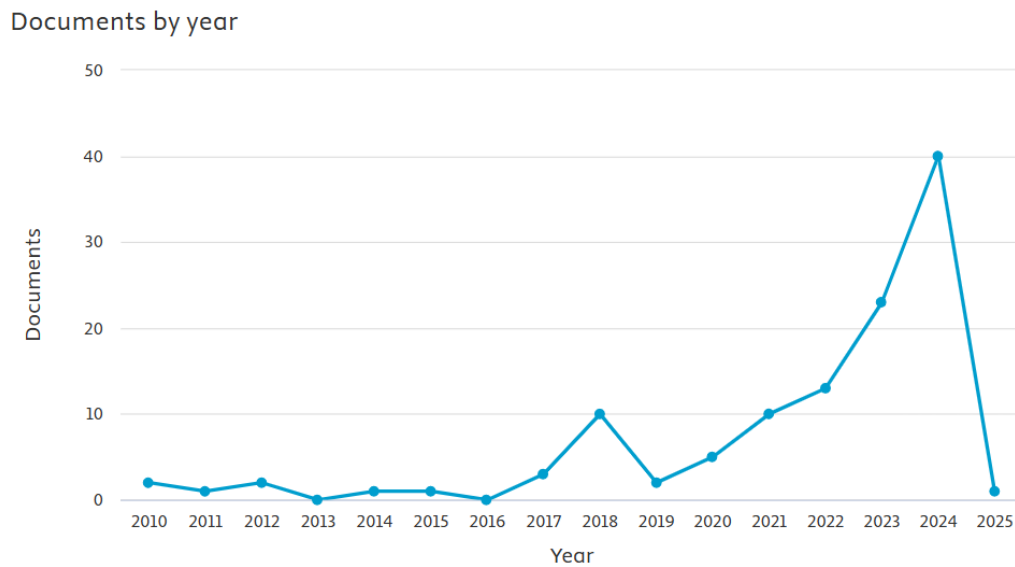


Figure 4.2: Documents published by year for the search string on Scopus

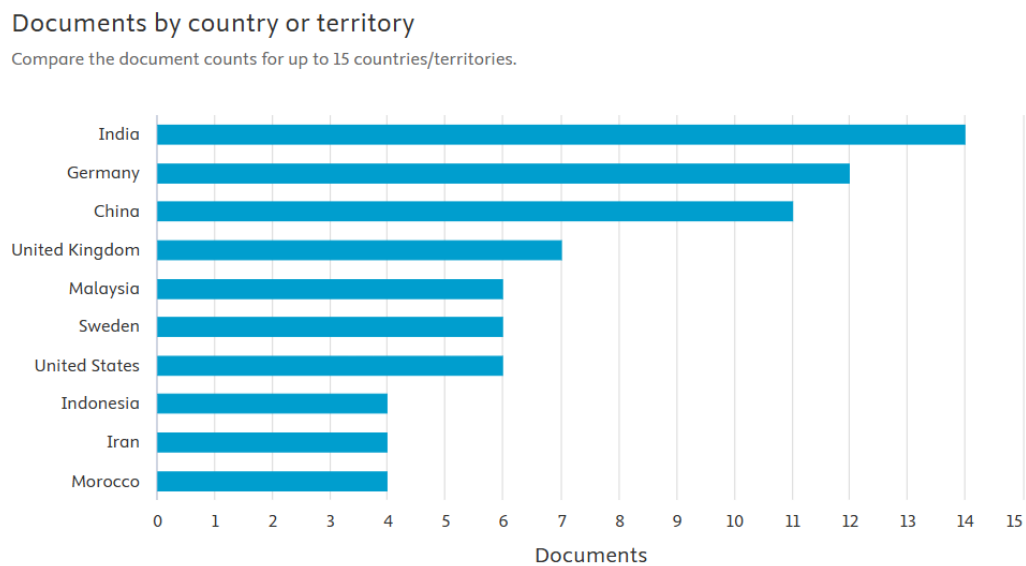


Figure 4.3: Documents published by country for the search string on Scopus

Paper	RQ1	RQ2	RQ3
[Ahm24]		X	X
[Esm24]		X	X
[SK+24]			X
[TLK24]	X		
[FKS24]	X		
[CKK24]			X
[ZC24]			X
[Den24]		X	X
[AV24]		X	
[Abu24]	X		
[BSB24]			X
[Smi+24]		X	
[CT24]		X	
[Son+24]	X	X	
[JC23]		X	
[Mir+23]	X		
[Hus23]	X		
[SWV21]	X	X	
[Asa+21]	X		
[RÆE20]	X		X
[NG20]	X		
[HOS20]	X	X	X
[San19]	X		
[TY19]	X		
[TY20]	X		
[Che+21]	X		
[FKS23]	X		
[YZJ18]	X		
[ASF23]	X		
[JWW21]	X		
[Lwa+19]	X		

Table 4.3: Identified literature mapped to their relevant RQs

Documents by subject area

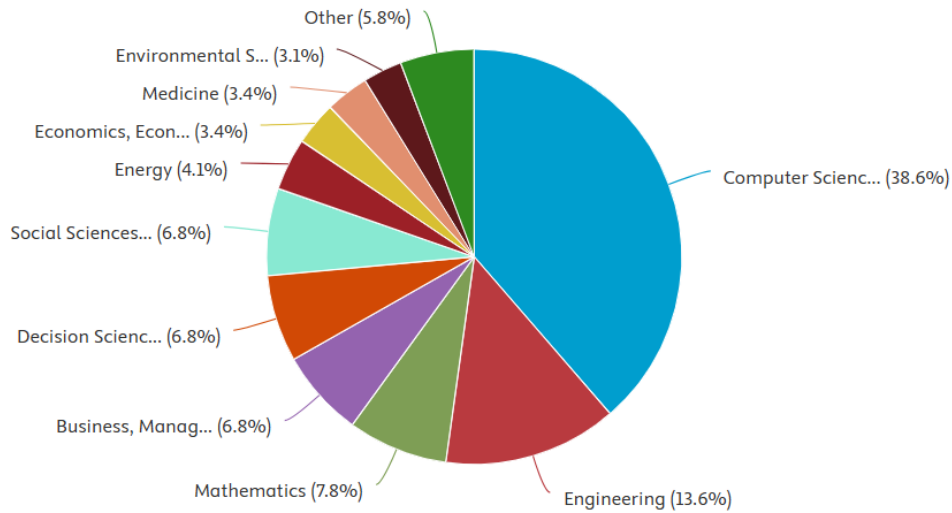


Figure 4.4: Documents published by research area for the search string on Scopus

Table 4.3 shows all relevant papers identified by the SLR and backward search. For each RQ, it is marked which paper includes information regarding it. One thing the majority of the papers have in common is that they acknowledge companies' need for support with introducing AI because of all the problems they still have to tackle, which often leads to the project's failure. The results regarding the defined RQs will be analyzed next.

4.3.4.1 RQ1: What methodological support for AI introduction in companies exists in related work?

Several papers investigated methods to support companies' introduction of AI. However, they were often very generic processes, including classic software development process steps, or only focusing on the technological side. Some others only concentrated on specific areas of AI, like the framework by Tchuente et al. [TLK24], that concentrates on explainable AI (see Figure 4.5). Other papers uncovered different approaches like the idea of reducing the chance of problems during the introduction process by making sure that the organization is as ready as possible for AI (AI readiness/maturity) or the use of Enterprise Architecture Management (EAM) methods to support AI introduction. The different approaches and findings will be summarized in this section.

Processes & Frameworks Tchuente et al. developed their framework based on 37 studies found by conducting a literature review. Their proposed process consists of the steps "business question importance, data collection, feature engineering, ML modeling and evaluation, models outputs (predictions), robustness checking and validation of explanations by relevant

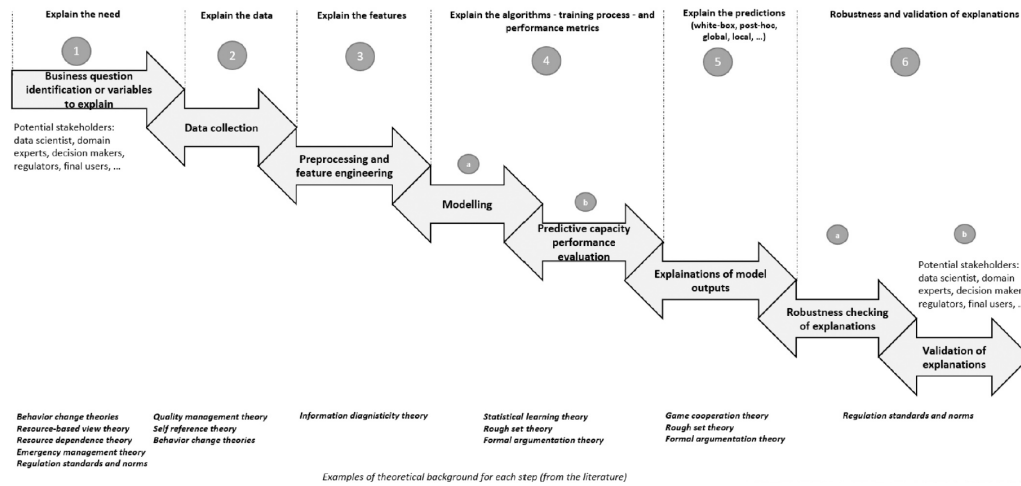


Figure 4.5: "Methodological and theoretical framework for ML model explanations" from Tchuente et al. [TLK24]

stakeholders," claiming that it can make "any decision-making process based on ML models" transparent and explainable. [TLK24] Similarly, Abuzaid designed a general five-step method for strategically integrating AI into the decision-making process of companies, with the steps being data acquisition, model development, decision implementation, ethical considerations, and alignment with organization goals. [Abu24]

Mirje et al. [Mir+23] focus on democratizing AI, which they describe as an approach to making the technology more inclusive for people from diverse backgrounds and striving for ethical goals while implementing and using AI, e.g., to "address societal challenges, and improve quality of life." They developed a framework for democratically adopting AI in organizations. The framework includes the following parts: "setting clear objectives, assessing the current data and AI technology landscape, promoting education and skill development, fostering collaboration, establishing ethical guidelines and governance, addressing policy and regulatory considerations, and securing funding and investment." [Mir+23]

Another rather general approach can be seen in [Hus23], where a recommended process for implementing AI is defined, and examples for when to better use generative AI or computer vision are provided. The approach's steps start with the identification of key business challenges, the definition of the company's objectives, the assessment of real-time data needs, the consideration of content generation needs, the evaluation of available resources, the planning for long-term scalability, and end with the exploration of industry-specific solutions, that maybe already exist. [Hus23]

Similar to Tchuente et al. [TLK24], many articles deduced their frameworks or methods from literature reviews like Reim et al.'s [RÆ20] roadmap that should guide the implementation of AI in a company's business model within four steps. However, the steps are again very general, like understanding AI, organizational capabilities (1), and the business model itself

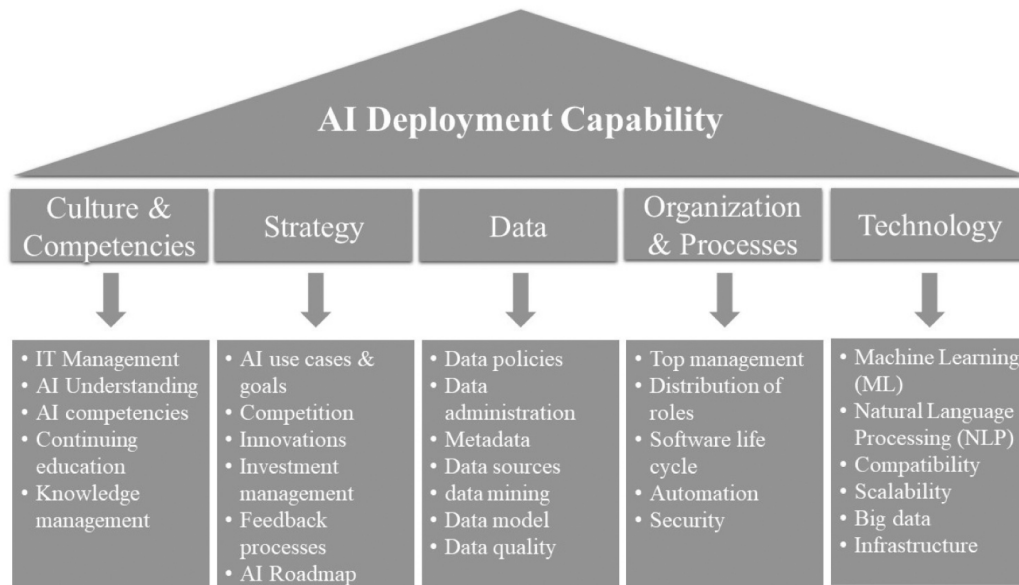


Figure 4.6: Dimensions and indicators of the AI MM from Sonntag et al. [Son+24]

(2), developing capabilities to be able to implement AI (3), and finally reaching organizational acceptance (4). [RÅE20]

AI Maturity Models A topic that does not directly discuss the implementation process of AI itself, but is highly connected to it because it also provides methodological support for the overall process, is AI readiness/maturity. The papers considering this topic often deal with the question of how it can be measured if a company is ready or mature enough for using AI and by which factors this can be determined.

For example, Sonntag et al. [Son+24] designed a MM for AI in manufacturing companies consisting of five maturity levels and five dimensions. For each dimension, they defined several indicators. The dimensions and indicators are depicted in Figure 4.6. It shows that, according to them, not only technical and data aspects but also social and organizational factors are relevant when preparing for AI introduction. Furthermore, for each indicator, they defined a question and an answer for each maturity level. Thereby, a company can choose a suitable answer from the provided ones to assess its maturity level. They weighed each indicator differently according to its importance. Because of that, they offer several formulas to calculate the maturity level for a company based on their answers. They developed the model from literature based on 81 papers and 11 existing AI MM and applied it to three company divisions. [Son+24]

Before Sonntag et al. [Son+24], Schuster et al. [SWV21] presented a general MM for AI. In 2021, they conducted a literature review to identify MMs for AI and discovered 15. However, only three were developed scientifically and holistically, according to the authors, because the remaining ones had, e.g., no empirical basis, lacked documentation, or could be seen as "con-

sulting offers of AI solutions by companies”. [SWV21] They compared the three MMs regarding their focus, dimensions, maturity stages, and purpose. They further summarized all dimensions found in the mentioned three models and three additional models. Based on their findings, they designed their own AI MM containing seven dimensions: (1) culture/mindset, (2) data, (3) ethics, (4) organization, (5) privacy, (6) strategy, and (7) technology across five maturity levels. [SWV21]

AI Readiness Similarly, Nortje and Grobbelaar [NG20] conducted two SLRs and developed an AI readiness model based on the literature with seven identified readiness dimensions: (1) employee and culture, (2) technology management, (3) organizational governance and leadership, (4) strategy, (5) infrastructure, (6) knowledge and information, and (7) security. It can be seen that many of the dimensions are the same or similar to the previously described MMs. Nortje and Grobbelaar then further defined several readiness elements for each dimension, like “job security” and “perceived ease of use” for “employee and culture” or “cloud resources”, “network connectivity” and “technology risk management” for “technology management”. For some readiness elements, they deduced readiness variables, like “identification and selection of cloud computing models” or “identification and satisfaction of requirements regarding cloud computing models” for “cloud resources.” [NG20]

In summary, AI readiness is the basis for introducing AI according to Jöhnk et al. [JWW21] Therefore, AI readiness shall be defined for this thesis. This thesis defines AI readiness as “the state of an organization in terms of willingness and ability of its stakeholders, and suitability of its environment, processes, data, and resources for adopting and operating AI” [Teh+24]. Accordingly, AI readiness characterizes the state of an organization and describes how ready and how capable the individual actors are for the introduction of AI. In addition, it is shown that AI readiness is a multidimensional concept that highlights various aspects of readiness.

A higher level of readiness increases the chances of successful innovation adoption and reduces the risk of failure. Accordingly, AI readiness is of crucial importance for the successful introduction of AI [JWW21]. Before organizations adopt a technology such as AI, it is recommended that a high level of readiness is achieved [Teh+24]. However, according to Jöhnk et al. [JWW21], AI readiness is not just a simple prerequisite but a foundation and an integral element of the entire AI adoption process. Therefore, it is not enough to achieve AI readiness just once before the introduction, as both readiness and the introduction are highly interdependent, mutually reinforcing, and dependent. A company should deal extensively with AI readiness before introducing AI and become ready, i.e., try to fulfill as many AI readiness aspects as possible [JWW21].

EAM Another approach that was discovered in five papers explored the field of supporting the integration of AI by using EAM and showing examples of its integration in the business

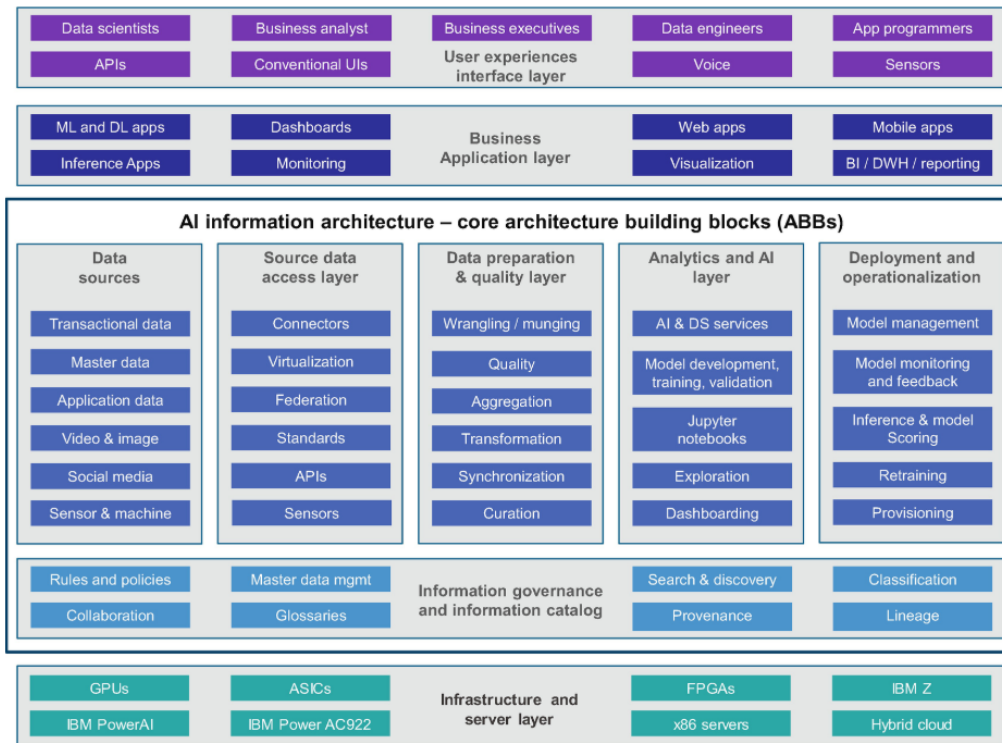


Figure 4.7: AI information architecture from Hechler et al. [HOS20]

(e.g., [FKS24]) or IT architecture (e.g., [HOS20]). Figure 4.7 shows the overview of the AI information architecture recommended by Hechler et al. [HOS20]. In that, AI can be found in several areas, like in the ML and DL apps on the business application layer as well as the newly designed core architecture building blocks, including a specified AI layer.

Moreover, they discuss further relevant topics in their book. They name three options for AI adaptation: (1) retraining an existing AI model, (2) adjusting an existing AI model, or (3) developing a new AI model. For monitoring the AI model, they recommend reviewing the AI model performance (via receiver operating characteristic and precision-recall), bias, and fairness of the AI models, and whether the outcome of the AI models is explainable. The outcome of the AI model should be interpretable, trustworthy, consumable, and accountable. [HOS20]

Two papers related to EAM were from Takeuchi and Yamamoto [TY19; TY20] and one from Sandkuhl [San19]. The following description of the papers cites from a SLR previously conducted by the author of this thesis and presented in [RS21]:

In the first paper from Takeuchi and Yamamoto, they use EAM in the form of the ArchiMate modeling language to develop a model that supports the development and implementation of AI service systems in companies. The model's objective is to mediate between the business and IT departments of a company so that they get a common understanding of development projects that the IT department completes for the business department. Ultimately, using their model shall reduce the risk of such projects' failure. They used ArchiMate for modeling to cover various application domains and the whole architecture of a company, including its

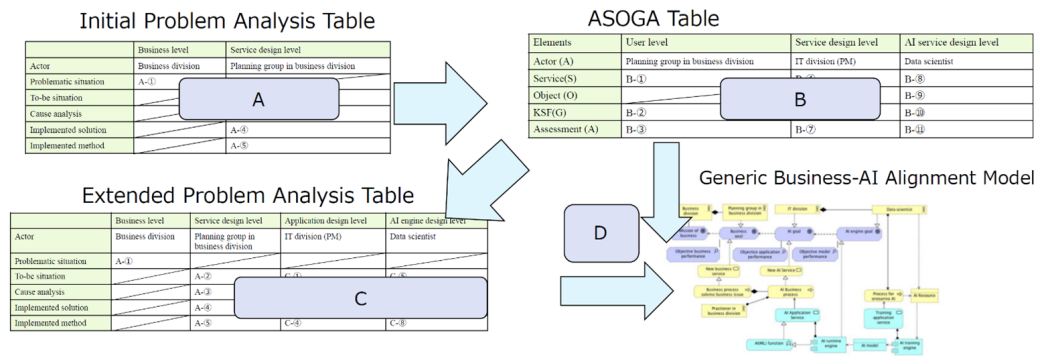


Figure 4.8: "Overview of the business analysis flow" from Takeuchi and Yamamoto [TY20]

goals, business elements, and main actors. The results were a goal tree for AI system functionality and an AI system development model with two views: The "Why-What-Who-View" answers the question "Why should we execute this process and who should lead this project?" The "Who-What-How-View" makes it easier for business division participants to understand how each process will be executed. The model was applied and tested only on project analysis results of one of their past projects, in which they developed a system containing AI technologies for an office environment. [TY19]

Based on their previous work described in [TY19], Takeuchi and Yamamoto created a generic business-AI alignment model using ArchiMate [TY20]. They propose a method for applying their general model to create project-specific models. Further, the application of the model and its method is shown in a case study where a system including ML technologies was developed. First, they introduce a generic business-AI alignment model based on their previous findings [TY19]. The model and its parts were explicitly created with a focus on the requirements of AI applications during the model development. To create the application method, they used different requirements tables [YOM18; Shu21] and adapted them for their purposes, e.g., the ASOGA table, which includes actors, service objects, goals, and assessment. After defining the tables, they propose a four-step method called "business analysis flow," showing how to apply it. In the first three steps, the three tables are filled out (see Figure 4.8). In the final step, the results are combined with their generic business-AI alignment model to create the project-specific model [TY20]. After reviewing their research, they identify the need for an "AI technology catalogue (e.g., API documents) with the input, output, and capability of each AI technology". The motivation for such a catalog is that they needed industry experts to decide which information extraction service to use for the project. With such a catalog, a data scientist would not be required anymore. [TY20]

In his paper, Sandkuhl [San19] discusses that the expectations of companies regarding hyped technologies like AI are often unrealistic. They concentrate mainly on the technology itself and not on the organizational context where the application will be used, leading to the failure of many AI projects because of data availability or process integration problems. Sandkuhl used a DSR approach to develop an AI context model and applied it in a case study. The AI context

model is a method component based on EAM that helps determine the organizational context of AI, thereby supporting feasibility studies and requirements analysis for AI applications. In the case study, the AI context model was applied to an instant payment project of a small German payment service provider. To apply the model, he used the company's EA model. They conducted three interviews with different payment service providers to elicit requirements for instant payment. The paper concludes that EAM approaches contributed to "illustrating the context model and establishing architectural thinking when preparing AI introduction" [San19].

The paper shows that contextualizing AI should include the layers represented in EA models and that AI should not be reduced to the actual technological approach. It further reveals the need for support for the planning and introduction of AI applications regarding the overall organizational context to prevent AI projects from failing.

Requirements Engineering The last approach identified is the idea of using requirements engineering for integrating AI. The following passage by the author of this thesis is cited from [SR21]: A taxonomy for requirements engineering of AI applications has been proposed by [BVC19] that builds on [Lwa+19] and elaborates on challenges during the requirements engineering activities, elicitation, analysis, specification, validation, management, and documentation. Each activity divides the challenges into data, model, and system challenges. These challenges are:

- Elicitation: availability of (large) datasets; lack of domain knowledge required for the model; undeclared consumers of AI application results
- Analysis: imbalanced datasets; data silos; no trivial workflows to be supported
- Specification: data labeling is costly, minimum viable model, and end-to-end pipeline support
- Validation: training data critical analysis; various data dependencies; entanglement of aspects in the model; high scalability issues for ML

Summary Overall, the findings of the SLR have shown that many researchers agree on the need for methodological support for AI introduction in companies. However, they tackle the problems from different viewpoints. Some try to determine applicable process models that mainly concentrate on technological aspects. Others integrated social or organizational aspects into frameworks as they recognized their relevance for introducing AI. Techniques from EAM and the idea of AI readiness or maturity are used to analyze the current as-is situation of companies and thereby find possible stepping stones before trying to integrate AI.

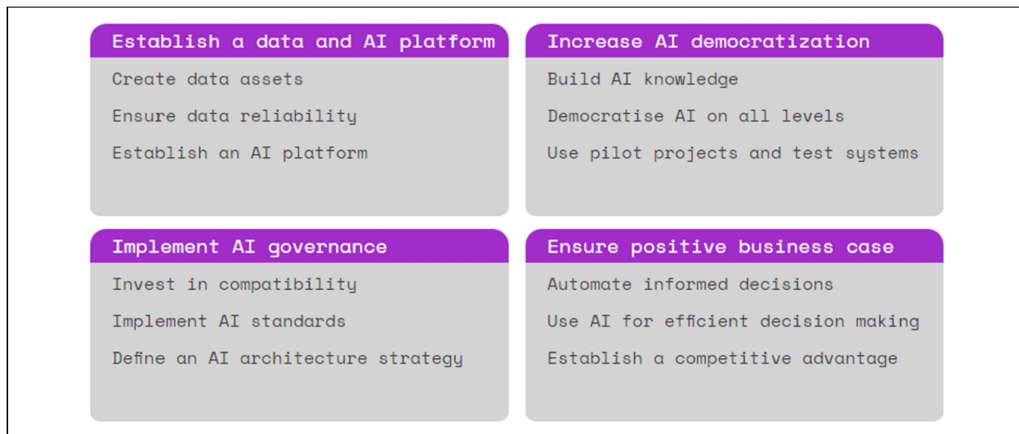


Figure 4.9: "Technical enabling factors to support AI adoption" from Smit et al. [Smi+24]

4.3.4.2 RQ2: Which relevant factors for introducing AI in companies does the literature specify?

This section summarizes the most relevant statements in the papers regarding factors for introducing AI.

Smit et al. [Smi+24] investigated precisely the question of which technical factors companies should consider. They acknowledge the existence of social or organizational factors but want to focus on the technical ones first, as they are more important in their eyes. Figure 4.9 summarizes their identified factors grouped into four main factors named by technical AI experts they consulted. Interestingly, the factors resemble process steps that sound like method support similar to some approaches presented in the previous section, like "democratize AI on all levels" or very general recommendations, like "establish an AI platform." [Smi+24]

Cioch et al. [CKK24] developed a fuzzy logic model that detects if there are potential social or technical risks in an enterprise when implementing new technologies, like AI, based on specific input factors. The model was assessed with expert knowledge and worked as planned. The input factors they deduced from the literature are shown in Figure 4.10. [CKK24]

Jankovic and Curovic [JC23] analyzed AI adoption in 240 SMEs in Serbia, confirming their thesis that the key factors positively influencing the adoption of AI in those kinds of enterprises are the number of AI applications already existing, investments in AI infrastructure and the share of employees trained for the use of AI. They further emphasized the importance of data ethics, data security, and regulatory compliance as factors for AI introduction. [JC23]

Akramov and Valiev [AV24] conducted a literature review focused on ethical and regulatory principles that are relevant to AI. They named fairness, transparency, accountability, and privacy the most important ethical aspects, and that the goal should be to prevent ethical dilemmas, like algorithmic bias, discrimination, and unintended outcomes, by taking them into

No.	Factors
1	Adequacy of quality indicators (for a specific production system)
2	Fear and uncertainty about replacing humans with robots on the job site
3	Ability to maintain co-bot infrastructure
4	Level of research on enterprise production systems
5	Compatibility with existing systems
6	Experience from previous implementations/changes in the enterprisec
7	Level of understanding of the technology (Clarity and comprehensibility)
8	Cost of implementation
9	The level of training and support for employees during and after the changes are implemented

Figure 4.10: Factors for implementing AI collaborative robots in manufacturing deduced from literature by Cioch et al. [CKK24]

account. Regarding the legal side, data protection, intellectual property, liability, and discrimination would be the major topics. [AV24]

Denni-Fiberesima [Den24] discovered the following ten critical success factors for AI adoption: "strategic assessment, data governance, risk management, infrastructure, human-AI collaboration, continuous innovation, deep industry knowledge, core process proficiency, digital literacy, data visualization, and analytical skills." [Den24]

According to Esmailzadeh [Esm24], relevant factors are model accuracy, data quality, liability, ethics, human capital, transparency, quality control, continuous monitoring, security standards, learning how to use AI, and a supportive environment (employee training), cybersecurity, hardware upkeep, and software maintenance. [Esm24]

Ahmad also emphasizes the relevance of ethical principles and to prevent algorithmic biases, legal and regulatory restrictions, data privacy and security, as well as to provide training and resources for workers who will be using AI. [Ahm24]

Cheng and Tajdini [CT24] tested several hypotheses in a survey study with 226 respondents. Relevant to this thesis is that they showed that a company's top management support and normative pressure positively relate to the company's AI adoption intensity. [CT24]

Age, gender, and education have an impact on the intention to use AI of a person, according to a survey with over 200 respondents by Bisht and Sengupta [BSB24]. They speculate that the younger generation is more open to new technologies because they grew up in a more digital environment. [BSB24]

Additionally, the dimensions of the various AI MMs and readiness factors can be seen as relevant aspects for introducing AI. Thereby, culture/mindset, data, ethics, organization, privacy, strategy, and technology can be deduced from Schuster et al.'s MM [SWV21] and culture

& competencies, strategy, data, organization & process, and technology can be found in the MM by Sonntag et al. [Son+24]

As the literature analysis shows, many technical, social, and organizational factors can be determined that can influence the introduction of AI in companies. However, it was not the primary goal of the search string to answer this question. Nevertheless, many results showed how relevant it is and that even more would presumably be found if one specifically searched for it.

4.3.4.3 RQ3: What challenges and problems of introducing AI in enterprises does the literature describe?

The challenges and problems of introducing AI heavily motivate this thesis. Therefore, while consulting the literature for methods to help with that, the problems and challenges were also summarized briefly. Luckily, many of the papers named several problems that motivated their research.

For AI in healthcare, Esmailzadeh [Esm24] determines production timelines, trust generation, privacy concerns, algorithmic biases, data scarcity, and cultural shift/the change in work culture as the main challenges. The employees should be motivated to see AI as an enabler, not a threat. [Esm24]

Sharma [SK+24] mentions data privacy and ethical concerns, and Ahmad [Ahm24] mentions the integration with existing systems as a relevant problem.

Nortje [NG20] identified the following problems for AI: transparency, a lack of trust for AI among employees, analog processes, and a misunderstanding of AI.

Zheng and Chen [ZC24] determined risks for AI introduction in education and calculated risk probabilities and the degree of influence for each risk. All risks are summarized in Figure 4.11. Not all risks apply to businesses, but some do, like health or data management risks. [ZC24]

As the results show, the problems are often not just technical but also social acceptance from the employees, as well as legal and ethical requirements that can hinder the introduction.

4.3.5 Step 5: Implications for a Morphological Box for AI Solution Integration

By conducting a SLR following the approach by Kitchenham [Kit04], the knowledge base was analyzed, and the RQs for the SLR were answered. Regarding the overall research goal of this thesis, the main findings from the SLR can be summarized as follows:

Primary indicator	Secondary indicator	Tertiary index
The health risks of teachers and students	Physical health risk A1	Technical dependence or fear
		Ego loss
	Mental health risk A2	Self-worth
		The autonomy personality is blocked.
	Social adaptation risk A3	Decreased interpersonal skills
		Decline in innovative learning ability
	Moral health risk A4	Reduced self-determination
		Moral apathy
		Vandalism
		Professional moral boundary consciousness is weakened.
Vocational risk	Occupational Literacy Risk B1	Occupational liability is reduced
		Teachers' education skills are weakened.
		In the process of teaching, accidents occurred.
	Occupational development risk B2	The employment polarization is serious.
		Collective power weakening
Education ethics risk	Emotional ethics risk C1	Affective dilution
		Human care deficiency
	Ethical risk of relationship C2	The trust crisis between teachers and students
		The main body weakens the education function.
	Technical ethics risk C3.	Technology sets against the idea of a person.
		Technical decision deviation and bias
	Resource service risk C4	Resource service privacy leaks
		Resource service information distortion
Education management risk	Education data management risk D1	Misacquisition of data
		The data is not clear.
	Education system governance risk D2	The subject of legal liability is blurred.
		Fuzzy legal liability boundary

Figure 4.11: Risks of introducing AI in education from Zheng and Chen [ZC24]

- SLR Finding 1: Companies have problems with the introduction of AI.
- SLR Finding 2: Existing methodological support either concentrates on technological aspects, is rather general, or focuses on analyzing a company's current situation (readiness/maturity).
- SLR Finding 3: Factors influencing the introduction of AI can be found in the literature.
- **SLR Conclusion:** Suitable methodological support for AI introduction is required.

Together with the studies and reports described in chapter 1 these findings show the problem that companies have with the introduction of AI. The continuously growing research on methodological support shows the need for such an artifact that can support the introduction and help with understanding the different facets of AI. This indicates the first step in the DSR process by Peffers et al. [Pef+07] (see section 2.1.1.1).

The next step in the DSR process is the definition of objectives for the planned solution and its development, which will be explained in the next chapter.

4.4 Requirements for a Morphological Box for AI Solution Integration

The problem identification and knowledge base analysis presented in the previous sections as well as the studies summarized in the introduction (see section 1.2) showed the business and scientific relevance of this research project. The next step in the DSR process by Peffers et al. [Pef+07] after the problem identification and motivation is the definition of objectives for the solution. Therefore, this chapter deduces requirements for an artifact that tackles the explicated problems by reducing the complexity of AI, thereby enhancing its understandability and ultimately supporting the integration of AI solutions in companies.

As explained, the main business problem that this thesis emerged from is that companies still struggle with introducing AI solutions for several reasons. The main reason is the complexity of AI and its application, including the lack of knowledge about the technology AI and its different characteristics. To help companies, an artifact should be developed that gives an overview of the distinct attributes of AI to reduce its complexity by breaking it down into its different areas, i.e. features, so that no critical aspect will be forgotten during the development and integration process. Visualization can make information more tangible and accessible. Visualizing complex connections can also make it easier to understand these relations compared to a textual explanation. This circumstance should be utilized for a complex topic like AI. In conclusion, for such an artifact, it was of the highest importance that it:

1. Summarizes the most critical features during the introduction of AI.
2. Can visualize those features to make it easier for users to understand and comprehend.
3. Should be easy to use and understand.
4. Should not only name the most critical features but also provide possible values for each feature that the users can choose from for their own project.
5. Should be easy to adapt to new advances (e.g., technological, social, legal) because AI is a very fast developing and changing technology. In the future, new aspects could always become relevant, or existing ones could become irrelevant or self-evident. Hence, the artifact will also arguably never be ultimately "finished."

The SLR showed that no such artifact currently exists, despite different efforts to develop methodological support for AI introduction. As explained, those efforts mainly embraced process models or frameworks that often only focus on one specific aspect, like technology. Additionally, the artifact that should be developed could not only be used in business to help with AI integration but also in research as a taxonomy to structure or explain AI applications. Thus, the application context of the artifact lies in business as well as in science. The SLR further indicated that the literature provides information about relevant aspects for AI integration that can be used to develop such an artifact.

However, those are not all requirements for such an artifact. According to Peffers et al. [Pef+07], additional concrete requirements will come up automatically during the development and its application. In this thesis, new requirements were identified during nearly all evaluation steps, including interviews, surveys, and the application of the artifact by a company.

When considering the requirements and already existing approaches to the topic, different scientific artifacts could have been chosen to tackle the problems. A method, e.g., would have been a well-established option. A method could have helped, especially in the form of a reference model or similar recommended process model for integrating AI solutions. However, the integration processes of AI can be very different depending on the organization and their desired solution when examined closely, making it complicated to find a generally recommendable process. However, if the processes were abstracted, it would certainly be possible to find generally valid recommendations. But it is doubtful whether these would differ from existing general software or AI-related development processes or recommendations, as one would then be back at a very abstract level.

Another artifact is a taxonomy, a classification schema for classifying information or objects according to specific criteria. Taxonomies provide a systematic way to group related elements, making it easier to understand the relations between the elements and the overall topic. A MB

can be seen as a special form of a taxonomy that focuses on the goal of breaking down a problem into many smaller problems that are then easier to understand and solve. Thereby enhancing the understandability of the topic of the MB and the relations between its elements. The author of this thesis argues that the artifact type *MB* is therefore appropriate to fulfill the requirements and that it is able to solve the global problem defined earlier, as its main goal is to reduce the complexity of the topic it summarizes. In comparison to a method, a MB does not require the definition of a clear process that has to be followed that covers all possible cases. It offers the possibility to include all the various facets of AI and comprise them in a single, easily understandable artifact, mostly in the form of a two-dimensional table. This also fulfills the requirement of visualizing the area of AI, thereby making it easier to get a first general overview of the topic. A MB can act as a structuring aid that includes the features that are relevant in every AI integration project, while it also provides values for all features that can differentiate between all projects. Thereby, it is able to depict the similarities as well as the differences of AI projects as shown in the local cases in the previous section.

As described in section 3.2, the first step in designing a MB is the scoping, which is accomplished by this section in combination with section 1.2, chapter 4.3 and this chapter. The next step in the process is the identification and selection of features and values for the box. The following chapter presents the MB for AI solution integration developed and evaluated in this research project.

A Morphological Box for AI Integration

The artifact of this thesis, the MB for AI integration, was developed over a plethora of application and evaluation episodes. In this chapter, the development of the first version of the MB based on the four industrial use cases presented in the previous chapter will be explained in detail (sections 5.1.1 and 5.1.2). Additionally, this chapter will precisely define the final version of the MB in the scope of this thesis (section 5.2). The evaluation episodes between the first and the current version of the MB will be presented in detail later in chapter 7, explaining how and why the box changed after each evaluation step. Finally, business and scientific use cases for the MB will be discussed (section 5.2).

5.1 Overview of the Morphological Box and its Features and Values

This section will first present and explain how the initial set of features and values of the MB was deduced from the previously described industrial cases to create the first version of the MB. After that, the final version of the MB will be shown, and new as well as reworked features and values will be defined.

5.1.1 Conceptualization of a Morphological Box for AI Solution Integration

The majority of this and the next section is based on the papers [RS22] and [SR21] and uses direct citations from them:

The initial features and values of the MB were deduced from the four case studies presented in section 4.1. In these cases, AI solutions were developed and integrated into the companies.

Feature	Values					
Computing source	cloud	local	device	hybrid		
Maturity	COTS	Commercial components	Open source components	Individual		
Special hardware required	Computing	Data capture	Data visualization	Data output		
Data source	Own data	Open data	Commercial collection	Synthetic data		
Data and model update frequency	Continuously	None	In case of changes in regulation	In case of quality problems		
Time to decision	Real-time	Near real-time	Several hours	Not time critical		
Primary data type	Audio	Video	Raster image	Vector image	Transaction records	Time series data
Primary purpose	assistance	decision making	forecasting	classification	anomaly detection	
AI use in solution development	Design time	Runtime	Accompanying runtime	Hybrid		
AI focus	Processing input	Generating output	Computing task			
Extent of effect on enterprise	Isolated solution	Effect on single process	Complete process	Work system	Business model	
Reliability and precision of results	100% required	Defined by enterprise	Defined by domain			

Figure 5.1: Initial version of the MB for introducing AI solutions (VI)

These cases were chosen for analysis specifically because they each showed different features of AI solutions (see Table 4.1).

In all case studies, documents, minutes of meetings, and interviews with company representatives were collected, and field notes were taken when working with the companies on models of processes, information structures, business models, and other relevant information. The material dealt with the situation before making changes to products and services. This information provided the first features and values for the MB.

5.1.2 First Version of the Morphological Box

The analysis of the industrial cases for characteristics and features included the analysis of decision criteria for introducing AI, configurations of solutions, general functionalities, and features of the application cases (see section 4.1). As a result of the analysis, the following features were identified:

- **Computing source** describes where the data processing and execution of AI algorithms physically takes place. For use case B (fraud detection), this needed to be the local computing center of the enterprise; for case D, it was mandatory to do the computing in the cloud, as some customers required this. Some applications in case A required computing on the actual device used in the process.

- **Maturity** refers to what extent the solution is a standard product or has to be developed from scratch for the requirements of the case. All cases preferred Commercial-of-the-Shelf (COTS) products, which were mostly unavailable. This is why collections of configurable components were accepted.
- **Special hardware required** describes the need for computing equipment or data capturing devices that deviate from established IT infrastructures in enterprises.
- **Data source** defines the origin of the data used for developing the model or training the algorithm underlying the solution. This could be publicly available data, such as in case C, private data from the enterprise (case A), or synthetic data.
- **Data and model update frequency** describes the expected time between developing the model or training the AI solution and having to update it due to changes in the domain.
- **Time to decision** describes the required time frame until the result of the AI solution has to be available (e.g., the decision it proposes), i.e., the time between a business event triggers the use of the solution until the result is computed. In case A, the decision was needed in close to real-time; in case D, there were scenarios where it would be sufficient several hours later.
- **Primary data type** describes the data the AI solution's functionality is based on: audio, video, images, time series, or transaction records.
- **Primary purpose** aims at characterizing the core functionality. From the cases, assistance to human actors, decision-making, forecasting, classification, and anomaly detection were identified.
- **AI use in solution development** denotes whether the AI is used during the design time of the overall solution, during run-time, accompanying run-time, or hybrid.
- **AI focus** helps the prospective users to understand the type of AI. Here, the values would be functionalities for processing information input (speech processing, image processing, text processing, ...), generating output (speech generation, text generation, image generation, ...), or the actual computing task.
- **Extent of effect on enterprise** describes if the AI solution replaces only isolated tasks or machinery without affecting the neighboring processes, is changing complete processes, work systems, or business functions, or is changing large parts of / the full business model.
- **Reliability and precision of results** of the AI solution: Should the results always be 100% correct, or could a lower level of precision and correctness also be acceptable? This could be defined by the enterprise itself or external factors.

Starting from observing recurring features of established AI solutions, the author developed the MB. The MB in this first state had several limitations and required more work. The development was primarily based on only four industrial cases, and the features visible in these cases or reflected in discussions with stakeholders related to these cases. More features were arguably expected to emerge when enriching the empirical base with additional cases, expert interviews, or literature analysis. The same is true for the values identified for the different features. At this point, the list of values could be expected to be complete only for a few features. Furthermore, the features needed to be analyzed for interference with each other and the values for completeness and potential overlaps.

Overall, this was just the initial version of the MB. The following section will define the current "final" version of the MB in the scope of this thesis ("final" because the MB will never be finished completely, as explained in the previous section).

Table 5.1 and Table 5.2 depict the iterations of and changes in the MB after each evaluation episode, from the initial to the newest version. More information about why the MB changed in which way after each evaluation will be explained in the corresponding evaluation section (see "Source" column in Table 5.1 and Table 5.2).

5.1.3 Final Version of the Morphological Box

The final version of the MB was developed over a number of iterations, summarized in Table 5.1 and Table 5.2 from the initial version presented in the previous section. Figure 5.2 shows the MB's final version in the scope of this thesis. Some of its features and values were already present in the initial version, and some were newly added or changed over the evaluation episodes. The final features of the MB are defined as follows:

- **AI Focus** helps the prospective users to understand the type of AI. Here, the values would be functionalities for processing information input (speech processing, image processing, text processing, ...), generating output (speech generation, text generation, image generation, ...), or the actual computing task. Nothing was changed for this feature.
- **End-User IT-Knowledge** and the following feature shift the focus of the planning process for an AI solution on thinking about the end-users of the solution. How much do they know about IT? How well can they handle it? According to that, the AI solution and its user interface and experience have to be designed. This applies not only to the users but also to maintenance personnel. Maintenance would always be necessary if there were no human end-user.

CHAPTER 5. A Morphological Box FOR AI INTEGRATION

Morphological Box						Version	Source	
Feature	Values					V1	Case studies and author's knowledge	
Computing source	cloud		local		device			hybrid
Maturity	COTS		Commercial components		Open source components			Individual
Special hardware required	Computing		Data capture		Data visualization			Data output
Data source	Own data		Open data		Commercial collection			Synthetic data
Data and model update frequency	Continuously		None		In case of changes in regulation			In case of quality problems
Time to decision	Real-time		Near real-time		Several hours			Not time critical
Primary data type	Audio	Video	Raster image	Vector image	Transaction records			Time series data
Primary purpose	assistance	decision making	forecasting		classification			anomaly detection
AI use in solution development	Design time		Runtime		Accompanying runtime			Hybrid
AI focus	Processing input		Generating output		Computing task			
Extent of effect on enterprise	Isolated solution		Effect on single process		Complete process			Work system
Reliability and precision of results	100% required		Defined by enterprise		Defined by domain			
Feature	Values					V2.1	Expert interviews (section 7.1)	
Computing Source	cloud		Local computing center		End-device			hybrid
Maturity	COTS		Commercial components		Open source components			Prototype
Special Hardware Required	Computing		Data capture		Data visualization			Data output
Data Source	Own data		Augmented Data		Open data			Commercial collection
Data Quantity								
Data Quality								
Data Security								
Data and Model Update Frequency	Continuously	In case of changes in regulation	In case of new documents / data	In case of changes in customer behavior	In case of quality problems			None
Ease of Use								
Time to Decision	Real-time	Near real-time		Several hours	Not time critical			
Primary Data Type	Audio	Video	Raster image	Vector image	Transaction records			Time series data
Primary Purpose	Assistance	Decision making	Forecasting	Classification	Anomaly Detection			Context & Content Understanding
Point in Time of AI Use in Solution development	Design-Time	Runtime		Accompanying runtime	Hybrid			
AI Focus	Processing input		Generating output		Computing task			
Extent of Effect on Enterprise	Isolated solution		Single process	Workflow	Work system	Business model		
Added Value								
Reliability and Precision of Results	~ 99,9 % Required		Defined by Enterprise		Defined by Domain	Defined by Competitors		
Communication								
Feature	Values					V2.2	Literature (section 7.1)	
Computing Source	cloud		Local computing center		End-device			hybrid
Maturity	COTS		Commercial components		Open source components			Prototype
Special Hardware Required	Computing		Data capture		Data visualization			Data output
Data Source	Own data		Augmented Data		Open data			Commercial collection
Data Quantity	Very High		High		Moderate			Low
Data Quality	Excellent		Good		Fair			Poor
Data Security	High		Moderate		Fair			Low
Data and Model Update Frequency	Continuously	In case of changes in regulation	In case of new documents / data	In case of changes in customer behavior	In case of quality problems			None
Ease of Use	Intuitive		Intermediate		Technical			
Time to Decision	Real-time	Near real-time		Several hours	Not time critical			
Primary Data Type	Audio	Video	Raster image	Vector image	Transaction records			Time series data
Primary Purpose	Assistance	Decision making	Forecasting	Classification	Anomaly Detection			Context & Content Understanding
Point in Time of AI Use in Solution development	Design-Time	Runtime		Accompanying runtime	Hybrid			
AI Focus	Processing input		Generating output		Computing task			
Extent of Effect on Enterprise	Isolated solution		Single process	Workflow	Work system	Business model		
Added Value	Significant benefits & improvements		Some benefits & improvement		Minimal benefits & improvement			
Reliability and Precision of Results	~ 99,9 % Required		Defined by Enterprise		Defined by Domain	Defined by Competitors		
Communication	Frequent & detailed, active collaboration		Regular, some collaboration		Minimal, min collaboration	None		
Feature	Values					V3	Rework of interview results (section 7.1)	
Computing Source	Cloud		Local computing center		End-Device			Hybrid
Maturity	COTS		Commercial Components		Open Source Components			Prototype
Special Hardware Required	Computing		Data Capture		Data Visualization			Data Output
Data Source	Own Data		Augmented Data		Open Data			Commercial Collection
Data Quantity	Very High		High		Moderate			Low
Data Quality	Inconsistent		Duplicate		Incomplete			Outdated
Data Security	Compliance		Data Encryption		Access Control			Data Integrity
Data and Model Update Frequency	Continuously	In Case of Changes in Regulation	In Case of New Documents/Data	In case of Changes in Customer Behavior	In Case of Quality Problems			
End-User	IT-Expert		IT-Savvy		No IT-Knowledge			
Time to Decision	Real-time	Near Real-Time		Several Hours	Later			
Primary Data Type	Audio	Video	Raster Image	Vector Image	Transaction Records			Time Series Data
Primary Purpose	Assistance	Decision Making	Forecasting	Classification	Anomaly Detection			
Point in Time of AI Use in Solution Development	Design-Time	Runtime		Accompanying Runtime	Hybrid			
AI Focus	Processing Input		Generating Output		Computing Task			
Extent of Effect on Enterprise	Isolated Solution		Single Process	Workflow	Work System	Business Model		
Reliability and Precision of Results	~ 99,9 % Required		Defined by Enterprise		Defined by Domain	Defined by Competitors		
Communication	Frequent & Detailed, Active Collaboration		Regular, Some Collaboration		Minimal, Minimum Collaboration	Specific Moments		

Table 5.1: Versions of the MB over time - part 1

CHAPTER 5. A Morphological Box FOR AI INTEGRATION

Morphological Box										Version	Source
Feature		Values									
AI Focus	Processing input		Generating output			Computing task					
End-User IT-Knowledge	IT-Expert		IT-Savvy			No IT-Knowledge					
End-User AI-Knowledge	AI-Expert	AI-Savvy (not just Gen. AI Apps)		Only Generative AI Apps (ChatGPT, Copilot, etc.)				No AI-Knowledge			
Computing Location	Cloud		Local computing center		End-Device		Hybrid				
Execution Time	Real-time		Near Real-Time		Several Hours		Later				
Additional Hardware for specific Task	Computing		Data Capture		Data Visualization		Data Output				
Reliability and Precision of Results	~ 99,9 % Required		Defined by Enterprise		Defined by Domain		Defined by Competitors				
Point in Time of AI Use in Solution Development	Design-Time		Runtime		Accompanying runtime		Hybrid				
Primary Purpose	Assistance	Decision Making	Content Generation		Forecasting	Classification	Anomaly Detection				
Data Source	Own Data		Augmented Data		Open Data		Commercial Collection				
Data Quantity	Very High		High		Moderate		Low				
Maturity	COTS		Commercial Components		Open Source Components		Prototype				
Data and Model Update Frequency	Continuously		In Case of Changes in Regulation		In case of New Documents/Data		In case of Changes in Customer Behavior				
Extent of Effect on Enterprise	Isolated Solution		Single Process		Workflow		Work System				
Communication	Frequent & detailed, active collaboration		Regular, some collaboration		Minimal, min. collaboration		Specific moments				
Primary Data Type	Audio		Video		Image		Transaction Records				
Data Quality	Inconsistent		Duplicate		Incomplete		Outdated				
Data Security	Compliance		Data Encryption		Access Control		Data Integrity				
						Data Privacy		Incident Management	Audit & Monitoring		
Feature		Values									
AI Focus	Processing input		Generating output			Computing task					
End-User IT-Knowledge	IT-Expert		IT-Savvy			No IT-Knowledge					
End-User AI-Knowledge	AI-Expert	AI-Savvy (not just Gen. AI Apps)		Only Generative AI Apps (ChatGPT, Copilot, etc.)				No AI-Knowledge			
Computing Location	Cloud		Local computing center		End-Device		Hybrid				
Execution Time	Real-time		Near Real-Time		Several Hours		Later				
Additional Hardware for specific Task	Computing		Data Capture		Data Visualization		Data Output				
Reliability and Precision of Results	~ 99,9 % Required	> 70 % Required	> 50 % Required		Defined by Enterprise		Defined by Domain				
Point in Time of AI Use in Solution Development	Design-Time		Runtime		Accompanying runtime		Hybrid				
Primary Purpose	Assistance	Decision Support		Forecasting		Classification	Anomaly Detection				
Data Source	Own Data		Augmented Data		Open Data		Commercial Collection				
Data Quantity	Big Data	High (up to 10,000 documents or 100 database tables)		Moderate (up to 1000 documents or 20 database tables)		Low (up to 50 documents or 10 database tables)		No Data			
Make-or-Buy Decision	COTS		Commercial Components		Open Source Components		Prototype				
Data and Model Update Frequency	Continuously		In Case of Changes in Regulation		In case of New Documents/Data		In case of Changes in Customer Behavior				
Extent of Effect on Enterprise	Isolated Solution		Single Process		Workflow		Work System				
Communication	Frequent & detailed, active collaboration		Regular, some collaboration		Minimal, min. collaboration		Specific moments				
Primary Data Type	Audio		Video		Raster Image		Vector Image				
Data Quality	Inconsistent		Duplicate		Incomplete		Outdated				
Data Security	Compliance		Data Encryption		Access Control		Data Integrity				
						Data Privacy		Incident Management	Audit & Monitoring		
Feature		Values									
AI Focus	Processing input		Generating output			Computing task					
End-User IT-Knowledge	IT-Expert		IT-Savvy			No IT-Knowledge					
End-User AI-Knowledge	AI-Expert	AI-Savvy (not just Gen. AI Apps)		Only Generative AI Apps (ChatGPT, Copilot, etc.)				No AI-Knowledge			
Computing Location	Cloud		Local computing center		End-Device		Hybrid				
Execution Time	Real-time		Near Real-Time		Later						
Additional Hardware for specific Task	Computing		Data Capture		Data Visualization		Data Output				
Reliability and Precision of Results	~ 99,9 % Required	> 70 % Required	> 50 % Required		Defined by Enterprise		Defined by Domain				
Point in Time of AI Use in Solution Development	Design-Time		Runtime		Accompanying runtime		Hybrid				
Primary Purpose	Assistance	Decision Support	Content Generation		Forecasting	Classification	Anomaly Detection				
Data Source	Own Data		Augmented Data		Open Data		Commercial Collection				
Data Quantity	Big Data	High (up to 10,000 documents or 100 database tables)		Moderate (up to 1000 documents or 20 database tables)		Low (up to 50 documents or 10 database tables)		No Data			
Make-or-Buy Decision	Commercial of the Shelf Product (COTS)		Commercial Components		Open Source Components		Individual				
Data and Model Update Frequency	Continuously		In Case of Changes in Regulation		In case of New Documents/Data		In case of Changes in Customer Behavior				
Extent of Effect on Enterprise	Isolated Solution		Single Process		Workflow		Work System				
Communication	Frequent & detailed, active collaboration		Regular, some collaboration		Minimal, min. collaboration		Specific moments				
Primary Data Type	Audio		Video		Image		Transaction Records				
Data Quality	Inconsistent		Duplicate		Incomplete		Biased				
Data Security	Compliance		Data Encryption		Access Control		Data Integrity				
						Data Privacy		Incident Management	Audit & Monitoring		
Feature		Values									
AI Focus	Processing input		Generating output			Computing task					
End-User IT-Knowledge	IT-Expert		IT-Savvy			No IT-Knowledge					
End-User AI-Knowledge	AI-Expert	AI-Savvy (not just Gen. AI Apps)		Only Generative AI Apps (ChatGPT, Copilot, etc.)				No AI-Knowledge			
Computing Location	Cloud		Local computing center		End-Device		Hybrid				
Execution Time	Real-time		Near Real-Time		Later						
Additional Hardware for specific Task	Computing		Data Capture		Data Visualization		Data Output				
Reliability and Precision of Results	~ 99,9 % Required	> 70 % Required	> 50 % Required		Defined by Enterprise		Defined by Domain				
Point in Time of AI Use in Solution Development	Design-Time		Runtime		Accompanying runtime		Hybrid				
Primary Purpose	Assistance	Decision Support	Content Generation		Forecasting	Classification	Anomaly Detection				
Data Source	Own Data		Augmented Data		Open Data		Commercial Collection				
Data Quantity	Big Data	High (up to 10,000 documents or 100 database tables)		Moderate (up to 1000 documents or 20 database tables)		Low (up to 50 documents or 10 database tables)		No Data			
Make-or-Buy Decision	Commercial of the Shelf Product (COTS)		Commercial Components		Open Source Components		Individual				
Data and Model Update Frequency	Continuously		In Case of Changes in Regulation		In case of New Documents/Data		In case of Changes in Customer Behavior				
Extent of Effect on Enterprise	Isolated Solution		Single Process		Workflow		Work System				
Communication	Frequent & detailed, active collaboration		Regular, some collaboration		Minimal, min. collaboration		Specific moments				
Primary Data Type	Text		Audio		Video		Image				
Data Quality	High Quality Data		Inconsistent		Duplicate		Incomplete				
Data Security	Normal - Damage effects are limited and manageable		High - Damage effects can be significant		Very High - Damage effects can reach existentially threatening, catastrophic proportions						

V4.1

Survey 2 (section 7.4)

V4.2

Expert Discussions (section 7.5)

V5

Survey + expert discussion results (section 7.6)

V6

Application 3 (sections 6.3 & 7.6.1)

Table 5.2: Versions of the MB over time - part 2

- **End-User AI-Knowledge** concerns the same questions as the previous feature, but regarding the AI knowledge of the end-users. A difference is made to the values because the case can occur that people think they are well-experienced with AI only from often using ChatGPT or similar widely used generative AI applications.
- **Computing Location** describes where the data processing and execution of AI algorithms physically takes place. In some cases, the solution must run in the local computing center of an enterprise; in other cases, it is necessary to be available in a cloud or run on the device itself. The feature's name (formerly "computing source") and some values' names were refined during the evaluation.
- **Execution Time** describes the required time frame until the result of the AI solution has to be available (e.g., the decision it proposes), i.e., the time between a business event triggers the use of the solution until the result is computed. Often, the results are required close to or in real-time. If not time-critical, it can also be acceptable to get them later. According to the evaluation, differentiating between several hours later or even more is unnecessary. "Later" thus also includes the case if it is not time-critical.
- **Additional Hardware for specific Task** describes the need for additional computing equipment or data-capturing devices to be able to carry out the necessary calculations for the AI solution. The change of the feature's name reflects the shift in the feature to cover all additional hardware required for specific AI tasks. This is based on statements from the evaluation that often additional traditional hardware like graphics cards would be required (section 7.5).
- **Reliability and Precision of Results** of the AI solution: Have the results to be always nearly 99,9 % correct, or could a lower level of precision and correctness also be acceptable? The necessary precision could also be defined by the enterprise itself or external factors like the domain, or to be better than the competition. The gradations were recommended during the evaluation. The values for specific cases exist in case no concrete number, but other factors are known while consulting the MB.
- **Point in Time of AI Use in Solution Development** denotes whether the AI is used during the design time of the overall solution, during run-time, accompanying run-time, or hybrid. The former title of the feature, "AI use in solution development," was adjusted because it was perceived as not precise enough.
- **Primary Purpose** aims at characterizing the core functionality. This includes assisting human actors, decision support, content generation, forecasting, classification, and anomaly detection. It is important that this feature includes the perceived purposes of AI from a practitioner's viewpoint. This feature does not claim that all values are fundamentally on the same level of abstraction (for more discussion about that, see section 7.5.4).

- **Data Source** defines the origin of the data used for developing the model or training the algorithm underlying the solution. This could be publicly available data, private data from the enterprise, synthetic data, or augmented data (new).
- **Data Quantity** encourages thinking about how much data will be necessary to train the AI to a satisfactory extent. This heavily depends on the AI technology used and can vary between high and low quantities or even big data with more than 10.0000 documents or no data in a few instances.
- **Make-or-Buy Decision** refers to what extent the solution is a standard product or has to be developed from scratch for the requirements of a case. Companies have to decide between buying a completely pre-made solution (COTS) (if available), making use of available commercial or open-source components to build their solution, or developing it entirely from scratch. The evaluations showed that the term "maturity" did not convey this and that the abbreviation COTS is not known by everyone. Therefore, both terms were adjusted to make them easier to understand.
- **Data and Model Update Frequency** describes the expected time between developing the model or training the AI solution and having to update it due to changes in the domain. Updates could be necessary either continuously or at specific events, like changes in regulation, quality problems, changes in customer behavior, or when new documents/-data need to be processed. The last two values were added during the evaluation. "None" is practically not relevant according to the evaluation because AI systems nearly always have to stay up-to-date in one way or another.
- **Extent of Effect on Enterprise** describes if the AI solution replaces only isolated tasks or machinery without affecting the neighboring processes, is changing complete processes, work systems, or business functions, or is changing large parts of / the whole business model. The wording of two values was adjusted to distinguish them more clearly from each other.
- **Communication** characterizes how much communication and collaboration between the developers of the AI solution and the domain experts/end-users will be required to develop and integrate the solution successfully. This heavily depends on the specific case. If a solution is to be developed that interacts a lot with a human end-user or if the developers need a lot of domain knowledge, more communication is required than if that is not the case. Sometimes, communicating only when specific milestones are reached could also be sufficient. The development can probably always be finished without much or any communication at all, but the question is how good such a solution will perform and how accepted it will be by its users. This should be considered during the planning of the solution.
- **Primary Data Type** describes the data the AI solution's functionality is based on: text (new), audio, video, images, time series, or transaction records.

Feature	Values								
AI Focus	Processing input			Generating output			Computing task		
End-User IT-Knowledge	IT-Expert			IT-Savvy			No IT-Knowledge		
End-User AI-Knowledge	AI-Expert	AI-Savvy (not just Gen. AI Apps)		Only Generative AI Apps (ChatGPT, Copilot, etc.)				No AI-Knowledge	
Computing Location	Cloud		Local computing center		End-Device		Hybrid		
Execution Time	Real-time			Near Real-Time			Later		
Additional Hardware for specific Task	Computing		Data Capture		Data Visualization		Data Output		
Reliability and Precision of Results	~ 99,9 % Required		> 70 % Required	> 50 % Required	Defined by Enterprise		Defined by Domain	Defined by Competitors	
Point in Time of AI Use in Solution Development	Design-Time		Runtime		Accompanying runtime		Hybrid		
Primary Purpose	Assistance	Decision Support		Content Generation		Forecasting	Classification		Anomaly Detection
Data Source	Own Data		Augmented Data		Open Data		Commercial Collection		Synthetic Data
Data Quantity	Big Data	High (up to 10,000 documents or 100 database tables)			Moderate (up to 1000 documents or 20 database tables)		Low (up to 50 documents or 10 database tables)		No Data
Make-or-Buy Decision	Commercial-of-the-Shelf-Product (COTS)			Commercial Components		Open Source Components		Individual	
Data and Model Update Frequency	Continuously		In Case of Changes in Regulation		In Case of New Documents/Data		In case of Changes in Customer Behavior		In Case of Quality Problems
Extent of Effect on Enterprise	Isolated Solution		Single Process		Workflow		Work System		Business Model
Communication	Frequent & detailed, active collaboration		Regular, some collaboration		Minimal, min. collaboration		Specific moments		None
Primary Data Type	Text	Audio	Video	Image	Transaction Records			Time Series Data	
Data Quality	High Quality Data	Inconsistent	Duplicate	Incomplete	Biased		Noisy	Corrupted	
Data Security Requirements	Normal - Damage effects are limited and manageable			High - Damage effects can be significant		Very High - Damage effects can reach existentially threatening, catastrophic proportions			

Figure 5.2: Final version of the MB for introducing AI solutions (V7)

- **Data Quality** describes the data that a user of the MB currently has available. The data can either be of high quality, meaning it has no flaws that need to be fixed before processing, or the data has quality problems that should probably be fixed before using it. Quality problems can be manifold and range from inconsistency to duplicates, incomplete data sets, or biased, noisy, or corrupted data.
- **Data Security Requirements** highlights the relevance of an AI application by summarizing how much damage defects would cause to the company. The choice of one of the three categories should help the MB's user to figure out how much emphasis on data security aspects should be put for the application. The categories range from limited and manageable effects (normal) over significant (high) to existentially threatening and catastrophic effects (very high).

After defining the final version of the artifact of this thesis, the following section will present possible use cases for it.

5.2 Use-Cases of the Morphological Box for AI Solutions

Use cases for the MB can generally be grouped into business and scientific use cases, although some cases are relevant to both areas. Firstly, the business use cases will be described, followed by the scientific use cases. The use cases were deduced by deductive reasoning by the author.

5.2.1 Business Use Cases

This section will present five ideas for business-related use cases for the MB.

5.2.1.1 Support of the Introduction of AI in Companies

The first use case is based on the original idea that the MB originated from supporting the introduction of AI in companies. This should be achieved by providing practitioners with an artifact that includes information about relevant aspects for the introduction of AI and that influence its success. While planning the development and introduction, the features help not to forget relevant aspects and provide possible solutions with their values. The user of the MB can choose the values that apply to them or that they want and thereby easily design the fundamentals for their AI solution. In this case, the MB acts as a checklist or guideline. The following business use cases can also contribute to this case.

5.2.1.2 Comparing AI Solutions and Vendors

As the MB provides relevant aspects for AI introduction, its features can be used as a comparison framework to compare AI solutions and their vendors. The MB does not just include technical aspects but also some that can be even more relevant when working with vendors or developers outside of the own company, like the communication or data and model update frequency, because they should be planned and agreed upon. Therefore, the MB provides standardized evaluation aspects that can be used to compare solutions and vendors by visualizing the most relevant factors to support making an informed decision. An example for this use case will be presented and discussed in section 6.2.

5.2.1.3 Cost-Benefit Analysis

The MB can facilitate quantitative and qualitative comparisons not only between purchasable solutions but also for calculating whether the in-house development would be profitable. The MB includes features that are arguably even more relevant in this case, like the additional hardware required for specific tasks or the data quantity and data source, as well as the extent of the effect on the enterprise.

5.2.1.4 Support of the Development of AI-related Solutions

The included relevant aspects about AI could not only be used to develop AI solutions themselves but also for developing solutions that concern AI. These could be solutions that require knowledge about AI's features, like an AI use case evaluation tool. How the MB was used to develop and enhance such a tool will be explained in section 6.3.

5.2.1.5 Training of Employees

Lastly, as the MB provides knowledge about AI, it can be used for training employees about the topic. It provides a compact overview of what is relevant when thinking about developing or introducing an AI solution in a company. The definitions and explanations of its features provided by this thesis can further be used to avoid ambiguities.

5.2.2 Scientific Use Cases

After describing possible business use cases for the MB, this section will present scientific use cases for it.

5.2.2.1 Enhancing Scientific AI-related Artifacts and Approaches

The information included in the MB could be used to enhance other scientific artifacts or approaches that concern the topic of AI or try to tackle problems related to AI introduction. An example of such a use case will be described in section 6.1. In this case, the MB was used to enhance an AI context modeling method.

5.2.2.2 Comparing Scientific AI-related Artifacts and Approaches

Similarly to the second business-related use case, the MB can also be used as a comparative framework to compare scientific AI-related artifacts and approaches. The features could be used to compare e.g., recommended AI architectures or development processes. They could also be evaluated to determine which of the relevant aspects they tackle based on the features.

5.2.2.3 Classification of AI Solutions

This use case returns to the original idea of the MB as a tool in product development. The idea was that a product could be designed by checking one characteristic (i.e., value) in each dimension (i.e., feature) of the MB, thereby creating the product's specifications. The combination of characteristics then classifies the object of the MB. Vice versa, the objects of a MB, i.e., the AI solutions, should be classifiable by the box, meaning that for every AI solution, a combination of values can be identified. In this way, the MB can be used like a taxonomy framework to structure and classify AI solutions by standardizing the categorization of AI approaches and thereby fostering comparative research. How objects can be classified by the MB of this thesis will be shown in sections 7.2 and 7.4.

5.2.2.4 Teaching of Students/Researchers

Mirroring how employees can be trained on AI, the MB can be used to teach students or researchers. In this case, the MB acts as a teaching tool that visualizes and summarizes the most critical aspects of AI introduction compactly and demonstrates a systematic way to categorize them.

All use cases explained in this section are ideas argued for by the author of this thesis. The practicability and usefulness have to be evaluated. However, the use cases indicate that the MB can be used as a comparison framework, a knowledge base about AI, or a guideline to plan AI solutions. The following chapter will demonstrate how the MB was applied to three of the presented use cases.

Application Examples

This chapter depicts the fourth step, demonstration, in the DSR process by Peffers et al. [Pef+07]. It will present several application examples and use cases of the MB and how they benefited from it. The application examples show that the MB can be used in various cases other than the initial goal of using it in companies to support AI introduction. The new use cases arose during the development and evaluation of the MB over time and illustrate its versatility.

In the first case, the MB was used to enhance an AI context modeling method, thereby showing its ability to be used together with and enhance other scientific artifacts (section 6.1). In the following application example, the MB was used to compare AI on-premise and AIaaS solutions (section 6.2). Thus revealing its potential to be used as a comparison framework for AI solutions. In the third application, the MB was used by a company to develop an AI use case evaluation tool (section 6.3). With its features and values, the MB provided the aspects that were necessary for the evaluation of AI use cases.

As it was unfortunately not possible to conduct a real-world case study in which an AI solution was developed and integrated into a company with the MB, the author decided to illustrate the potential of applying the MB along the IS development process (section 6.4). Finally, the thesis will reflect on the conducted applications of the artifact (section 6.5).

6.1 Application 1: Enhancing an AI-Context Modelling Method

The goal of this first application case was to investigate how the MB could be used to improve and enrich other scientific AI-related methods or frameworks. This was achieved by analyzing the potential of using the MB when preparing the introduction of AI solutions in enterprises.

The initial version of the MB (V1) was used for that, as it was the first application for it conducted in 2022.

Suitable for this goal is a method proposal developed by Sandkuhl for elaborating organizational requirements for AI solutions ([San19], [SR21]). The core idea of this method is to identify the “context” of planned AI solutions in enterprise architecture models and extract requirements and frame conditions from this context. The leading question was, could the MB be used as an instrument to enrich the context model and, thereby, make the organizational requirements more detailed and complete? To answer this, this section will first describe the AI context modeling method. Secondly, it will explain how the MB was used to improve it. This section is based on paper [RS22].

6.1.1 AI Context Modelling Method

The motivation of the AI context modeling method is that many organizations investigate the introduction or development of AI solutions but do not have experience with the technical complexity of AI applications. The method proposal assumes that an EA model for the enterprise under consideration exists. If this is not the case, the organizational context (see step 1 below) for the EA has to be developed. The method proposal consists of five steps, summarized below:

- Step 1. Model organizational AI context: aims at extracting all information of organizational structures, processes, and resources required for or affected by the planned AI solution from the EA model of the organization under consideration. The extracted information is captured in a conceptual model, i.e., represented by using a modeling language. This conceptual model ideally is a subset or view of the analyzed EA model of the organization.
- Step 2. Elicit AI requirements: aims at documenting the requirements from candidate AI technologies that have to be fulfilled if a certain candidate technology is to be used in an organization (it is recommended that an AI expert is involved in this step).
- Step 3. Analyze AI context: systematically analyzes the AI context model (from step 1) using the AI requirements (from step 2) for each EA layer of the context model separately.
- Step 3a. Enrich the EA model: this is as a complement to step 3 “analyze AI context” to be performed optionally if step 3 discovers incompleteness of the model attributes or descriptions. The step is particularly important, e.g., for (a) images, videos, and audio recordings where repository or storage systems can only be identified by company

insiders due to the naming in the EA model, (b) AI applications depending on the evaluation of historic data, where the extent of stored historic data and its quality are not described in the attributes of the model elements, and (c) data sources to be integrated for joint evaluation, which cannot be done with good performance and efficiency “on the fly,” but need detailed information about acceptable processing times or possibilities to extract data from operational systems

- Step 4. Decide on feasibility: gives support for deciding on feasibility based on the results from step 3.
- Step 5. Designing the future EA: a serious investigation on feasibility has to include the initial design of new or changed data, the preparation of the application and business architectures for the AI application, and migration planning. Only if migration is not only possible but also economically acceptable and resource-wise doable, should the implementation be started.

In addition to these procedural steps, the method provides important concepts to observe and document, and a notation on how to do this.

6.1.2 Applying the MB to the AI Context Modelling Method

Based on the features of AI solutions identified within the MB, this section investigates if these features can help to improve the AI-context modeling method. First, all method steps and their descriptions were analyzed in search of potential uses for the features:

- In „Model organizational AI context“ (step 1), the features were not applicable, as the focus here is on working with the current situation in the enterprise represented by the existing EA model. Features of the envisioned AI solution should be determined after the requirements are defined (step 2), not before.
- In „Elicit AI requirements“ (step 2), the list of AI solution features and the different values of the features seem to be useful. Some of the features can help to clarify frame conditions of the future AI solutions, which can then lead to new requirements. Examples are „computing source“ and „data source“. If the enterprise wants the computing of the AI solution to happen locally, the usage of existing cloud services has to be ruled out, which will lead to a higher complexity of the solution and in-house maintenance. If primarily open data are required for training purposes, the existence and suitability of such data sets need to be investigated.
- In „Analyze AI context“ (step 3) and „Enrich the EA model“ (step 3a), the features are not very useful. The main reason is that detailed instructions exist on how to do the analysis or enrichment steps. An additional checklist or hints are not needed.

- In „Decide on feasibility“ (step 4), on the other hand, the features and their different values seem helpful. Some features are relevant for the overall feasibility of the approach, such as “time to decision” and the required “reliability and precision of the results.” If real-time decisions are required but not possible due to the amount of data or complexity of computing, another solution than the AI-based approach might be necessary. If 100 % correctness is mandatory but not possible due to missing information in the specification, more refinement work is required before deciding on feasibility.
- In „Designing the future EA” (step 5), the features can help to validate the initial design of new or changed data, application, and business architectures. If 100 % correctness is mandatory, the design of the solution has to be adapted accordingly.

6.1.3 Discussion

The initial analysis of the method steps shows that two of the five steps seem to benefit from using the features (requirements analysis; feasibility analysis), and one more step (designing the future EA) probably also has advantages.

To further investigate the initial results, for the use cases described in section 4.1, it was examined for every feature and every case, in what method step (if at all) this feature was discovered or elaborated. Table 6.1 shows the result of this step.

The analysis shows that some features should have been elaborated in requirements analysis but were only discovered in later method steps (e.g., computing source in cases B and C). Other features must be known before the project starts and thus are not helpful for the method.

The analysis of feature use in the AI context method steps showed that requirements analysis (step 2) and feasibility analysis (step 4) gain benefits from using the features. The benefits are a more complete set of requirements and, as a result, more efficient method steps. Furthermore, in the step of designing the future EA, inspiration can be gained from the features for what potential solutions could be envisioned. All this improvement potential has to lead to a minor revision of the method that includes the use of the features in the instructions for the method steps.

This application showed how the MB can enrich an artifact like the AI context modeling method.

6.2 Application 2: Comparing On-Premise and Artificial Intelligence as a Service

In this use case, the V3 of the MB (see Table 5.1) developed in section 7.1 was used to contrast differences between AI on-premise and Artificial Intelligence as a Service (AIaaS) solutions. The content of this section was presented in [GRS23].

Case / Feature	A – ACT energy optimization	B – fraud detection	C – object recognition	D – forecast for operations	Recommended
<i>Computing source</i>	Requirements Analysis	Feasibility Analysis	Design Future EA	Requirements Analysis	Requirements Analysis
<i>Maturity</i>	Requirements Analysis	Design Future EA	Design Future EA	Design Future EA	(depends on case)
<i>Special hardware required</i>	Requirements Analysis	Design Future EA	Design Future EA	Requirements Analysis	Requirements Analysis
<i>Data source</i>	Requirements Analysis	Feasibility Analysis	Feasibility Analysis	Requirements Analysis	Requirements Analysis
<i>Data and model update frequency</i>	Feasibility Analysis	Requirements Analysis	Feasibility Analysis	Requirements Analysis	Requirements Analysis
<i>Time to decision</i>	Requirements Analysis	Requirements Analysis	Requirements Analysis	Requirements Analysis	Requirements Analysis
<i>Primary data type</i>	Requirements Analysis	Before project start	Before project start	Requirements Analysis	Latest at Requirements Analysis
<i>AI use in solution development</i>	Requirements Analysis	Requirements Analysis	Before project start	Before project start	Latest at Requirements Analysis
<i>AI focus</i>	Before project start	Before project start	Before project start	Before project start	Before project start
<i>Extent of effect on enterprise</i>	Design Future EA	Feasibility Analysis	Design Future EA	Feasibility Analysis	(depends on case)
<i>Reliability and precision of result</i>	Requirements Analysis	Requirements Analysis	Feasibility Analysis	Feasibility Analysis	Requirements Analysis

Table 6.1: Analysis of Features in Use Case

In difference to AI on-premise solutions that are developed and implemented individually for a company, AIaaS solutions are usually COTS products that can be bought and operated in a cloud. Hence, AIaaS show a considerable potential for SMEs that lack the knowledge or personnel to develop and implement AI on-premise solutions. The research presented in [GRS23] investigated and discussed the current state of this topic. As part of this research, the MB was used to contrast the differences between both approaches. The MB was chosen because factors for successful AI solution implementation were needed that could be compared for both cases. Here, the focus was especially not only on technology factors regarding the software solution itself, but it should also include factors that are important for the introduction process, precisely because the main differences between AI on-premise and AIaaS comes from the fact that there is a need to develop the first one yourself, meaning a company needs employees and knowledge who can do that and maintain it. AIaaS, on the other hand, could come with other restrictions regarding flexibility, adaptability, suitability, or cost structure.

6.2.1 Case Study Description

For the comparison, a case study with a company was conducted that wanted to implement an AI on-premise as well as an AIaaS solution. This case company is from Germany, had 58 employees at that time, and specialized in back-office services for insurance agents and financial product brokers. The goal of the company was to improve its document processing capabilities with AI.

The company received around 2,500 documents weekly through different channels like surface mail, BIPRO electronic messages, and email attachments. Usually, the existing IT system converted all the incoming documents into PDFs, performed OCR if required, and applied basic keyword-based filtering for classification and information extraction. Only 58% of documents were automatically classified, and less than 20% of the necessary information was extracted, resulting in high manual work. To increase the level of automation, the company implemented two AI solutions in parallel: a ML on-premise approach and a cloud-based AIaaS solution from the company PlanetAI. For the on-premise approach, a data processing toolchain was developed. A corpus of 1200 documents was built to train a Naïve Bayes Classifier and a k-Nearest Neighbors model. For the cloud-based approach, the same corpus was used to train PlanetAI's Intelligent Document Analysis suite.

6.2.2 Comparing the Approaches by using the MB

The case study showed aspects of using AI on-premise and AIaaS solutions that are similar and different. The MB with its features and values was used as a framework to further compare the two approaches on an abstract level. The two approaches were compared feature by

feature, and it was checked if their values were similar or different. The differing features were the following: computing source, maturity, hardware, data source, security, the extent of the effect on enterprise, and communication. In the case study, the "computing source" of the on-premise solution was established locally in the company's computing center, while they used a cloud solution for the AIaaS case. The remaining features were also considered, but no difference between AIaaS and on-premise solutions could be found for them. Hence, only the features that showed significant differences will be discussed further in this section.

Regarding the "maturity" in the on-premise case, a new individual solution was developed, but they also used open-source components for the development. This shows that it is also possible to choose several values for a feature for one solution. For the AIaaS case, a ready-to-use COTS solution was bought from the provider.

For the on-premise solution, the company needed to have its own "new hardware," while for the AIaaS solution, the company did not have to acquire hardware.

The "data source" also differed between the two solutions. While for the on-premise solution, own data was needed, the AIaaS solution already offered commercial collections in the form of pre-made data sets that can be used. However, also in the AIaaS, the data sets of the provider were combined with the data from the company.

Regarding the "data security" aspect, it highly depends on the specific case, but what could be shown overall is that AIaaS must be General Data Protection Regulation (GDPR) compliant.

Lastly, the "extent of the effect on the enterprise" and "communication" features can be reviewed together because, for both, the main difference is that in the on-premise case, you have to manage the development of your solution yourself in your company, and everything that is included in this development process. On the other hand, in the AIaaS case, you only have to manage the contact, collaboration, and communication with your service provider and, depending on the service, also the maintenance later.

6.2.3 Discussion

Overall, the MB was able to help discover essential aspects in advance during the planning phase of the development process so that they could be prepared thoroughly. For the systems integration itself, the MB can show that there will be some effects and communication that must be done to succeed at the end of the integration process.

6.3 Application 3: Developing an AI Use Case Evaluation Tool

One of the goals of the MB is to summarize the most critical aspects for the introduction of AI in companies. Because of that, the MB was used for this application example: the development

of an AI use case evaluation tool. The DVZ of Mecklenburg-West Pomerania wanted to develop a tool that helps with evaluating the AI use cases of their customers. To be able to evaluate the cases, they needed criteria and characteristics of AI that can be evaluated. Because those are precisely the things the MB provides, they wanted to use it as a basis for their tool.

During a kick-off meeting in November 2024, the author of this thesis presented the MB V3 to employees of the DVZ and explained all features and values in detail to them. They then used it for the development of the tool. Currently, the tool is still in development, but a prototype was presented to the author of this thesis in January 2025. In this meeting, it was discussed how the MB was used during the development and how it influenced the prototype. To understand how the application benefited from the MB, the structure of the application will be explained in general first.

6.3.1 Structure of the Application

Naturally, the application offers the functionalities of creating and editing use cases. A use case can be submitted by customers of the DVZ. Besides the name and a short description of it, the process duration and expected time savings from the AI in hours are collected together with the number of processes per week, the number of people involved, and the information about how clear and unambiguous the rules for processing are. For the last information, the tool offers three options to choose from. Based on this initial information, the tool calculates a ranking value. This ranking gives a first impression of how promising the use case could be.

Then, a use case can pass up to four stages from the first "rough assessment", over the "detailed assessment" to the "requirements elicitation", and lastly, the "implementation". During the first two stages, several aspects of the use case are checked, and if the use case passes the checks, it proceeds to the next stage. In this thesis, only the rough assessment stage will be described in detail for confidentiality reasons and because the rough assessment stage is the part of the tool that the MB was used for. After learning about the MB, the tool's developers decided that the MB provides suitable information for this part of the use case evaluation with its features and values.

The rough assessment itself consists of five parts, and the MB inspired two of those: the "rough requirements" and the "data quality check." In both steps, the user is asked to answer several questions regarding their AI use case and their wished AI solution. The developers created one question for each of the MBs features. The answer options to the questions are the values of each feature. Figure 6.1 shows a screenshot of how the questions and answers were integrated into the tool. Unfortunately, the prototype is currently only available in German. For example, the question above the third column asks: "What is the primary purpose of the AI solution?" The dropdown menu then offers to choose between the different values. When one of the

arrows on the right is clicked, the next batch of questions will be shown. In this way, the tool includes questions including all features of the MB.

Nevertheless, the developers did not copy the MB one by one as they changed and added a few features and values. The changes they made will be summarized next.

6.3.2 Differences to the MB

For the end-user, they used the existing values and an "AI expert" and "no human user" value.

For the data quality, they added a "structured + homogeneous" value in case the existing data is already of satisfactory quality. Additionally, for the "data quality check," they added a question asking about the homogeneity of the data with the answer options: "homogeneous," "few formats (2-5 species)," and "strongly different."

In addition to the existing values, they added the concrete data types "PDF," "Excel," and "CSV," as well as "paper" and "other" as options for the "primary data type" feature.

For the reliability and precision of results, they asked for the "probability of the correctness of the results" using different levels:

- High (100-85 %)
- Middle (84-70 %)
- Low (69-50 %)
- Unknown (<50 %)

Next, the data security feature was changed to asking for the protection demand of the processed data. The answer options to this question are:

- N — normal protection demand (no special requirements)
- HIS — high protection demand regarding information security
- HDS — high protection requirements regarding data security

For the data amount, they choose to differentiate between:

- Big data

Figure 6.1: Screenshot of the first page of the "rough requirements" step of the AI evaluation tool from the DVZ of Mecklenburg-West Pomerania

- High (up to 10,000 documents or 100 database tables)
- Moderate (up to 1000 documents or 20 database tables)
- Low (up to 50 documents or 10 database tables)
- No data

Finally, they added a question asking for the desired output format of the AI solution, offering "text," "table," "image," and "video" as possible options, making it similar to the "primary data type" feature, but concerning the output of the solution.

6.3.3 Discussion

The structure of the AI use case evaluation tool shows that the MB massively influenced the design of the first "rough assessment" of the AI ideas. In this tool, the features and values of the MB built a scientifically evaluated basis for the employees of the DVZ of Mecklenburg-West Pomerania to ground their evaluation on. In this case, the MB acted as a checklist to collect the most important information about an AI idea. When confronted with the questions, the users have to think about the different aspects represented in the MB to be able to answer them.

First, this supports the planning process of the users by forcing them to think about the relevant topics. Second, it offers the employees of the DVZ the possibility to collect structured information about their customers' ideas, ultimately supporting their requirements engineering and planning process.

How users accept the tool and how much support and relief it provides for the assessment and evaluation of use cases will have to be evaluated in the future when it leaves the prototype phase. Then, it can also be examined how helpful the information about the features of the applications really was for the project planning and requirements engineering.

Besides the influence of the MB on the tool, the application of the MB by the employees of the DVZ influenced the MB itself. The reason for this is that, ultimately, this, as well as the other application examples, can be seen as additional evaluation episodes. By reflecting on how others applied the MB, lessons can be deduced. The implications of this application example (based on the differences presented in section 6.3.2) will be discussed in section 7.6.1 at the end of the following evaluation chapter. This makes it easier to understand the maturing process of the MB as this application example was conducted parallel to the final two evaluation episodes.

6.4 Application Potential along the IS Development Process

In this application example, the applicability of the MB for IS development should be investigated. This was conducted in [RS23a]. Hence, again, V3 of the MB presented in section 7.1 (refined after conducting expert interviews) was used for this case.

In an initial step, the author evaluated the applicability by using the different phases and steps of the IS development process described in section 3.1.4. Table 6.2 presents the phases and how the MB could be used in each by deductive reasoning.

As shown in Table 6.2, the MB could potentially be useful in several stages of the solution development process. However, because the assumptions were just made by deductive reasoning, they should be evaluated in practice as well.

6.5 Summary of the Demonstration & Reflection on the Applicability and Utility of the Morphological Box

This chapter presented various application examples of the MB, thus representing the fourth step of Peffers et al.'s DSR process [Pef+07]. It was explained how the MB was used as an artifact that can help to enhance other AI-related artifacts, how it can act as a framework allowing to compare different AI solutions, and how it can be used to evaluate AI solution ideas by providing relevant aspects concerning the introduction of AI in companies.

On the one side, those are a number of new use cases for the MB that were not initially planned. However, the new use cases emerged over time while applying and evaluating the

Phase	Step	Use of the morphological box
Decision Making	Analysis of AI potential	Features support the understanding of the variety of possible AI applications
	Feasibility analysis	Features support the understanding of the general preconditions for AI
	Readiness check	Features support the understanding of the general preconditions for AI
Specification	Specify operational integration	Features and values contribute to an analysis of the AI solution context in an organization, as demonstrated in [RS22]
	Technical specification	No significant application potential
Contracting & realization	Make or buy decision	Features and values contribute to outlining the desired AI solution from which the company's experts can use to decide if they have the knowledge to develop it themselves
	Development of AI solution	Features and values contribute to requirements engineering as demonstrated in [RS22]
	Integration of AI solution	Values help to know the end-user if training will be necessary, the extent of impact the solution will have on the company, and how much communication will be required
Acceptance and introduction	Acceptance test	No significant application potential
	Implementation of operational integration	No significant application potential
	Training	"End-user" helps to determine the end-user and necessary training early

Table 6.2: Application potential of the MB along the IS development process

artifact, ultimately showing its versatility. On the other side, the initially planned use case for the artifact could not be conducted and evaluated. Hence, it could not be evaluated if companies would actually benefit from using the MB when implementing an AI solution. The evaluation episodes that will be presented in the next chapter focus on the correctness of the features and values as well as their utility and relevance. Additionally, it was illustrated how the MB could be used along the IS development process, thereby showing how the implementation process for AI could benefit from it.

Regarding the ease of use of the artifact, the MB was briefly introduced to developers of the DVZ. Its features and values were explained as in the description presented in chapter 5. Some questions arose, especially regarding the wording of some features and values in German, but overall, no further training or learning time was required. However, the introduction of the MB by its author could play a role in its understandability. The question arises whether the DVZ members would have also understood all the features and values only from the textual descriptions provided in this thesis. A personal explanation, together with the possibility to directly ask for clarifications, naturally makes it easier to understand an artifact.

The developers' feedback about the MB was generally positive. They also provided constructive feedback about additional features and possible adjustments, as described in section 6.3. This shows that the development of the MB was not finished at this point, but a usable and satisfying state was reached. The changes made to the artifact based on their recommendations are discussed in section 7.6.1 and show the adaptability and flexibility of the artifact. According to the developers, they benefited the most from the compiled information about relevant aspects of AI implementation without having to read through dozens of pages or websites first. They stated that they had not found such a compressed artifact before.

For the first and second application examples, the information included in the MB was easily accessible and applicable to the cases. The structure of it made it easy to use as a comparative framework.

Overall, using the MB in different application scenarios showed its versatility, general ease of use, and adaptability, showing that it reached an applicable state. However, the initial use case for the artifact could not be conducted and evaluated as no suitable cooperation was found. The artifact showed its applicability and usefulness for the described cases only. If this applies also to the introduction of an actual AI solution can currently only be argued and has to be practically tested in the future.

The following chapter will present a thorough scientific evaluation of the artifact over five evaluation episodes. It will further illustrate how the MB changed after each episode and finally reflect on its overall development and design.

Evaluation of the Morphological Box for Artificial Intelligence Integration

This chapter depicts the fifth step in the DSR process by Peffers et al. [Pef+07], the evaluation. The goal of the evaluation step is to, amongst others, evaluate the effectiveness, efficiency, correctness, and suitability of an artifact.

To conduct the evaluation, different scientific approaches described in chapter 2 were used, like interviews, surveys, and the taxonomy development process by Nickerson et al. [NVM13]. This process, discovered during the first evaluation episode, builds the basis for the planning of the evaluation of the MB. Therefore, the evaluation episodes are based on the two different general approaches presented by Nickerson et al. [NVM13] (see 2.12). For each evaluation episode, it had to be decided whether to use the empirical-to-conceptual or the conceptual-to-empirical approach. Which approach should be chosen at which point in time depends on the situation of the research, their knowledge, possibilities, and resources. For example, the design of the initial version of the MB followed the conceptual-to-empirical approach because the MB was developed based on the author's knowledge about the topic (step 4c) combined with examining past AI introduction projects (step 5c). However, it is not possible to clearly categorize all evaluation steps to one of the two approaches, as, e.g., interviews or surveys, could be interpreted in both ways. For example, the expert interviews conducted in the first evaluation episode were used to discover new features and values and to confirm or adjust the existing ones. The first can be seen as identifying common characteristics (step 5e) that are grouped into dimensions after the interview (step 6e), whereas the latter counts as an examination of the existing features and values based on objects from the interviewee, i.e., AI projects (step 5c).

However, it is not critical which of the two approaches was chosen, but rather that an approach was conducted that follows the idea of the two approaches in general. Additionally, the most

important aspect that the taxonomy development process provides to the MB development is a basis for a scientifically accepted process and ending conditions to measure how mature the artifact is. Therefore, Nickerson et al. [NVM13] provided subjective and objective ending conditions (see section 2.2.1) that are used as the main goals for the MB to reach after a number of evaluation episodes. How the MB fulfills these conditions was evaluated thoroughly after the second (section 7.2) and fifth evaluation episode (section 7.6).

In the following sections of this chapter, the five evaluation episodes of the MB will be explained, analyzed, and discussed. The chapter concludes with a summary of the entire evaluation process and reflects on the changes of the MB during the time.

7.1 Evaluation Episode 1: Expert Interviews

To ensure that the artifact included all relevant features and values and that the existing features and values were truly relevant, guideline-based interviews were chosen as a qualitative method for the first evaluation episode. Interview participants were selected based on their experience developing and/or introducing AI applications. By targeting this audience, it was possible to gain insights from experts who have real-world experience with the challenges and opportunities of AI application integration. The interview guideline and notes from the interviews can be found in Appendix A. This section is based on the paper: [RS23a].

7.1.1 Interview Planning and Conduction

As explained, the purpose of the interviews was a qualitative evaluation of the MB and its parts. To achieve this, a mixed-method approach was employed by combining two standard interviewing techniques: narrative and focused interviews. While focused interviews are guideline-based and concentrate on a specific object of research (i.e., the MB), narrative interviews allow interviewees to talk openly about a topic without the influence of already existing theories or leading questions. As the goal was to identify new features and values, the four phases of the narrative interview were incorporated into a guideline to combine both approaches. The complete interview guideline can be found in Appendix A.1. The narrative part should provide unbiased information about AI integration processes, while the guideline should help to focus on the MB and evaluate it after the narrative part.

The interview guideline comprised seven parts:

1. Greeting
2. Entry Questions

3. Narrative Phase
4. Question Phase
5. Evaluation of the MB
6. Summary
7. Ending

The interviews were conducted by two researchers. One researcher asked the questions while the other directly noted down essential statements that could be relevant to the MB and any potential features and values (for notes, see Appendix A.2). All interviews were conducted and recorded using the software "Zoom" so that it was possible to transcribe and analyze them thoroughly later, as well as for practical reasons.

The greeting served as an icebreaker to help the interviewee feel comfortable and familiar with the interview topic. This was followed by entry questions such as age, gender, and work experience to ease the interviewee into the interview and to gather statistical data. These two phases served as the opening phase.

Next, the interview proceeded to the narrative phase, where the interviewees were asked to describe one of their past AI projects and guide the interviewers through its development and introduction process. This approach helped to gain an unaffected view of an AI project and all its potentially relevant aspects. During this phase, the interviewee mostly spoke, and the interviewers observed and listened.

Following the narrative phase was the question phase, where the interviewee was asked to clarify any unclear points and elaborate on features or values. The interviewee was also asked to reflect on lessons learned, what worked well or not, and the most critical aspects for a successful AI development and introduction. The questions were formulated openly to elicit unaltered responses.

After the narrative part of the interview, the MB was introduced to the interviewee. Since the initial version of the MB had twelve features with up to six values each, only two features with their respective values were shown and explained to them at a time, so they could comprehend all the information. After every two features, the interviewee was given time to think about them and was asked to agree or disagree with the values for the corresponding feature. Finally, the interviewee was asked whether the values were sufficient to describe all possible characteristics of the feature or if additional values were necessary.

At the end of this phase, the interviewee was asked again to reflect on what aspects are relevant for successful AI development and integration and whether the features of the MB represent

all of them or if further features are necessary. The interviewee was also asked to identify which features are fundamental and which are less critical for successful AI development and integration.

Finally, the recording interviewer summarized the most important points of the interview and asked the interviewee if everything was understood correctly and whether they wished to add anything. For the closing, the interviewee was asked to provide feedback about the interview, whether they enjoyed it, what they liked/did not like, if any answers were too complex, and if they wished to add anything that was missed. The interviewee was thanked for their time and effort, and the interview concluded.

7.1.2 Results of the Interview

Three interviews were conducted between June and August 2022 with male participants aged between 20 and 40. Each interview lasted 45–60 minutes. In this section, the findings from each interview will be summarized, including the interviewees' AI projects and their thoughts on the various features and values of the MB.

To summarize the results of the interviews, qualitative content analysis according to Mayring & Fenzl [MF19] was used. This approach allowed to use the existing features and values as a starting set for the categories used to label the data. The advantage of this approach was that it helped to leverage the existing knowledge and understanding of the field while also gaining insights from the experiences and perspectives of the interview participants.

7.1.2.1 Interview A

Interviewee A was the head of sales for a company that develops AI solutions for other companies. His AI example was a photo/picture analysis software that extracts information from photos of insurance policy documents, adds the data to a customer relationship management system, and then makes a counteroffer. The solution replaced a process that generally took around 15–20 minutes for an employee, but the AI-based solution only needed about two seconds. The recognition rate is approximately 97 %, which was only possible due to close cooperation between the developers and the business department of the customer. The project took them twelve instead of six months because they had insufficient suitable data. In this case, the AI must be trained continuously to hold the 97 % precision rate, especially when new documents occur. The interviewee also mentioned that data security was critical for the customer because the AI would work with personal and confidential data.

Regarding the MB, Interviewee A thought that the "cloud" was the most important "computing source," and the term "device" was unclear to him. In an ideal case, only "own data" would

be used, and "open data" would be complementary. Continuous updating of the AI is crucial to maintain precision, and any failure to update the model or data could be dangerous. In his opinion, an AI's decision is always time-critical, so the value "not time-critical" would be unrealistic. It would be best to use the AI in all steps of solution development, with the "AI focus" combining input and output. After explaining the difference between "effects on a single process" and "complete process," he suggested "workflow" as a suitable term. A precision of 100 % would not be realistic, and the goal should instead be 99.9 %. Another relevant aspect for him was how well his market competitors were performing. According to him, the most essential features for a successful AI implementation are the "data source," "computing source," "model and data update frequency," "time to decision," "primary data type," "the primary purpose," and "reliability and precision of results."

7.1.2.2 Interview B

Interviewee B was a developer for a financial company with eight months of experience in this role. He worked on a project where an AI for fraud detection in the financial sector was developed. During the narrative part, he quickly emphasized that close cooperation with the relevant departments was important. On one side, the end-users wanted to understand the AI. On the other side, the developers needed to understand the data. They were able to reach an error detection rate on the same level as a human could achieve. But to hold this level, the application has to be updated continuously, mainly to prevent mistakes when customer behavior changes, which happens occasionally in the financial industry, according to him. They also had to acquire new servers and virtual machines for their application. He also stated that a new application needs to provide additional value to a company to be accepted by the employees.

Interviewee B did not provide as much feedback as Interviewee A regarding the MB. However, he noted the importance of continuous updating to prevent mistakes and maintain a high error detection rate.

7.1.2.3 Interview C

Interviewee C was a director for a software development company that develops AI applications for their customers, with eight years of experience in this role. He chose a project where they created an AI for document processing. He mentioned the importance of data quality and quantity for AI applications, and he emphasized the importance of knowing what level of knowledge the employees of their customers have and if the AI has to be trained continuously after implementation by themselves. For example, if the users of the solution are not IT-savvy, the user interface and experience must be as simple as possible. Also, the question arises if

the employees may need some training before they can update the AI continuously. He also highlighted the importance of data security, which can be a concern when handling sensitive data that cannot be stored on a cloud-based solution.

Considering the MB, the interviewee suggested adding "augmented data" as a new value for "data source" and emphasized the importance of context and content understanding for the "primary purpose" feature. He doubted that 100 % reliability could ever be achieved and suggested that pursuing such a goal could hinder development. In terms of "computing source," he considered "cloud computing" to be the most crucial factor, although it would need to be supported by appropriate hardware. He identified the most critical features as "data source", "special hardware required", and "time to decision". The interviewee stressed the importance of careful consideration and planning when developing and implementing AI applications. Factors such as data quality and security, user interface and experience, and ongoing employee training and support are all crucial elements that must be addressed to ensure the successful implementation and adoption of AI technologies.

In summary, the three interviews highlighted the importance of close cooperation between the developers and the affected business departments to develop successful AI solutions. All three interviewees emphasized the importance of data quality and quantity for AI applications and the need to continuously update the AI to hold a high precision rate. The interviewees also discussed the importance of data security, particularly when handling personal and confidential data. Regarding the MB, the "computing source" and "data source" were identified as the most important features, while 100 % reliability was deemed unrealistic. The "primary purpose" of the AI solution and the "time to decision" were also highlighted as essential features. Overall, the interviews provided insights into the challenges and key factors in successfully developing and implementing AI solutions.

7.1.3 Analysis & Discussion

In this section, the interview findings will be analyzed and discussed. Most importantly, the interviews with three AI experts revealed new features and values for AI. Additionally, they uncovered room for improvement regarding some values and confirmed the current features and values as correct and relevant according to the interviewees' opinions.

7.1.3.1 Features

First, the following new features emerged from the interviews (interviewees that mentioned them in parenthesis): data quantity (A, C), data quality (A, C), data security (A, B, C), communication/coordination with end-user departments (A, B), added value for the Company (B), and ease of use/usability (C).

The interviews showed quite clearly that a number of features were currently missing, especially regarding the data aspect. This is an interesting observation because the vast amount of data required for practical AI applications is one of the main aspects that differentiates AI solutions from "classical" software. In the course of this, two interviewees mentioned "data quantity" and "data quality" as essential aspects because a considerable amount of high-quality data is usually required to train, e.g., neural networks. How much data is needed depends on the specific use case. The quality of data could be measured with different data quality metrics like consistency, completeness, noisiness, or duplicate records. The third data-related feature is "data security," which should also include legal requirements and, therefore, could be measured by aspects like compliance, data encryption, access control, or data integrity. This feature contains dependencies to the features computing source and data source because it can be relevant for data security where the data is processed (e.g., in a cloud on a server somewhere in the USA or on a device in one's company) and which data is processed (e.g., personal or user data compared to open data).

The next feature, "communication" with the end-user (department), is especially relevant if the AI development will be outsourced to another company, and the interviewees emphasized that this aspect highly influences the success of an AI project because the end-users have to use the application later and are often the ones who deliver the training data. This leads to the fact that most of the time, frequent, detailed, and active communication is required, but depending on the size and impact of the application, less communication or communication only at specific points during the development process could be enough.

This also leads to the last possible new features, "added value" for the company, and "ease of use." As mentioned, the end-users are often other people than the developers of an application, making it essential first to know who the end-users will be (e.g., are they IT-experts, IT-savvy or do they have no IT knowledge at all) and then to design the user interface and experience suitable for this user group. This also connects to the "data and model update frequency" because if the solutions have to be updated continuously, e.g., trained further with new data to stay up-to-date, the end-user could also be responsible for this. If this is the case, it must also be as easy as possible for the user to update the model. It could also be the case that the end-user needs to be trained first to be able to update the model continuously. Because the level of accessibility of the application, as well as other aspects, depends on the end-user, it was decided to add a feature "end-user" instead of "ease of use." The values can then be determined as "IT-expert," "IT-savvy," and "no IT knowledge."

To know the added value of an AI application is highly important to calculate if the investments in developing and integrating it (time, money, personnel, etc.) are worth the effort in the long term. The added value can also be a vital aspect for accepting a new application, especially because often employees are skeptical regarding AI applications because they cannot completely understand how they function, or are afraid to lose their jobs because of them. To

be able to show them how they can also benefit from a new application could potentially help with the acceptance and boost the integration as well. Besides that, the main problem with this possible feature is how the value can be determined. This is highly individual and depends on many aspects of a company. Because of that, it was decided not to include added value as a feature, but its importance should still be emphasized at this point.

7.1.3.2 Values

Similarly to the features, the following new values were revealed: One interviewee suggested "prototype" as a new value between "open-source components" and "individual" for "maturity" (A), as well as "augmented data" as another "data source" (C).

Regarding the update frequency of the data and the model, two new cases were revealed. According to the experience of the interviewees, the AI should be trained with new data when new additional documents need to be recognized (in the case of document recognition applications and similar cases) (A, B) and when customer behavior changes (B). It could be argued that both values are specific and could be covered by the "in the case of quality problems" value. In the author's opinion, both cases are events that could be relevant for many AI applications similar to the "changes in regulation" value. Furthermore, as the MB itself should also help companies that have no knowledge about AI, it would be helpful for them to be provided with as many scenarios as possible so that they can decide if those events could be relevant for them.

A new primary purpose could be the "context and content understanding" (C). According to the interviewee, this understanding of the relevant content from images, documents, etc. builds the basis for other values like "decision-making," "classification," or "anomaly detection." The question that arose was, is context and content understanding a value of its own? Are there AI applications that only understand the context and content and then do nothing else based on that? From the author's perspective, there will always be another action after the understanding step. Because all existing values indirectly already include the context and content understanding as a necessary part of their purpose, it was decided not to add this as a new value.

Regarding "reliability and precision of results," all interviewees agreed that a precision rate of 100 % is impossible and not practical (A, B, C). They suggested lowering it to approximately 99,9 %. Additionally, two interviewees clarified that the necessary reliability and precision are often "determined by their competitors" and how well their solutions perform (A, B).

Finally, two values were marked as not possible or incorrect. First, no data or model updates at all would be unrealistic because there would always be changes, and if the AI would not be updated, it would be guaranteed to be outdated at one point and then produce wrong or unreliable results (B). Similarly, it would never be the case that the "time to decision" would

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Feature	Values									
Computing Source	cloud		Local computing center			End-device		hybrid		
Maturity	COTS		Commercial components		Open source components		Prototype		Individual	
Special Hardware Required	Computing			Data capture		Data visualization			Data output	
Data Source	Own data	Augmented Data			Open data		Commercial collection		Synthetic data	
Data Quantity										
Data Quality										
Data Security										
Data and Model Update Frequency	Continuously	In case of changes in regulation	In case of new documents / data		In case of changes in customer behavior			In case of quality problems	None	
Ease of Use										
Time to Decision	Real-time			Near real-time			Several hours			Not time critical
Primary Data Type	Audio	Video	Raster image	Vector image	Transaction records			Time series data		
Primary Purpose	Assistance	Decision making	Forecasting	Classification	Anomaly Detection		Context & Content Understanding			
Point in Time of AI Use in Solution development	Design-Time			Runtime			Accompanying runtime			Hybrid
AI Focus	Processing input				Generating output				Computing task	
Extent of Effect on Enterprise	Isolated solution		Single process		Workflow		Work system		Business model	
Added Value										
Reliability and Precision of Results	~ 99,9 % Required			Defined by Enterprise			Defined by Domain			Defined by Competitors
Communication										

Figure 7.1: Version V2.1 of the MB for AI solutions after the expert interviews

not entirely be time-critical (A). Even if the results are not needed directly or in a few hours, at some point, they will be required (after days, months, etc.) because otherwise, the application itself would be unnecessary. A suggestion was to use days or just at a "later" time as a value instead.

Also, some values were not clear and precise enough for the interviewees: Regarding the "computing source," "device" was unclear (A), and for the extent of the effect, the difference between "single process" and "complete process" was unclear. To make the wording of the values more precise, the value "device" was changed to "end-device" and "complete process" to "workflow." The difference is that a single process consists of only one process, and a workflow can consist of several processes.

All the discussed new and updated features and values led to a revised version (V2.1) of the MB (see Figure 7.1). The new features and values are highlighted in green, and values that were deemed irrelevant are highlighted in red. Not for all new features, values could be extracted from the interviews. Therefore, a small literature search for suitable values was conducted,

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Feature	Values									
Computing Source	cloud		Local computing center			End-device		hybrid		
Maturity	COTS		Commercial components		Open source components		Prototype		Individual	
Special Hardware Required	Computing			Data capture		Data visualization			Data output	
Data Source	Own data	Augmented Data			Open data		Commercial collection		Synthetic data	
Data Quantity										
Data Quality										
Data Security										
Data and Model Update Frequency	Continuously	In case of changes in regulation	In case of new documents / data		In case of changes in customer behavior			In case of quality problems	None	
Ease of Use										
Time to Decision	Real-time			Near real-time			Several hours			Not time critical
Primary Data Type	Audio	Video	Raster image		Vector image		Transaction records		Time series data	
Primary Purpose	Assistance	Decision making	Forecasting		Classification		Anomaly Detection		Context & Content Understanding	
Point in Time of AI Use in Solution development	Design-Time			Runtime			Accompanying runtime			Hybrid
AI Focus	Processing input				Generating output				Computing task	
Extent of Effect on Enterprise	Isolated solution		Single process			Workflow		Work system		Business model
Added Value										
Reliability and Precision of Results	~ 99,9 % Required			Defined by Enterprise			Defined by Domain			Defined by Competitors
Communication										

Figure 7.2: Version V2.2 of the MB for AI solutions after a literature search

CHAPTER 7. EVALUATION OF THE Morphological Box FOR Artificial Intelligence INTEGRATION

Feature	Values					
Computing Source	Cloud	Local computing center	End-Device	Hybrid		
Maturity	COTS	Commercial Components	Open Source Components	Prototype	Individual	
Special Hardware Required	Computing	Data Capture	Data Visualization	Data Output		
Data Source	Own Data	Augmented Data	Open Data	Commercial Collection	Synthetic Data	
Data Quantity	Very High	High	Moderate	Low	Very Low	
Data Quality	Inconsistent	Duplicate	Incomplete	Outdated	Biased	Noisy
Data Security	Compliance	Data Encryption	Access Control	Data Integrity	Data Privacy	Incident Management
Data and Model Update Frequency	Continuously	In Case of Changes in Regulation	In Case of New Documents/Data	In case of Changes in Customer Behavior	In Case of Quality Problems	
End-User	IT-Expert	IT-Savvy	No IT-Knowledge			
Time to Decision	Real-time	Near Real-Time	Several Hours	Later		
Primary Data Type	Audio	Video	Raster Image	Vector Image	Transaction Records	Time Series Data
Primary Purpose	Assistance	Decision Making	Forecasting	Classification	Anomaly Detection	
Point in Time of AI Use in Solution Development	Design-Time	Runtime	Accompanying Runtime	Hybrid		
AI Focus	Processing Input	Generating Output	Computing Task			
Extent of Effect on Enterprise	Isolated Solution	Single Process	Workflow	Work System	Business Model	
Reliability and Precision of Results	~ 99,9 % Required	Defined by Enterprise	Defined by Domain	Defined by Competitors		
Communication	Frequent & Detailed, Active Collaboration	Regular, Some Collaboration	Minimal, Minimum Collaboration	Specific Moments	None	

Figure 7.3: Version V3 of the MB for AI solutions

and the remaining values were determined based on the literature and the author's knowledge. This led to another version of the MB (V2.2) that included those values (see Figure 7.2). Especially for the features "data quantity," "data quality," and "data security," it was difficult to define precise values. One could argue for using values in a range from very high to very low regarding what the requirements for the solutions are. However, as the MB should help to implement AI solutions, such values should be clearer and tangible so that they can be measured, making it easier for businesses to follow.

For "data quality" and "data security," suitable values were found that can be analyzed as Figure 7.3 depicts. However, those values are still on another level of abstraction than the remaining values. Because of that, further research is required to refine the values of the new features. One possibility could be to create different views for the MB depending on the user (e.g., AI expert or no AI knowledge). Because of the increased number of features, grouping the features into categories like technical features (e.g., "computing source," "data source") and business features (e.g., "extent of effect on enterprise," "communication," "end-user") could also make it more user-friendly.

Figure 7.3 further depicts a new version V3 of the MB that incorporates all previously discussed changes (markings in V2.1 and V2.2).

7.1.4 Summary

In summary, the first evaluation episode consisted of three interviews with experienced AI experts. The experts reported on their work and experience with implementing AI solutions in companies and reviewed the MB. Based on their insights and feedback, the MB was revised by adding new features and values and removing irrelevant and outdated ones. This ultimately resulted in the second iteration of the MB (V3), which is depicted in Figure 7.3. However, the interviews also led to the question of how to determine and evaluate the values for the new data-related features. This will be part of the following evaluation episodes.

The ending conditions by Nickerson et al. [NVM13] were not fulfilled after this first evaluation episode because many new features and values were added to the artifact.

7.2 Evaluation Episode 2: Taxonomy Development Process Application & Classification of Objects in Form of AI Use Cases

After revising the MB in the first evaluation episode, experiences in applying the MB (see section 6.1) showed its utility. However, it also resulted in the question: When will the MB reach a state of maturity? One option to answer this question is using development approaches for taxonomies, as MBs and taxonomies share many characteristics. In this evaluation step, the author aimed to investigate if approaches for developing taxonomies are suitable for guiding the MB development, what the level of maturity of the second version of the MB is from the perspective of taxonomy development, and what improvements have to be made. The taxonomy development method by Nickerson et al. [NVM13] presented in section 2.2.1 was used for this step. This section is based on [RS23b].

7.2.1 Taxonomy Development Process Application

On the one hand, the taxonomy development method by Nickerson et al. [NVM13] was used to evaluate the approach for developing the MB for AI solutions up to this point. On the other hand, the method should be followed further to revise and mature the MB. Firstly, it should be stated that the taxonomy development method can also be used for the development of a MB because Nickerson et al. [NVM13] specifically say that they created their method in such an open way that it can be used not only for taxonomies but also for typologies, frameworks, classifications, or similar artifacts.

The method by Nickerson et al. [NVM13] starts with the definition of the meta-characteristic, the potential users/target audience, the projected use, and the main questions that the taxonomy should be able to answer. First, with the meta-characteristic, the author defines that all

characteristics (i.e. features) of the artifact should be “relevant factors that highly influence the success or failure of introducing AI applications in companies” (step 1). Potential users of the MB are enterprises that want to implement and use AI. Notably, an artifact shall be created that is useful for non-IT companies that lack the necessary knowledge to introduce AI in their companies successfully. Therefore, the target audience is general users, but it can also be used by IT-experts in the companies. The projected use of the artifact is that it helps its users to understand the topic of introducing AI better and to not miss any highly relevant factors that could significantly influence the successful introduction of it as early as possible, in the best case, already at the beginning while evaluating a possible AI usage (e.g. during requirements elicitation). The main questions that should be answered for the users are: What do I have to consider, what must I not forget, where should I start, and what should I focus on? It is intended to provide a decision-making aid so that an AI introduction can be successful or that a consideration can be made whether AI is worthwhile or not.

For the ending conditions of the MB, it was decided to use the subjective and objective ending conditions provided by Nickerson et al. [NVM13] that are listed in section 2.2.1 (step 2). Because the artifact was already developed, the ending conditions were reviewed directly for V3 of the MB (see Figure 7.3).

For the subjective ending conditions, it could be argued that the MB was already concise, robust, and extendible. It was concise because it was meaningful without being too overwhelming. It was robust because the features and values could differentiate between objects. In this case, features and values are the dimensions and characteristics. Further, it is extendible because new dimensions or characteristics can be added easily. The conditions, comprehensive and explanatory, needed to be evaluated first. For comprehensiveness, it needed to be checked if the MB can “classify all known objects in the domain” and if it includes “all dimensions of objects of interest” [NVM13]. Whether the MB was explanatory could be tested by checking “if someone knows the characteristics of an object, he/she will find the object in an identifiable spot in the taxonomy, or if someone finds an object [...], he/she will be able to identify the characteristics without having to know the complete details of the object” [NVM13].

For the objective ending conditions, the author argues from his observation that the following four conditions were already met and that the remaining conditions were not met yet:

- No dimensions or characteristics were merged or split in the last iteration.
- Every dimension is unique and not repeated (i.e., there is no dimension duplication).
- Every characteristic is unique within its dimension (i.e., there is no characteristic duplication within a dimension).
- Each cell (combination of characteristics) is unique and is not repeated (i.e., there is no cell duplication).

Next, the steps of the taxonomy development method will be mapped to the previous steps for developing the MB. So far, the development of the MB cycled through three loops of the method (step 3). In summary, in the first and third cycles, the conceptual-to-empirical approach was used, while in the second cycle, the empirical-to-conceptual approach was applied.

At the beginning of the development, the conceptual-to-empirical approach was chosen because a lot of experience and knowledge about the introduction of AI solutions in companies had been accumulated, and only a small amount of data was available. Then the author proceeded to conceptualize potential characteristics and dimensions of objects (step 4c) based on industrial cases (see section 4.1). After that, objects were examined for their characteristics and dimensions (in the MB's case, the features and values) by deploying the initial set of them to the context modeling method by Sandkuhl [SR21] as explained in section 6.1 (step 5c). Finally, the initial version of the MB was created (see section 5.1.2), which was first presented in [RS22] (step 6c). After reviewing the ending conditions, it can be concluded that they were not met yet, as it was just the first development step (step 7).

According to the method, the author returned to step three but chose the empirical-to-conceptual approach this time. In this second run, the goal was to gather more data to have a quantitative basis for the research project. To gather data, it was decided to conduct expert interviews with experts who have experience with introducing AI solutions in companies. It was decided not to go for a questionnaire because of the required knowledge about the topic of AI introduction. The expert interviews helped to identify new subsets of objects (step 4e). The interview findings were used to identify common characteristics and grouped objects (step 5e), followed by grouping the characteristics into dimensions (i.e., features) (step 6e). Steps 4e to 6e are described in section 7.1. Again, not all ending conditions were met because new features and values were added in the last iteration.

For the third iteration of the process, the conceptual-to-empirical approach was used again. As explained in section 7.1, values could not be identified for all new features during the interviews alone. Therefore, a small literature search, as well as the author's knowledge, was used to find and conceptualize new values for those features (step 4c). Then, objects were examined in the form of outlining the application potential of the MB with its new features and values along the IS development process as explained in section 6.4 (step 5c). At the end of the third iteration, the revised version V3 of the MB with values for all new features (as shown in the section 7.1) was finished (step 6c). The ending conditions that were currently met, as described earlier in this chapter, were also deduced from this version of the MB (i.e., of the MB). Because still, not all objective and subjective ending conditions were met, the development cycle had to continue. The next iteration will be described in the following section.

7.2.2 Classification of Objects in Form of AI Use Cases

For the next iteration that is presented in this section, it was decided to switch to the empirical-to-conceptual approach again. First, it will be described how a classification of objects with the MB was conducted (section 7.2.2), followed by a discussion of the classification's results (section 7.2.2.2).

7.2.2.1 Classifying the Objects

The goal of this approach was to test whether the MB is able to classify objects. Objects in the case of the MB can be e.g., AI introduction projects. Therefore, the AI use cases that were used to develop the initial version of the MB (presented in section 4.1) could be used as objects to classify.

Because the initial features and values were based on those cases, the MB should have been able to classify them. However, the second version of the MB included new features and values that were not discovered within the use cases previously. Therefore, it was informative to see if those new features could also be identified in the cases. The objects (i.e., the AI introduction projects) were classified with the MB in a table as shown in Nickerson et al. [NVM13].

Starting the classification, own experience, records, and recorded data from the projects were used to check which value of each feature was true for each project. The results of this classification process are shown in Table 7.1. Each "X" shows which of the values of a feature applies to a use case. For every feature, one value was chosen, except for data security in use case B. In this case, two data security aspects were highly relevant and had to be met/considered. According to Nickerson et al. [NVM13], normally, only one value should be chosen for each feature, but in this case, it made sense that several security aspects could be relevant to an AI solution. Similarly to the feature "computing source," a "hybrid" value could have been added, but in that case, it would not have been clear which of the other values were meant by "hybrid." Because of that, the author decided to offer the possibility to choose several values for this feature of the MB.

According to Nickerson et al. [NVM13], in general, the goal for a taxonomy or similar artifact should be that for each value, at least one object can be identified that has this value. The reason for that is that if there is not a single object for one value, the question arises whether that value is really relevant. Although there were still several values without an identified object, as can be seen in Table 7.1, the author argued that they could still be relevant because the set of only four objects is too small to draw empirical conclusions. In future evaluation steps, the goal should be to classify a significant number of objects (i.e., AI introduction projects) to meaningfully evaluate which values are relevant and which are not. This was accomplished later by a survey presented in section 7.4.

7.2.2.2 Discussion

Despite the small number of objects, some tendencies could be identified from the classification. Firstly, in three of four use cases, the main "AI focus" was a "computing task", and in only one case, the focus was to "generate output", and in zero cases, to "process input".

The planned "end-user" was distributed nearly evenly among all values. Only the end-user with "no IT-knowledge" at all was chosen two times.

For the "computing source," all use cases were split up between "cloud computing" and "local computing centers," but there were no cases of "end-device" or "hybrid" for the computing source.

Also noticeable was the distribution of the feature "time to decision" because one could assume that mostly, decisions of AI solutions have to be delivered immediately, but in the industrial cases, it was acceptable to receive the results after "several hours" and only in the financial industry case, it was necessary to receive them "near real-time."

The "required special hardware" was also split up evenly between hardware for "computing" and "data-capturing" tasks only.

"Reliability and precision of results" showed an intriguing outcome because, in none of the cases, a percentage of around 99,9 % was required. In two cases, the necessary precision and reliability were "determined by the enterprise" and, in one case, by the "domain" and "competitors." One reason for this result could be that none of the use cases were from a sector or solution that could potentially risk human lives, as in medicine or nuclear power plants. Conversely, in the use cases of air conditioning and the financial industries, one could have expected a required percentage of 99,9 %.

In two cases, the AI solution was used in more than one of the different development phases ("hybrid"), one was used during "runtime," and one was "accompanying runtime."

The "primary purpose" varied between all use cases and ranged from "assistance" and "decision-making" to "forecasting" or "classification," leaving only "anomaly detection" open.

Another result that should be highlighted is that in three of four cases, the "own data" of the company was used, and only in the marketing use case, a "commercial collection" was bought. This makes sense in this case because, with data from outside, it is possible to learn new marketing techniques or strategies that are currently not known in the company. On the other side, it was noticeable that only data from outside was used and no "own data". The remaining values did not apply to the presented use cases.

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Features	Values / Industrial Cases	Clean Room and Air Conditioning (A)	Financial Industries (B)	Marketing (C)	Garden Products (D)
AI Focus	Processing Input				
	Generating Output			X	
	Computing Task	X	X		X
End-User	IT-Expert			X	
	IT-Savy		X		
	No IT-Knowledge	X			X
Computing Source	Cloud	X			X
	Local Computing-Center		X	X	
	End-Device				
	Hybrid				
Time to Decision	Real-Time				
	Near Real-Time		X		
	Several Hours	X		X	X
	Later				
Special Hardware Required	Computing		X	X	
	Data Capture	X			X
	Data Visualization				
	Data Output				
Reliability & Precision of Results	~ 99,9 % Required				
	Defined by Enterprise	X			X
	Defined by Domain		X		
	Defined by Competition			X	
Point of Time of AI Use in Solution Development	Design Time				
	Runtime		X		
	Accompanying runtime	X			
	Hybrid			X	X
Primary Purpose	Assistance	X			
	Decision Making		X		
	Forecasting				X
	Classification			X	
	Anomaly Detection				
Data Source	Own Data	X	X		X
	Augmented Data				
	Open Data				
	Commercial Collection			X	
	Synthetic Data				
Data Quantity	Very High		X		
	High			X	X
	Moderate	X			
	Low				
	Very Low				
Maturity	COTS				
	Commercial Components		X		X
	Open Source Components	X		X	
	Prototype				
	Individual				
Data & Model Update Frequency	Continuously				
	In Case of Changes in Regulation		X		
	In Case of New Documents/Data	X			
	In Case of Changes in Customer Behavior				
	In Case of Quality Problems			X	X
Extent of Effect on Enterprise	Isolated Solution				
	Single Process				
	Workflow		X		
	Work System	X			X
	Business Model			X	
Communication	Frequent & detailed, active collaboration				
	Regular, some collaboration		X	X	
	Minimal, min. collaboration	X			X
	Specific Moments				
	None				
Primary Data Type	Audio			X	
	Video				
	Raster Image				
	Vector Image				
	Transaction Records		X		X
	Time Series Data	X			
Data Quality	Inconsistent		X		X
	Duplicate				
	Incomplete	X			
	Outdated				
	Biased				
	Noisy			X	
	Corrupted				
Data Security	Compliance		X		
	Data Encryption				
	Access Control				X
	Data Integrity				
	Data Privacy		X	X	
	Incident Management	X			
	Audit & Monitoring				

Table 7.1: Classification of AI projects using the MB

As expected, the required amount of data was either "very high" (one case), "high" (two cases), or at least "moderate" (one case). During the determination of this feature, the question arose: What counts as, e.g., moderate? Here, it should be evaluated if a possibility exists that can distinguish more clearly between the different options, and that would make it easier for the users of the MB to choose their required value.

For "maturity," in all cases, collections of configurable components were used. It is noteworthy that the project partners would have preferred COTS solutions if they had been available for their cases. On the other side, they did not want to start completely from scratch. Hence, they decided to use either "commercial" (B, D) or "open source components" (A, C). These findings also opened the question if "prototype" was a useful value because it is difficult to imagine that a prototype for a specific AI solution already exists somewhere, except if you start a new project based on an old project or if you are really lucky to find a prototype for a similar topic online.

It was not necessary to update the data and model of the AI solutions continuously in these cases. They only need to be updated when specific events occur, like a "change in regulation" (B), when "new documents" need to be processed (A), or when "quality problems" occur (C, D).

Additionally, in all the cases, the AI solution had a medium to large effect on the whole enterprise. In case B, a "workflow" was changed. In cases A and D, a "work system" was affected, and in case C, the whole "business model" of the company was modified. It seemed that in all of these projects, the AI solutions were of high importance and led to significant changes in the companies.

The "communication" in the projects between the developers (either internal or external ones) and the affected business units was either "minimal with minimum collaboration" (A, D) or "regular with some collaboration" (B, C). Similarly to the data quantity, the question arose as to how to measure the degree of communication and collaboration, if possible at all. Another question was what differentiates minimal communication from communication only in specific moments. For the author, the difference was that for minimal communication, not much communication is required during the whole development and implementation process, but with specific moments a lot of communication could be required but only in very specific and short moments during the process, e.g., only at the beginning and the end of a project with no communication in between.

The "primary data types" that should be processed in the projects were "video" (C), "time series data" (A), and "transaction data" (B, D).

The "data quality" feature describes potential data quality issues of the available datasets of a company. Those issues can be handled in two ways: either the data has to be cleaned before using it for the AI solution, or the AI solution has to be able to handle and process the data

successfully despite its quality issues. In cases B and D, the available data were "inconsistent," whereas in case A, the data were "incomplete," and in case C, it was "noisy."

As discussed earlier, the "data security" feature showed the anomaly that in case B, "compliance" and "data privacy" were highly important for the AI solution. The focus in the other projects laid more on "incident management" (A), "access control" (D), and also "data privacy" (C). This should not mean that, e.g., data privacy played no role in projects A and D. It should instead help to figure out and to make clear which are the most critical data security aspects for an AI solution during the planning of its development.

7.2.3 Summary

At the beginning of this evaluation section, it was presented how the taxonomy development process by Nickerson et al. [NVM13] was applied to the development process of the MB by mapping its previous development stages to the steps of the taxonomy development process. Thereby, it was possible to show that the development of the MB followed a scientifically proven development approach that can be further followed for future development. As a part of that, the taxonomy development method helped to find and define ending conditions for the development of the MB that are not met at this stage. Thus, the author decided to use an empirical-to-conceptual approach for the next iteration by investigating if and how the MB could classify AI introduction projects.

In conclusion, the classification of the four projects showed that the MB was able to classify AI solutions, respectively, the development and introduction projects for AI solutions successfully. But it also revealed that a few aspects of the MB required more clarity, which would be beneficial for potential users. All ending conditions were still not met because the data-related values needed to be optimized, as they seemed not to fit perfectly and were different from the other values. This led the refinement process of the MB back to step three of the taxonomy development method (see Figure 2.12).

Despite that only four use cases were analyzed, some first tendencies could be recognized regarding which values could be more common for some features. But if those tendencies are true, needed to be evaluated with a considerably more extensive set of data, maybe in the form of a survey. With more data, it could also be analyzed if, e.g., in specific domains or when specific AI technologies are used (e.g., neural networks, rule-based systems, support-vector-machines), specific values occur significantly more often than others. This will be part of a survey presented in section 7.4. Before this survey was conducted, another survey was carried out first to ensure the correctness and completeness of the features and values, which will be presented in the following section.

7.3 Evaluation Episode 3: Survey 1

In the third evaluation episode, the MB was evaluated quantitatively by using a survey. Thereby, this evaluation step depicts an empirical-to-conceptual approach according to the process by Nickerson et al. [NVM13]. The goal of this survey was to review the correctness and completeness of the features and values of the MB. The evaluation was carried out by conducting and analyzing a survey in which participants rated the individual features and values, as well as their structure. The KMO and Bartlett tests were conducted, and a correlation matrix was created as statistical measures to identify overlap between the elements of the MB.

After analyzing the data, further improvement opportunities were discovered in the form of new possible features. On the other side, the participants' ratings for the individual elements were overall satisfactory.

First, the design and preparation of the questionnaire will be explained (section 7.3.1). Second, the resulting answers will be summarized and analyzed (section 7.3.2), followed by a discussion of the overall results of the survey (section 7.3.3). Material from the survey like the survey itself with all its questions and the thorough analysis of the results can be found in Appendix B. This section is based on the paper: [RS24].

7.3.1 Survey Design and Conduction

This section will explain the structure of the questionnaire developed for this evaluation episode. The questionnaire primarily consisted of closed questions. However, at the beginning of each group of questions, an open question was implemented that allowed respondents to express their own opinions.

The survey began with an introductory text that explained the topic, goal, and structure of the survey to the participants. After the participants read this text, the survey continued with the collection of demographic data to gain an overview of the participants. The following data was collected in this step:

- Level of IT experience (expert, experienced, starter, no IT knowledge, no answer)
- Level of AI experience (expert, experienced, starter, no AI knowledge)
- Employment status
- Employment sector
- Level of education
- Current job title

- Duration of work in the current role
- In case of work experience with AI: duration of work with AI

The demographic questions were followed by an open question asking for the respondent's personal opinion on the topic of the survey and to share their own knowledge or suggestions. Specifically, the participant was asked what they believed was important for successfully introducing and integrating an AI solution in a company. Are there, e.g., any factors that could potentially influence a successful integration of an AI solution? This question was deliberately asked before the main part of the survey began to get an uninfluenced answer from the participants. The goal of the main part of the survey was to evaluate whether the features and their associated values were correct or whether any aspects were missing. In the entire survey, the respondent could only give one answer per question unless it was an open question. The main part consisted of 17 groups of questions. These 17 question groups represented the 17 features of the MB. Each of these 17 question groups was structured identically.

Each feature was first introduced to the respondent with a short information text. The purpose of this text was to ensure comprehensibility. Despite making the survey significantly longer, it was the only way to ensure that the respondents could answer the questions meaningfully. Furthermore, if someone were to work with the MB, they would also read the explanation of each feature first to ensure they understand it correctly.

After the introduction, it was asked whether the values belonging to the respective feature were meaningful or not. The evaluation system was based on the following five possibilities:

1. Not at all meaningful
2. Less meaningful
3. Partly/partly (neutral)
4. Partly meaningful
5. Very meaningful

This was followed by two open questions to give the participant the opportunity to express their own opinion on the respective feature. First, it was asked whether they could see other possible values for the feature, and second, whether the subdivision of the respective characteristic made sense to them or if they would have divided them differently. The last question of each group of questions was again an assessment. This time, the question referred to the feature in general. It explicitly asked whether the overall feature itself was a relevant factor for the introduction of AI according to the participant. The answer options were:

- Yes
- Partly
- No
- No answer

After the participant had answered all the questions, the survey was closed with an ending text. This text thanked the participant for their participation once again.

Initially, the survey was sent to various IT SMEs in Mecklenburg-West Pomerania via an e-mail distribution list. Unfortunately, no participants could be acquired with this approach. One reason for that could be that the survey was too long because tests showed that it took around 30–40 minutes to fill it out. Additionally, it could have been too impersonal to contact the SMEs via an e-mail distribution list, which often leads to low survey return rates in general.

Nevertheless, the survey was then conducted among master's students in the Business Information Systems course at the University of Rostock. The survey lasted approximately 3.5 weeks, starting on June 20, 2023, and ending on July 14, 2023. The survey as a whole can be reviewed in Appendix B.1.

7.3.2 Results of the Survey

This section presents descriptive statistics about the survey participants and the data collected. It is divided into four sections: Section 7.3.2.1 summarizes information about the participants of the survey, their experience, and their background. Section 7.3.2.2 describes the statistical analysis of the survey results. This is followed by an analysis of the descriptive statistics created from the questions about the features of the MB (section 7.3.2.3). In the final section 7.3.2.4, the ratings for all values will be compared.

7.3.2.1 Participants

Overall, 14 complete and eight incomplete surveys were received. Two of the eight incomplete surveys were actually complete regarding the content, only lacking the personal information. Therefore, after data cleansing, 16 usable surveys were collected for data analysis. However, for the analysis of the participants, only the 14 surveys with personal information could be used. The participants were students of the University of Rostock. All but two had a bachelor's degree. The remaining two already had a master's degree. Most of the participants worked in

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	Endnutzer	KIFokus	Rechenquelle	Antwortzeit	Spezielle_Hard ware	Zuverlässig	Primäre Aufgabe	Datenquelle	Datenmenge	Reifegrad	Auswirkungen	Kommunikation	Primärer Datentyp	Datenqualität	Datensicherheit
Endnutzer		0.716	0.481	0.609	0.395	0.299	0.307	0.219	-0.230	0.595	0.664	0.323	0.579	0.632	0.433
KIFokus	0.716		0.912	0.115	0.124	-0.252	0.006	0.024	-0.251	0.031	0.361	0.192	0.168	0.275	0.213
Rechenquelle	0.481	0.912		0.512	0.499	0.590	0.831	0.465	0.081	0.861	0.709	0.776	0.863	0.543	0.629
Antwortzeit	0.609	0.115	0.512		0.167	0.531	0.330	0.602	0.134	0.759	0.614	0.473	0.664	0.346	0.513
Spezielle_Hardware	0.395	0.124	0.499	0.167		0.362	0.584	0.313	0.158	0.603	0.553	0.376	0.610	0.646	0.481
Zuverlässig	0.299	-0.252	0.590	0.531	0.362		0.630	0.620	0.636	0.686	0.369	0.464	0.685	0.477	0.391
PrimäreAufgabe	0.307	0.006	0.831	0.330	0.584	0.630		0.580	0.246	0.750	0.604	0.693	0.868	0.515	0.552
Datenquelle	0.219	0.024	0.465	0.602	0.313	0.620	0.580		0.322	0.659	0.569	0.724	0.744	0.506	0.607
Datenmenge	-0.230	-0.251	0.081	0.134	0.158	0.636	0.246	0.322		0.210	-0.009	0.151	0.202	0.653	0.221
Reifegrad	0.595	0.031	0.861	0.759	0.603	0.686	0.750	0.659	0.210		0.791	0.742	0.941	0.668	0.728
Auswirkungen	0.664	0.361	0.709	0.614	0.553	0.369	0.604	0.569	-0.009	0.791		0.711	0.834	0.695	0.921
Kommunikation	0.323	0.192	0.776	0.473	0.376	0.464	0.693	0.724	0.151	0.742	0.711		0.786	0.532	0.746
PrimärerDatentyp	0.579	0.168	0.863	0.664	0.610	0.685	0.869	0.744	0.202	0.941	0.834	0.786		0.653	0.765
Datenqualität	0.632	0.275	0.543	0.346	0.646	0.477	0.515	0.506	0.053	0.668	0.605	0.532	0.653		0.507
Datensicherheit	0.433	0.213	0.629	0.513	0.481	0.391	0.552	0.607	0.221	0.728	0.921	0.746	0.765	0.507	

Figure 7.4: The correlation matrix for the survey results

the telecommunications and information technology industries, with a few also working in the services or business/political sectors. This suggested that most of the participants were likely to be IT savvy, i.e., interested or knowledgeable about IT and likely to be interested in the progress and development of AI, ML and similar emerging technologies.

Out of 14 complete responses, two identified themselves as IT experts, eight as IT experienced, and four as IT novices. The AI experience measures painted a different picture: Only one person claimed to be an expert regarding AI. In addition, only two were AI-experienced, and the vast majority, 11, described themselves as AI-beginners. But on the other hand, no one stated to have no IT or AI knowledge. The students from the business IT masters course were chosen because the author could be sure that they have at least some knowledge about AI because of the courses in their curriculum.

7.3.2.2 Statistical Evaluation

To verify the constructs measured in the survey, two tests were performed using the survey data. The first was a correlation matrix, which is a table showing correlation coefficients between variables. Each cell in the table shows the correlation between two variables. A correlation matrix is used to summarize data, as an input into a more advanced analysis, and as a diagnostic for advanced analyses [VJ90].

In this case, it was used to check for any dependencies between features. The matrix is presented in Figure 7.4. Some features showed a high correlation with one another (0.7+, red cells), indicating potential dependencies between the features “Primary Datatype”, “Communication”, “Data Security”, “Extent of Effect on Enterprise”, “Maturity”, and “Data Source.

Secondly, the KMO and Bartlett tests were conducted. The KMO measure of sampling adequacy is a statistic that indicates the proportion of variance in your variables that might be caused by underlying factors. High values (close to 1.0) generally indicate that a factor analysis may be useful for your data. If the value is less than 0.50, the results of the factor analysis

The first notable observation from this figure is the range of responses. For the following features, no participant chose "no": "End User," "AI Focus," "Hardware," "Reliability and Accuracy," "Primary Purpose," "Data Source," "Maturity," "Update Frequency," and "Data Security." This strongly supports the relevance of these features. Regarding the average rating of the features, "Primary Purpose", "Data Quality", and "Data Security", highlighted in yellow, ranked highest with an average score of 4.62 out of 5. As one can see, the majority of features (12 out of 16) achieved a score of four or higher. These high scores on a scale of one to five suggest that for most respondents, these characteristics are important factors regarding the implementation of AI in enterprises and should be included in the MB. On the other hand, even the three lowest-performing features, highlighted in red, still achieved scores above 3.50, which corresponds to an average neutral to positive rating. This indicates that participants still believed that these features fit into the context of AI implementation but that they may have potential for further improvement.

The feature "Maturity" is particularly interesting because it has one of the lowest average performances without anyone choosing "does not fit", which means that for this particular feature, participants were uncertain and mostly chose "partly" (3). The further evaluation of those features should be part of future research. Overall, the sentiment towards these features was highly positive, with an average score of 4.2/5 across all features, supporting the combination of features in the MB.

7.3.2.4 Value Analysis

The next part of the analysis focuses on the values, as the second major goal of the survey was to assess how participants evaluate the existing values, as well as to discover if any values are missing. The latter will be discussed in the following section, with all free-text answers that participants provided during the survey.

For the assessment of the values for each feature, a 5-point Likert scale was used with the following possible responses to calculate the meaningfulness of these values: very meaningful (5), partially meaningful (4), neutral (3), less meaningful (2), and not meaningful at all (1). It's important to note that meaningfulness always refers to the trait itself. This means that when outliers are found, they need to be compared with values in the same group to determine if they are redundant or outdated.

Figure 7.7 presents the average performance results of all values grouped by feature. The evaluation here is similar to the evaluation of the features in the previous section. All value groups achieved rounded scores around four. Even the lowest value groups, "End-user" and "AI Focus," reached scores of 3.6875/5 and 3.7292/5, respectively, indicating that most of the values were perceived as meaningful and appropriate. This is quantified by the average value

Descriptive Statistics					
	N	Minimum	Maximum	Mean	Std. Deviation
Endnutzer_4	16	3	5	4,50	,894
KI-Fokus_4	16	3	5	4,25	1,000
Rechenquelle_4	16	1	5	4,25	1,238
Antwort-/Reaktionszeit_4	16	1	5	4,38	1,204
Spezielle_Hardware_Anforderung_4	16	3	5	4,13	1,025
Zuverlässigkeit/Genauigkeit_Ergebnisse_4	16	3	5	4,13	1,025
Zeitpunkt_der_KI-Nutzung_4	16	1	5	3,50	1,155
Primaere_Aufgabe_4	16	3	5	4,63	,806
Datenquelle_4	16	3	5	4,37	,957
Reifegrad_4	16	3	5	3,75	1,000
Häufigkeit_der_Daten-und_Modellaktualisierung_4	16	3	5	4,13	1,025
Auswirkungen_Unternehmen_4	16	1	5	3,88	1,258
Kommunikation_4	16	1	5	3,69	1,302
Primaerer_Datentyp_4	16	1	5	4,37	1,204
Datenqualitaet_4	16	1	5	4,63	1,088
Datensicherheit_4	16	3	5	4,62	,806
Valid N (listwise)	16				

Figure 7.6: Minimum and maximum ratings, mean and standard deviation for all features

Descriptive Statistics					
	N	Minimum	Maximum	Mean	Std. Deviation
MEAN_Endnutzer	16	1,75	5,00	3,6875	,98531
MEAN_KIFokus	16	1,67	5,00	3,7292	,98296
MEAN_Rechenquelle	16	3,00	5,00	4,0156	,82900
MEAN_Antwortzeit	16	2,50	5,00	3,7500	,73598
MEAN_Spezielle_Hardwa re	16	3,00	5,00	4,1563	,50724
MEAN_Zuverlaessig	16	3,00	5,00	3,8438	,61830
MEAN_PrimaereAufgabe	16	3,00	5,00	4,2750	,70000
MEAN_Datenquelle	16	2,60	5,00	3,8625	,77535
MEAN_Datenmenge	16	3,00	5,00	3,7375	,71075
MEAN_Reifegrad	16	3,00	5,00	4,1750	,77589
MEAN_Auswirkungen	16	1,80	5,00	3,9125	,94366
MEAN_Kommunikation	16	2,60	5,00	3,7375	,92871
MEAN_PrimaererDatenty p	16	3,00	5,00	4,2292	,69355
MEAN_Datenqualitaet	16	2,14	5,00	4,0000	1,01015
MEAN_Datensicherheit	16	2,86	5,00	4,3036	,66163
MEAN_ALL	16	3,01	4,86	3,9610	,56230
Valid N (listwise)	16				

Figure 7.7: Mean statistics of all values for each feature

of meaningfulness of 3.96/5. The best-performing value groups were “Primary Purpose,” “Primary Data Type,” and “Data Security,” each with an average perceived importance of more than 4.2/5. However, how to improve the lower-rated value groups, especially those below 4.0, should be part of future research. Figures containing the results for each individual value can be found in Appendix B.2.

Most of the values reached an average perception of 4 or higher, while the values of the “End-User” only reached averages of 3.5, 3.69, 3.94, and 3.63. The same applied to the “AI Focus,” with averages of 3.88, 3.81, and 3.5. The first two values of the “Computing Source” were rated above the average of 3.96 (“Cloud”, “Local Computing Center”), whereas the last two were rated below average (“End-Device”, “Hybrid”). For the “Time to Decision,” only “Real-time” was rated above average, with “Several Hours” and “Later” having comparably low ratings of 3.31 each. The “Special Hardware Required” values all scored above average, except for “Data Output,” which reached a score just below the average (3.88). For “Reliability and Precision of Results,” “99.9 % Required” and “Defined by Competitor” scored below average. For the “Point in Time of AI Use,” all values were rated above the average. The same applied to “Primary Purpose,” with “Assistance” and “Anomaly Detection,” which reached some of the highest scores overall with 4.56. Regarding the “Data Source,” only “Open Data” fell shortly below the average, and “Synthetic Data” reached the lowest score overall with 3.0. For the “Data Quantity” required

for an AI solution, only the values from “Very High” to “Moderate” were rated above average. Not surprisingly, a “Low” or “Very Low” amount of data was deemed below average, opening the question if those values are necessary at all, as most AI applications need data to work.

For the features “Maturity” and “Data and Model Update Frequency,” all values were rated above average, with just “In Case of Changes in Customer Behavior” falling 0.02 points short. The values for “Extent of Effect on Enterprise” reach mixed scores, with “Isolated Solution” and “Work System” being above average, the whole “Business Model” just -0.02 below average, and “Single Process” and “Workflow” being below average as well. It seemed like the participants assumed that an AI solution mostly either functions as a small isolated solution or directly as one that has a huge impact on a company. For “Communication,” the first two values representing that a regular collaboration is required were rated the best, with the remaining three values scoring below average. All of the “Primary Datatype” values easily scored above average. The same applied to “Data Security,” where “Data Integrity” scored the highest overall rating. For “Data Quality,” all values besides “Noisy” (-0.02) and “Biased” (-0.17) were rated above average. Even the lowest value overall, the data source value “Synthetic Data,” achieved a neutral rating. The fact that no value was perceived negatively and that the average perceived meaningfulness is 3.96/5 further supported the current status of the values of the MB.

However, 3.0 was still no good rating, and the average below 4.0 still showed room for improvement. Therefore, future evaluations should focus on the lowest-rated values. The next section will focus on all the improvements to the MB suggested by the participants in the survey and on indicated areas for possible improvement that can be deduced from the low ratings discussed in this section.

7.3.3 Analysis & Discussion

This section discusses possible changes of the MB that were either directly suggested by the survey participants or could be deduced from the analyzed data (section 7.3.2). The first subsection concentrates on possible new features, whereas the second subsection focuses on possible new values. The final subsection discusses possible changes in the allocation of the values within each feature.

7.3.3.1 Possible New Features

At the start of the survey, the participants were asked about key factors for successfully implementing and integrating an AI solution in a company. This question aimed to stimulate thinking about AI and potentially uncover new features or values for the MB. The answers were systematized by labeling and grouping them into general topic areas, resulting in the

graph shown in Figure 7.8. The answers to the open questions and the results of the grouping process can be found in Appendices B.4 and B.5.

11 areas were identified that were deemed important for successful AI introduction by the participants. Most frequently mentioned were “Purpose,” “Knowledge,” “Data,” and “Legal Framework.” Other areas included “Cultural Factors,” “Technological Resources,” “Measuring Success of AI Implementation,” “Ethics,” “Change Management,” and “Flexibility.” The term “Knowledge” had many variations, indicating the need for someone knowledgeable about AI implementation in the company. This aligned with the purpose of the MB, which is to aid those in SMEs who may lack an AI expert. The “Purpose” category elicited a range of responses, but all agreed that AI needs a clear reason for use, linked to business goals, and an AI strategy.

This was represented by the “Extent of Effect on Enterprise” feature, which includes potential automation or business model changes, and the “Primary Purpose” feature from a technological perspective.

The same was true for the need for “Data,” which is considered by several data-related features. No indications for further required data-related information were found.

“Cultural Factors” primarily involved fostering acceptance of AI among employees and customers. Key to this was alleviating employee fears of being replaced by AI. This could be addressed by identifying the “End-User,” planning their preparation, and considering the “Extent of Effect” on processes and organizational structures.

The communication aspect, originally focused on developers and users, could also encompass communication with company employees.

The “Measuring Success of AI Implementation” category included testing the AI against common metrics such as accuracy or precision before implementation. Some participants suggested measuring success by return on investment. However, the MB’s goal is to aid successful AI implementation and introduction, not to guarantee financial profit.

The “Reliability and Precision of Results” feature fulfills the technical measurement aspect. The “Technological Resources” area is represented by the “Special Hardware Required”. The “Legal Framework” and “Ethics” areas depend on the country where the AI solution is used, the industry, and the type of AI application. These areas were not represented in the MB so far and could be the objective of future iterations. It should be analyzed if they fit the scope of the MB and, if so, what values they could have.

For “Ethics,” universally applicable ethical aspects for the usage of AI could be collected, while for a “Legal Framework,” some examples like the GDPR and European AI Act could be provided. One step further would have been to extract the most important regulations from such documents, but this was decided to be out of the scope of the MB.

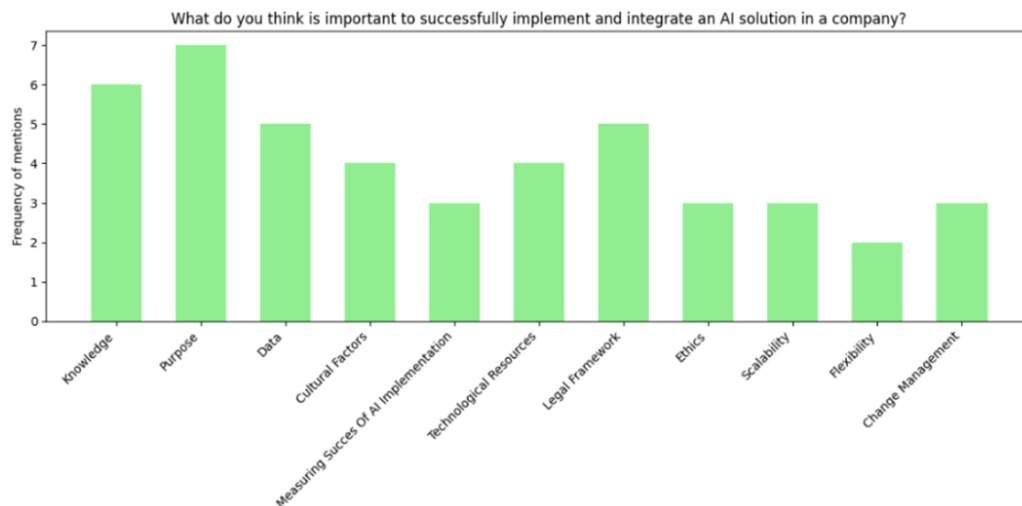


Figure 7.8: Systematized answers for factors influencing AI introduction

“Scalability” and “Flexibility,” like measuring the financial success of an AI solution, are not part of the MB’s scope as they are not necessary for successful implementation.

The “Change Management” area could be covered by a combination of several features like “Extent of Effect,” “End-User,” and “Communication.”

In summary, the author argues that the MB provides the most necessary areas important for introducing AI solutions, as mentioned by the participants. However, the “Ethics” and “Legal Framework” could be added as new features, but require further investigation first. The “Communication” feature could be extended to include communication with a company’s employees.

7.3.3.2 Possible New Values

For each feature, an open-ended question was posed to identify any potential missing values. The responses were generally less detailed than those in the previous section, with fewer answers, and not every feature received possible new values. Table 7.2 groups all suggested values by their features. Any additional comments from participants that did not suggest new values but could still be relevant to the research are included in the comment column.

As highlighted in section 7.3.2.4, all values were generally accepted, as none received a negative rating. However, some values were rated higher or lower than average. The features with the lowest average ratings were “End-User,” “AI Focus,” “Time to Decision,” “Data Quantity,” and “Communication.” This was reflected in the free-text responses and the suggestions for additional values in Table 7.2, as only those received suggestions for possible new values. Most additions were suggested for the “AI Focus.” Suggestions included prediction, optimization,

Feature	Values	Comments
AI-Focus	Prediction Optimization Autonomous driving Data analysis Automation	No additional comments.
End-User	Users, who only know ChatGPT as AI.	Applications should be as user-friendly as possible without technical prerequisites.
Computing Source	SaaS IaaS PaaS	No additional comments.
Time to Decision	On request	No additional comments.
Data Quantity	No proposed values.	Specific values would be helpful.
Data Quality	Complete Uncorrupted	No additional comments.

Table 7.2: Suggested new values grouped by features

autonomous driving, data analysis, and automation. However, none of these fit the feature. Prediction was already included as “Forecasting” in the “Primary Purpose” feature. Optimization was a broad term that could be achieved by all primary purposes. Autonomous driving was too specific, while data analysis was too broad. Automation could potentially be added as an additional value to the primary purposes, but it would overlap with other values like “Assistance” or “Decision Making,” which also offer a form of automation. Therefore, it was decided not to add automation as a new value.

For the “End-User,” a suggestion was made to add a user who only knows “AI as ChatGPT.” However, this was irrelevant for determining the knowledge level of the end user, as this feature should help design the AI solution. It was further noted that applications should be user-friendly and usable without technical prerequisites.

In the case of “Computing Source,” there was a suggestion to expand the values to include “as a service” components such as “Software as a Service (SaaS),” “Platform as a Service (PaaS),” and “Infrastructure as a Service (IaaS).” While generally correct, these suggestions were merely specifications of “Cloud” as a computing source or COTS as a “Maturity” if a company would buy the entire solution externally. In this case, it could also be an AIaaS solution.

For “Time to Decision,” a value “on request” was submitted. However, if a solution only delivers results on request, it still needs to be determined if the results have to be shown immediately (requiring processing before the request or very fast) or if it would be sufficient to deliver the results after a specific time.

The most significant comment from the question about further values per feature was the desire for concrete values for the amount of data required (“Data Quantity”). This was desired

Feature	New Value Structure	Comments
AI-Focus		Meaning of <i>Computing Task</i> unclear.
End-User	Level of application of the software.	
Special Hardware Required		<i>Data Output</i> and <i>Data Visualization</i> unclear.
Maturity	Make Take Buy	

Table 7.3: Suggested new values grouped by features

by several survey participants, with 18.75 % explicitly stating they would like a measurable specification, e.g., in gigabytes. This should be investigated further. The main question would be how the required amount of data can be grouped. Could it be grouped according to specific AI technologies, like how much data is recommended for ML, DL, or others?

The final proposal was to add values for complete and uncorrupted data for the “Data Quality” feature. Although these are two important qualities that data should fulfill, the approach for this feature was to mention all qualities in their negative forms, hence what should be avoided. Here, negative forms of the suggested values are already included as “Incomplete” and “Corrupted” data.

7.3.3.3 Possible Reorganization of the MB

In the final open-ended question, participants were asked if they would organize the values for each feature differently. The aim was to uncover potentially new and improved ways to structure the features, stimulate open thinking among participants, and identify any undiscovered overlap between values. The responses were categorized into “New Value Structure” for suggestions on reorganizing the values and “Comments” for more general feedback relevant to the topic. The findings are displayed in Table 7.3.

The limited number of suggestions could indicate satisfaction with the current distribution of values. However, it was important to note potential bias, as participants were first introduced to the distribution established by the MB. Two comments indicated that the values “Computing Task” for “AI Focus” and “Data Output” and “Data Visualization” for “Special Hardware Required” were unclear.

For future evaluation steps, the descriptions of those values should be reworked and made clearer. There was a suggestion to further distinguish the “End-User” according to the degree of software application, but the participant’s intent was not entirely clear. The only concrete proposal was to divide the maturity level of the application into the classic make, take, or buy levels. However, this was already represented by the existing values.

7.3.4 Summary

In this evaluation episode, a survey was conducted that aimed at evaluating version V3 of the MB. First, a detailed description of the survey's structure and its application was provided. Subsequently, this section delved into an explanation and analysis of the survey results, which paved the way for a discussion on potential adjustments to the features, values, and structure of the MB based on the survey findings.

The data analysis, coupled with the open-ended responses, indicated that the features and values of the MB appear to be accurate overall. For the features, the two new areas, "Ethics" and "Legal Framework," were discovered. The quantitative results were satisfactory in general but also showed some room for improvement for the features and values that performed below average (especially the ones rated below 4.0). Additionally, dependencies between features may exist and should be investigated further.

Although these two new areas have not been added to the MB immediately, they should be added if suitable values can be found. Thereby, this evaluation episode again fails to fulfill the ending condition of the taxonomy development process, that no new dimensions were added after this iteration.

The survey has strong limitations, including the number of participants and the fact that all participants were students from the same university who mostly learned about AI from their university courses. The survey should be revised and conducted again with AI experts from a diverse and international background. However, rather than a measurement of the completeness of the MB as initially planned, the answers of the students and this survey can also be seen as a test of understandability for the MB and its features and values as the students might be on a similar level of IT knowledge as possible users of the MB in companies.

The next section will present another survey teased at the end of the last section that focused on classifying more objects with the MB.

7.4 Evaluation Episode 4: Survey 2

The fourth evaluation episode pursues several goals. First, the relevance of the current features and values of the MB shall be evaluated by classifying a significant number of AI projects with it. As discussed at the end of the second evaluation step (section 7.2.2.2), more objects need to be classified with the MB to see if a use case can be found for each value (i.e., all values are relevant).

While classifying AI projects, the AI technology used will also be collected to be able to possibly identify correlations between AI technologies and specific value combinations.

Furthermore, the evaluation episode should be used to discover possible values and structures for the possible new features of "legal frameworks" and "ethics" that emerged from the survey presented in the last section (section 7.4).

At the same time, it can again be checked if values are still missing for the existing features or if they are complete.

A suitable method to collect a large number of AI project data is to use an online survey again. From the lessons learned from the first survey presented in the previous section, this time, the survey should be significantly smaller and quicker to conduct. Additionally, the survey should be available in German and in English to address a broader audience. Research partners should also be contacted to share the survey in their networks.

Material from the survey like the survey itself with all its questions and all answers are provided in Appendix C.

7.4.1 Survey Design and Conduction

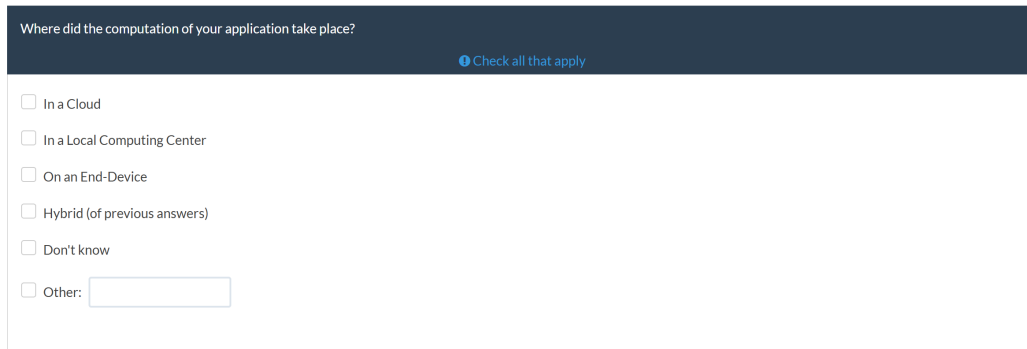
Similarly to the first survey, a LimeSurvey instance by the University of Rostock was used to create and host this survey, as the tool is easily accessible and widely accepted at the University of Rostock for conducting scientific surveys. It provided all functionalities necessary for the planned structure and the questions of the survey.

The survey was structured into five parts:

1. Introduction
2. General AI Project Information
3. AI Project Classification
4. Demographic Questions
5. Final Question & Ending

On the first page, the participants were introduced to the topic of the survey and how it was structured. Of course, data privacy and anonymity were guaranteed as well. If the participants were already involved in several AI introduction projects, they were asked to choose the one that they were most familiar with to guide their responses.

In the next step, general information about the AI project was collected. The participants were asked for their professional background (academia, industry, both), which type of AI technology was primarily used in their project (e.g., ML, DL, computer vision, ...), in which industry



Where did the computation of your application take place?

Check all that apply

- ☐ In a Cloud
- ☐ In a Local Computing Center
- ☐ On an End-Device
- ☐ Hybrid (of previous answers)
- ☐ Don't know
- ☐ Other:

Figure 7.9: Example for a question about a feature (computing source) in the survey

the AI was implemented (e.g., IT, finance, manufacturing, healthcare, ...) and how large the enterprise was where the solution was introduced (micro, small, medium, large, very large). All questions and possible answers can be found in Appendix C.1.

The third part was the main part of the survey because here, the project would be "classified" into the MB. Hence, there was one question for each feature, asking which of the values were true in the participant's project. However, the terms "feature" and "value" were never mentioned to make it more practical. To achieve that, the questions were formulated as follows for the feature "computing source" as an example: "Where did the computation of your application take place?". The values formed the answers together with the options "don't know" for the case that the participant does not know or cannot remember the answer, and "other" to find possible missing values. In the final survey, the questions looked as follows:

As can be seen in Figure 7.9, the answers were sometimes altered minimally to make them more readable and better suited to the question. This should improve the reading flow of the participants and hopefully lead to more filled-out surveys.

After questions to all already existing features, the participants were asked open questions about legal requirements and ethical or cultural requirements specific to AI that were relevant to their AI solution, as follows:

- Were there any legal requirements specific to AI applications that were relevant to the development of your application or that you took into account? If so, please specify which.
- Were there any ethical or cultural requirements specific to AI applications that were relevant to the development of your application or that you took into account? If so, please specify which.

To close this part of the survey, it was asked openly what was required to implement the AI solution in general. This should reveal what the participants themselves thought were the

most important aspects while introducing AI. This should be checked against their responses to the features when analyzing the results.

Second to last, demographic information about the participants was collected, including:

- Gender
- Age (group)
- Highest Level of Education
- Current Employment Status
- Current Job Role/Title
- Their Industry
- Experience in their current Field
- Size of their Company/Employer
- Country of Residence

Finally, the participants were asked if they had anything to add or comment about the topic or the survey. After that, the participants were thanked for their time and effort, and they were offered the possibility to get in contact with the author of this thesis if they were interested in the results of the survey. The complete survey is provided in Appendix C.1.

The survey was conducted between the end of October and the end of December 2024. It was distributed via personal and fellow researchers' accounts on LinkedIn as well as via an e-mail newsletter by a colleague from the University of Applied Sciences and Arts Northwestern Switzerland.

7.4.2 Results of the Survey

The data collected with the survey can be found in Appendix C.2. Overall, 41 people participated in the survey. However, 18 of them only opened the first page of the survey but did not start it (closed it after a few seconds). Nevertheless, 16 participants filled out the survey completely. Seven participants only filled out the first question block (general AI project information). This page was also their last one. They did not even go to the next page with all the questions about the features. If they had looked onto the next page with all the MB-related questions, one could have assumed that this page was too overwhelming, but maybe even the first question block was too much for them. Those participants took around one to three minutes to fill out the page, besides one who took 11 minutes for it.

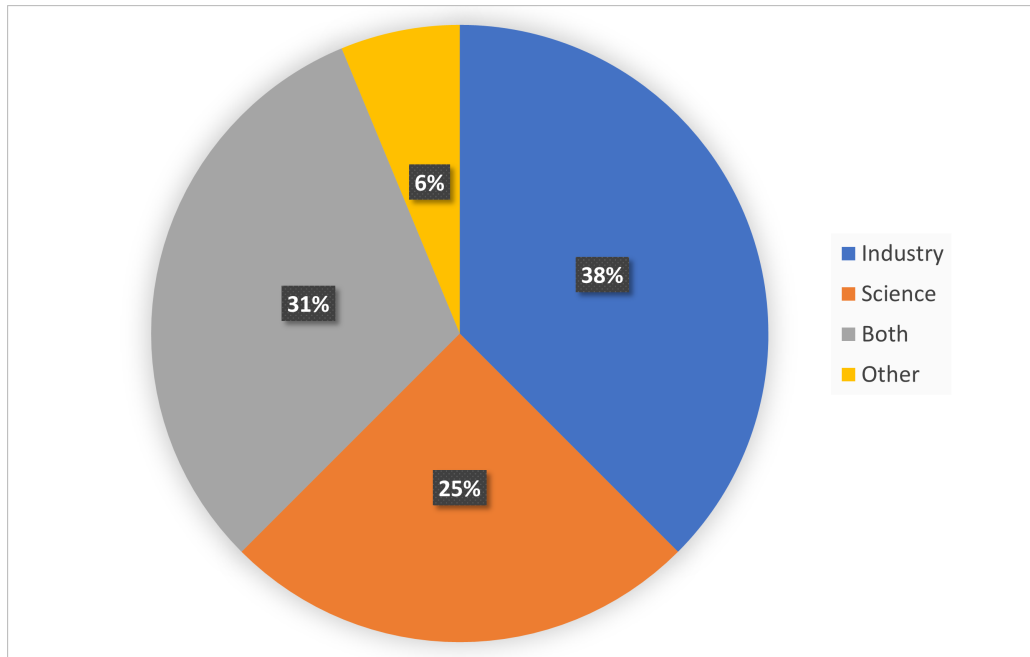


Figure 7.10: Background of the participants

The quickest time to complete the survey was five minutes; the longest was 21 minutes, respectively, 20 minutes. However, the next longest after those two took only 14 minutes. The remaining participants took either 6–7 minutes or 11–14 minutes (around half of the participants for each time span).

The analysis and discussion of the results will concentrate only on the 16 complete responses (see section 7.4.3).

7.4.2.1 AI Projects

This section will provide a brief overview of the AI projects and the companies in which the AI solutions of the participants were implemented. This data was collected in the second part of the survey, "General AI Project Information."

Of the participants, six had an industry background, four had a scientific background, five had both, and one chose "other," specifying "consulting" as their background. Figure 7.10 provides a quick overview of the distribution.

For the types of AI they used in their projects, 11 said ML, six DL, six NLP, one computer vision, two Reinforcement Learning (RL), two SVM, one decision tree, three neural networks, one expert system, one fuzzy logic and zero genetic algorithms and robotics. One participant commented that an established LLM was used, and a generative AI solution was developed based on it. The multiple answers from several participants show that many projects included

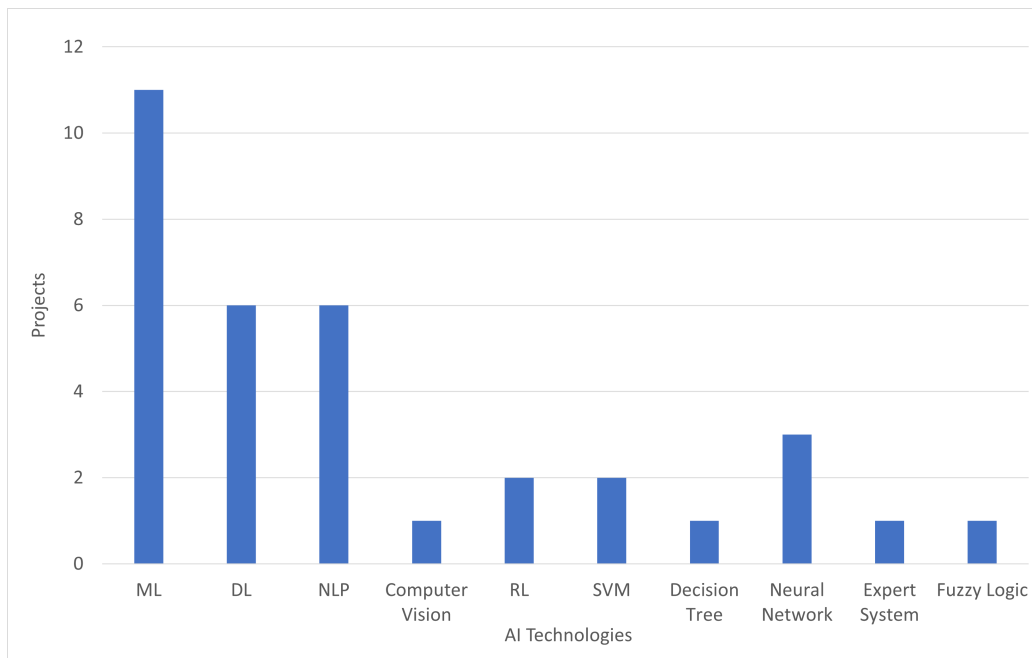


Figure 7.11: AI technologies used in the participants' projects

more than one type of AI. Nevertheless, Figure 7.11 shows that the majority of participants used neural network technologies like ML and DL but also NLP. As expected, some of the participants who chose ML or DL also chose neural networks. However, the majority that used ML and/or DL did not check neural networks as well. This leads to the question if they used ML approaches that did not require neural networks or if they just thought that it was enough to mark ML.

The industry distribution presented in Figure 7.12 depicts the industries in which the AI solutions of the participants were implemented. The numbers show again that the participants were not able to decide on only one industry, as some participants chose several industries. One reason for that could be that the companies had e.g., a broad service portfolio. The majority of projects were conducted in the areas of education, manufacturing, and healthcare, followed by IT and the government.

Figure 7.13 shows that the companies were mostly medium-sized and that the remaining companies are distributed nearly evenly between very large and micro-enterprises.

7.4.2.2 Participants

This section will describe the participants, their backgrounds, and their employees in more detail according to their answers.

Figure 7.14 shows that the participants were nearly equally distributed between female (8) and male (7), plus one identifying as non-binary.

CHAPTER 7. EVALUATION OF THE Morphological Box FOR Artificial Intelligence INTEGRATION

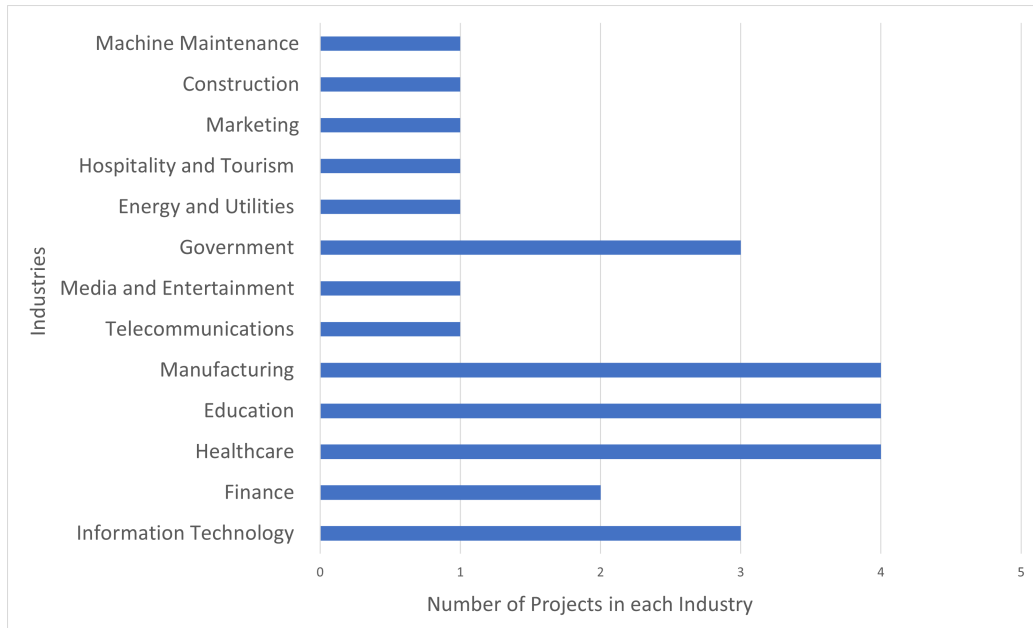


Figure 7.12: Industries the AI solutions of the participants were developed for

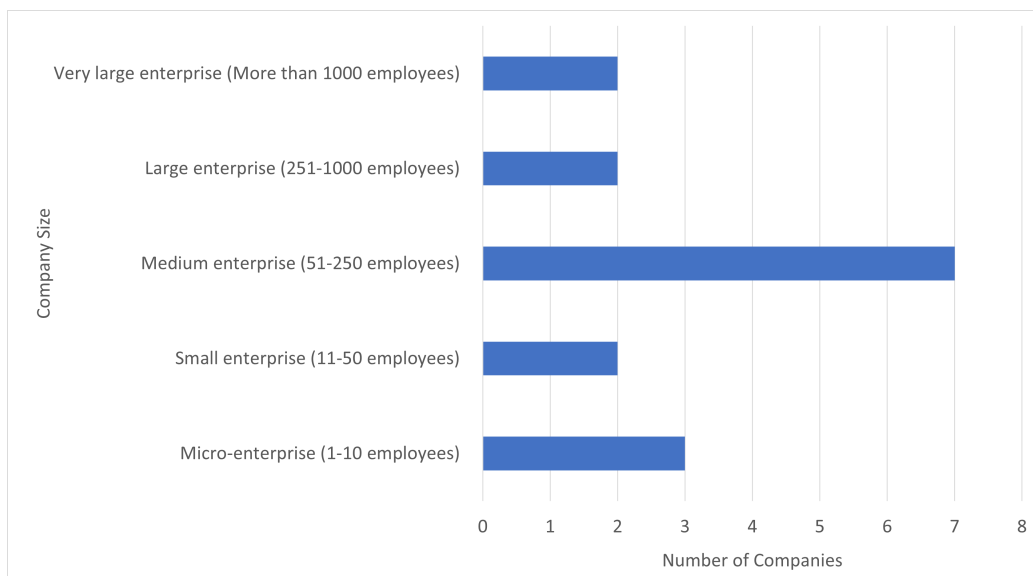


Figure 7.13: Size of the companies that implemented AI solutions

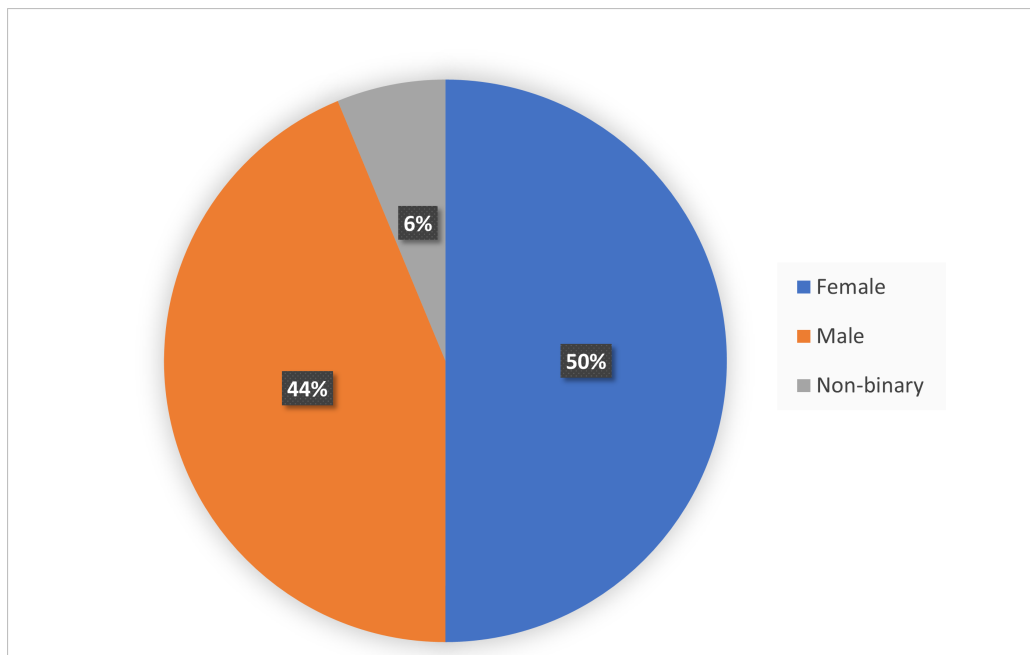


Figure 7.14: Gender distribution of the participants

The age of the participants showed an even distribution between the present age groups, with five participants between 25-34 years, three between 25-44 years, four between 45-55 years, and three between 55-64 years. However, there were no participants under 25 or over 65 years old. The following figure summarizes the distribution:

Regarding the level of education of the participants, three of them had a Bachelor of Science, nine a Master of Science, and four a doctorate / PhD (Doctor of Philosophy). This shows that all participants had an academic background and a university degree (see Figure 7.16).

The participants were mainly part (5) or full-time (7) employees (see Figure 7.17). Two were self-employed and had their own companies, while one was unemployed at the time of the survey.

Besides the two business owners, the job roles of the participants showed a wide variety. Three were lecturers/research assistants, one was a professor, and one assistant professor, while the rest were a technology consultant, project employee, CEO (chief executive officer), head of marketing and communication, and head "ESG" (not knowing what "ESG" stands for), each. The remaining four participants did not answer this question.

Regarding the industry the participants themselves work in, they answered as pictured in Figure 7.18. Firstly, the figure shows they did not choose only one industry again. Secondly, it shows that the majority of participants were from the fields of IT, research, and/or education. It was noticeable that many participants chose a combination of those three industries. It seemed that these participants worked at universities or other research or education-related employers.

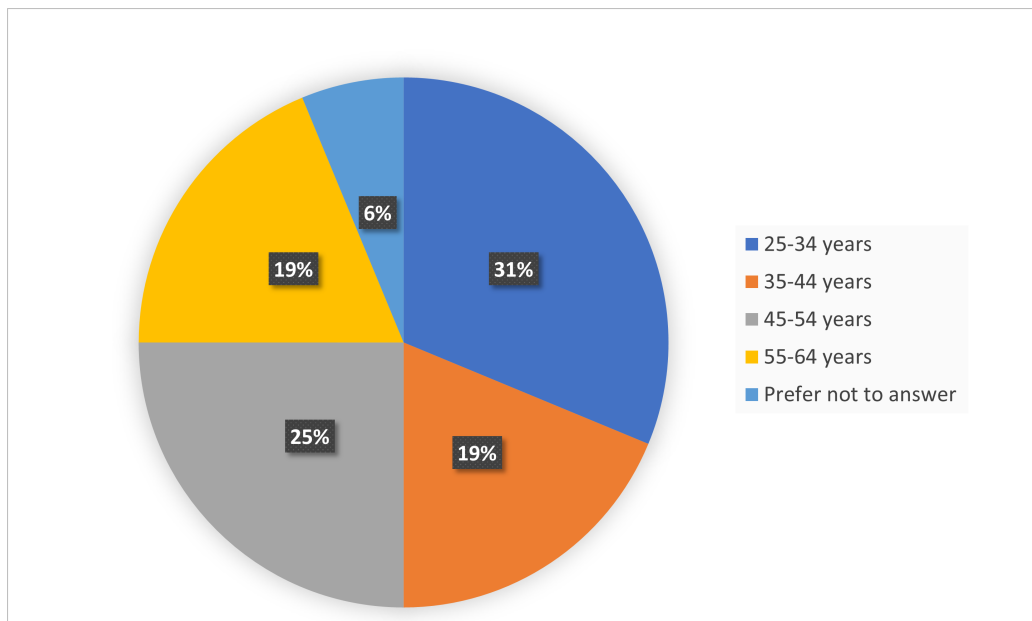


Figure 7.15: Age distribution of the participants

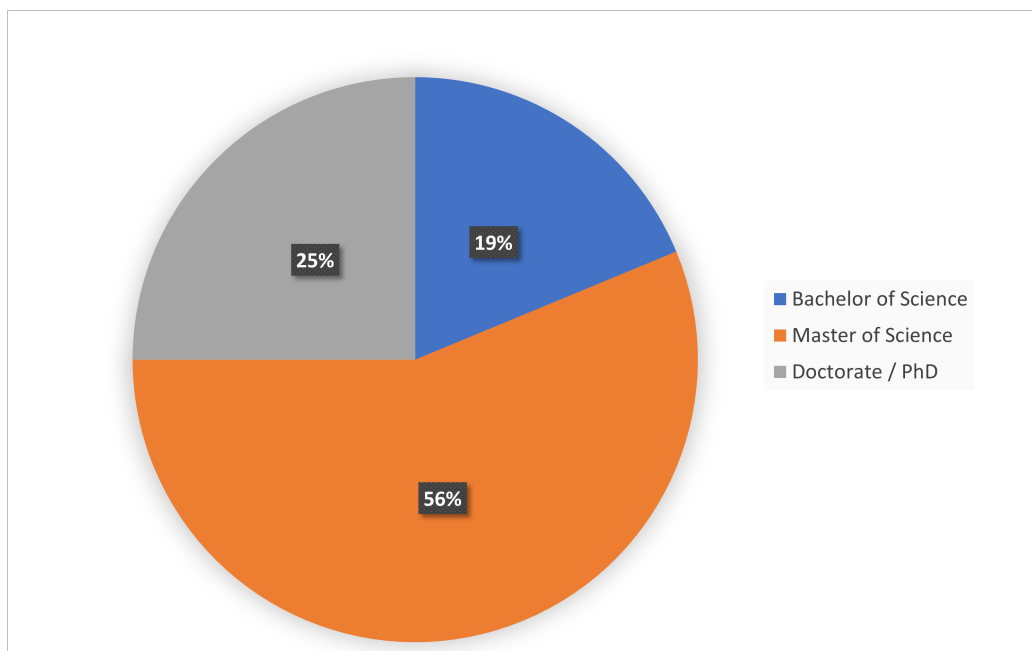


Figure 7.16: Level of education of the participants

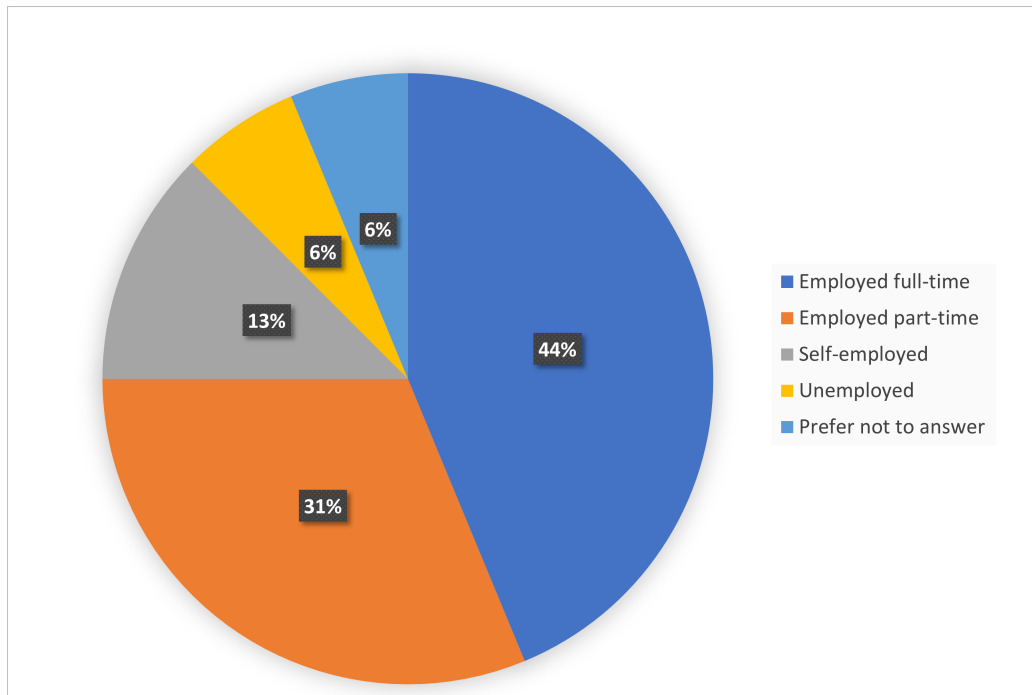


Figure 7.17: Employment status of the participants

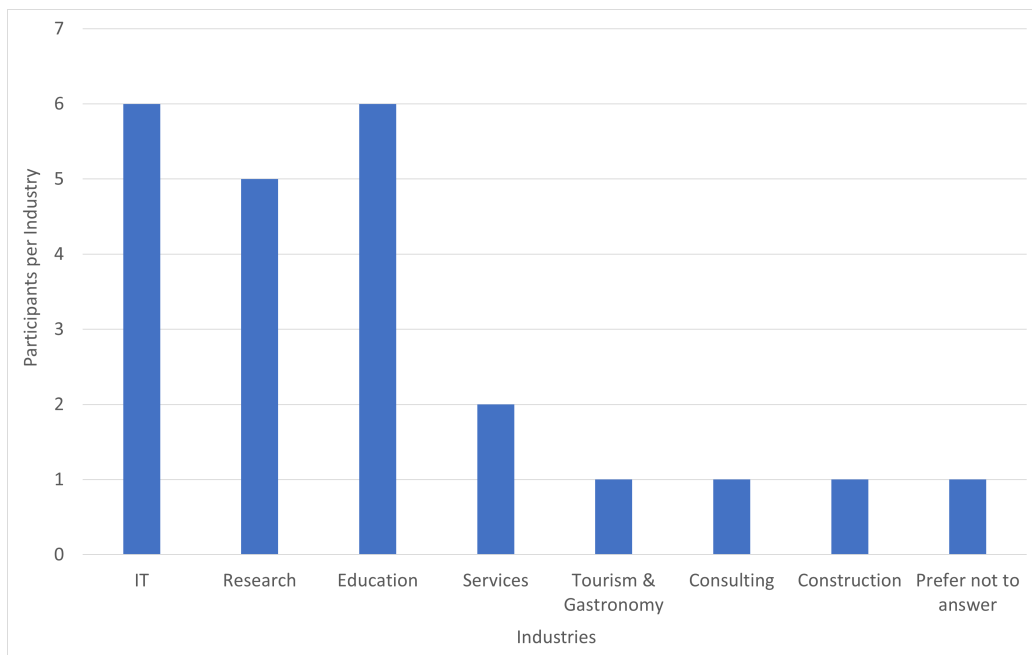


Figure 7.18: Industry affiliation of the participants

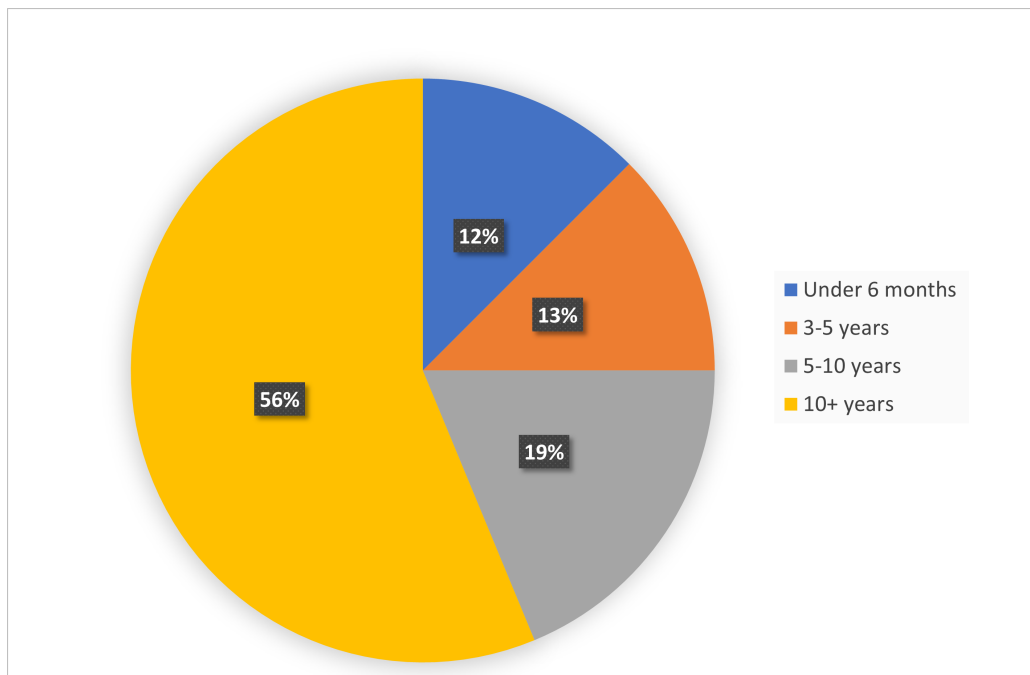


Figure 7.19: Experience in their current field of the participants

As expected from the age of the participants presented earlier, their experience in their current field was also mostly very high, with nine participants having more than ten years of experience (see Figure 7.19). At the same time, only three participants had between five and ten years of experience, two between three and five years, and two under six months of experience.

The companies the participants worked for were all SMEs. Five worked for very small companies with one to ten employees, one for a company with 11–50 employees, three for companies with 51–100 employees, one for a company with 101–200 employees, and three worked for companies with even more than 200 employees.

Finally, the majority of participants came from Switzerland (9), thanks to the help and distribution of the survey by fellow researchers from the University of Applied Sciences and Arts Northwestern Switzerland. The remaining participants were from Germany (5) and from India (1), as shown in the following Figure.

7.4.3 Analysis & Discussion of Features & Values

In this section, the survey results for each feature and its values will be summarized and discussed, and implications for the MB will be deduced.

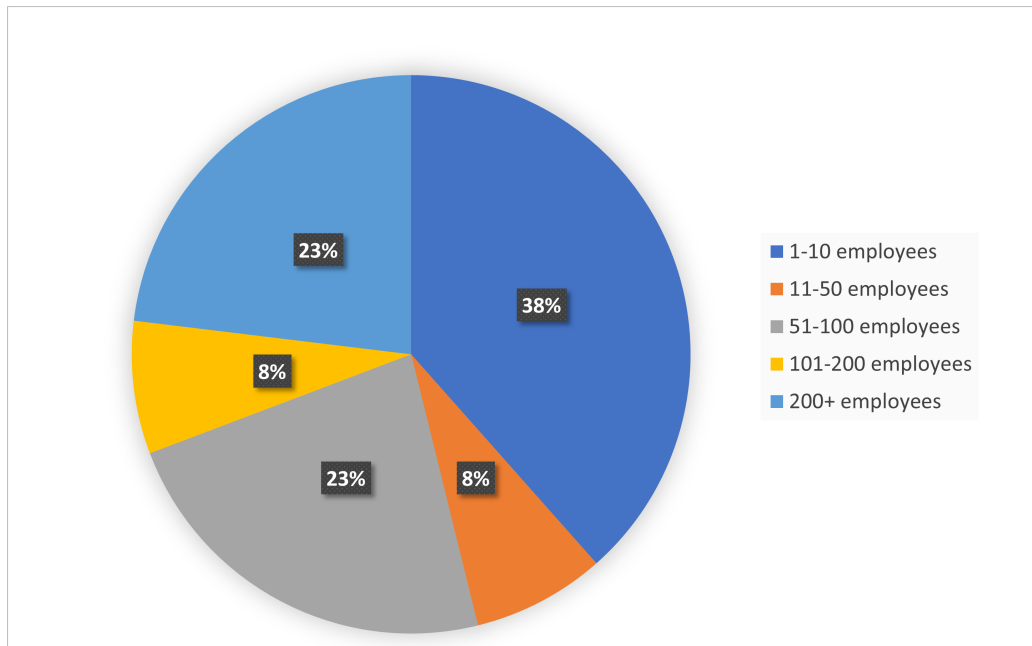


Figure 7.20: Size of the participants' companies

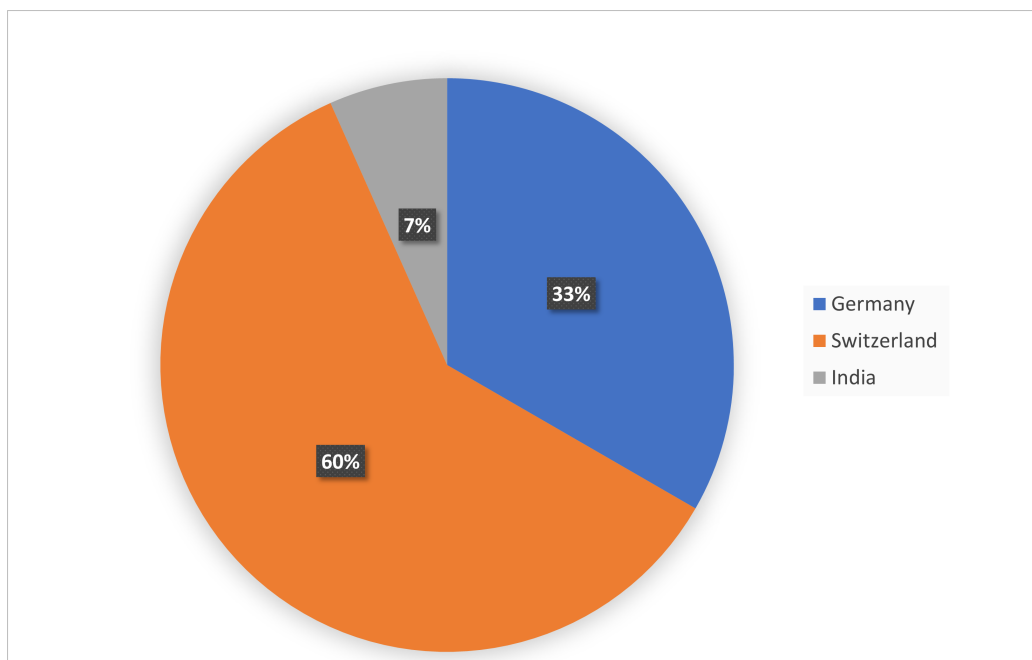


Figure 7.21: Current country of residence of the participants

7.4.3.1 AI Focus

The "AI focus" was on processing input in 11 cases, generating output in 12 cases, and only in one case on a general computing task. Interestingly, in eight cases, the focus was on processing input and generating output simultaneously. In three cases, the focus was only on processing input, and in four cases, only on generating output. Two participants added that in their case, the focus was on quality control in the process of additive manufacturing and on pattern recognition on "LHF." However, it is not known what "LHF" means.

Overall, the results raised the question of whether the "general computing task" should necessarily be an individual value, with only one case using it. Even in this case, the participant also chose the other two values, leading to the fact that there was no case with only this value being relevant. It could be that the majority of cases are already covered by the other two values. Because there were eight cases with both "processing input" and "generating output" as values, it could also be discussed if not in most cases, both were relevant, and the feature was thereby not necessary at all. However, in three respectively four cases, only one of the two values was relevant. Additionally, the goal of the MB is to help its users identify all relevant features of AI. If the feature were to be deleted, this aspect would be missed entirely. However, it is crucial to choose the focus while planning an AI solution because it potentially influences other features like the "special hardware required."

7.4.3.2 End-User

Regarding the "end-user," nine participants said that their end-users had "no IT-knowledge" at all, while five were "IT-savvy," and in one case, the users were "IT-experts." In five cases, the users had some AI-experience (not just "chatGPT"), while there were no AI-experts, and one had no human end-users. The one project with no human end-users also had users with no IT-knowledge. In two of the five cases with some AI-experience, the end-users were also "IT-savvy." Unfortunately, for the remaining three cases with end-users that had some AI-experience, no state of IT knowledge was chosen. In only one case, the end-users were people with "no IT-knowledge" and "IT-savvy." They applied to one case with "IT-savvy" and "IT-expert" users.

This showed that all current values were relevant. Furthermore, AI related knowledge could be added as either additional values or as its own feature. The case of no human end-user did appear once, but only in connection with "no IT-knowledge." Therefore, it seemed like it was not very relevant on its own. Because of that, it should only be added as an individual value if further cases can be detected in future evaluation periods, as the MB strives to be a useful artifact according to Nickerson et al. [NVM13]. To be useful, the MB does not need to include all possible values but only the ones that are useful and relevant for practice.

7.4.3.3 Computing Source

In eight cases, the computing took place in the "cloud," in five cases in a "local computing center," in two cases on an "end-device," and in one case in a "hybrid" solution of the aforementioned locations. In one case, the computation took place in a "cloud" and a "local computing center," so this would actually be a second hybrid case. Therefore, all values seemed to be relevant.

7.4.3.4 Time to Decision

For the "time to decision," two participants claimed that their solutions had to deliver the results in "real-time." On the other hand, the majority of 10 participants needed the results "near real-time." Surprisingly, in none of the cases was it acceptable to receive the results in "several hours," but in two cases, "later" was accepted. Two participants did not remember the required time.

The results raised the question of whether the value of "several hours" is necessary. It could potentially be merged with the "later" value to at least offer one option that is not in or near real-time, and "later" seems to be more suitable. Also, it could be seen that the majority of the solutions had to deliver the results "near real-time."

7.4.3.5 Special Hardware Required

First of all, regarding whether special hardware was required for the solution, only one case did not require any. All other 15 projects did require special hardware, some for even more than one task, respectively value. Seven projects required special hardware for "computing," four for "data capturing," four for "data visualization," six for "data output," and four did not specify. However, one of the four who did not know said they needed "not special hardware, but conventional hardware used specifically for this purpose (dedicated servers in the farm)."

This showed that special hardware was required in one more case, but the participant did not understand the term "special" in the question, respectively, the feature as intended. Therefore, the feature should maybe be renamed from "special hardware required" to "additional hardware required." This would still include the need for special hardware for specific tasks, but it would also include "conventional" hardware for those tasks (which could be called "special hardware" as well). This could make the feature more straightforward to understand and prevent misunderstandings like the one explained.

Additionally, in two cases, all four main values were chosen, and in another two cases, "computing," "data capture," and "data output" were all chosen together. In one case, hardware for

"computing" and "data visualization" was required." In summary, "computing" was never required alone. It always occurred with at least one of the other values, raising the question of its relevance and if the other values together can depict the "computing" value. On the other hand, it was relevant seven times in the opinion of the participants, which shows that it was a relevant factor for the solutions, and the goal of the MB is to provide information about all relevant factors.

7.4.3.6 Reliability and Precision of Results

The next feature evaluated is "reliability and precision of results." In three cases, around 99.9 % were necessary. In comparison, in seven cases, it was "defined by the enterprise" itself, in three cases, "by the domain," in one case, "by the competitors," in one case, the participant did not know, and in another case, the participant chose "other," stating that their solution had to be "as good as required to still provide a speed-up when compared to manual processing." The last case was a special one, as the solution had to be at least faster than the manual process, but it seemed like it was not defined how much faster it had to be. Furthermore, in only one case did someone choose two values (defined by enterprise and domain).

Overall, the majority of values were relevant to the projects. However, "defined by competitors" was chosen only once. As the database was still small, it should be evaluated further on how often it occurs and, thereby, how relevant it is. Additionally, "better than manual processing" could be a new value. Nevertheless, it only occurred once as well, and it could be depicted with the "defined by enterprise" value, as this would be a decision by the enterprise.

7.4.3.7 Point of Time of AI Use in Solution Development

Regarding the question during which time the AI was actually used, four answered during "design-time," nine during "runtime," two "accompanying runtime," three "hybrid," and one did not know. If looked at the answers precisely, it had to be distinguished that from the four cases during "design-time," only one was an individual case. In two cases, "during runtime" was chosen as well, actually making them two more "hybrids." In another case, the participant chose "during design-time" and "hybrid." This led to the fact that in only one case, the AI was solely used during design time. On the other side, in seven cases, the AI was only used during runtime, and in five, in a hybrid form.

In general, the answers showed that in the majority of cases, the AI was at least used during "runtime" and only in a few cases just "accompanying runtime" or even only during "design-time." Despite that "design-time" was only solely relevant in one case, it was relevant six times in combination with other values, respectively, as parts of other values ("hybrid"), showing its relevance for the overall development process.

7.4.3.8 Primary Purpose

The primary purpose of the projects was distributed between the values as follows: assistance (eight), anomaly detection (six), classification (five), decision-making (five), and forecasting (four). In six of 16 projects, more than one primary purpose was selected in various combinations. In four of the six projects, at least anomaly detection and classification occurred together. One participant chose "other" and wrote: "searching for specific word strings in large data and predicting users that have written that." One of the participants who chose "decision-making" added that the solution was for "communication (blog, newsletter, PR articles, social media, etc.)." However, it could also be argued that content generation is just a (very prominent) special type of assistance. Hence, the "assistance" value covered the content generation. If content generation were to occur more often in this or future evaluations, it should be added as its own value because of its perceived relevance from the users' perspective.

The addition of the second comment raised the question of whether "decision-making" alone was not enough, or only as close as possible to describe the primary purpose of this solution. In marketing, AI was often used for content creation (e.g., text, images, or videos). It could have been the case that this was what the participant meant with the comment. "Content generation" would be a valid purpose of AI, especially since this is the primary purpose of established generative AI applications like ChatGPT.

From the first comment, it was unclear what was meant, but it sounded like some sort of prediction was the primary purpose. However, as a word, "prediction" can be a synonym for "forecasting." In the area of AI, prediction is a broader term that includes concepts like forecasting, a specialized form of prediction focused mainly on time-series data. In contrast, prediction uses historical data in general to estimate outcomes. Therefore, it could be said that e.g., classifications like determining if an email is spam or not is also a type of prediction. In the end, "prediction" could be added as its own value for all cases that do not fit into the existing value categories. However, the lack of information about the case made it impossible to determine if the case would not fit in one of the existing categories as well. As only one participant had this problem, the existing values seemed to cover the majority of projects. If "prediction" or another specialized form of prediction should be added as a new value should be investigated first.

Finally, the results showed that often, not only one AI activity was used solely. Nevertheless, for the purpose of the MB, this should still be acceptable as this would help companies to determine all relevant purposes for their solution, despite that one may make up a more significant part of the application. It is essential to know all the parts to be able to prepare for all of them.

7.4.3.9 Data Source

In the vast majority of projects (14), the data came from their own companies. "Augmented data," on the other side, was used in only one project together with "own data" and "synthetic

data." "Open data" was used in two projects, but also in both together with "own data." "Commercial collections" were never used. "Synthetic data" was used in two projects, but again only in combination with "own data" (and "synthetic data" in one project). The remaining two participants selected "other" data sources. One commented that their data came from "IP traffic," which could be own or open data, depending on where it was from or how it was acquired. The other one said that the data came from "e-mails from phishing cyberattacks." It was not clear if this meant that their data were phishing e-mails and where they got them from (own experience or collected from external resources).

Both other cases seemed to be somewhat unique and could potentially be depicted by the existing values if understood correctly. Therefore, no new values needed to be added. On the other side, it should be emphasized that all values besides "own data" were relevant only two or even zero times. However, besides the "commercial component," all values were at least relevant in one case. As the amount of data was still small, with 16 projects, it could also be a coincidence that the participating projects all had their "own data" to use. From the author's viewpoint, it was normal to start the idea of an own AI solution from "own data," but the results show that in some cases, "own data" was not enough (as in four cases, additional data was necessary). One participant who also used "synthetic data" added that "synthetic data was specifically required to reduce the training time," emphasizing its importance. Finally, the "commercial data" value should be questioned because it did not occur even once.

7.4.3.10 Data Quantity

As one could have probably expected, in nine of the 16 cases, the participants claimed that the amount of data they needed was "moderate" (the middle answer), and in none of the cases, a "very low" amount was needed. Nevertheless, three participants needed a "very high" amount of data, and two needed a "high" and "low" amount each.

The fact that the majority of people chose the middle answer, "moderate," could indicate that they were not able to really estimate what the different values meant or how they were to be assessed. On the other hand, seven participants were able to distinguish a tendency, which showed that it was possible to distinguish the amount from the existing values. Whether a user of the MB can determine the value beforehand is another question. One idea could be to make this value dependent on a combination of other values, like the "primary purpose" and "primary data type."

7.4.3.11 Maturity

Regarding "maturity," nine participants stated that they started completely from scratch with "individual" development. On the contrary, only two bought a ready "COTS" product, although

single "commercial components" were used in three cases. The second most projects used "open source components" (six), but none used existing "prototypes." The "COTS" products and "commercial components" were used individually, while "open source components" were used individually in only two cases. In the remaining four cases, they were used with one of the other values.

One reason for the nearly non-existent use of "COTS" products could be that no suitable "COTS" products for the specific use cases were available. The chances that a "prototype" for a specific use case already exists somewhere is arguably even less, making "prototype" arguably unnecessary as a value.

7.4.3.12 Data and Model Update Frequency

The next feature to be analyzed is the "data and model update frequency." Six participants stated that their solution needed to be updated continuously. For the different cases, the distribution looked as follows: "changes in regulations" (4), "new documents/data" (7), "changes in customer behavior" (3), and "quality problems" (4). Combinations existed between all the values, so no particular pattern was recognizable. Hence, no changes needed to be made to this feature.

7.4.3.13 Extent of Effect on Enterprise

For the "extent of effect on the enterprise," in five cases, it was an "isolated solution," although, in two of them, work systems" were affected as well. In six cases, a "single process" was changed. In five cases, the "workflow" was altered. However, in four of those five cases, the "workflow" was not affected alone. The "works system" was changed in three cases but never alone as well. This raised the question if it was clear enough what a "work system" meant in this context or if it was too similar to other values. The whole "business model" was only affected in two cases. In both cases also, the "work system" was affected, according to the participants. In two cases, the participants choose no existing value. One commented that they "replaced the traditional forecast completely." Here, the question is whether the forecasting was just another tool that was replaced or a person who did the forecasting, and whether that changed the processes.

In summary, as for all values, at least two objects were found, and the values did not require further changes.

7.4.3.14 Communication

The results showed that in the majority of projects, either "frequent and detailed communication (active collaboration)" (five) or "regular communication (some collaboration)" (seven) happened. In only two projects, "minimal communication (minimum collaboration)" was practiced. One claimed that they also had regular communication, which does not make much sense. In two cases, communication was necessary only in "specific moments." One of those moments was when they had to "train the team." Finally, in one case, no communication was necessary at all.

Interestingly, no communication occurred at least once. Mostly, frequent and regular communication was required, but in some cases, also minimal communication and communication only in specific moments seemed to be enough, showing the relevance of those values.

7.4.3.15 Primary Data Type

For the "primary data type," a similar phenomenon occurred as for the "primary focus," as many participants selected several data types, showing that often more than just one data type was used in an application. "Audio" data was used in two cases, although "video" data was also used. On the other side, there were two cases where "video" data was used, seemingly without "audio" data (4x "video" overall). Surprisingly, "raster images" were not used at all, and "vector images" only once. However, one comment mentioned that they used "e-mail and scan of documents," and scans of documents typically are images as well. Most projects used "transaction data" (five) and/or "time series data" (eight). Additionally, four comments pointed to a new data type currently not represented by the values: "text" data. Three comments stated "text" as data that their solution used, and one mentioned "office documents," which mainly include text and images.

Hence, "text" or "textual data" should be added as a value. The reason for the dependency of "audio" on "video" data could be that the "audio" was probably used as part of videos. This led to the question of whether there are cases where only "audio" data is processed or generated. Examples of that could be applications in the area of music. Therefore, both values should be kept. Conversely, "raster images" and "vector images" could be combined into one "image data" value because no case used "raster images" and only two cases used "vector images."

7.4.3.16 Data Quality

Regarding the data quality, the participants were asked about the most significant data quality problems that occurred during the development, introduction, and use of their application.

The distribution between the data quality problems looked as follows: "inconsistent data" (six), "incomplete data" (five), "noisy data" (four), "duplicate data" and "biased data" (two each), "corrupted data" (one), "outdated data" (none) and three participants did not know. One participant commented that they had no data quality problems. Another one stated that the "end users were extremely tech illiterate," which sounded more like a data security problem. Finally, one participant who chose "biased data" commented that they (also) had the "wrong data." One combination that occurred more often in the same project was "inconsistent data" and "incomplete data" (four times). Additionally, "duplicated data" did not occur without "inconsistent data." The latter, as well as "corrupted data," also never occurred on its own.

As "outdated data" was never a problem in any of the cases, its relevance was questionable. It was similar for "corrupted data" with only one case. However, the idea of this feature was to remind the user of the MB of possible data quality problems they should have in mind. Therefore, in this case, as well as for the "data security" feature, it was important to collect possible problems, no matter how unlikely their occurrence was. This was also why "none" did not need to be added as a value for any of those features.

7.4.3.17 Data Security

Surprisingly, three values of the "data security" feature were not relevant in any of the cases: "data encryption," "incident management," and "audit & monitoring." Additionally, five participants stated that they did not face any data security problems at all. "Data privacy" was relevant in seven cases, followed by "compliance" in five cases and "access control" and "data integrity" in four cases each.

On the one hand, this raised the question of the relevance of the three values that never occurred. On the other hand, as mentioned before, all data security aspects were important for the goal of the MB. Additionally, one reason for their non-existence could be the formulation of the question, as it was asked if they were "confronted with data security problems during the development, introduction or use of your AI application?" And "if yes, in which areas?" It would have maybe been better to ask which of the data security fields were relevant or did they have to pay attention to. The question formulated in the survey only asked for problems that actually occurred.

7.4.3.18 Open Questions

The remaining three questions of this part of the survey were open questions about legal requirements, ethics, and requirements in general. The answers of the participants to these questions will be summarized in this subsection.

Regarding legal requirements, five participants stated that there were none. One of them added that the reason for that was that the AI did not make decisions, and another one added that there were no applicable requirements for their AI in 2017-2018 (presumably the time they integrated their solution). Two explained that they had to follow requirements regarding data security. One of them also added requirements regarding data management and hosting of the AI. Another participant mentioned that they had the problem that, according to the laws of the European Union, it is not allowed to read e-mails without a reason, but machines would not read them. It sounded as if this would rather be a data privacy requirement. Finally, one participant stated that the problem was that they could not use a Generative Pre-trained Transformer (GPT) by ChatGPT because of data security and compliance concerns, because ChatGPT servers were in America. Hence, an alternative had to be found.

Regarding ethical or cultural requirements, five participants again stated that they did not have to meet any. In one case, no use of the personal data of third parties was allowed. From the author's point of view, this sounded more like a legal requirement rather than an ethical requirement. Another participant stated that his solution operates in a "sensitive health-related domain," and because of that, it was essential to "ensure factual information and transparency" and to "avoid medical advice." In the area of medicine, it was easily imaginable that ethical requirements or problems would arise. Additionally, they would most definitely be connected to legal requirements as they concern human lives. Another participant reported about cultural problems in their project as "the employees as well as the management were skeptical and had to be informed, sensitized, trained and given practical instruction" to such an extent that "follow-up and internal marketing activities were necessary". From the other answers of this participant, it was known that their AI was implemented in a governmental organization, which is known to be skeptical regarding technological changes, at least in Germany, from the author's knowledge.

Overall, it can be summarized that the two questions regarding legal and ethical requirements did not help to identify suitable values for those features. Nevertheless, the answers pointed to the fact that such requirements are often data-related and exist when human lives are involved. Additionally, they can be defined by government institutions like the European Union. Presumably, this could be broken down to a country level (e.g., German data privacy laws) and probably even to a local level of requirements (e.g., own data privacy laws of a federal state like Mecklenburg-West Pomerania).

The final content-related question asked what was, in general, required to implement their AI solution. Nine participants provided the following answers:

- *"Hardware computing power, data diodes"*
- *"Understanding of employees, close cooperation with the AI supplier"*

- *"Human resources"*
- *"Domain-specific facts and FAQs. Knowledge of the cultural and socioeconomic background of end users. Technology in terms of AI tools, frameworks, cloud-based infrastructure in a Swiss data center."*
- *"Getting the data was not so easy, and it was also structured/prepared differently than previously discussed in the project planning. It was not possible to speak directly with the end-users because they did not have time/ were not given time for this. So we only communicated with them via questionnaires."*
- *"Large Language Models, fine-tuning, creation of synthetic training data/data augmentation, as well as re-balancing of data"*
- *"Well, for research and knowledge base contribution!"*
- *"Budget for the subscription, training of the team, development of a workflow"*
- *"Knowledge of the subject matter, how exactly does the process work, what are the work steps"*

In those answers, many aspects can be found that are already depicted by the MB and its features and values, like hardware computing power and other technological aspects, understanding the employees, cooperation, and communication between developer and user, and the amount of data.

Aspects that were mentioned that were not depicted by the MB so far include necessary resources (human resources, training of the team, budget), domain/subject knowledge, and workflows/steps for development and/or integration.

However, the mentioned necessary resources are mainly the same as for any other/normal software development project, and, therefore, they did not need to be integrated into the MB. Specific resources in the form of special hardware required were already included in the MB. Domain or subject knowledge seemed to be naturally necessary in any case, and to provide a workflow or process model is not the goal of the MB. Other research projects that develop such artifacts were presented in chapter 4.3.

Overall, no additional changes to the MB could be derived from the final open question.

7.4.4 Summary

In summary, this survey conducted between the end of October and December 2024 collected information about 16 AI implementation projects in companies of varying sizes, from micro to very large enterprises, from Switzerland and Germany. The participants were mostly employees from SMEs and research institutions from both countries that used ML, DL, and NLP

techniques for their AI solutions. They all had a university education, were at least 25 years old, and 56 % of them already had ten or more years of experience in their current field.

The participants were asked one question for each feature of the MB and to choose the values that applied to their AI introduction project. The goal of that was to find out which values were relevant during their respective projects. This opened the possibility to discover if some values are highly relevant (if they applied to the majority of projects) or not relevant at all (if they applied to no project at all), despite that they probably are correct in terms of their content.

The results analyzed and discussed in section 7.4.3 showed that for the majority of values, objects (i.e. AI introduction projects) were found. This showed the relevance of those values and justified their existence. However, some values did not apply to any project at all or just one project. From the discussed values, it was decided to delete the values "outdated" for "data quality" and "prototype" for "maturity" as it could be argued that they will not occur as often as the other values of their respective feature. On the other side, the values "computing task," "several hours," and "commercial collection" were marked as questionable and would undergo another round of evaluation by experts (see section 7.5.4).

The revised version V4.1 of the MB after this evaluation episode is shown in Figure 7.22. The figure depicts the questionable values in blue, the to-be-deleted values in red, and the new values and features in green. As discussed in the previous section, the hardware-related feature required a new name as well as the newly deduced representation of the end-users' AI knowledge. Additionally, "content generation" was added as a new "primary purpose" and "image" as a new combination of the two previous image values. Regarding the legal and ethical requirements, the survey alone was not enough to discover suitable values that should be directly implemented into the MB.

Nevertheless, the changes in the MB showed that still not all ending conditions by Nickerson et al. [NVM13] were fulfilled.

This evaluation step showed that there were still some adjustments to the MB needed. However, it should be emphasized that the number of participants was again relatively low, with just 16. The number of participants did not allow for the deduction of generalizations from the survey results. However, the survey showed tendencies that discovered room for improvement for the MB. The next and, for this thesis, last evaluation step evaluated the MB an additional time and also re-evaluated the questionable values from this survey with a group of experts. This should examine whether the changes were justified or not.

7.5 Evaluation Episode 5: Expert Discussion

After evaluating the MB four times, the goal of this last evaluation episode was to present the MB to experts whose job it is to evaluate if AI solutions are reasonable for given use cases

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Feature	Values							
AI Focus	Processing input			Generating output		Computing task		
End-User IT-Knowledge	IT-Expert			IT-Savvy		No IT-Knowledge		
End-User AI-Knowledge	AI-Expert	AI-Savvy (not just Gen. AI Apps)		Only Generative AI Apps (ChatGPT, Copilot, etc.)			No AI-Knowledge	
Computing Source	Cloud		Local computing center		End-Device		Hybrid	
Time to Decision	Real-time		Near Real-Time		Several Hours		Later	
Additional Hardware Required	Computing		Data Capture		Data Visualization		Data Output	
Reliability and Precision of Results	~ 99,9 % Required		Defined by Enterprise		Defined by Domain		Defined by Competitors	
Point in Time of AI Use in Solution Development	Design-Time		Runtime		Accompanying runtime		Hybrid	
Primary Purpose	Assistance	Decision Making	Content Generation		Forecasting	Classification	Anomaly Detection	
Data Source	Own Data		Augmented Data		Open Data		Commercial Collection	Synthetic Data
Data Quantity	Very High		High		Moderate		Low	Very Low
Maturity	COTS		Commercial Components		Open Source Components		Prototype	Individual
Data and Model Update Frequency	Continuously		In Case of Changes in Regulation		In Case of New Documents/Data		In case of Changes in Customer Behavior	In Case of Quality Problems
Extent of Effect on Enterprise	Isolated Solution		Single Process		Workflow		Work System	Business Model
Communication	Frequent & detailed, active collaboration		Regular, some collaboration		Minimal, min. collaboration		Specific moments	None
Primary Data Type	Audio		Video		Image		Transaction Records	Time Series Data
Data Quality	Inconsistent	Duplicate	Incomplete		Outdated	Biased	Noisy	Corrupted
Data Security	Compliance	Data Encryption	Access Control	Data Integrity	Data Privacy	Incident Management	Audit & Monitoring	

Figure 7.22: The revised MB (V4.1) after the second survey (text color: green = new, red = to be deleted, blue = questionable)

and develop and integrate solutions for customers. The second part of this evaluation step also offered the possibility to re-evaluate the changes to the MB from the previous survey by a group of experts. Thus, this represents a participatory and formative evaluation of the artifact while collecting qualitative data.

7.5.1 Preparation and Procedure

In this evaluation episode, the MB was presented to a group of six experts from the DVZ of Mecklenburg-West Pomerania. Additionally, two researchers who study the field of AI application and advise companies completed the expert group.

Because of time constraints and practical reasons, the group discussion was conducted on the 17th of December 2024. This means that it was conducted in parallel to the second survey (section 7.4), and the survey results, therefore, could not be included in this first step.

Because the participants already knew each other, the meeting started with a quick introduction of the MB by the author of this thesis. All participants had seen the MB before, as it had been shared with them beforehand via e-mail. Hence, the participants had some knowledge about the structure and parts of the MB.

The procedure for evaluating the MB and gathering feedback from the experts on each feature and value was as follows: One feature, together with each of its values, was presented and explained by the author. After that, the participants were asked to discuss what they thought

about the feature and its values in general, whether they were correct, useful, made sense, if values were missing, and if they could see dependencies on other features. In some cases, the participants agreed immediately. In other cases, there were lengthy and heated discussions. The author tried not to intervene in the discussions and only provided information in case of ambiguities, questions, or incorrect statements. This procedure was repeated for each feature. Overall, the discussion of the whole MB and all its features and values took around 60 minutes. The author of this thesis took notes about the recommendations regarding the features and values while guiding the discussion.

After the meeting, the meeting notes were summarized (section 7.5.2) and discussed (section 7.5.3), deducing implications and changes for the MB from the discussion results.

The revised version V4.2 of the MB was then again shown to four of the experts on the 4th of February 2025 to assess the changes made, ask for their feedback, ask if they agree to the changes, and if their input was included satisfactory. This second meeting took 45 minutes. After that, the version V4.1 of the MB with the changes from the second survey presented in section 7.4.3 was shown to the experts, asking whether they would agree to the changes made in this version or not.

7.5.2 Results of the first Meeting

The discussion between the experts during the first meeting showed that they generally agreed with the features and values and the overall structure of the MB. However, they argued for some changes, especially regarding the phrasing of some parts.

First, the name "computing source" was too unclear for the feature, according to the experts. "It should be clearer what is meant by that," one of them said.

The same applied to the "time to decision" feature. They recommended naming it "execution time."

Furthermore, they said that the term "intended use" would fit the "special hardware required" feature better.

For the "reliability and precision of results," the participants agreed that additional values that are directly measurable, similar to the already existing "99.9 %," would be beneficial to have in case companies already know what percentage they need. Hence, they recommended adding values with a gradation of 70 % and 50 %.

The most discussed feature by far was the "primary purpose." In the eyes of all experts, the level of abstraction of the values of this feature did not fit very well. From their viewpoint, things

like "assistance," "decision-making," and "forecasting" were purposes of AI. However, "classification" and "anomaly detection" would be more like types or techniques of AI to achieve the purposes. If the values of the feature were kept like they were, they recommended naming it "AI purpose" instead.

Furthermore, according to them, an AI solution should never make a final decision alone. Hence, the "decision-making" should be renamed to "decision-support".

It would be helpful for companies to have concrete numbers for the amount of "data quantity," according to the experts. They proposed a combination of the current values with exemplary numbers for each value. The experts of the DVZ suggested using the following gradation they use internally:

Big data, high (up to 10,000 documents or 100 database tables), moderate (up to 1000 documents or 20 database tables), low (up to 50 documents or 10 database tables), no data.

According to the experts, "maturity" would "actually describe a classic make-or-buy decision." Because of that, they also recommended naming it like that: "make-or-buy decision." They added that this feature would be derived from the other features. Depending on them, a make-or-buy decision should be made. This would also be the case for the "special hardware required" and "data and model update frequency." They argued that those features could depend on the other features, like how reliable and precise a result needs to be delivered ("reliability and precision of results"), how much data needs to be processed ("data quantity"), or which AI technology should be used.

Regarding the "extent of effect on enterprise," the experts argued for calling it "scope of the AI solution" because that would "suit the values better."

The "communication" feature was not self-explanatory enough for the experts. Therefore, they proposed a name like "coordination effort during development and maintenance." Additionally, they even argued about the usefulness of this feature and whether it is even necessary. However, they concluded that the planning of necessary communication between developers and domain experts is important for AI introduction, but it would be complicated to find a suitable name for the feature.

When asked for legal and ethical requirements that are relevant from their viewpoint, they listed the German General Data Protection Regulation (GDPR/DSGVO) and Criteria Catalogue for AI Cloud Services (AIC4) as well as the EU AI Act and Digital Operational Resilience Act (DORA). When also asked how they would imagine a feature providing information about those requirements, they stated that they see the option to differentiate between the location, meaning if e.g., German or also European or international laws would be relevant for a German company. This would depend on a company's target audience and size. Regarding ethics, the experts only counted the generally known principles of accountability, non-discrimination, and reliability, but they had no idea how to incorporate them as a feature.

7.5.3 Discussion

The expert discussion of the MB provided valuable insights into the perception, understandability, and correctness of its features and values. The summarized statements and recommendations by the experts will be discussed, and a revised version V.4.2 of the MB incorporating their feedback will be presented in this section (see Figure 7.23).

7.5.3.1 Computing Source & Time to Decision

The first two statements regarding the lack of clarity of the "computing source" and "time to decision" were reasonable. Therefore, the two features were renamed to "computing location," putting more focus on the "location" where the computing will take place, and "execution time," as suggested by the experts, to make it easier and clearer to understand.

7.5.3.2 Special Hardware Required

When reviewing the "special hardware required feature," it was true that "intended use" would describe the values "computing," "data capture," "data visualization," and "data output" correctly. However, renaming the feature like that would get rid of the actual goal of this feature: to make companies think about additional hardware they might need for specific AI tasks as AI solutions often have specific requirements, e.g., require a lot of computing resources. To combine the focus on hardware with the different tasks that the values are, the author decided to name the feature "additional hardware for specific tasks."

7.5.3.3 Reliability and Precision of Results, Data Quantity & Maturity

Regarding the new values for the "reliability and precision of results" and "data quantity" features, the suggestions of the experts were comprehensible and were, therefore, added to the MB. The same applied to the renaming of the "maturity" feature to "make-or-buy decision," as it can be seen in Figure 7.23.

7.5.3.4 Extent of Effect on Enterprise

However, for the "extent of effect on enterprise" feature, it was similar to the hardware feature, from the viewpoint of the author. The goal of this feature is to remind a business user that the AI can have extended effects on a company, even if its initial scope is to be an isolated solution, and to encourage thinking about this. For example, the scope of a solution could be to replace a

small recurring process. However, the automation of this small process could potentially have a significant effect on the overall workflow. This should be represented by the feature, and the author argues that, although "scope of the AI" would be correct, it would not get across the intended message as the "extent of effect on the enterprise" does.

7.5.3.5 Communication

As the proposed new name for the "communication" feature was too wordy and long, and the experts themselves discussed that the feature was still important but not easy to summarize in the short term, the name should stay as it is for now, but it could be re-evaluated in the future.

7.5.3.6 Primary Purpose

For the "primary purpose" as the most discussed feature, the experts argued that the values were not all on the same level of abstraction. However, if split up into "AI purpose" and "AI technique," each feature would currently only include two, respectively, three values each. Additionally, it should be pointed out that, although the argument of the experts was true, it might not have been the best option from the viewpoint of the user of the MB. If the user of the MB were a company employee, they would presumably only know roughly what AI can do and for what they would like to use it. Therefore, a scientifically sharp differentiation is probably not necessary and could make the MB too complex for general users. Hence, when the implications from the first meeting were presented in the second meeting, the experts were also presented with a possible restructuring of this feature. However, the author agreed with the experts on the change from "decision making" to "decision support."

7.5.3.7 Legal Requirements

During the discussion of the experts, they came up with the idea of structuring a possible legal requirements feature according to the different geographical regions a company operates. A similar idea came up after reviewing the answers of the survey participants in evaluation episode four (see section 7.4). Another idea was to integrate concrete regulatory documents like the European AI Act. However, such documents were only relevant for specific regions and would have to be updated regularly. Additionally, there were many of them, which would make it complicated to choose the "most important" ones. If such requirements were grouped by regions, they could have been divided into local (city or federal state level), national (country level), regional (continent level or group of associated countries like the EU), and international (global or multi-regional level). This would have enhanced the MB and provided its users with

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Feature	Values											
AI Focus	Processing input				Generating output				Computing task			
End-User	IT-Expert				IT-Savvy				No IT-Knowledge			
Computing Location	Cloud			Local computing center			End-Device			Hybrid		
Execution Time	Real-time			Near Real-Time			Several Hours			Later		
Additional Hardware for specific Task	Computing			Data Capture			Data Visualization			Data Output		
Reliability and Precision of Results	~ 99,9 % Required	> 70 % Required	> 50 % Required	Defined by Enterprise			Defined by Domain			Defined by Competitors		
Point in Time of AI Use in Solution Development	Design-Time			Runtime			Accompanying runtime			Hybrid		
Primary Purpose	Assistance		Decision Support		Forecasting		Classification		Anomaly Detection			
Data Source	Own Data		Augmented Data		Open Data		Commercial Collection		Synthetic Data			
Data Quantity	Big Data	High (up to 10,000 documents or 100 database tables)			Moderate (up to 1000 documents or 20 database tables)			Low (up to 50 documents or 10 database tables)		No Data		
Make-or-Buy Decision	COTS		Commercial Components		Open Source Components		Prototype		Individual			
Data and Model Update Frequency	Continuously		In Case of Changes in Regulation		In Case of New Documents/Data		In case of Changes in Customer Behavior		In Case of Quality Problems			
Extent of Effect on Enterprise	Isolated Solution		Single Process		Workflow		Work System		Business Model			
Communication	Frequent & detailed, active collaboration		Regular, some collaboration		Minimal, min. collaboration		Specific moments		None			
Primary Data Type	Audio		Video		Raster Image		Vector Image		Transaction Records		Time Series Data	
Data Quality	Inconsistent	Duplicate		Incomplete		Outdated		Biased		Noisy		Corrupted
Data Security	Compliance	Data Encryption		Access Control		Data Integrity		Data Privacy		Incident Management		Audit & Monitoring

Figure 7.23: The revised MB with renamed and new features and values marked in green

the information that AI specific legal requirements are important for AI introduction and that they exist on the named different levels. Nevertheless, it was questionable if companies would actually benefit from this information alone, as they then would have to search for relevant laws themselves. Moreover, it could be argued that there would often be legal requirements on all levels for many cases, as e.g., the EU as well as Germany have data privacy policies. In conclusion, this feature was not integrated into the MB as it includes a relevant aspect of AI integration on the one side, but on the other side, justifiable doubts existed that indicate that a feature in this form would not be useful and would not provide a real additional benefit for the MB's users.

7.5.3.8 Ethical Requirements

The same applied to the ethical requirements. A differentiation based on geographical regions or different recommendation providers (governmental, intergovernmental, academic, non-profit) could have been established. Another option could have been the use of ethical principles like accountability, transparency, fairness, etc. However, this would have just informed the user of the MB that these principles exist and that they should take all of them into account. There would have been no choice which one is relevant for them or applies to them. Therefore, these ideas for values for an ethical requirements feature were deemed not suitable from the author's opinion.

7.5.4 Re-evaluation and Discussion of the Results

This section describes the re-evaluation of the collected feedback on the MB from the expert discussion. Therefore, the revised version V4.2 of the MB (see Figure 7.23) was shown to four of the experts again, and the changes were explained to them briefly for each individual feature. For each feature, the experts were then asked to vote if they were satisfied with the changes and if they would agree with the feature and its values as they are now. In summary, the experts agreed to all changes despite the "primary purpose."

For the "primary purpose," they were presented with the idea to split the feature up as wished by them into "purpose" and "technologies" of AI with a plethora of values collected from literature:

- AI Purpose:
 - Assistance
 - Decision-support
 - Forecasting
 - Automation
 - Content Generation
 - Anomaly Detection
 - Pattern Recognition
 - Classification
 - Clustering
 - Optimization
 - NLP
 - Robotics
- AI Technologies:
 - Neural Network
 - Decision Tree
 - Agent-System
 - Expert-System
 - Ontology
 - Computer Vision

Despite that the distinction between purpose and technique was incorporated, three of the four experts were not satisfied with the features. They argued that the "AI purpose" would still include values not on the same level of abstraction. They then suggested splitting it up even further into overall purposes like assistance and forecasting on the one side, and technical procedures like classification and pattern recognition on the other side. Although they agreed with the new feature "AI technologies," they all admitted that this layer would be too technical for general non-technical employees. After that, they even concluded that the overall distinction they suggested would be correct scientifically, but "not practically useful" for general users if it were too complicated.

Because of this discussion, the author of this thesis decided not to split the feature up and to continue with the feature "primary purpose" as it was (see e.g., Figure 7.23) because, from the viewpoint of potential users in companies that do not have much technical AI knowledge, too many technical values would be too overwhelming and deterrent for them. It can be argued that they are mainly interested in what AI can do on a very basic and general level, like assistance, forecasting, etc.. Therefore, the MB should only include such purposes that the users can understand and work with. In this case, it is also acceptable that the values might not be on the same level of abstraction.

After the changes based on the previous meeting were discussed, version V4.1 of the MB deduced from the second survey shown in Figure 7.22 was presented to the experts. Each change was explained individually, followed by asking them if they would agree or disagree with the change, meaning if the change made sense and enhanced the MB. Then, for the four values that were arguable after the survey, their survey results were explained, and the experts were asked if they thought, based on the survey results and their own opinion, that the values in question should be kept or deleted.

Two of the four experts said that they think the "computing task" is still valuable, especially after the seven cases in the survey. At the same time, the other two stated that it is already covered by "processing input" and "generating output." They questioned if there were AI solutions that only do a computing task while not processing input or generating output. Because of the disagreement combined with the seven cases that chose "computing task," the value was kept.

Regarding the "several hours," the experts all agreed with the idea of including it within the "later" value and therefore deleting it. They argued that "later" already covers "several hours" as well as even later times, and if no one in the survey chose it, its relevance would be questionable.

The "commercial collection" was voted to be kept, with three votes against one. The reason was that three of them were confident that there are companies that use commercial collections, but they were just not represented in the survey, which would be explainable with the

small database. Additionally, the relevance of this value was proven by the application example presented in section 6.2. Here, the AIaaS solution offered the option to use commercial collections in the form of pre-made data sets that can be used.

7.5.5 Summary

In summary, the expert discussion and re-evaluation offered an easily realizable possibility to evaluate the MB as well as the results of the second survey. On the other hand, it was a relatively unstructured approach as the only structure for the discussions was the box itself, without a concrete interview guideline as used for the expert interviews in section 7.1. Nevertheless, the MB itself already provides a structure that one can follow during a conversation as a guideline.

The discussion offered valuable insights into the perception of the MB and which features and values required some adjustments. With the feedback gained, the features and values were reworked, and a new version of the MB (V4.2) could be developed (see Figure 7.23).

The presentation of the results from the second survey (section 7.4) could also be evaluated in the second meeting. The experts agreed to the changes made and provided their input on the values that were questionable after the survey.

For the final step of the evaluation of the MB, the results and changes of the last two evaluation episodes will be combined into the final version of the MB. This will be conducted in the next section, where the complete evaluation process of the MB will be summarized and reflected on. There, the ending conditions for taxonomy development will be reviewed for the final version of the MB.

7.6 Summary of the Evaluation & Reflecting on the Morphological Box Design

The evaluation of the MB consisted of five distinct episodes. First, the initial version of the MB was evaluated with expert interviews. The interviews added many new features and values to the MB and confirmed the initial set of them. This ultimately concluded in V3 of the MB.

The second evaluation episode was the application of an established taxonomy development process to the MB while showing how AI projects can be classified with it. This strengthened the overall development process of the MB with a more structured and scientifically proven basis and validated its structure.

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Feature	Values									
AI Focus	Processing input			Generating output		Computing task				
End-User IT-Knowledge	IT-Expert			IT-Savvy		No IT-Knowledge				
End-User AI-Knowledge	AI-Expert	AI-Savvy (not just Gen. AI Apps)		Only Generative AI Apps (ChatGPT, Copilot, etc.)			No AI-Knowledge			
Computing Location	Cloud		Local computing center		End-Device		Hybrid			
Execution Time	Real-time			Near Real-Time		Later				
Additional Hardware for specific Task	Computing		Data Capture		Data Visualization		Data Output			
Reliability and Precision of Results	~ 99,9 % Required	> 70 % Required	> 50 % Required	Defined by Enterprise		Defined by Domain	Defined by Competitors			
Point in Time of AI Use in Solution Development	Design-Time		Runtime		Accompanying runtime		Hybrid			
Primary Purpose	Assistance	Decision Support	Content Generation		Forecasting	Classification		Anomaly Detection		
Data Source	Own Data		Augmented Data		Open Data		Commercial Collection	Synthetic Data		
Data Quantity	Big Data	High (up to 10,000 documents or 100 database tables)		Moderate (up to 1000 documents or 20 database tables)		Low (up to 50 documents or 10 database tables)		No Data		
Make-or-Buy Decision	Commercial-of-the-Shelf-Product (COTS)			Commercial Components		Open Source Components		Individual		
Data and Model Update Frequency	Continuously		In Case of Changes in Regulation		In Case of New Documents/Data		In case of Changes in Customer Behavior		In Case of Quality Problems	
Extent of Effect on Enterprise	Isolated Solution		Single Process		Workflow		Work System		Business Model	
Communication	Frequent & detailed, active collaboration		Regular, some collaboration		Minimal, min. collaboration		Specific moments		None	
Primary Data Type	Audio		Video		Image		Transaction Records		Time Series Data	
Data Quality	Inconsistent		Duplicate		Incomplete		Biased		Noisy	Corrupted
Data Security	Compliance	Data Encryption	Access Control	Data Integrity	Data Privacy	Incident Management		Audit & Monitoring		

Figure 7.24: The MB after combining the results from the last two evaluation episodes (V5)

The third evaluation episode included a survey that evaluated each feature and value thoroughly. Highly likely because of its length, only students could be won as participants. Nevertheless, the survey provided some insights into new possible features, and it validated the new features and values added in the previous steps.

The fourth evaluation episode consisted of a second survey. This time, data from 16 professionals from the field of AI could be collected. The results helped to adjust some features and values and refine some of their titles (MB V4.1). The main addition in this episode was the new feature concerning the end-user's AI knowledge.

Similarly, the final evaluation episode mainly introduced concrete numbers for the data quantity values and refined some titles (MB V4.2). The data was collected by conducting two semi-structured expert discussions, where the MB itself worked as a guideline.

As the two final evaluation episodes ran partly in parallel, two versions of the MB emerged (MB V4.1 and V4.2). Those two versions were merged together to build the next version V5 of the MB, depicted in Figure 7.24. This shows the merged version with the new and adjusted features and values highlighted in green.

7.6.1 Implications for the Morphological Box from its Application

As described in the previous chapter, applications of an artifact can act as a form of evaluation as well. This thesis, especially the final application case of the MB, i.e. the development of an AI use case evaluation tool (section 6.3), provided essential insights regarding its features

and values. As summarized in section 6.3, the developers of the DVZ added new features and values to their tool that were not yet present in the MB. Because the development of the tools prototype ran in parallel to the two final evaluation episodes, the implications from the application example for the MB will be discussed in this section.

The new aspects added to the tool by the employees of the DVZ involve the features "reliability and precision of results," "data security," "data amount," and "primary data type," as well as the new areas "output format" and "data homogeneity."

To estimate the required reliability of the AI solution, the DVZ used groups from high to unknown based on different percentages. This approach is similar to the structure of feature in the MB despite the fact that the percentages are a bit different and are not labeled from high to unknown. It also provides additional options if no concrete percentages can be estimated at the moment. Therefore, this feature will not be changed.

The "data security" and "data quality" features are both different from the other features of the MB as they are on another abstraction level and provide negative examples about what should not be forgotten. As a result, they do not fit perfectly into the MB. The adaptation of the two features by the DVZ, however, shows possibilities of how both features could fit better into the overall idea and appearance of the MB.

First, they added "structured and homogeneous data" as an additional value for the "data quality" feature. This allows the tool's users to choose if their data is in a suitable format and ready to use or if it has flaws (the remaining values). Because their name is too specific from the author's perspective, an online search was conducted on what "good" data is called, generally. Thereby, the term "high-quality data" was discovered. The quality of data can be measured by different dimensions. Those dimensions are already depicted by the existing values of the feature, although the dimension can differ from literature to literature. For example, Fox et al. [FLR94] differentiate between the dimensions of accuracy, consistency, completeness, and currentness, while Batini and Scannapieca name accuracy, consistency, completeness, currency, and other time dimensions. Hence, "high-quality data" will be added as a new value to the feature.

On the one side, the "data security" feature informs the MB's users what data security areas exist that could be relevant for them. However, it can be argued that a practitioner could potentially just choose all values. The idea of the DVZ to use this feature to ask for the required security level forces the users to still think about the security aspects of their application. Additionally, the options offered are more similar to the remaining values and offer a more straightforward possibility to choose from. Again, a search for similar data security levels was conducted and a categorization by the German Federal Office for Information Security. They define three protection demand categories [Bun22]:

- Normal - Damage effects are limited and manageable.

- High - Damage effects can be significant.
- Very High - Damage effects can reach existentially threatening, catastrophic proportions.

Because the categorization by the German Federal Office for Information Security is similar to the one by the DVZ and it is easily accessible, comprehensible, and approved by the Government, the three categories will be used for the MB. Due to this change, the feature will also be renamed to "data security requirements."

Concerning the "primary data type" feature, the DVZ added additional concrete data types like PDF, Excel, CSV, as well as paper. However, paper is mostly scanned and saved as a PDF or image, and PDF files often include text and/or images. Excel and CSV files, on the other hand, can include all kinds of data. Therefore, these will not be added as values. Though, as paper and PDF can include text, this should be added as a value that was not depicted by the MB so far. An option to choose "other" data types was also offered by the DVZ, but in the case of the MB itself, this is not necessary. First, "other" could then probably be added to all features. Second, the goal of the MB is to offer the most common and usable values following the goal of the taxonomy development process by Nickerson et al. [NVM13].

Finally, the DVZ added two completely new features regarding the "output format" and "data homogeneity". First, the "output format" is important, but often arguably automatically results from the application. Additionally, a feature "output format" would be nearly a copy of the "primary data type" feature.

Second, "data homogeneity" describes a very specific part of data quality. Besides, in none of the evaluation episodes was the desire for both such features communicated. If the scope of the MB were to include all aspects concerning the introduction of AI, they would need to be added. However, the goal is to provide a useful artifact that includes helpful information. Hence, both would have to be evaluated before being added to the MB, which will not be part of this thesis anymore.

Figure 7.25 shows the current final version V6 of the MB, including the final changes discussed in this section marked in Green.

7.6.2 Final Review of the Objective and Subjective Ending Conditions

The author deliberately calls it the *current final version* to emphasize that it is only the final version in the scope of this thesis. As discussed earlier, AI is a continuously and fast-changing field. Therefore, a MB that summarizes a part of this field, i.e., the introduction of AI in companies, will always change as AI develops further. This is also the reason some of the ending

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End-User AI-Knowledge	AI-Expert	AI-Savvy (not just Gen. AI Apps)			Only Generative AI Apps (ChatGPT, Copilot, etc.)					No AI-Knowledge		
Computing Location	Cloud			Local computing center			End-Device			Hybrid		
Execution Time	Real-time				Near Real-Time				Later			
Additional Hardware for specific Task	Computing			Data Capture			Data Visualization			Data Output		
Reliability and Precision of Results	~ 99,9 % Required		> 70 % Required		> 50 % Required		Defined by Enterprise		Defined by Domain		Defined by Competitors	
Point in Time of AI Use in Solution Development	Design-Time			Runtime			Accompanying runtime			Hybrid		
Primary Purpose	Assistance	Decision Support		Content Generation		Forecasting	Classification			Anomaly Detection		
Data Source	Own Data		Augmented Data		Open Data		Commercial Collection			Synthetic Data		
Data Quantity	Big Data	High (up to 10,000 documents or 100 database tables)			Moderate (up to 1000 documents or 20 database tables)			Low (up to 50 documents or 10 database tables)		No Data		
Make-or-Buy Decision	Commercial-of-the-Shelf-Product (COTS)				Commercial Components			Open Source Components		Individual		
Data and Model Update Frequency	Continuously		In Case of Changes in Regulation		In Case of New Documents/Data		In case of Changes in Customer Behavior			In Case of Quality Problems		
Extent of Effect on Enterprise	Isolated Solution		Single Process		Workflow		Work System		Business Model			
Communication	Frequent & detailed, active collaboration		Regular, some collaboration		Minimal, min. collaboration		Specific moments			None		
Primary Data Type	Text		Audio		Video		Image		Transaction Records		Time Series Data	
Data Quality	High Quality Data		Inconsistent		Duplicate		Incomplete		Biased		Noisy	Corrupted
Data Security Requirements	Normal - Damage effects are limited and manageable			High - Damage effects can be significant			Very High - Damage effects can reach existentially threatening, catastrophic proportions					

Figure 7.25: The final V6 MB with updated features and values

conditions for taxonomy development by Nickerson et al. [NVM13] that say that in the last evaluation step, nothing must have changed, will probably never apply to the MB for AI solution integration.

To conclude the evaluation for now, the final version of the MB will be reviewed using the criteria from Nickerson et al. [NVM13]. To sum it up briefly, in section 7.2, the author decided to use the subjective and objective ending conditions provided by Nickerson et al. [NVM13] to assess the maturity of the MB. For the subjective ending conditions, they defined that the artifact has to be concise, robust, comprehensive, extendible, and explanatory to be useful. Additionally, they defined the following objective ending conditions [NVM13]:

- All objects or a representative sample of objects have been examined.
- No object was merged with a similar object or split into multiple objects in the last iteration.
- At least one object is classified under every characteristic of every dimension.
- No new dimensions or characteristics were added in the last iteration.
- No dimensions or characteristics were merged or split in the last iteration.
- Every dimension is unique and not repeated (i.e., there is no dimension duplication).

- Every characteristic is unique within its dimension (i.e., there is no characteristic duplication within a dimension)
- Each cell (combination of characteristics) is unique and is not repeated (i.e., there is no cell duplication)

In section 7.2, it was already argued why the MB already fulfilled the conditions of being concise, robust, and extendible. The conditions are still met in the final version because, despite that the MB grew in size, the author argues that it is still not too overwhelming for the wide field of AI. The remaining subjective conditions that had to be evaluated were comprehensiveness and explainability.

For comprehensiveness, it needed to be checked if the MB can “classify all known objects in the domain” and if it includes “all dimensions of objects of interest” [NVM13]. As it will never be possible to classify all known objects in the domain (if the objects are AI integration projects), the research approach tried to show that it is possible to classify every project that was chosen by the author (see section 7.2.2) as well as by several practitioners via a survey (see section 7.4). For now, all relevant dimensions of AI projects are also depicted in the MB, ensured by the several evaluation episodes. However, as discussed earlier, there will possibly always be new emerging dimensions, i.e., features, in the future. Therefore, the author argues that this condition is also fulfilled by the MB as far as it can.

Whether an artifact is explanatory can be tested, according to Nickerson et al. [NVM13], by checking “if someone knows the characteristics of an object, he/she will find the object in an identifiable spot in the taxonomy, or if someone finds an object [...], he/she will be able to identify the characteristics without having to know the complete details of the object” [NVM13]. This condition is arguably also fulfilled by the MB because it was possible for the participants of the second survey to identify the characteristics of their project, despite at least one being several years old, so it can be expected that not all the details of the object were known anymore.

Concerning the objective ending conditions, the author argues that the following conditions are fulfilled by the last iteration of the MB:

- All objects or a representative sample of objects have been examined.
- No object was merged with a similar object or split into multiple objects in the last iteration.
- Every dimension is unique and not repeated (i.e., there is no dimension duplication).
- Every characteristic is unique within its dimension (i.e., there is no characteristic duplication within a dimension)

- Each cell (combination of characteristics) is unique and is not repeated (i.e., there is no cell duplication)
- At least one object is classified under every characteristic of every dimension.

On the other side, the following two conditions are arguably not fulfilled:

- No dimensions or characteristics were merged or split in the last iteration.
- No new dimensions or characteristics were added in the last iteration.

For the ending condition that at least one object is classified under every characteristic of every dimension, it could be said that for the "commercial collection" value of the "data source" feature, no object was found in the survey. However, as explained earlier, the AIaaS presented in section 6.2 was a case where commercial collections were used. In addition, the expert discussion showed that the value is important in the opinion of the experts.

The first ending condition that is not fulfilled is that no dimensions or characteristics were merged or split in the last iteration. This failed because two characteristics, vector and raster images, were merged, were merged into the "image" value. However, no characteristics were split. Still, the ending condition was missed marginally.

The second condition, that no new dimensions or characteristics were added, is also missed, because one new feature and several new values were added during the last iteration. Though a reason why this condition might never be reached by the MB lies in the nature of AI, as explained.

Overall, the five evaluation episodes presented in this chapter constitute a thorough evaluation of the artifact of this thesis, as most of the objective and subjective ending conditions by Nickerson et al. [NVM13] are fulfilled. This represents the conclusion of the fifth step of the DSR process by Peffers et al. (see Figure 2.1) [Pef+07].

The next chapter will bring this thesis to a conclusion by summarizing its overall results, discussing threats to validity and limitations, as well as its contributions, lessons learned, and future research possibilities.

Discussion and Conclusion

In this final chapter, the results of this thesis will be summarized, threats to validity and limitations will be pointed out, and its contributions will be discussed. The thesis finished with reviewing lessons learned and picturing future research possibilities.

8.1 Summary of the Results in the Context of Design Science Research

From a DSR perspective, the research was initiated by the perceived demand for an artifact that can support companies with the introduction of AI based on own experiences and a plethora of studies (chapter 1). The problem was further motivated by the results of a SLR that (1) emphasized the struggle of companies with AI introduction, (2) showed that methodological support is required, and (3) that the existing support mostly either concentrates on technological aspects, was too broad or focused on AI maturity/readiness (chapter 4.3). All of that represented the first step of problem identification and motivation of the DSR process, leading directly into the definition of objectives for a solution. Based on the SLR results and experiences, the following requirements were deduced for the artifact:

1. Summarizes the most critical features during the introduction of AI.
2. Visualizes the features to make it easier for its users to understand them.
3. Easy to use and understand.
4. Provide possible values for each feature.
5. Easily adaptable to new advances (e.g., technological, social, legal).

Because the MB fulfills the requirements very well, a MB for AI solution integration was developed (chapter 5). The MB was then applied in three use cases (chapter 6) and evaluated over five evaluation episodes (chapter 7). Thereby, the artifact was refined by cycling through Peffers et al.'s [Pef+07] DSR process several times. Further use cases for the MB emerged during those cycles, showing its versatility.

Finally, the research project not only followed the DSR process by Peffers et al. [Pef+07], it also followed the DSR guidelines by Hevner et al. (see Figure 2.4). First, the projects produced a viable artifact in the form of a MB. Second, the MB depicts a technology-based solution that helps to tackle relevant business problems by supporting the development and introduction of applications as shown in use case three (see section 6.3). Thirdly, the artifact was thoroughly evaluated and applied in several use cases and evaluation episodes. For the fourth guideline, the major contribution of this DSR project is the MB for AI solution. The research rigor required for the fifth guideline was guaranteed by using well-established scientific methods like questionnaires and expert interviews, and approaches like the taxonomy development process. The artifact was developed over several years and design cycles, fulfilling the design as a process guideline (Guideline 6). Lastly, the MB was presented to scientific audiences during several conferences as well as to business audiences during expert interviews and discussions.

In summary, this shows how the research process of this thesis followed established DSR principles. Nevertheless, there are limitations and validity threats concerning the project, which will be discussed in the following section.

8.2 Threats to Validity and Limitations

Despite being evaluated through several evaluation episodes and application examples, the MB as an artifact still has limitations, and questions regarding its validity can be raised.

Validity in the context of research results means that the results are truthful, trustworthy, and not biased. It can be differentiated between types of validity. Wieringa [Wie09] differentiates between internal and external validity. Internal validity concerns whether the artifact can fulfill the requirements/objectives defined for it in the defined problem domain, whereas external validity tackles the question of whether the same still applies if the artifact is used in a slightly different problem context.

As discussed earlier, the MB fulfills the objects defined in section 4.4. This was ensured by the five evaluation episodes conducted. Therefore, internal validity is achieved. On the other hand, the application of the MB for other use cases that were not initially planned shows its external validity. In addition, the artifact was not always applied by the author alone, e.g., for the AI use case evaluation tool. In other cases, like in both surveys, the MB was not deeply

explained at all. According to Wieringa and Morali [WM12], the influence of the artifacts developer is normally one of the threats to external validity.

Regarding the limitations, most significantly, the initial use case of the artifact, the use during the development and introduction of an AI solution in a company, could not be conducted because no suitable industry case could be found. This raises the question of whether the MB would really be helpful in such a scenario and, therefore, fulfill its initial goal. However, it was possible to apply the artifact for the development of an AI use case evaluation tool and show its usage. The main benefit for the developers was the knowledge accumulated compactly in the MB. The author further tried to illustrate how an application along the IS development process could look.

Additionally, the surveys and interviews conducted do not form a broad data basis. The number of survey participants was too low to derive general statements and conclusions regarding the relevance of the features and values. All adjustments made to them, discussed after each evaluation episode, can only be seen as tendencies. To be able to make general statements, it would be necessary to conduct a survey similar to the second survey (section 7.4) with several hundred participants. Then, quantitative conclusions could be drawn. Nevertheless, the expert interviews and discussions provide a strong qualitative evaluation of the artifact.

Finally, even though the MB could be applied in three use cases, its real benefit was not measured quantitatively. No comparative experiments were conducted to analyze how the results of the use cases would have looked without using the MB.

8.3 Discussion of the Contributions

The main contribution of this thesis and the result of the applied DSR process by Peffers et al. [Pef+07] is the MB for AI solution integration. The artifact depicts a collection of knowledge about the most relevant factors for integrating AI, which were collected over five evaluation episodes. The thesis further presents several use cases for the MB and how it can be applied in those cases. The artifact can be used by researchers and practitioners alike for their specific cases, thanks to its versatility. For practitioners who want to develop and integrate AI or AI-related applications, the artifact provides a compact collection of relevant information about AI. The same can be used by researchers for developing or enhancing new artifacts or as a comparative framework.

The results of a DSR process can be different depending on the maturity of the domain and already existing solutions. In section 2.1, Gregor and Hevner's matrix of contribution maturity was presented. When looking at the MB, the author argues that it is an improvement. The domain of AI already existed for a long time and has been researched even more over the last

10 years with the advancements in AI technologies. However, the area of support for introducing AI introduction is still concentrated on specific aspects like technological development or training of neural networks. As the SLR presented in chapter 4.3 showed, there is still a need for methodological support.

Regarding the maturity of the MB, if one looks at the three maturity levels of Gregor and Hevner (see Figure 2.6), the author argues that the MB would be on Level 2. It is a general overview of AI features and is, hence, on the same level as e.g., models or design principles. An object of the MB, meaning a combination of values, would be an instantiation of the artifact and therefore be on Level 1.

8.4 Lessons Learned

After developing the artifact and evaluating, and applying it, the author of this thesis can draw many lessons learned for future research projects.

A significant problem that ran like a common thread through the entire research process was the acquisition of suitable participants for evaluating the artifact and business partners for its application. Today, everyone wants to use AI, but actual AI experts are still rare. It is even more complicated to find a large number of them. Furthermore, acquiring participants for the surveys proved to be even more challenging than for the interviews and discussions.

A problem connected to this was that it turned out to be complicated to evaluate all features and values of the MB in one survey in a short form. Even with just one question regarding each feature, as in the second survey, the survey included 19 questions in addition to the questions for collecting demographic data. Most of the time, people do not want to participate in a questionnaire if it takes too long, and the number of participants in both surveys proved that. However, the second survey should have probably been even shorter, as the number of participants who discontinued the questionnaire after the first page was more than 50 %. Further, smaller lessons can be drawn regarding conducting surveys, like that in some cases it would have been better to only allow a single answer and no multiple selection.

Regarding the overall research process, the author of this thesis notes that the first version of the MB was developed just shortly after the problem was identified. This led to the fact that the first design was conducted before the problem and objectives could be analyzed more thoroughly. Because of that, requirements for the artifact and other use cases became apparent over time. This is not definitely a problem, but it could have made the development easier if the requirements had been elicited more precisely earlier.

When reviewing the MB, the evaluation showed that it is not always easy to decide which features and values should be included. Some aspects of AI were discovered that definitely exist

and, in some cases, were even relevant to introducing AI, like ethical and regulatory requirements, but even then they might not be relevant to the MB because they are e.g., too broad to be included in the MB or suitable values could not be discovered so far that would be suitable for the MB. To draw a line between what is in the scope of the MB and what is not was not always 100 % clear, and arguments for and against it can be made in most cases.

8.5 Future Research

Future research possibilities concerning the MB are manifold. Firstly, the MB could be evaluated further with a questionnaire with over 100 participants to substantiate it with a quantitative data basis. With such numerous participants, different aspects could be analyzed.

On the one hand, it could be analyzed if patterns for specific AI technologies, industries, or company sizes occur, which could indicate that particular combinations of values would be more applicable for such cases. A similar recommender system could be established for the case when a few values are predetermined by a company, and the system then recommends which values should be chosen for the remaining features based on their input values. When thinking far ahead, one could even think about using the MB and this data to train an AI that recommends how to develop an AI, i.e., which values of the MB are recommended for each feature.

On the other hand, if it is possible to collect information about the success of the AI projects in the survey, this information could be used to discover patterns that influence the failure or success of AI introduction. This impact assessment could also be conducted via expert interviews. In qualitative interviews, it could be easier to collect information about the success of AI projects by directly discussing connections between specific features and whether the participants see which value is a success or failure factor in retrospect.

Additionally, instead of developing recommender systems based on the MB, the MB could be enhanced into a guideline or checklist that should be followed so that no relevant aspects are missed during AI integration.

Most importantly, real development and integration processes of AI in companies should apply the MB to show its utility in practice. However, proving its benefits will still be difficult. Developers or project managers could be interviewed about the perceived benefit of using the MB. Another idea could be to conduct a laboratory experiment where two groups of participants have to develop the same AI application, but only one group will be provided with the MB at the beginning. However, this would only concentrate on the development aspect and not on the integration into real processes and structures. To examine that, similar projects would have to be conducted in one company or similar companies. But then the outside factors would always influence the results, and no clear conclusions could be drawn. However, in

CHAPTER 8. DISCUSSION AND CONCLUSION

both the laboratory and business settings, for example, the time required for the overall development process or specific tasks could be measured and compared, as well as the quality of the final results.

Appendix

Appendix: Guideline-based Interviews

Appendix A contains material from the guideline-based interviews explained in section 7.1. To secure traceability, the texts are left in the original language the interviews were conducted, German.

A.1 Interview Guideline

This section contains the interview guideline that was used for conducting the experts interviews in section 7.1.

Interviewleitfaden

I. Begrüßung

Guten Tag, mein Name ist Niclas Carlsson/Matteo Wiese: Haben Sie vorab schon einmal vielen Dank, dass Sie sich für uns Zeit nehmen.

Ich möchte Sie darauf hinweisen, dass die Befragung ausschließlich Forschungszwecken dient. Rückschlüsse von den Daten auf die interviewte Person werden nicht möglich sein. Wir werden alle genannten Namen von Personen, Unternehmen etc. unkenntlich machen. Wenn Sie nichts dagegen haben, würden wir das Gespräch gerne auf Tonband aufnehmen, da der genaue Wortlaut für unsere späteren Auswertungen sehr wichtig ist.

[Einverständnis einholen und Tonband einschalten und mitschreiben!]
(Bitte voll und ganz auf das Interview konzentrieren (keine weiteren Tabs offen, keine Beschäftigungen nebenbei))

II. Einstiegsfragen

Was ist Ihre Berufsbezeichnung?
Wie lange sind Sie bereits in Ihrem Job tätig?
Wie alt sind Sie?
In welchen Sektoren haben Sie mit KI gearbeitet?

III. Narrativer Teil (Erzählphase)

Können Sie uns anhand eines Beispiels frei und so ausführlich wie möglich den Ablauf eines KI-Projekts, in welchem Sie involviert waren, erläutern und gegebenenfalls auch entstandene Erfolge oder Misserfolge aus Ihrer Sicht erklären.

Können Sie [angesprochenen Punkt] etwas näher erläutern?

- *Anforderungen an KI-Systeme*
- *Eigenschaften/Features*
- *Ergebnisse (Erfolge/Misserfolge)*
- *Situation Vor/Nach Implementierung*

IV. Narrativer Teil (Nachfrage Phase)

Bitte fassen Sie zusammen welche Aspekte Sie für die Implementierung von KI als wichtig empfinden.

V. Morphologischer Kasten

[Präsentation öffnen]

Wir werden Ihnen jetzt verschiedene Aspekte der Implementierung mit den dazugehörigen Werten vorstellen.

[Vorstellung von 2 Zeilen]

Was halten Sie von diesem Aspekt und den vorgestellten Werten?

Sind die Werte ausreichend oder würden Sie etwas hinzufügen wollen?

Welche dieser Aspekte sind für die Implementierung von KI besonders wichtig/wertvoll?

Welche dieser Aspekte sind für die Implementierung von KI zu vernachlässigen?

Welche Aspekte fehlen Ihrer Meinung nach in diesem Schaubild?

VI. Bilanzierung

Vielen Dank für die von Ihnen vermittelten Eindrücke. Bevor wir das Interview abschließen, wollen wir die wichtigsten Punkte noch einmal zusammenfassen.

Im Laufe des Interviews haben Sie folgende Punkte genannt...

... [wesentliche Punkte nennen]

Haben wir diese korrekt und vollständig wiedergegeben?

VII. Abschluss

Damit wären wir am Ende des Interviews angelangt. Wir bedanken uns herzlich, dass Sie sich Zeit für das Gespräch genommen haben. Sie haben uns damit sehr geholfen. Wenn Sie Interesse an unseren Auswertungen haben, lassen wir Ihnen gerne unsere Ergebnisse zukommen.

Wie fanden Sie das Interview?

Welche Fragen fanden Sie schwierig?

Gibt es noch etwas, dass ich Sie nicht gefragt habe, Sie aber noch wichtig für die Thematik finden und ergänzen möchten?

Haben Sie noch einmal vielen Dank, dass Sie Zeit für uns gefunden haben. Ich wünsche Ihnen alles Gute!

A.2 Interview Notes

The following notes were taken during the first two expert interviews from section 7.1:

Interview 1:

Einstiegsfragen:

Berufsbezeichnung: Head Of Sales (Zuständig für Vertrieb, Marketing und Außendarstellung)

Seit ca. 2 Jahren im Job tätig

30-40 Jahre alt

Sektoren:

Narrativer Teil:

Beispiel aus der Dokumentenanalyse

- KI Teil verhältnismäßig gering, die Technologie ist allerdings entscheidend für den Erfolg des Projekts
- Fotoanalyse

Projektstart mit "Kennenlerncoil"

- Kennenlernen des Unternehmens (Welche Spezifikationen, welche Projekte sind relevant, wichtige Kennzahlen, welches Ziel soll mit dem Projekt umgesetzt werden)

Dann "Solution Lab"

- Wie soll der Prozess am Ende aussehen?
- Was für Daten sind vorhanden? Wie groß ist der Datensatz (für Training)

Labeln der Datensätze

- Aufbereitung der Trainings- und Testdaten
- Unternehmen labelt die Daten und schickt diese an den Entwickler

Training der Daten

- Schleifenweise werden die Daten trainiert, Ergebnisse an das Unternehmen zurückgeschickt, evaluiert, und weitere Trainingsdaten an den Entwickler geschickt
- Solange bis zufriedenstellende Genauigkeit

Übergabe der Technologie

- Cloud, On-premise, etc

Ende des Projekts

Nachtrainingsphase ("Live Learning")

- Dokumente die nicht bekannt waren werden für zukünftige Prozesse trainiert

Grundsätzlich fortlaufende Weiterentwicklung

Anforderungen:

Bereitstellung eines Frameworks, das für den Use Case geeignet ist
Nicht viele Trainingsdaten nutzen

Erfolge/Misserfolge:

Hohe erreichte Erkennungsrate (95%), viele Informationen werden extrahiert

geplante Dauer des Projekts hat sich verdoppelt

Aspekte:

Datenschutz muss geklärt werden
Datengrundlage (Menge und Qualität muss stimmen)
enge Zusammenarbeit/Kommunikation Fachbereichen

Morphologischer Kasten:

Features aus Tabelle:

- Rechenquelle: Zustimmung (Fokus auf Cloud, ext. Geräte nicht klar)
- Reifegrad: keine Stellungnahme
- Hardware: alle relevanten Aspekte
- Datenquelle: die wichtigsten Punkte sind genannt (öffentliche Daten schwer einzusetzen, eigene Daten am besten,)
- Aktualisierungen: Fokus auf laufend, "keine" ist kritisch,
- Zeit bis zur Entscheidung: nicht zeitkritisch ist unrealistisch
- Primärer Datentyp: Zustimmung
- Primäre Ausgabe: Gegner von Entscheidungsfindung ausschließlich über KI
- Zeitpunkt der KI Nutzung: Im Optimalfall alle Werte abdecken
- KI Fokus: Im Bestfall Input- und Output verbinden
- Ausmaß der Auswirkungen:
- Zuverlässigkeit: 100% nicht realistisch

Besonders wichtige Aspekte:

- Datenquelle
- Aktualisierung
- Zeitpunkt der Entscheidung
- Datentyp
- Aufgabe
- Zuverlässigkeit und Genauigkeit

zu vernachlässigen:

- alle relevanten Aspekte, die man klären muss

Interview 2:

Einstiegsfragen:

Berufsbezeichnung: Wissenschaftlicher Mitarbeiter
Seit 8 Monaten im Job tätig
20-30 Jahre alt
Sektoren: Finanzwesen, Forschung und Entwicklung

Narrativer Teil:

Momentan in keinem Projekt aktiv

Wir haben in einer Bank an einer Betrugserkennungs-KI gearbeitet
Ursprünglich gab es die **Idee**: Verbesserung der Betrugserkennung in der Bank
Dann betreibt man zu Beginn etwas **Forschung** und schaut was gibt es für **aktuelle Entwicklungen, Technologien**
Danach folgt der **Entwurf einer Lösungsskizze** in **Abstimmung** mit den beteiligten Personenkreisen
Man braucht in der Regel auch **Input von der fachlichen Seite**

(Wiederholung)

Grobe Idee → Forschung → Zusammenarbeit mit den Fachabteilungen

Dann geht es in die **technische prototypische Umsetzung** (funktioniert das, was man aus der Forschung gefunden hat, auch mit den eigenen Daten)
Ergebnisse können sich stark abhängig von den verwendeten Daten unterscheiden
Auswahl der Technologie dementsprechend stark abhängig von dem spezifischen Anwendungsfall
Man erprobt die ausgewählten Lösungsansätze. Wenn unzufrieden → erneute Forschung/andere Technologie testen

Wenn zufrieden → Versuch in die **produktive Umsetzung** zu gehen
Ggf. müssen Anschaffungen gemacht werden(z.B. weitere virtuelle Maschinen beantragt oder Server eingerichtet werden)
Abstimmung mit anderen Fachabteilungen

Zwischendurch folgt immer auch Evaluation

- Ist das, was wir wollen
- Sind die Ergebnisse gut
- Funktioniert das in der Praxis

Gegebenfalls müssen die Problemstellungen neu definiert werden
Betonung auf iterativem Prozess
Betrachtung der Ergebnisse
Neue Evaluierung

Ende des Prozesses

Anforderungen:

Anforderungen kommen auf den Anwendungsfall drauf an

Beispiele: Genauigkeiten, Priorisierungen

von fachlicher Seite: Verständliche Erklärungen

Erfolge/Misserfolge:

Ein Fehler (Es wurden zu viele Parameter bei der Klassifikation berücksichtigt) hat für zu gute wahrgenommene Ergebnisse gesorgt.

Ergebnis/Erkenntnis, dass die Fehlererkennung in etwa auf dem Niveau eines Menschen automatisiert mit KI durchgeführt werden kann

Aspekte:

Datenanalyse/gemeinsames Verständnis von Daten aufbauen (sowohl technisches als auch fachliches Verständnis der Daten)

Parameterauswahl

Mehrwert für das Unternehmen sollte klar sein

Auswahl der Technologie

Anschaffung der Hard- und Software

Morphologischer Kasten:

Features aus Tabelle:

- Rechenquelle: Zustimmung
- Reifegrad: vllt. Prototyp hinzufügen (Unsicher, ob das zu Individuell passt)
- Hardware: Datenvisualisierung und Datenausgabe können über die Rechenleistung abgebildet werden
- Datenquelle: Zustimmung
- Häufigkeit der Aktualisierung (Unterscheidung zwischen "bei neuen Daten" und "zeitplan")
- Zeit bis zur Entscheidung (großer Sprung zwischen "mehrere Stunden" und "nicht zeitkritisch")
- KI Fokus (schwierig als eigenständiger Aspekt, Es sollten auf alle Ausprägungen Fokus gelegt werden, es muss sich mit allem gleichermaßen beschäftigen)
- Auswirkungen (ggf. Unterscheidung zwischen Prozess und Teilprozess)
- Genauigkeit (100% nahezu unmöglich → annähernd 100%)

Aspekte nach Wichtigkeit:

- Datenquelle

- Zuverlässigkeit/Genauigkeit
- Rechenquelle
- Häufigkeit der Aktualisierung

zu vernachlässigen:

- Ausmaß der Auswirkungen
- Zeitpunkt der KI Nutzung
- (Primärer Datentyp)
- Reifegrad
- KI-Fokus

Aspekte fehlen:

- Qualitätskriterium
- Rechtlicher Rahmen der Datenquellen/Verwertungsvorschrift/ Datenschutz

Appendix

Appendix: Survey 1

Appendix B includes a plethora of material from the first survey presented in section 7.3.

B.1 Survey 1: Questions & Structure

This section shows the first survey conducted in the scope of this thesis (see section 7.3). The survey was directly exported from LimeSurvey. Therefore, the text was left in the survey's original language, German.

0%

Untersuchung von Erfolgsfaktoren für die Einführung von KI-Lösungen in Unternehmen

Sehr geehrte Teilnehmer/-innen,

im Rahmen eines Forschungsprojekts untersuchen wir Faktoren, die den Erfolg oder das Scheitern von KI-Projekten in Unternehmen beeinflussen. Obwohl immer mehr, besonders kleine und mittelständische, Unternehmen Interesse daran haben, die Zukunftstechnologie Künstliche Intelligenz (KI) zu nutzen, scheitern solche Projekte oft an der Umsetzung. Vor allem, wenn das Unternehmen selbst keine eigenen IT-Experten besitzt. Ziel des Projekts ist es ein Werkzeug zu entwickeln, dass Unternehmen an die Hand gegeben werden kann, um diese in der Orientierungsphase und bei der Anforderungserhebung zu unterstützen und für vollständigere Anforderungen zu sorgen.

Wir haben bereits einen ersten Satz an Faktoren und deren mögliche Ausprägungen identifiziert. Jetzt kommen Sie ins Spiel! Wir möchten Sie gerne bitten, uns zu den einzelnen Ausprägungen der Faktoren Ihre Meinung mitzuteilen. Im Folgenden werden wir Ihnen nun nach und nach jeden Faktor einmal kurz vorstellen und um Ihre Meinung bitten.

Die Bearbeitungsdauer dieser Umfrage beträgt etwa 20 Minuten.

Ihre Teilnahme ist freiwillig und Ihre Antworten bleiben anonym und vertraulich. Die gesammelten Daten werden ausschließlich zu wissenschaftlichen Zwecken verwendet und nicht an Dritte weitergegeben.

Falls das Thema und die Forschungsergebnisse für Sie und Ihr Unternehmen interessant sein könnten, zögern Sie bitte nicht, mich persönlich per E-Mail an jack.rittelmeyer@uni-rostock.de zu kontaktieren.

Wir bedanken uns im Voraus für Ihre Teilnahme!

Mit freundlichen Grüßen

Jack Rittelmeyer

In dieser Umfrage sind 76 Fragen enthalten.

Weiter

0%

Demografische Angaben

Diese Fragengruppe dient der Sammlung demografischer Daten.

Wie würden Sie ihre Erfahrung im Bereich Informationstechnologie (IT) einschätzen?

❗ Bitte wählen Sie eine der folgenden Antworten:

- ☐ IT-Experte
- ☐ IT-Erfahren
- ☐ IT-Anfänger
- ☐ Kein IT-Wissen
- ☐ Keine Antwort

*Welche der folgenden Kategorien beschreibt Ihren Beschäftigungsstatus am besten?

❗ Bitte wählen Sie eine der folgenden Antworten:

Bitte auswählen..



Wie würden Sie ihre Erfahrung im Bereich Künstliche Intelligenz einschätzen?

❗ Bitte wählen Sie eine der folgenden Antworten:

- ☐ KI-Experte
- ☐ KI-Erfahren
- ☐ KI-Anfänger
- ☐ Kein Wissen über KI.

Was ist Ihre höchste Qualifikation oder Bildungsgrad?

❗ Bitte wählen Sie eine der folgenden Antworten:

Bitte auswählen..



In welcher Branche arbeiten Sie aktuell?

❗ Bitte wählen Sie eine der folgenden Antworten:

Bitte auswählen..



Wie lautet ihr aktueller Jobtitel?

*Wie lange arbeiten Sie bereits in Ihrem aktuellen Job?

❗ Bitte wählen Sie eine der folgenden Antworten:

Bitte auswählen..



Falls Sie beruflich KI-Erfahrungen gesammelt haben: Wie lange arbeiten Sie bereits mit KI?

❗ Bitte wählen Sie eine der folgenden Antworten:

Bitte auswählen..



Weiter

5%

Einschätzung

Zunächst einmal würden wir gern Ihre persönliche Meinung zum Thema hören: Was denken Sie, ist wichtig, um eine KI-Lösung erfolgreich in einem Unternehmen einzuführen und zu integrieren? Gibt es z. B. bestimmte Faktoren, die Ihrer Meinung nach Einfluss nehmen können auf die Einführung von KI? Oder was gilt es vielleicht zu beachten?

[Weiter](#)

10%

Endnutzer

Nun stellen wir Ihnen mögliche Faktoren, die die Einführung von KI in Unternehmen beeinflussen könnten, vor. Bitte seien Sie offen und geben Sie uns Ihre ehrliche Meinung.

Der erste Faktor wird von der Frage bestimmt, wer die KI-basierte Anwendung bzw. ihre Ergebnisse am Ende nutzen wird? Dabei werden *Endnutzer* anhand ihres Wissens über KI und IT allgemein differenziert. Wir unterscheiden zwischen Nutzern mit KI-Wissen, Nutzern ohne KI-Wissen, aber mit IT-Wissen und Nutzern ohne jegliches Wissen über KI oder IT.

***Wie sinnvoll finden Sie die Unterscheidung folgender Endnutzer (linke Spalte)?**

	Überhaupt nicht sinnvoll	Weniger sinnvoll	Teils / Teils	Teilweise sinnvoll	Sehr sinnvoll
Nutzer mit KI-Wissen	☐	☐	☐	☐	☐
Nutzer mit viel IT-Wissen	☐	☐	☐	☐	☐
Nutzer mit grundlegendem IT-Wissen	☐	☐	☐	☐	☐
Nutzer ohne KI- oder IT-Wissen	☐	☐	☐	☐	☐

Gibt es Ihrer Meinung nach noch weitere, möglicherweise relevante Endnutzer?

Würden Sie die Endnutzer anders unterteilen? Falls ja, wie würde Ihre Unterteilung aussehen?

Halten Sie den Endnutzer für einen relevanten Faktor für die Einführung von KI-Anwendungen in Unternehmen?

❗ Bitte wählen Sie eine der folgenden Antworten:

Ja

Teilweise

Nein

Keine Angabe

Weiter

15%

KI-Fokus

Der Faktor *KI-Fokus* wird von der Frage bestimmt, welchen Aufgabenfokus die KI-Lösung haben soll. Soll der Fokus eher auf der Verarbeitung von Eingabedaten liegen (z. B. Sprachverarbeitung oder Bildbearbeitung), auf der Erzeugung von Ausgaben (z. B. Sprach- oder Textgenerierung) oder geht es allgemein um Berechnungsaufgaben?

*Wie sinnvoll finden Sie die Unterscheidung folgender KI-Fokusse (linke Spalte)?

	Überhaupt nicht sinnvoll	Weniger sinnvoll	Teils / Teils	Teilweise sinnvoll	Sehr sinnvoll
Eingaben verarbeiten	☐	☐	☐	☐	☐
Ausgaben erstellen	☐	☐	☐	☐	☐
Rechenaufgabe	☐	☐	☐	☐	☐

Gibt es Ihrer Meinung nach noch weitere, möglicherweise relevante KI-Fokusse oder würden Sie die Fokusse anders unterscheiden?

Würden Sie die KI-Fokusse anders unterteilen? Falls ja, wie würde Ihre Unterteilung aussehen?

Halten Sie den KI-Fokus für einen relevanten Faktor für die Einführung von KI-Anwendungen in Unternehmen?

❗ Bitte wählen Sie eine der folgenden Antworten:

Ja

Teilweise

Nein

Keine Angabe

Weiter

21%

Rechenquelle

Der Faktor *Rechenquelle* wird von der Frage bestimmt, wo die Datenverarbeitung und die Ausführung von KI-Algorithmen stattfindet. Passiert dies in einer Cloud, auf einem lokalen Server des eigenen Unternehmens, auf dem Endgerät, auf dem die KI-betriebene Anwendung läuft, selbst oder an diversen Orten (hybrid)?

*Wie sinnvoll finden Sie die Unterscheidung folgender Betriebssysteme (linke Spalte)?

	Überhaupt nicht sinnvoll	Weniger sinnvoll	Teils / Teils	Teilweise sinnvoll	Sehr sinnvoll
Cloud-Server	☐	☐	☐	☐	☐
Lokaler Server	☐	☐	☐	☐	☐
Endgerät	☐	☐	☐	☐	☐
Hybrid	☐	☐	☐	☐	☐

Gibt es Ihrer Meinung nach noch weitere, möglicherweise relevante Rechenquellen?

Würden Sie die Rechenquellen anders unterteilen? Falls ja, wie würde Ihre Unterteilung aussehen?

Halten Sie die Rechenquelle für einen relevanten Faktor für die Einführung von KI-Anwendungen in Unternehmen?

❗ Bitte wählen Sie eine der folgenden Antworten:

Ja

Teilweise

Nein

Keine Angabe

Weiter

26%

Antwort-/Reaktionszeit

Der Faktor *Reaktionszeit* bestimmt den gewünschten Zeitraum, in welchem die KI-Anwendung ein Ergebnis liefern soll. Dabei geht es um die Dauer zwischen dem Start der Anwendung und Zeitpunkt, wann die Ergebnisse der Anwendung für einen funktionierenden Geschäftsprozess benötigt werden.

*Wie sinnvoll finden Sie die Unterscheidung folgender Antwort-/Reaktionszeiten (linke Spalte)?

	Überhaupt nicht sinnvoll	Weniger sinnvoll	Teils / Teils	Teilweise sinnvoll	Sehr sinnvoll
Echtzeit	☐	☐	☐	☐	☐
Nahezu Echtzeit	☐	☐	☐	☐	☐
Mehrere Stunden	☐	☐	☐	☐	☐
Später	☐	☐	☐	☐	☐

Gibt es Ihrer Meinung nach noch weitere, möglicherweise relevante Antwort-/Reaktionszeiten?

Würden Sie die gewünschten Antwort-/Reaktionszeiten anders unterteilen? Falls ja, wie würde Ihre Unterteilung aussehen?

Halten Sie die Antwort-/Reaktionszeit für einen relevanten Faktor für die Einführung von KI-Anwendungen in Unternehmen?

❗ Bitte wählen Sie eine der folgenden Antworten:

Ja

Teilweise

Nein

Keine Angabe

Weiter

31%

Spezielle Hardware Anforderungen

Der Faktor der *speziellen Hardwareanforderungen* behandelt die Frage, ob es bestimmte Fälle gibt, in denen eine KI-Lösung weitere Hardware-Ressourcen, wie z. B. zusätzliche Rechenpower oder Datenerfassungsgeräte benötigt, die von der etablierten IT-Infrastruktur abweichen?

***Wie sinnvoll finden Sie die Unterscheidung folgender Fälle, für die spezielle Hardware benötigt werden könnte (linke Spalte)?**

	Überhaupt nicht sinnvoll	Weniger sinnvoll	Teils / Teils	Teilweise sinnvoll	Sehr sinnvoll
Rechenleistung	☐	☐	☐	☐	☐
Datenerfassung	☐	☐	☐	☐	☐
Datenvisualisierung	☐	☐	☐	☐	☐
Datenausgabe	☐	☐	☐	☐	☐

Gibt es Ihrer Meinung nach noch weitere, möglicherweise relevante spezielle Hardware Anforderungen?

Würden Sie die Fälle, für die spezielle Hardware benötigt wird, anders unterteilen? Falls ja, wie würde Ihre Unterteilung aussehen?

Halten Sie spezielle Hardware-Anforderungen für einen relevanten Faktor für die Einführung von KI-Anwendungen in Unternehmen?

❗ Bitte wählen Sie eine der folgenden Antworten:

Ja

Teilweise

Nein

Keine Angabe

Weiter

36%

Zuverlässigkeit und Genauigkeit der Ergebnisse

Der Faktor *Zuverlässigkeit und Genauigkeit der Ergebnisse* wird von der Frage bestimmt, wie genau die Ergebnisse der KI-Lösung sein müssen und ob Abweichungen in den Ergebnissen akzeptabel sind.

*****Wie sinnvoll finden Sie die Unterscheidung folgender Zuverlässigkeits- und Genauigkeitsanforderungen für die Ergebnisse von KI-Lösungen (linke Spalte)?

	Überhaupt nicht sinnvoll	Weniger sinnvoll	Teils / Teils	Teilweise sinnvoll	Sehr sinnvoll
99,9% erforderlich	☐	☐	☐	☐	☐
Definiert durch Unternehmen selbst	☐	☐	☐	☐	☐
Definiert durch Domäne	☐	☐	☐	☐	☐
Definiert durch die Konkurrenz	☐	☐	☐	☐	☐

Gibt es Ihrer Meinung nach noch weitere, möglicherweise relevante Zuverlässigkeits- und Genauigkeitsgrade?

Würden Sie die Zuverlässigkeits- und Genauigkeitsanforderungen anders unterteilen? Falls ja, wie würde Ihre Unterteilung aussehen?

Halten Sie den Faktor "Zuverlässigkeit und Genauigkeit der Ergebnisse" für einen relevanten Faktor für die Einführung von KI-Anwendungen in Unternehmen?

❗ Bitte wählen Sie eine der folgenden Antworten:

Ja

Teilweise

Nein

Keine Angabe

Weiter

42%

Zeitpunkt der KI-Nutzung

Der Faktor Zeitpunkt der KI-Nutzung behandelt die Frage, zu welchem Zeitpunkt im Entwicklungsprozess einer Anwendung die KI-Komponente gebraucht wird bzw. eingesetzt werden soll. Wird die KI-Lösung nur während der Entwicklung (Entwurfszeit) einer größeren Anwendung gebraucht oder wird sie während der Laufzeit, begleitend zur Laufzeit einer anderen Anwendung oder zu verschiedenen Zeitpunkten (hybrid) benötigt?

***Wie sinnvoll finden Sie die Unterscheidung folgender Zeitpunkte der KI-Nutzung (linke Spalte)?**

	Überhaupt nicht sinnvoll	Weniger sinnvoll	Teils / Teils	Teilweise sinnvoll	Sehr sinnvoll
in der Entwurfszeit	☐	☐	☐	☐	☐
zur Laufzeit	☐	☐	☐	☐	☐
laufzeitbegleitend	☐	☐	☐	☐	☐
Hybrid	☐	☐	☐	☐	☐

Gibt es Ihrer Meinung nach noch weitere, möglicherweise relevante Zeitpunkte, wann die KI im Entwicklungsprozess genutzt werden könnte?

Würden Sie die möglichen Zeitpunkte der KI-Nutzung anders unterteilen? Falls ja, wie würde Ihre Unterteilung aussehen?

Halten Sie den Zeitpunkt der KI-Nutzung für einen relevanten Faktor für die Einführung von KI-Anwendungen in Unternehmen?

❗ Bitte wählen Sie eine der folgenden Antworten:

Ja

Teilweise

Nein

Keine Angabe

Weiter

47%

Primäre Aufgabe

Die **primäre Aufgabe** beschreibt, was die Hauptaufgabe der zu entwickelnden KI-Anwendung sein soll: Soll die Anwendung primär jemanden oder etwas unterstützen, soll sie bei der Entscheidungsfindung helfen, soll sie Vorhersagen treffen können, soll sie klassifizieren können oder soll sie Anomalien identifizieren können?

*Wie sinnvoll finden Sie die Unterscheidung folgender primärer Aufgaben von KI-Lösungen (linke Spalte)?

	Überhaupt nicht sinnvoll	Weniger sinnvoll	Teils / Teils	Teilweise sinnvoll	Sehr sinnvoll
Unterstützung	☐	☐	☐	☐	☐
Entscheidung	☐	☐	☐	☐	☐
Vorhersagen	☐	☐	☐	☐	☐
Klassifizierung	☐	☐	☐	☐	☐
Fehlerfindung	☐	☐	☐	☐	☐

Gibt es Ihrer Meinung nach noch weitere, möglicherweise primäre Aufgaben für KI-Lösungen?

Würden Sie die primären Aufgaben von KI-Lösungen anders unterteilen? Falls ja, wie würde Ihre Unterteilung aussehen?

Halten Sie die primären Aufgaben für einen relevanten Faktor für die Einführung von KI-Lösungen in Unternehmen?

❗ Bitte wählen Sie eine der folgenden Antworten:

Ja

Teilweise

Nein

Keine Angabe

Weiter

52%

Datenquelle

Der Faktor *Datenquelle* beschäftigt sich damit, woher man die Daten bekommt, die für die Entwicklung bzw. das Training des Algorithmus einer KI-Lösung benötigt werden. Dabei wird zwischen eigenen, fremden oder künstlich erzeugten Daten unterschieden.

*Wie sinnvoll finden Sie die Unterscheidung folgender Datenquellen (linke Spalte)?

	Überhaupt nicht sinnvoll	Weniger sinnvoll	Teils / Teils	Teilweise sinnvoll	Sehr sinnvoll
Eigene Daten	☐	☐	☐	☐	☐
Augmentierte (aufbereitete/erweiterte) Daten	☐	☐	☐	☐	☐
Öffentliche Daten	☐	☐	☐	☐	☐
Käuflich erwerbliche Datensammlungen	☐	☐	☐	☐	☐
Synthetische (künstlich erzeugte) Daten	☐	☐	☐	☐	☐

Gibt es Ihrer Meinung nach noch weitere, möglicherweise relevante Datenquellen?

Würden Sie die Datenquellen anders unterteilen? Falls ja, wie würde Ihre Unterteilung aussehen?

Halten Sie die Datenquelle für einen relevanten Faktor für die Einführung von KI-Anwendungen in Unternehmen?

❗ Bitte wählen Sie eine der folgenden Antworten:

Ja

Teilweise

Nein

Keine Angabe

Weiter

57%

Datenmenge

Der Faktor *Datenmenge* beschäftigt sich mit der Frage, wie groß die Menge an Daten ist, die für die Umsetzung der KI-Lösung (z. B. für das Training eines neuronalen Netzes) benötigt wird.

*Wie sinnvoll finden Sie die Unterscheidung folgender Datenmengen (linke Spalte)?

	Überhaupt nicht sinnvoll	Weniger sinnvoll	Teils / Teils	Teilweise sinnvoll	Sehr sinnvoll
Sehr Hoch	☐	☐	☐	☐	☐
Hoch	☐	☐	☐	☐	☐
Mittel	☐	☐	☐	☐	☐
Niedrig	☐	☐	☐	☐	☐
Sehr Niedrig	☐	☐	☐	☐	☐

Sollte die benötigte Menge an Daten Ihrer Meinung nach anderweitig unterschieden werden?

Halten Sie die Datenmenge für einen relevanten Faktor für die Einführung von KI-Anwendungen in Unternehmen?

❗ Bitte wählen Sie eine der folgenden Antworten:

Ja

Teilweise

Nein

Keine Angabe

Weiter

63%

Reifegrad

Der Faktor „Reifegrad“ beschäftigt sich mit der Frage, inwieweit die KI-Lösung ein Standardprodukt sein soll, dass man fertig einkaufen und im Unternehmen einführen kann oder ob eine Lösung für das Unternehmen komplett individuell entwickelt werden muss? Evtl. gibt es auch schon Prototypen oder Open-Source-Lösungen, die als Basis für die eigene Entwicklung genutzt werden können.

*Wie sinnvoll finden Sie die Unterscheidung folgender gewünschter Reifegrade (linke Spalte)?

	Überhaupt nicht sinnvoll	Weniger sinnvoll	Teils / Teils	Teilweise sinnvoll	Sehr sinnvoll
Commercial-off-the-Shelf (COTS) / Fertiglösung	☐	☐	☐	☐	☐
Kommerziell-erwerbliche Komponenten	☐	☐	☐	☐	☐
Open-Source Komponenten	☐	☐	☐	☐	☐
Prototyp	☐	☐	☐	☐	☐
Individuelle Entwicklung	☐	☐	☐	☐	☐

Gibt es Ihrer Meinung nach noch weitere, möglicherweise relevante Reifegrade?

Würden Sie die Reifegrade anders unterteilen? Falls ja, wie würde Ihre Unterteilung aussehen?

Halten Sie den Reifegrad für einen relevanten Faktor für die Einführung von KI-Anwendungen in Unternehmen?

❗ Bitte wählen Sie eine der folgenden Antworten:

Ja
Teilweise
Nein
Keine Angabe

Weiter

68%

Häufigkeit der Daten- und Modellaktualisierung

Der Faktor „Häufigkeit der Daten- und Modellaktualisierung“ beschäftigt sich mit der Frage, wann und wie oft die KI-Lösung bzw. die ihr zugrunde liegenden Daten und Modelle aktualisiert werden müssen. Differenziert werden kann zwischen einer kontinuierlichen bzw. regelmäßigen Aktualisierung und der Aktualisierung zu bestimmten Zeitpunkt, wie z. B. wenn sich Gesetze ändern, neue Daten oder Dokumente verarbeitet werden müssen, sich das Kundenverhalten verändert oder die Ergebnisse Qualitätsprobleme aufweisen.

***Wie sinnvoll finden Sie die Unterscheidung folgender Häufigkeiten und Zeitpunkte für die Daten- und Modellaktualisierung (linke Spalte)?**

	Überhaupt nicht sinnvoll	Weniger sinnvoll	Teils / Teils	Teilweise sinnvoll	Sehr sinnvoll
Kontinuierlich / Regelmäßig	☐	☐	☐	☐	☐
Bei regulatorischen Änderungen (z.B. Gesetzesänderungen)	☐	☐	☐	☐	☐
Bei neuen Dokumenten / Daten	☐	☐	☐	☐	☐
Bei Veränderungen im Kundenverhalten	☐	☐	☐	☐	☐
Bei Qualitätsproblemen	☐	☐	☐	☐	☐

Gibt es Ihrer Meinung nach noch weitere, möglicherweise relevante Häufigkeiten oder Zeitpunkte wie bzw. wann die Daten- und Modelle aktualisiert werden sollten/müssen?

Würden Sie die Häufigkeit und Zeitpunkte der Daten- und Modellaktualisierung anders unterteilen? Falls ja, wie würde Ihre Unterteilung aussehen?

Halten Sie die *Häufigkeit der Daten- und Modellaktualisierung* für einen relevanten Faktor für die Einführung von KI-Anwendungen in Unternehmen?

❗ Bitte wählen Sie eine der folgenden Antworten:

Ja
Teilweise
Nein
Keine Angabe

Weiter

73%

Ausmaß der Auswirkungen auf das Unternehmen

Der Faktor „Ausmaß der Auswirkungen auf das Unternehmen“, beschäftigt sich mit der Frage, in welchem Rahmen durch die Einführung KI-Lösung Veränderungen im Unternehmen hervorgerufen werden. Dabei wird differenziert, ob die KI-Lösung nur einzelne Aufgaben oder Maschinen ersetzt, ohne die angrenzenden Prozesse zu beeinflussen, ob sie komplette Prozesse, Arbeitssysteme oder Geschäftsfunktionen verändert oder ob sie große Teile / das gesamte Geschäftsmodell verändert.

*Wie sinnvoll finden Sie die Unterscheidung folgender Ausmaße an Auswirkungen auf Unternehmen (linke Spalte)?

	Überhaupt nicht sinnvoll	Weniger sinnvoll	Teils / Teils	Teilweise sinnvoll	Sehr sinnvoll
Isolierte Lösung	☐	☐	☐	☐	☐
Einzelner Prozess	☐	☐	☐	☐	☐
Workflow	☐	☐	☐	☐	☐
Arbeitssystem	☐	☐	☐	☐	☐
Geschäftsmodell	☐	☐	☐	☐	☐

Gibt es Ihrer Meinung nach noch weitere, möglicherweise relevante Ausmaße an Auswirkungen auf Unternehmen?

Würden Sie die Ausmaße an Auswirkungen auf Unternehmen anders unterteilen? Falls ja, wie würde Ihre Unterteilung aussehen?

Halten Sie das Ausmaß an Auswirkungen auf Unternehmen für einen relevanten Faktor für die Einführung von KI-Anwendungen in Unternehmen?

❗ Bitte wählen Sie eine der folgenden Antworten:

Ja

Teilweise

Nein

Keine Angabe

Weiter

78%

Kommunikation

Der Faktor „Kommunikation“ behandelt die Frage, wie eng die Entwickler der KI-Lösung mit der betroffenen Fachabteilung (Domänenexperten) zusammenarbeiten müssen, um die KI-Lösung erfolgreich zu entwickeln. Die Fachabteilung meint in diesem Fall die späteren Nutzer der KI-Anwendung. Die Entwickler können im Unternehmen arbeiten oder extern beauftragt sein.

***Wie sinnvoll finden Sie die Unterscheidung folgender Arten der Kommunikation (linke Spalte)?**

	Überhaupt nicht sinnvoll	Weniger sinnvoll	Teils / Teils	Teilweise sinnvoll	Sehr sinnvoll
Häufig und detailliert, sehr aktive Kollaboration	☐	☐	☐	☐	☐
Regelmäßig, einige Kollaboration	☐	☐	☐	☐	☐
Selten, minimale Kollaboration	☐	☐	☐	☐	☐
Nur zu bestimmten Zeitpunkten / Ereignissen	☐	☐	☐	☐	☐
Keine Kollaboration	☐	☐	☐	☐	☐

Gibt es Ihrer Meinung nach noch weitere, möglicherweise relevante Grade der Kommunikation zwischen Entwicklern und Fachabteilungen/Domänenexperten?

Würden Sie den benötigten Grad der Kommunikation anders unterteilen? Falls ja, wie würde Ihre Unterteilung aussehen?

Halten Sie den Grad der Kommunikation für einen relevanten Faktor für die Einführung von KI-Anwendungen in Unternehmen?

❗ Bitte wählen Sie eine der folgenden Antworten:

Ja
Teilweise
Nein
Keine Angabe

Weiter

84%

Primärer Datentyp

Der primäre Datentyp beschäftigt sich mit der Frage, welche Art von Daten die KI-Lösung primär verarbeiten soll. Dabei wird differenziert zwischen Audio-, Video-, Bild-, Transaktions- und Zeitreihendaten.

*Wie sinnvoll finden Sie die Unterscheidung folgender primärer Datentypen (linke Spalte)?

	Überhaupt nicht sinnvoll	Weniger sinnvoll	Teils / Teils	Teilweise sinnvoll	Sehr sinnvoll
Audiodaten	☐	☐	☐	☐	☐
Videodaten	☐	☐	☐	☐	☐
Rastergrafiken	☐	☐	☐	☐	☐
Vektorgrafiken	☐	☐	☐	☐	☐
Transaktionsdaten	☐	☐	☐	☐	☐
Zeitreihendaten	☐	☐	☐	☐	☐

Gibt es Ihrer Meinung nach noch weitere, möglicherweise relevante primäre Datentypen?

Würden Sie die primären Datentypen anders unterteilen? Falls ja, wie würde Ihre Unterteilung aussehen?

Halten Sie den *primären Datentyp* für einen relevanten Faktor für die Einführung von KI-Anwendungen in Unternehmen?

❗ Bitte wählen Sie eine der folgenden Antworten:

Ja

Teilweise

Nein

Keine Angabe

Weiter

89%

Datenqualität

Der Faktor *Datenqualität* beschäftigt sich mit der Frage, welche Qualitätsprobleme die zur Verfügung stehenden Daten haben, die von der KI-Lösung genutzt bzw. verarbeitet werden sollen. Muss die KI-Lösung z. B. in der Lage sein, mit inkonsistenten oder unvollständigen Daten umgehen zu können? Weitere relevante Qualitätsprobleme in den Daten können Duplikate, Bias, veraltete Daten oder beschädigte Daten sowie noisy Data (Datensätze mit großen Mengen irrelevanten Daten) sein.

*Wie sinnvoll finden Sie die Unterscheidung folgender möglicher Datenqualitätsprobleme (linke Spalte)?

	Überhaupt nicht sinnvoll	Weniger sinnvoll	Teils / Teils	Teilweise sinnvoll	Sehr sinnvoll
Inkonsistente Daten	☐	☐	☐	☐	☐
Duplikate	☐	☐	☐	☐	☐
Unvollständige Daten	☐	☐	☐	☐	☐
Veraltete Daten	☐	☐	☐	☐	☐
Bias	☐	☐	☐	☐	☐
Noisy Daten	☐	☐	☐	☐	☐
Beschädigte Daten	☐	☐	☐	☐	☐

Gibt es Ihrer Meinung nach noch weitere, möglicherweise relevante Qualitätsprobleme, die Daten haben können?

Würden Sie die potenziellen Probleme der Datenqualität anders unterteilen? Falls ja, wie würde Ihre Unterteilung aussehen?

Halten Sie die Datenqualität für einen relevanten Faktor für die Einführung von KI-Anwendungen in Unternehmen?

❗ Bitte wählen Sie eine der folgenden Antworten:

Ja
Teilweise
Nein
Keine Angabe

Weiter

94%

Datensicherheit

Der Faktor *Datensicherheit* beschäftigt sich mit der Frage, welche Datensicherheitsaspekte bzw. Maßnahmen für den Erfolg der zukünftige KI-Lösung besonders wichtig sind und auf jeden Fall mit hoher Sorgfalt behandelt werden müssen. Es wird unterschieden zwischen Maßnahmen für die Bereiche Compliance, Datenverschlüsselung, Zugriffskontrolle, Datenintegrität, Data Privacy, Notfallmanagement, Audit & Monitoring.

*Wie sinnvoll finden Sie die Unterscheidung folgender Datensicherheitsaspekte (linke Spalte)?

	Überhaupt nicht sinnvoll	Weniger sinnvoll	Teils / Teils	Teilweise sinnvoll	Sehr sinnvoll
Compliance	☐	☐	☐	☐	☐
Datenverschlüsselung	☐	☐	☐	☐	☐
Zugriffskontrolle	☐	☐	☐	☐	☐
Datenintegrität	☐	☐	☐	☐	☐
Datenschutz	☐	☐	☐	☐	☐
Notfallmanagement	☐	☐	☐	☐	☐
Kontrolle & Überwachung (Audit & Monitoring)	☐	☐	☐	☐	☐

Gibt es Ihrer Meinung nach noch weitere, möglicherweise relevante Aspekte der Datensicherheit?

Würden Sie die Aspekte der Datensicherheit anders unterteilen? Falls ja, wie würde Ihre Unterteilung aussehen?

Halten Sie die Datensicherheit für einen relevanten Faktor für die Einführung von KI-Anwendungen in Unternehmen?

❗ Bitte wählen Sie eine der folgenden Antworten:

Ja
Teilweise
Nein
Keine Angabe

Absenden

Vielen Dank für Ihre Teilnahmen an der Umfrage!

Mit Ihren Antworten leisten Sie einen signifikanten Beitrag zur Forschung im Bereich der Einführung von KI in Unternehmen. Wie eingangs erwähnt, können Sie mich gern kontaktieren, falls das Thema und die Forschungsergebnisse für Sie und Ihr Unternehmen interessant sein könnte. Am besten erreichen Sie mich per E-Mail an jack.rittelmeyer@uni-rostock.de.

Mit freundlichen Grüßen
Jack Rittelmeyer

B.2 Survey 1: Descriptive Statistics

This section presents the descriptive statistics that were calculated for the survey. This includes the minimum, maximum and mean value as well as the standard deviation for all features and each of their values.

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
Endnutzer_4	16	3	5	4,50	,894
KI-Fokus_4	16	3	5	4,25	1,000
Rechenquelle_4	16	1	5	4,25	1,238
Antwort-/Reaktionszeit_4	16	1	5	4,38	1,204
Spezielle_Hardware_Anforderung_4	16	3	5	4,13	1,025
Zuverlässigkeit/Genauigkeit_Ergebnisse_4	16	3	5	4,13	1,025
Zeitpunkt_der_KI-Nutzung_4	16	1	5	3,50	1,155
Primaere_Aufgabe_4	16	3	5	4,63	,806
Datenquelle_4	16	3	5	4,37	,957
Reifegrad_4	16	3	5	3,75	1,000
Haeufigkeit_der_Daten-und_Modellaktualisierung_4	16	3	5	4,13	1,025
Auswirkungen_Unternehmen_4	16	1	5	3,88	1,258
Kommunikation_4	16	1	5	3,69	1,302
Primaerer_Datentyp_4	16	1	5	4,37	1,204
Datenqualitaet_4	16	1	5	4,63	1,088
Datensicherheit_4	16	3	5	4,62	,806
Valid N (listwise)	16				

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
MEAN_Endnutzer	16	1,75	5,00	3,6875	,98531
MEAN_KIFokus	16	1,67	5,00	3,7292	,98296
MEAN_Rechenquelle	16	3,00	5,00	4,0156	,82900
MEAN_Antwortzeit	16	2,50	5,00	3,7500	,73598
MEAN_Spezielle_Hardware	16	3,00	5,00	4,1563	,50724
MEAN_Zuverlaessig	16	3,00	5,00	3,8438	,61830
MEAN_PrimaereAufgabe	16	3,00	5,00	4,2750	,70000
MEAN_Datenquelle	16	2,60	5,00	3,8625	,77535
MEAN_Datenmenge	16	3,00	5,00	3,7375	,71075
MEAN_Reifegrad	16	3,00	5,00	4,1750	,77589
MEAN_Auswirkungen	16	1,80	5,00	3,9125	,94366
MEAN_Kommunikation	16	2,60	5,00	3,7375	,92871
MEAN_PrimaererDatentyp	16	3,00	5,00	4,2292	,69355
MEAN_Datenqualitaet	16	2,14	5,00	4,0000	1,01015
MEAN_Datensicherheit	16	2,86	5,00	4,3036	,66163
MEAN_ALL	16	3,01	4,86	3,9610	,56230
Valid N (listwise)	16				

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
Endnutzer_1_1	16	1	5	3,50	1,549
Endnutzer_1_2	16	1	5	3,69	1,138
Endnutzer_1_3	16	2	5	3,94	1,124
Endnutzer_1_4	16	2	5	3,63	1,310
KI-Fokus_1_1	16	2	5	3,88	1,204
KI-Fokus_1_2	16	2	5	3,81	1,109
KI-Fokus_1_3	16	1	5	3,50	1,155
Rechenquelle_1	16	3	5	4,56	,727
Rechenquelle_1_2	16	3	5	4,19	,834
Rechenquelle_1_3	16	1	5	3,44	1,413
Rechenquelle_1_4	16	2	5	3,88	,957
Antwort- /Reaktionszeit_1_1	16	1	5	4,50	1,155
Antwort- /Reaktionszeit_1_2	16	2	5	3,88	1,258
Antwort- /Reaktionszeit_1_3	16	1	5	3,31	1,078
Antwort- /Reaktionszeit_1_4	16	2	5	3,31	,793
Spezielle_Hardware_Anf ordnung_1_1	16	3	5	4,56	,629
Spezielle_Hardware_Anf ordnung_1_2	16	3	5	4,13	,719
Spezielle_Hardware_Anf ordnung_1_3	16	3	5	4,06	,574
Spezielle_Hardware_Anf ordnung_1_4	16	2	5	3,88	1,025

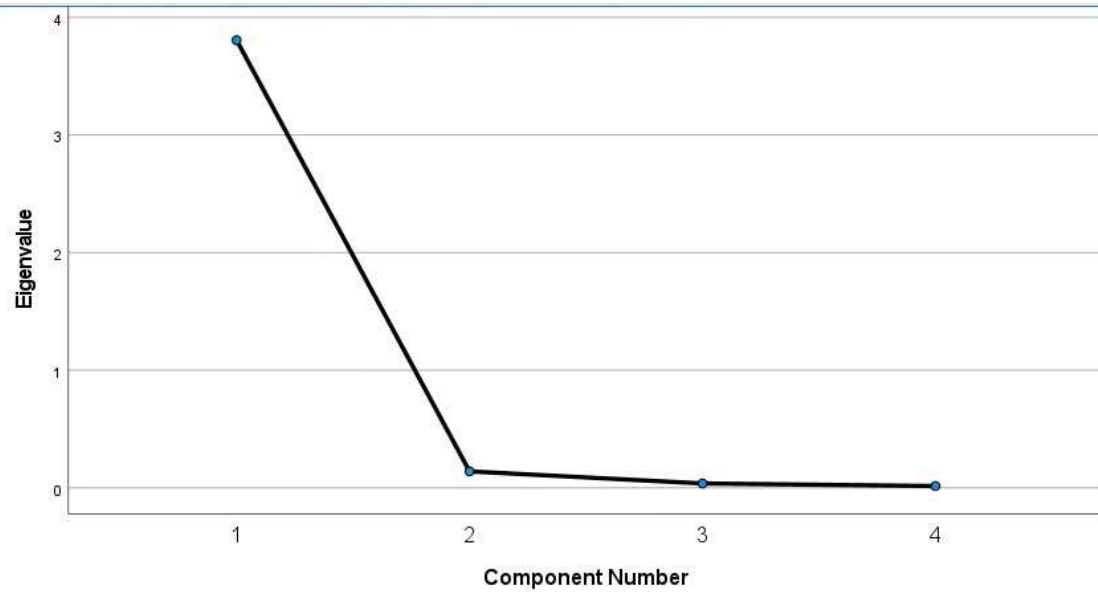
Zuverlässigkeit/Genauigkeit_Ergebnisse_1_1	16	1	5	3,81	1,377
Zuverlässigkeit/Genauigkeit_Ergebnisse_1_2	16	3	5	4,37	,806
Zuverlässigkeit/Genauigkeit_Ergebnisse_1_3	16	3	5	4,00	,894
Zuverlässigkeit/Genauigkeit_Ergebnisse_1_4	16	2	5	3,19	1,109
Zeitpunkt_der_KI-Nutzung_1_1	16	2	5	4,25	1,000
Zeitpunkt_der_KI-Nutzung_1_2	16	3	5	4,31	,793
Zeitpunkt_der_KI-Nutzung_1_3	16	3	5	3,94	,854
Zeitpunkt_der_KI-Nutzung_1_4	16	2	5	3,94	1,181
Primaere_Aufgabe_1_1	16	3	5	4,56	,814
Primaere_Aufgabe_1_2	16	2	5	4,06	1,063
Primaere_Aufgabe_1_3	16	2	5	4,06	1,181
Primaere_Aufgabe_1_4	16	2	5	4,13	,957
Primaere_Aufgabe_1_5	16	3	5	4,56	,629
Datenquelle_1_1	16	2	5	4,25	,931
Datenquelle_1_2	16	2	5	4,19	,911
Datenquelle_1_3	16	2	5	3,88	1,204
Datenquelle_1_4	16	2	5	4,00	1,095
Datenquelle_1_5	16	1	5	3,00	1,461
Datenmenge_1_1	16	2	5	4,31	1,078
Datenmenge_1_2	16	2	5	4,00	1,033
Datenmenge_1_3	16	3	5	3,94	,854
Datenmenge_1_4	16	2	5	3,31	1,138
Datenmenge_1_5	16	1	5	3,12	1,455

Reifegrad_1_1	16	2	5	4,13	,957
Reifegrad_1_2	16	3	5	4,06	,929
Reifegrad_1_3	16	3	5	4,50	,730
Reifegrad_1_4	16	2	5	4,06	,929
Reifegrad_1_5	16	2	5	4,13	1,088
Haeufigkeit_der_Daten- und_Modellaktualisierung_1_1	16	3	5	4,56	,629
Haeufigkeit_der_Daten- und_Modellaktualisierung_1_2	16	2	5	4,44	,964
Haeufigkeit_der_Daten- und_Modellaktualisierung_1_3	16	3	5	4,13	,957
Haeufigkeit_der_Daten- und_Modellaktualisierung_1_4	16	2	5	3,94	1,181
Haeufigkeit_der_Daten- und_Modellaktualisierung_1_5	16	2	5	4,19	1,047
Auswirkungen_Unternehmen_1_1	16	1	5	4,06	1,237
Auswirkungen_Unternehmen_1_2	16	1	5	3,69	1,250
Auswirkungen_Unternehmen_1_3	16	2	5	3,88	1,147
Auswirkungen_Unternehmen_1_4	16	3	5	4,00	,816
Auswirkungen_Unternehmen_1_5	16	1	5	3,94	1,181

Kommunikation_1_1	16	2	5	4,31	1,078
Kommunikation_1_2	16	2	5	4,00	1,155
Kommunikation_1_3	16	2	5	3,50	1,155
Kommunikation_1_4	16	2	5	3,56	1,094
Kommunikation_1_5	16	1	5	3,31	1,537
Primaerer_Datentyp_1_1	16	2	5	4,12	,957
Primaerer_Datentyp_1_2	16	1	5	4,00	1,211
Primaerer_Datentyp_1_3	16	3	5	4,13	,806
Primaerer_Datentyp_1_4	16	2	5	4,13	1,025
Primaerer_Datentyp_1_5	16	2	5	4,50	,894
Primaerer_Datentyp_1_6	16	3	5	4,50	,730
Datenqualitaet_1_1	16	1	5	4,06	1,237
Datenqualitaet_1_2	16	1	5	4,06	1,389
Datenqualitaet_1_3	16	2	5	4,06	1,237
Datenqualitaet_1_4	16	2	5	4,06	1,124
Datenqualitaet_1_5	16	2	5	3,69	1,078
Datenqualitaet_1_6	16	2	5	3,94	,998
Datenqualitaet_1_7	16	2	5	4,13	1,088
Datensicherheit_1_1	16	2	5	4,19	,911
Datensicherheit_1_2	16	2	5	4,31	,873
Datensicherheit_1_3	16	2	5	4,31	,873
Datensicherheit_1_4	16	2	5	4,63	,806
Datensicherheit_1_5	16	2	5	4,25	1,125
Datensicherheit_1_6	16	2	5	4,00	1,033
Datensicherheit_1_7	16	3	5	4,44	,727
Valid N (listwise)	16				

B.3 Survey 1: KMO and Bartlett's Tests

This section presents the results of the KMO and Bartlett's test that was conducted for each feature.



Component Matrix^a

	Component 1
Zuverlässigkeit/Genauigkeit_Ergebnisse_1_1	,954
Zuverlässigkeit/Genauigkeit_Ergebnisse_1_2	,988
Zuverlässigkeit/Genauigkeit_Ergebnisse_1_3	,985
Zuverlässigkeit/Genauigkeit_Ergebnisse_1_4	,975

Extraction Method: Principal Component Analysis.

a. 1 components extracted.

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		,441
Bartlett's Test of Sphericity	Approx. Chi-Square	21,327
	df	6
	Sig.	,002

Communalities

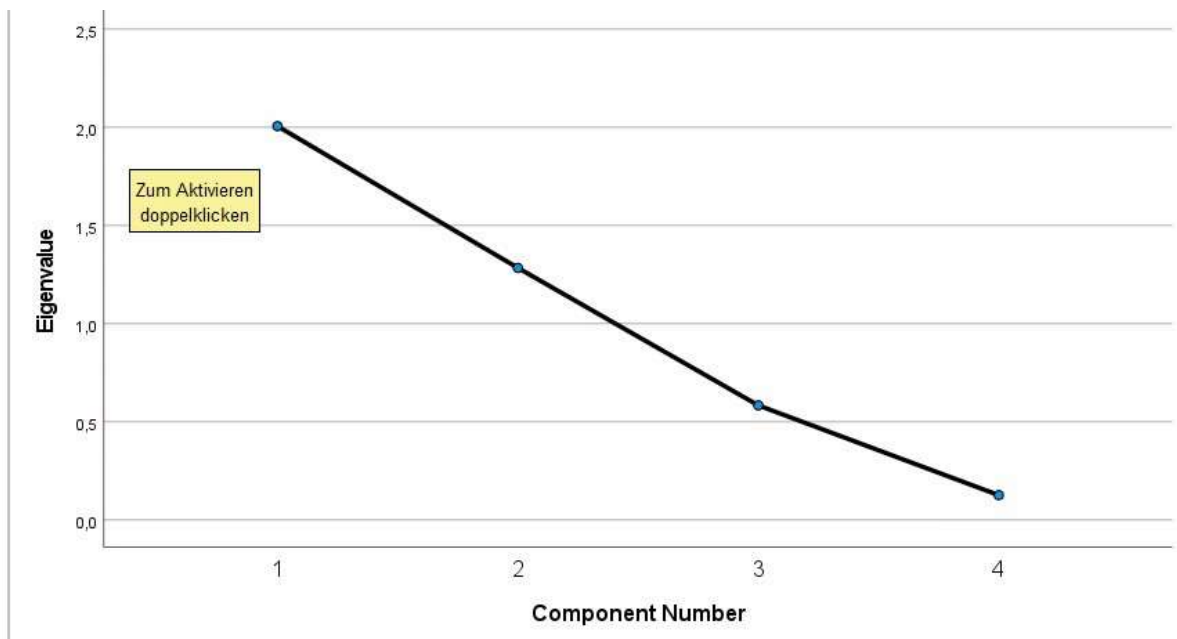
	Initial	Extraction
Antwort-/Reaktionszeit_1_1	1,000	,702
Antwort-/Reaktionszeit_1_2	1,000	,856
Antwort-/Reaktionszeit_1_3	1,000	,928
Antwort-/Reaktionszeit_1_4	1,000	,804

Extraction Method: Principal Component Analysis.

Total Variance Explained

Component	Total	Initial Eigenvalues		Extraction Sums of Squared Loadings		
		% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2,006	50,154	50,154	2,006	50,154	50,154
2	1,284	32,100	82,253	1,284	32,100	82,253
3	,584	14,590	96,844			
4	,126	3,156	100,000			

Extraction Method: Principal Component Analysis.



Component Matrix^a

	Component	
	1	2
Antwort-/Reaktionszeit_1_1	,457	-,702
Antwort-/Reaktionszeit_1_2	,921	-,088
Antwort-/Reaktionszeit_1_3	,942	,201
Antwort-/Reaktionszeit_1_4	,246	,862

Extraction Method: Principal Component Analysis.

a. 2 components extracted.

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		,800
Bartlett's Test of Sphericity	Approx. Chi-Square	39,607
	df	10
	Sig.	<,001

Communalities

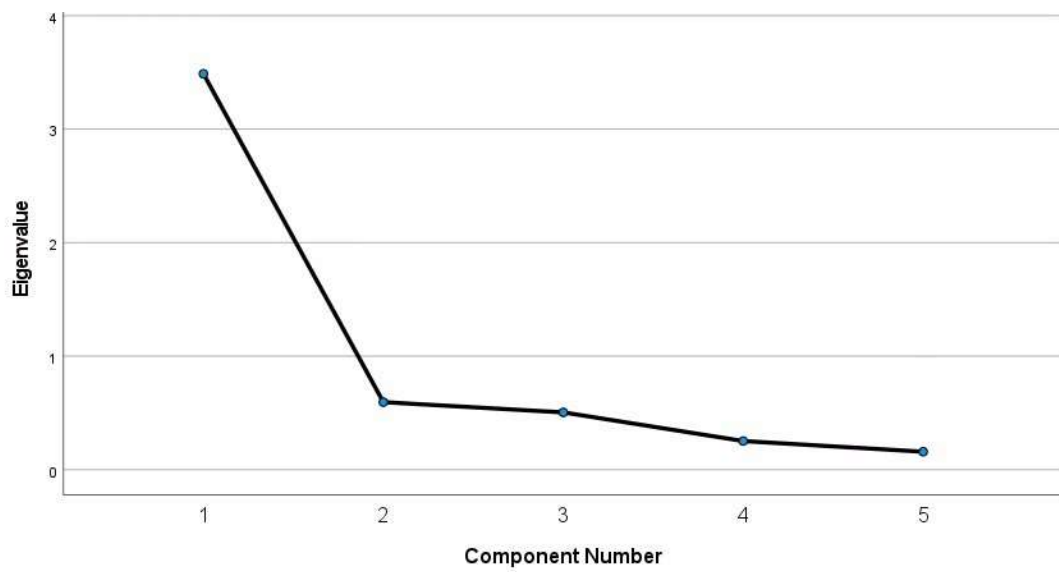
	Initial	Extraction
Auswirkungen_Unternehmen_1_1	1,000	,741
Auswirkungen_Unternehmen_1_2	1,000	,734
Auswirkungen_Unternehmen_1_3	1,000	,545
Auswirkungen_Unternehmen_1_4	1,000	,622
Auswirkungen_Unternehmen_1_5	1,000	,847

Extraction Method: Principal Component Analysis.

Total Variance Explained

Component	Total	Initial Eigenvalues		Extraction Sums of Squared Loadings		
		% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	3,488	69,761	69,761	3,488	69,761	69,761
2	,595	11,908	81,669			
3	,505	10,104	91,773			
4	,253	5,054	96,827			
5	,159	3,173	100,000			

Extraction Method: Principal Component Analysis.



Component Matrix^a

	Component 1
Auswirkungen_Unterneh men_1_1	,861
Auswirkungen_Unterneh men_1_2	,856
Auswirkungen_Unterneh men_1_3	,738
Auswirkungen_Unterneh men_1_4	,789
Auswirkungen_Unterneh men_1_5	,920

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		,283
Bartlett's Test of Sphericity	Approx. Chi-Square	35,732
	df	10
	Sig.	<,001

Communalities

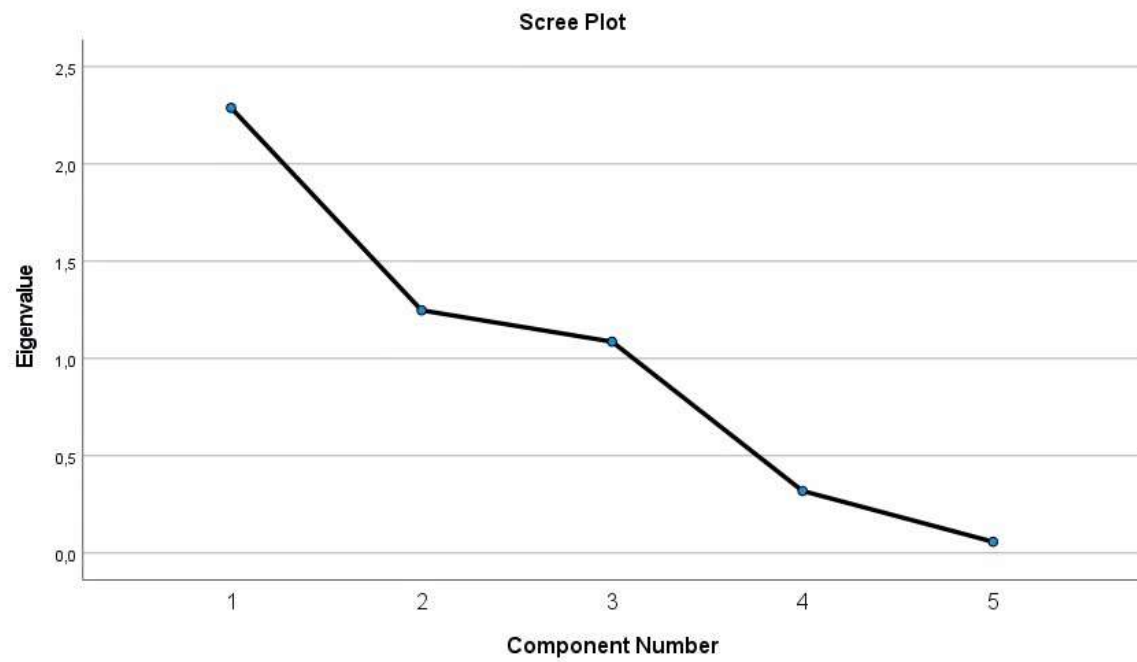
	Initial	Extraction
Datenmenge_1_1	1,000	,988
Datenmenge_1_2	1,000	,945
Datenmenge_1_3	1,000	,794
Datenmenge_1_4	1,000	,913
Datenmenge_1_5	1,000	,984

Extraction Method: Principal Component Analysis.

Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2,289	45,772	45,772	2,289	45,772	45,772
2	1,248	24,955	70,728	1,248	24,955	70,728
3	1,086	21,729	92,457	1,086	21,729	92,457
4	,319	6,385	98,842			
5	,058	1,158	100,000			

Extraction Method: Principal Component Analysis.



Component Matrix^a

	Component		
	1	2	3
Datenmenge_1_1	,254	-,337	,900
Datenmenge_1_2	,744	-,616	-,110
Datenmenge_1_3	,888	-,045	-,049
Datenmenge_1_4	,850	,305	-,313
Datenmenge_1_5	,400	,812	,405

Extraction Method: Principal Component Analysis.

a. 3 components extracted.

➔ Factor Analysis

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		,643
Bartlett's Test of Sphericity	Approx. Chi-Square	124,154
	df	21
	Sig.	<,001

Communalities

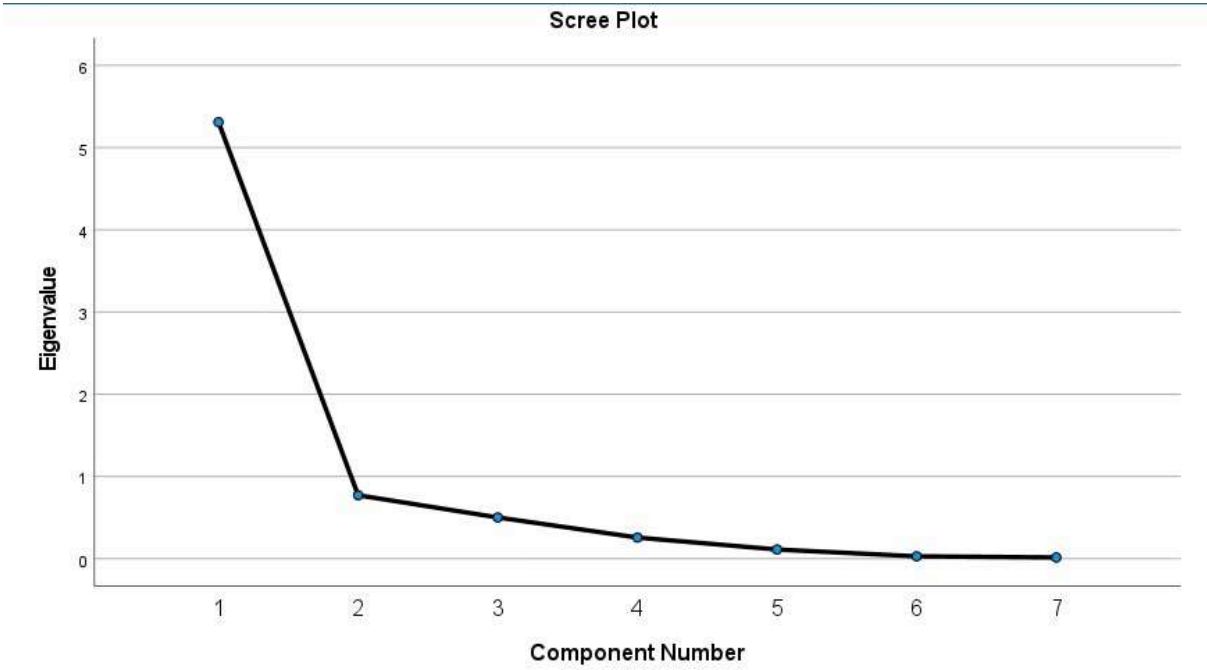
	Initial	Extraction
Datenqualitaet_1_1	1,000	,658
Datenqualitaet_1_2	1,000	,615
Datenqualitaet_1_3	1,000	,903
Datenqualitaet_1_4	1,000	,919
Datenqualitaet_1_5	1,000	,746
Datenqualitaet_1_6	1,000	,633
Datenqualitaet_1_7	1,000	,836

Extraction Method: Principal Component Analysis.

Total Variance Explained

Component	Total	Initial Eigenvalues		Extraction Sums of Squared Loadings		
		% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	5,310	75,853	75,853	5,310	75,853	75,853
2	,772	11,034	86,887			
3	,502	7,174	94,061			
4	,258	3,685	97,746			
5	,112	1,606	99,352			
6	,030	,424	99,776			
7	,016	,224	100,000			

Extraction Method: Principal Component Analysis.



Component Matrix^a

	Component 1
Datenqualitaet_1_1	,811
Datenqualitaet_1_2	,784
Datenqualitaet_1_3	,950
Datenqualitaet_1_4	,959
Datenqualitaet_1_5	,864
Datenqualitaet_1_6	,796
Datenqualitaet_1_7	,914

Extraction Method: Principal

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		,706
Bartlett's Test of Sphericity	Approx. Chi-Square	14,873
	df	10
	Sig.	,137

Communalities

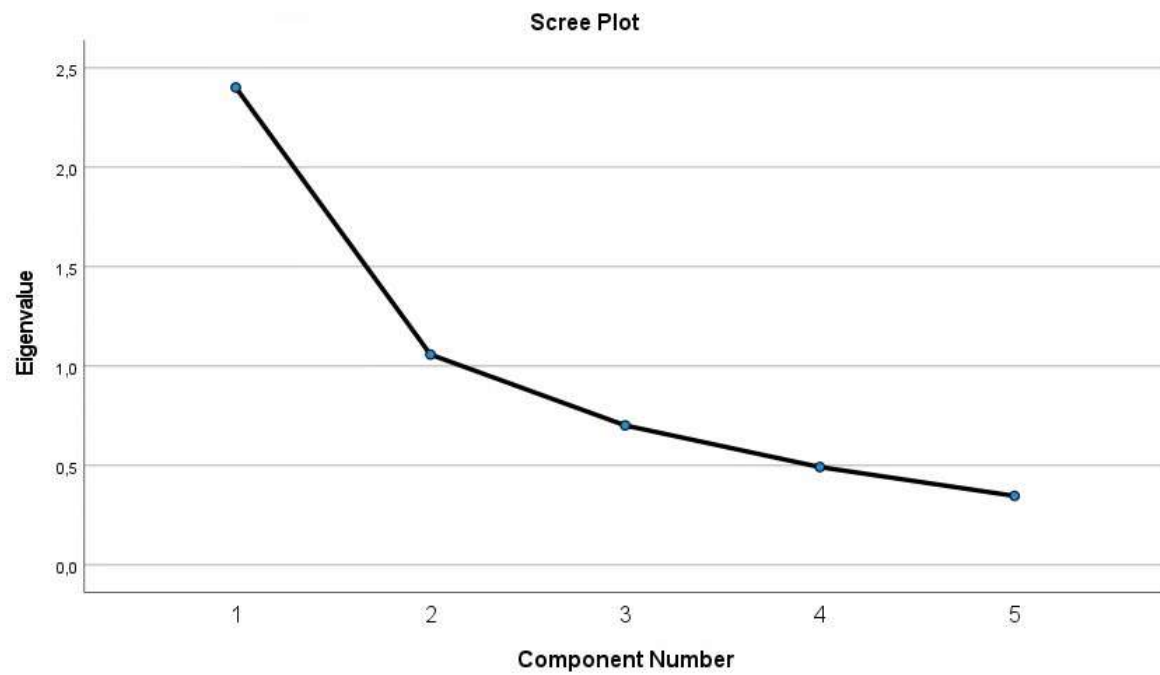
	Initial	Extraction
Datenquelle_1_1	1,000	,892
Datenquelle_1_2	1,000	,654
Datenquelle_1_3	1,000	,774
Datenquelle_1_4	1,000	,487
Datenquelle_1_5	1,000	,653

Extraction Method: Principal Component Analysis.

Total Variance Explained

Component	Total	Initial Eigenvalues		Extraction Sums of Squared Loadings		
		% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2,401	48,029	48,029	2,401	48,029	48,029
2	1,058	21,160	69,189	1,058	21,160	69,189
3	,702	14,032	83,221			
4	,492	9,841	93,062			
5	,347	6,938	100,000			

Extraction Method: Principal Component Analysis.



Component Matrix^a

	Component	
	1	2
Datenquelle_1_1	,261	,907
Datenquelle_1_2	,732	-,344
Datenquelle_1_3	,844	-,247
Datenquelle_1_4	,665	,211
Datenquelle_1_5	,802	,103

Extraction Method: Principal Component Analysis.

a. 2 components extracted.

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		,605
Bartlett's Test of Sphericity	Approx. Chi-Square	61,624
	df	21
	Sig.	<,001

Communalities

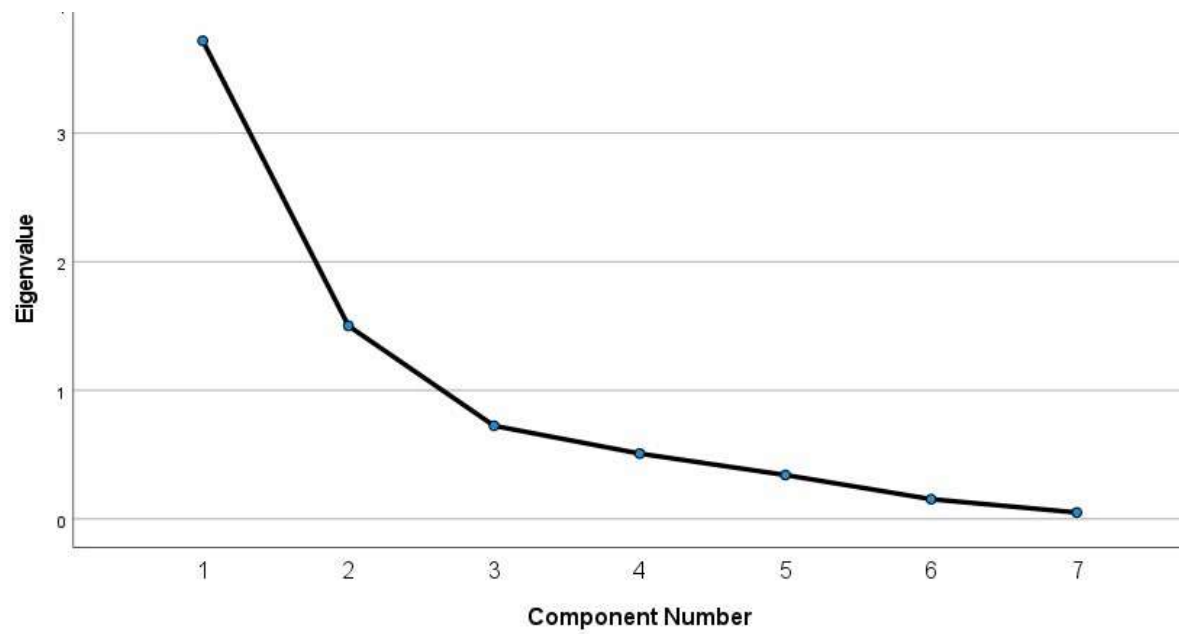
	Initial	Extraction
Datensicherheit_1_1	1,000	,587
Datensicherheit_1_2	1,000	,745
Datensicherheit_1_3	1,000	,919
Datensicherheit_1_4	1,000	,726
Datensicherheit_1_5	1,000	,797
Datensicherheit_1_6	1,000	,825
Datensicherheit_1_7	1,000	,622

Extraction Method: Principal Component Analysis.

Total Variance Explained

Component	Total	Initial Eigenvalues		Extraction Sums of Squared Loadings		
		% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	3,718	53,120	53,120	3,718	53,120	53,120
2	1,502	21,455	74,576	1,502	21,455	74,576
3	,725	10,353	84,929			
4	,508	7,264	92,193			
5	,342	4,885	97,078			
6	,154	2,200	99,278			
7	,051	,722	100,000			

Extraction Method: Principal Component Analysis.



Component Matrix^a

	Component	
	1	2
Datensicherheit_1_1	,557	-,526
Datensicherheit_1_2	,845	-,173
Datensicherheit_1_3	,823	,491
Datensicherheit_1_4	,658	,541
Datensicherheit_1_5	,832	-,322
Datensicherheit_1_6	,782	-,463
Datensicherheit_1_7	,527	,586

Extraction Method: Principal Component Analysis.

a. 2 components extracted.

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		,532
Bartlett's Test of Sphericity	Approx. Chi-Square	21,007
	df	6
	Sig.	,002

Communalities

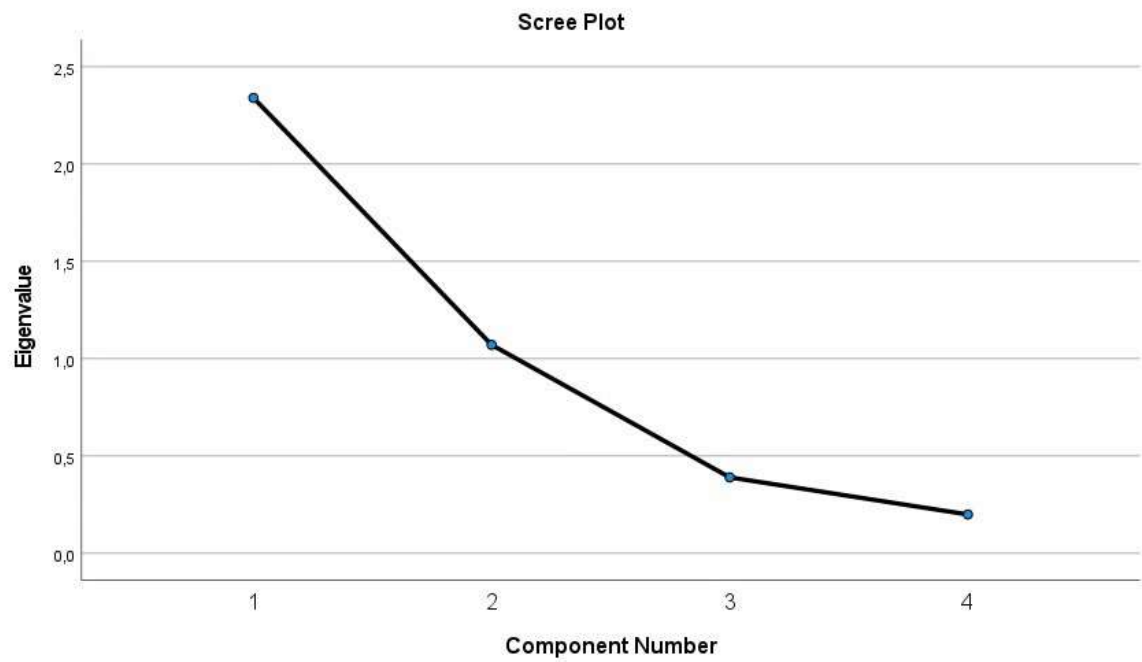
	Initial	Extraction
Endnutzer_1_1	1,000	,833
Endnutzer_1_2	1,000	,881
Endnutzer_1_3	1,000	,829
Endnutzer_1_4	1,000	,868

Extraction Method: Principal Component Analysis.

Total Variance Explained

Component	Total	Initial Eigenvalues		Extraction Sums of Squared Loadings		
		% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2,340	58,500	58,500	2,340	58,500	58,500
2	1,071	26,774	85,274	1,071	26,774	85,274
3	,390	9,748	95,022			
4	,199	4,978	100,000			

Extraction Method: Principal Component Analysis.



Component Matrix^a

	Component	
	1	2
Endnutzer_1_1	,826	,387
Endnutzer_1_2	,658	,670
Endnutzer_1_3	,766	-,492
Endnutzer_1_4	,799	-,480

Extraction Method: Principal Component Analysis.

a. 2 components extracted.

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		,645
Bartlett's Test of Sphericity	Approx. Chi-Square	44,681
	df	10
	Sig.	<,001

Communalities

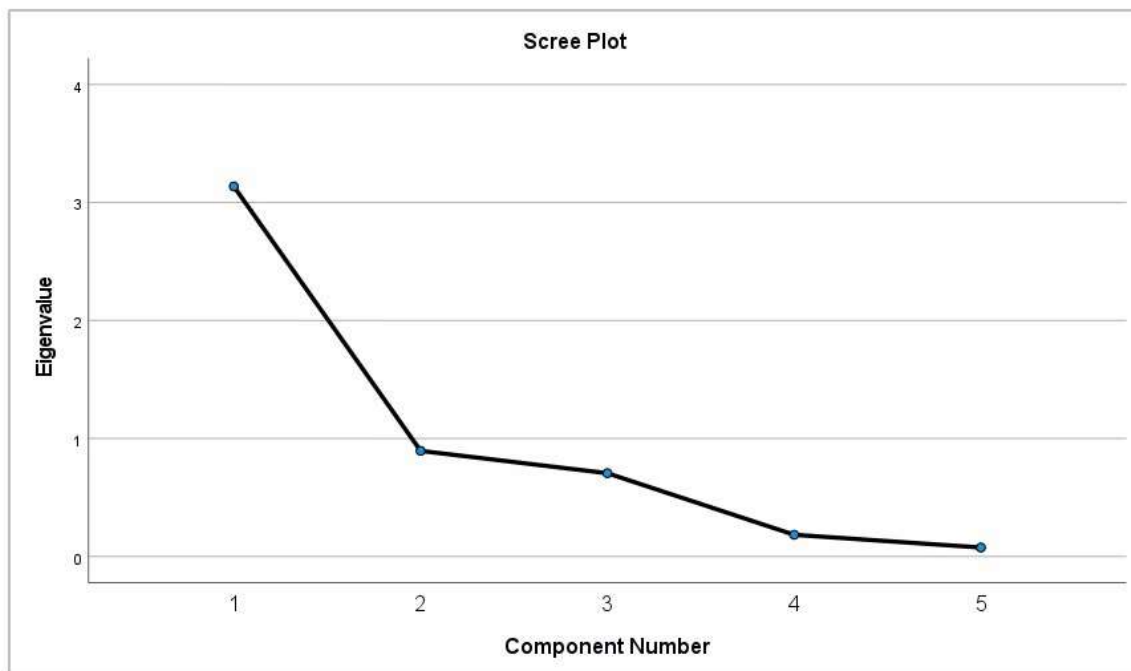
	Initial	Extraction
Haeufigkeit_der_Daten-und_Modellaktualisierung_1_1	1,000	,340
Haeufigkeit_der_Daten-und_Modellaktualisierung_1_2	1,000	,690
Haeufigkeit_der_Daten-und_Modellaktualisierung_1_3	1,000	,835
Haeufigkeit_der_Daten-und_Modellaktualisierung_1_4	1,000	,485
Haeufigkeit_der_Daten-und_Modellaktualisierung_1_5	1,000	,787

Extraction Method: Principal Component Analysis.

Total Variance Explained

Component	Total	Initial Eigenvalues		Extraction Sums of Squared Loadings		
		% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	3,137	62,735	62,735	3,137	62,735	62,735
2	,896	17,912	80,648			
3	,707	14,130	94,778			
4	,185	3,692	98,470			
5	,077	1,530	100,000			

Extraction Method: Principal Component Analysis.



Component Matrix^a

	Component 1
Haeufigkeit_der_Daten- und_Modellaktualisierun g_1_1	,583
Haeufigkeit_der_Daten- und_Modellaktualisierun g_1_2	,831
Haeufigkeit_der_Daten- und_Modellaktualisierun g_1_3	,914
Haeufigkeit_der_Daten- und_Modellaktualisierun g_1_4	,696
Haeufigkeit_der_Daten- und_Modellaktualisierun g_1_5	,887

Extraction Method: Principal Component Analysis.

a. 1 components extracted.

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		,694
Bartlett's Test of Sphericity	Approx. Chi-Square	13,734
	df	3
	Sig.	,003

Communalities

	Initial	Extraction
KI-Fokus_1_1	1,000	,758
KI-Fokus_1_2	1,000	,772
KI-Fokus_1_3	1,000	,642

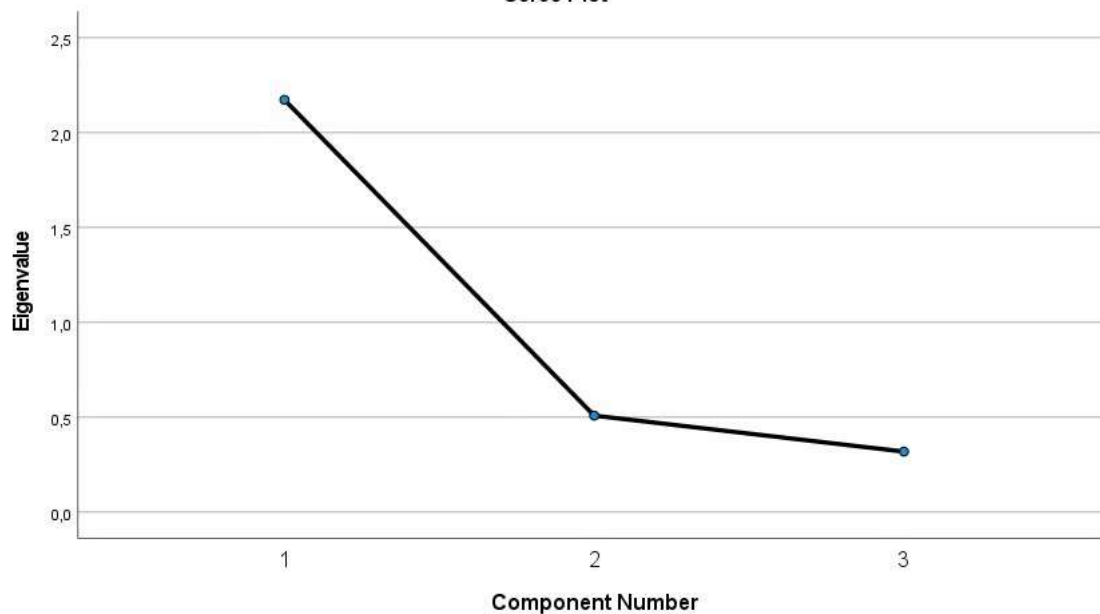
Extraction Method: Principal Component Analysis.

Total Variance Explained

Component	Total	Initial Eigenvalues		Extraction Sums of Squared Loadings		
		% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2,173	72,417	72,417	2,173	72,417	72,417
2	,509	16,954	89,371			
3	,319	10,629	100,000			

Extraction Method: Principal Component Analysis.

Scree Plot



Component Matrix^a

	Component 1
KI-Fokus_1_1	,871
KI-Fokus_1_2	,879
KI-Fokus_1_3	,801

Extraction Method: Principal Component Analysis.

a. 1 components extracted.

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		,645
Bartlett's Test of Sphericity	Approx. Chi-Square	36,611
	df	10
	Sig.	<,001

Communalities

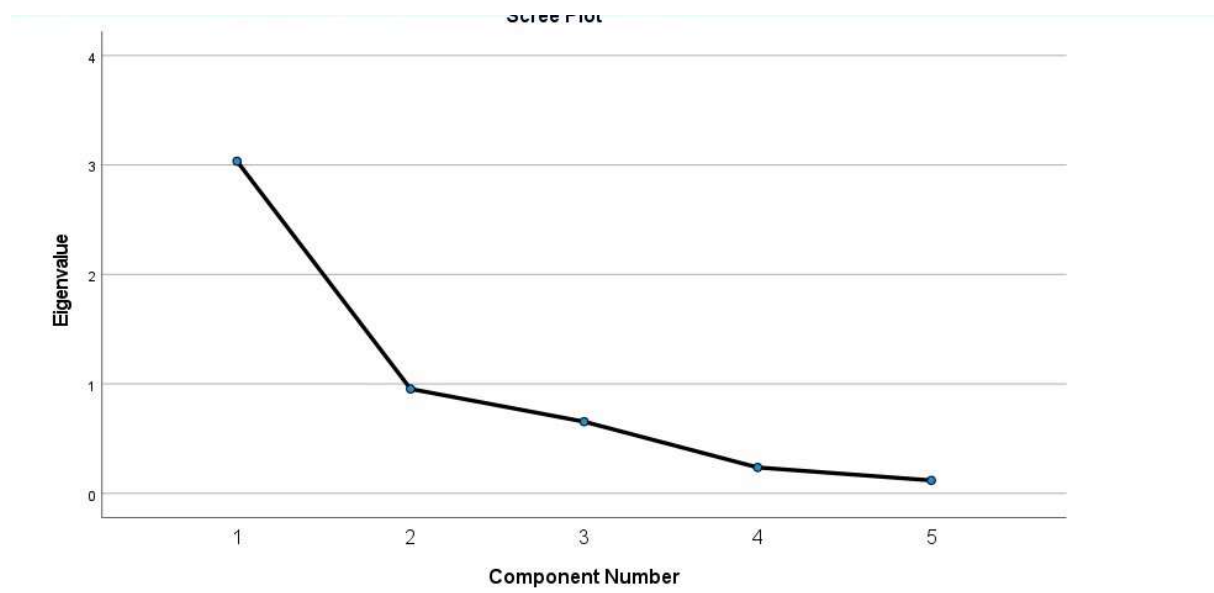
	Initial	Extraction
Kommunikation_1_1	1,000	,261
Kommunikation_1_2	1,000	,541
Kommunikation_1_3	1,000	,725
Kommunikation_1_4	1,000	,879
Kommunikation_1_5	1,000	,629

Extraction Method: Principal Component Analysis.

Total Variance Explained

Component	Total	Initial Eigenvalues		Extraction Sums of Squared Loadings		
		% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	3,035	60,697	60,697	3,035	60,697	60,697
2	,954	19,080	79,777			
3	,655	13,106	92,883			
4	,237	4,738	97,621			
5	,119	2,379	100,000			

Extraction Method: Principal Component Analysis.



Component Matrix^a

	Component 1
Kommunikation_1_1	,511
Kommunikation_1_2	,735
Kommunikation_1_3	,851
Kommunikation_1_4	,937
Kommunikation_1_5	,793

Extraction Method: Principal
Component Analysis.

a. 1 components extracted.

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		,624
Bartlett's Test of Sphericity	Approx. Chi-Square	28,530
	df	10
	Sig.	,001

Communalities

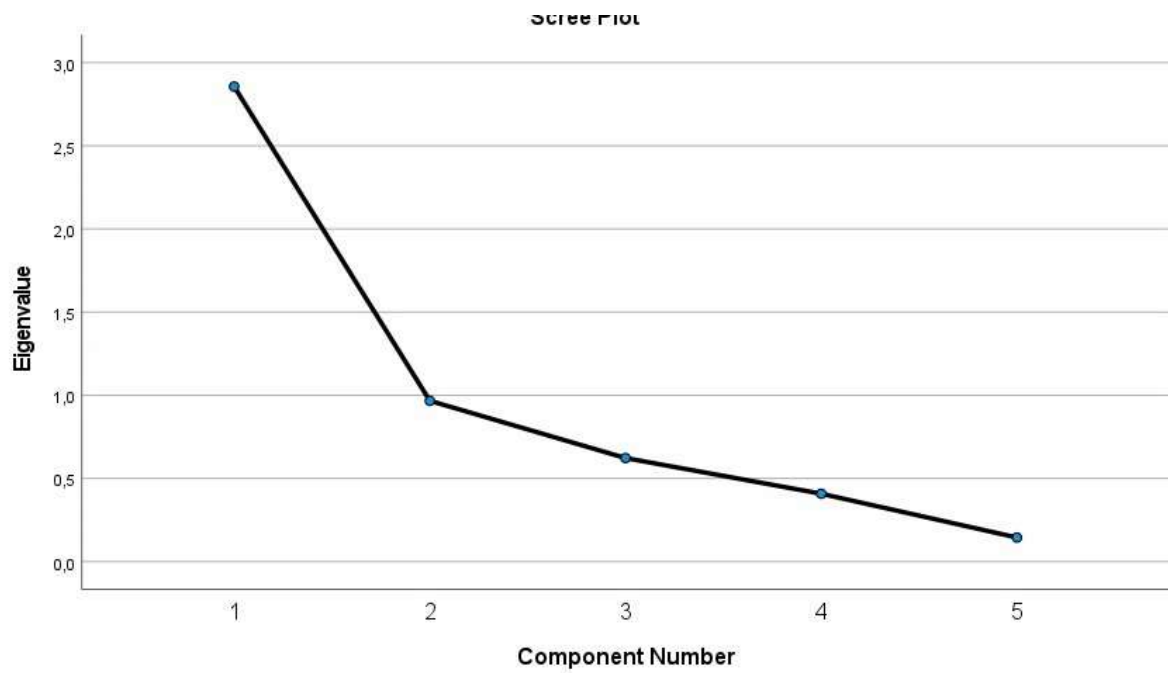
	Initial	Extraction
Primaere_Aufgabe_1_1	1,000	,606
Primaere_Aufgabe_1_2	1,000	,291
Primaere_Aufgabe_1_3	1,000	,750
Primaere_Aufgabe_1_4	1,000	,673
Primaere_Aufgabe_1_5	1,000	,536

Extraction Method: Principal Component Analysis.

Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2,856	57,124	57,124	2,856	57,124	57,124
2	,967	19,344	76,467			
3	,623	12,461	88,928			
4	,408	8,169	97,097			
5	,145	2,903	100,000			

Extraction Method: Principal Component Analysis.



Component Matrix^a

	Component 1
Primaere_Aufgabe_1_1	,779
Primaere_Aufgabe_1_2	,540
Primaere_Aufgabe_1_3	,866
Primaere_Aufgabe_1_4	,821
Primaere_Aufgabe_1_5	,732

Extraction Method: Principal Component Analysis.

a. 1 components extracted.

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		,643
Bartlett's Test of Sphericity	Approx. Chi-Square	56,090
	df	15
	Sig.	<,001

Communalities

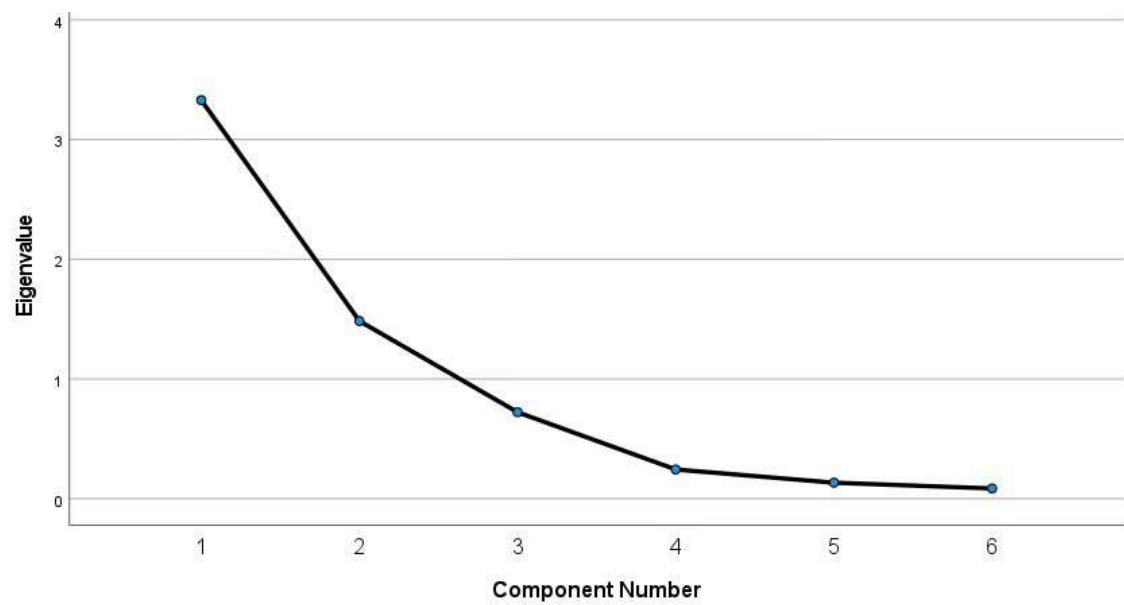
	Initial	Extraction
Primaerer_Datentyp_1_1	1,000	,914
Primaerer_Datentyp_1_2	1,000	,612
Primaerer_Datentyp_1_3	1,000	,663
Primaerer_Datentyp_1_4	1,000	,856
Primaerer_Datentyp_1_5	1,000	,850
Primaerer_Datentyp_1_6	1,000	,919

Extraction Method: Principal Component Analysis.

Total Variance Explained

Component	Total	Initial Eigenvalues		Extraction Sums of Squared Loadings		
		% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	3,330	55,499	55,499	3,330	55,499	55,499
2	1,484	24,740	80,240	1,484	24,740	80,240
3	,722	12,041	92,281			
4	,244	4,068	96,349			
5	,134	2,228	98,577			
6	,085	1,423	100,000			

Extraction Method: Principal Component Analysis.



Component Matrix^a

	Component	
	1	2
Primaerer_Datentyp_1_1	,623	,725
Primaerer_Datentyp_1_2	,722	,300
Primaerer_Datentyp_1_3	,536	,613
Primaerer_Datentyp_1_4	,855	-,353
Primaerer_Datentyp_1_5	,777	-,497
Primaerer_Datentyp_1_6	,894	-,347

Extraction Method: Principal Component Analysis.

a. 2 components extracted.

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		,568
Bartlett's Test of Sphericity	Approx. Chi-Square	43,517
	df	6
	Sig.	<,001

Communalities

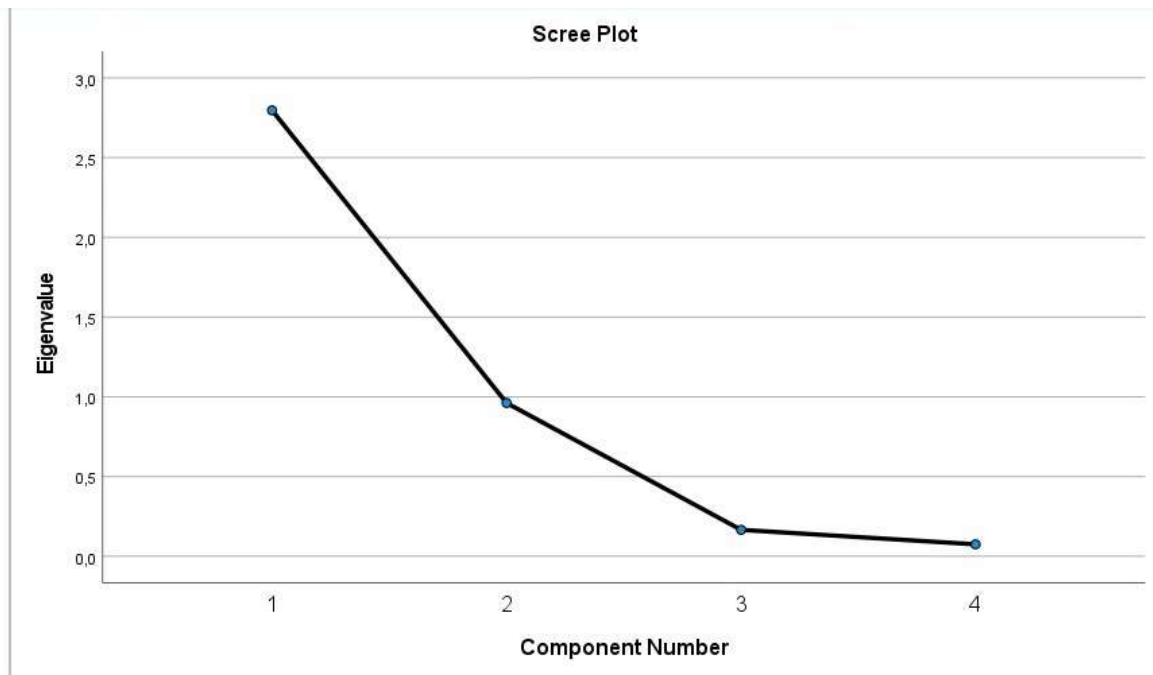
	Initial	Extraction
Rechenquelle_1	1,000	,366
Rechenquelle_1_2	1,000	,866
Rechenquelle_1_3	1,000	,768
Rechenquelle_1_4	1,000	,797

Extraction Method: Principal Component Analysis.

Total Variance Explained

Component	Total	Initial Eigenvalues		Extraction Sums of Squared Loadings		
		% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2,797	69,919	69,919	2,797	69,919	69,919
2	,962	24,043	93,962			
3	,166	4,154	98,116			
4	,075	1,884	100,000			

Extraction Method: Principal Component Analysis.



Component Matrix^a

	Component 1
Rechenquelle_1	,605
Rechenquelle_1_2	,931
Rechenquelle_1_3	,876
Rechenquelle_1_4	,893

Extraction Method: Principal Component Analysis.

a. 1 components extracted.

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		,674
Bartlett's Test of Sphericity	Approx. Chi-Square	50,526
	df	10
	Sig.	<,001

Communalities

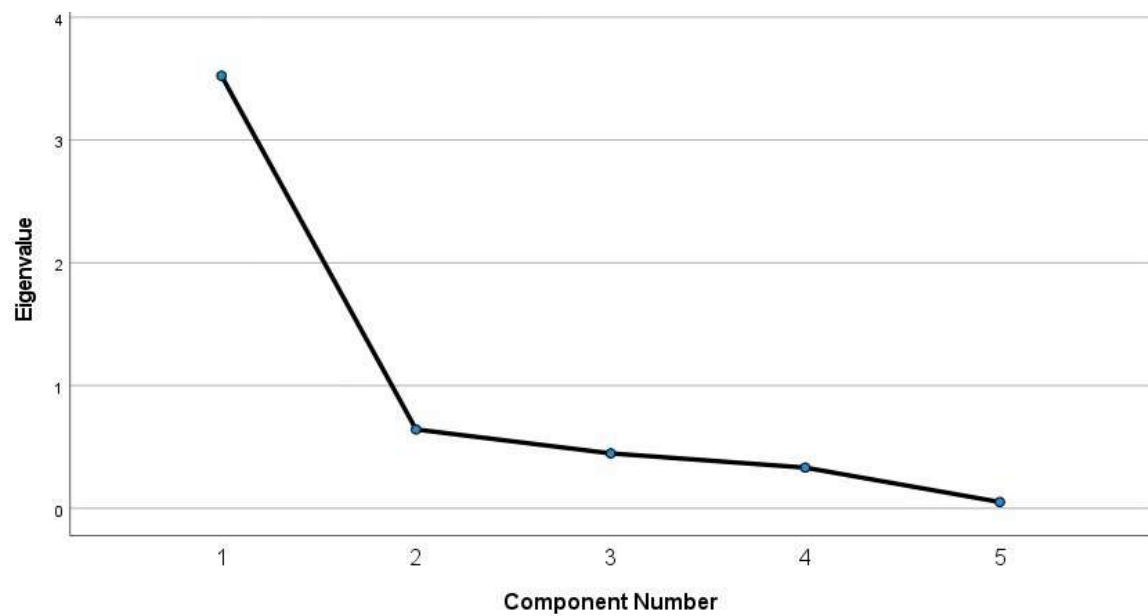
	Initial	Extraction
Reifegrad_1_1	1,000	,577
Reifegrad_1_2	1,000	,900
Reifegrad_1_3	1,000	,714
Reifegrad_1_4	1,000	,619
Reifegrad_1_5	1,000	,714

Extraction Method: Principal Component Analysis.

Total Variance Explained

Component	Total	Initial Eigenvalues		Extraction Sums of Squared Loadings		
		% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	3,524	70,484	70,484	3,524	70,484	70,484
2	,643	12,860	83,344			
3	,448	8,970	92,313			
4	,332	6,647	98,960			
5	,052	1,040	100,000			

Extraction Method: Principal Component Analysis.



Component Matrix^a

Component	
1	
Reifegrad_1_1	,760
Reifegrad_1_2	,948
Reifegrad_1_3	,845
Reifegrad_1_4	,787
Reifegrad_1_5	,845

Extraction Method: Principal Component Analysis.

a. 1 components extracted.

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		,645
Bartlett's Test of Sphericity	Approx. Chi-Square	7,255
	df	6
	Sig.	,298

Communalities

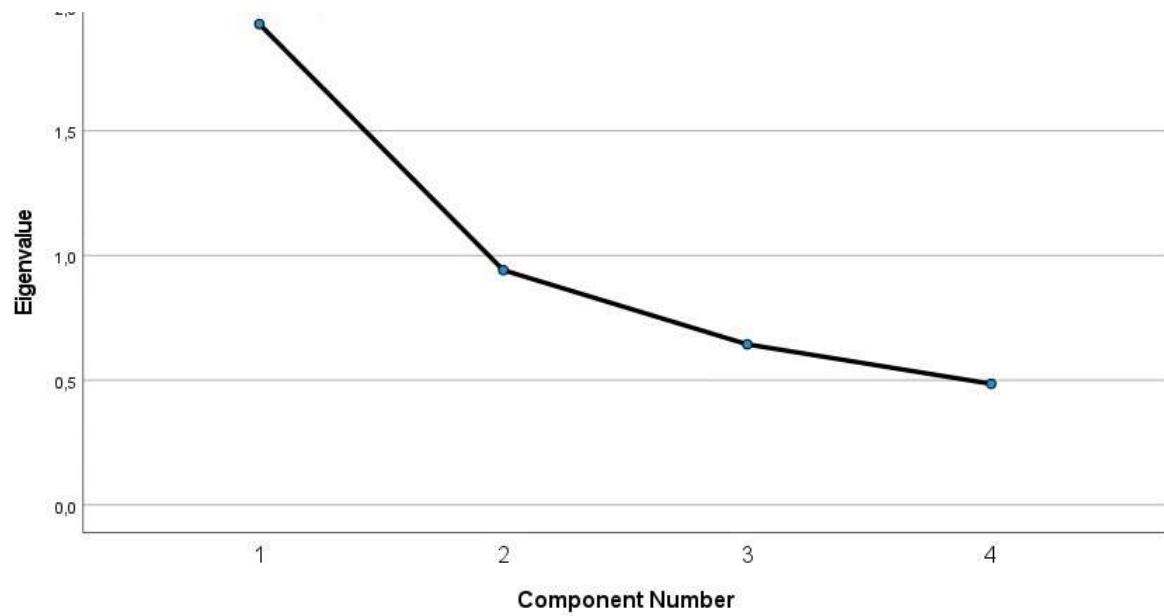
	Initial	Extraction
Spezielle_Hardware_Anforderung_1_1	1,000	,551
Spezielle_Hardware_Anforderung_1_2	1,000	,634
Spezielle_Hardware_Anforderung_1_3	1,000	,467
Spezielle_Hardware_Anforderung_1_4	1,000	,277

Extraction Method: Principal Component Analysis.

Total Variance Explained

Component	Total	Initial Eigenvalues		Extraction Sums of Squared Loadings		
		% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	1,929	48,213	48,213	1,929	48,213	48,213
2	,942	23,540	71,752			
3	,644	16,103	87,855			
4	,486	12,145	100,000			

Extraction Method: Principal Component Analysis.



Component Matrix^a

	Component 1
Spezielle_Hardware_Anforderung_1_1	,742
Spezielle_Hardware_Anforderung_1_2	,796
Spezielle_Hardware_Anforderung_1_3	,683
Spezielle_Hardware_Anforderung_1_4	,527

Extraction Method: Principal Component Analysis.

a. 1 components extracted.

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		,533
Bartlett's Test of Sphericity	Approx. Chi-Square	19,740
	df	6
	Sig.	,003

Communalities

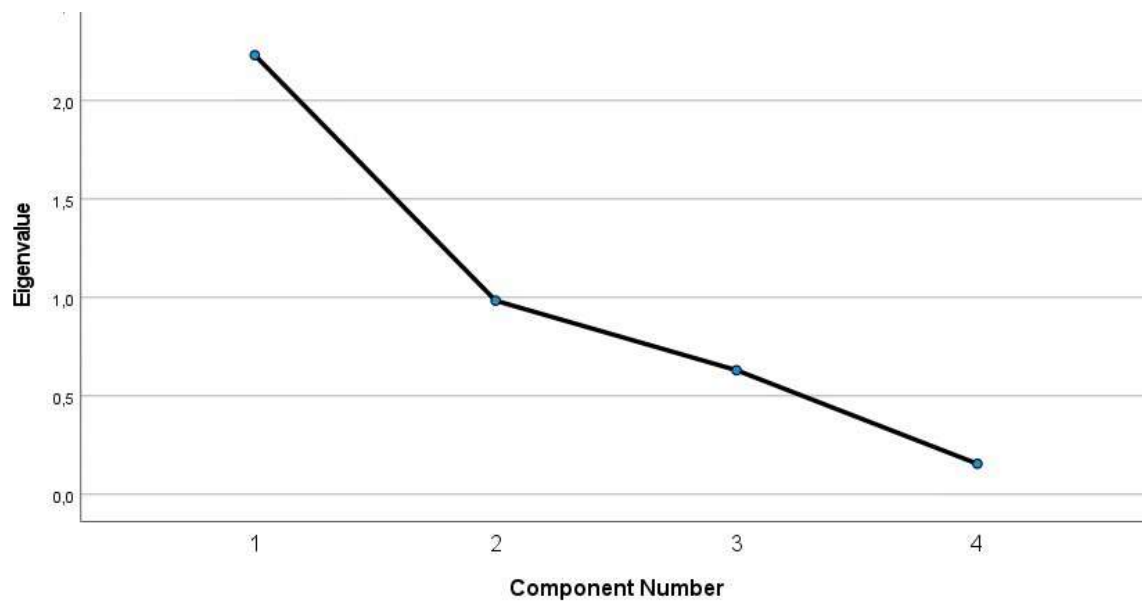
	Initial	Extraction
Zeitpunkt_der_KI-Nutzung_1_1	1,000	,234
Zeitpunkt_der_KI-Nutzung_1_2	1,000	,731
Zeitpunkt_der_KI-Nutzung_1_3	1,000	,797
Zeitpunkt_der_KI-Nutzung_1_4	1,000	,468

Extraction Method: Principal Component Analysis.

Total Variance Explained

Component	Total	Initial Eigenvalues		Extraction Sums of Squared Loadings		
		% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2,231	55,764	55,764	2,231	55,764	55,764
2	,984	24,591	80,356			
3	,631	15,763	96,119			
4	,155	3,881	100,000			

Extraction Method: Principal Component Analysis.



Component Matrix^a

	Component 1
Zeitpunkt_der_KI-Nutzung_1_1	,484
Zeitpunkt_der_KI-Nutzung_1_2	,855
Zeitpunkt_der_KI-Nutzung_1_3	,893
Zeitpunkt_der_KI-Nutzung_1_4	,684

Extraction Method: Principal Component Analysis.

a. 1 components extracted.

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		,788
Bartlett's Test of Sphericity	Approx. Chi-Square	7897,361
	df	6
	Sig.	,000

Communalities

	Initial	Extraction
Zuverlässigkeit/Genauigkeit_Ergebnisse_1_1	1,000	,909
Zuverlässigkeit/Genauigkeit_Ergebnisse_1_2	1,000	,977
Zuverlässigkeit/Genauigkeit_Ergebnisse_1_3	1,000	,971
Zuverlässigkeit/Genauigkeit_Ergebnisse_1_4	1,000	,950

Extraction Method: Principal Component Analysis.

Total Variance Explained

Component	Total	Initial Eigenvalues		Extraction Sums of Squared Loadings		
		% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	3,806	95,160	95,160	3,806	95,160	95,160
2	,140	3,507	98,667			
3	,038	,939	99,606			
4	,016	,394	100,000			

Extraction Method: Principal Component Analysis.

B.4 Survey 1: Open Question Answers

This section presents a summary of the answers to the open questions of the survey. To secure traceability, the text was left in the survey's original language, German.

Zusammenfassung der Antworten zur offenen Frage

„Einschätzung“:

- Man benötigt jemanden, der sich sehr gut in dem Bereich auskennt → **Experte**
- **Grund zum Einsatz** (Einsparung von Kosten, Optimierung von Prozess-Abläufen...) Vorhandene **Trainingsdaten** für Anwendungsfälle
- Der **Einsatzzweck** der KI sollte klar definiert sein. Auch sollte **die Mitarbeiter darüber informiert** werden, da es doch häufig vorkommt, dass Menschen denken, dass sie durch eine KI ersetzt werden. Die ordnungsgemäße **Funktionsfähigkeit** sollte **vor der Einführung getestet werden**.
- **Technologien (KI-Algorithmen/Modelle, etc.) Daten** (Qualität, Verfügbarkeit, Datensicherheit) **Organisation** (Geschäftsprozesse, Ressourcen, etc.) **Gesetzliche und ethische Einschränkungen**
- **AI-readiness Faktoren, Technik-Affinität**
- Der **erwartete Nutzen** hat neben der **digitalen Datenspeicherung** eine hohe Priorität bei der Einführung von KI. Gibt auch andere Gründe...
- **Sicherheit. Konkrete Regeln**
- **Planung, KI-Strategie, Kompetenzen** überprüfen, **Ressourcen**
- alles
- **Datenschutz** (Kundendaten, Kundendaten von Kunden), **Akzeptanz** bei Kunden, **Nützlichkeit** und **Performance** der KI-Lösung
- Um eine KI-Lösung erfolgreich in einem Unternehmen einzuführen und zu integrieren, sind meiner Meinung nach folgende Faktoren wichtig: **klare Geschäftsziele, hochwertige Daten, Fachwissen, Veränderungsmanagement, ethische Aspekte, Skalierbarkeit und Flexibilität**.
- Jemand sollte sich grob mit KI auskennen

Zusammenfassung der Antworten auf die offene Fragen zu jedem Feature (1. Frage nach fehlenden Values / 2. Frage nach Zustimmung oder Ablehnung zur Strukturierung des Features):

- **Gibt es Ihrer Meinung nach noch weitere, möglicherweise relevante Endnutzer?**
 - Frage mit Unterscheidungen komisch formuliert. Anwendungen sollten möglichst benutzerfreundlich sein und meist ohne technische Voraussetzungen bedienbar sein. Kenntnisse in der Thematik helfen natürlich, die Hintergrundprozesse zu verstehen
 - Nutzer, die unter KI eigentlich nur ChatGPT verstehen
 - nein 3x
- **Würden Sie die Endnutzer anders unterteilen? Falls ja, wie würde Ihre Unterteilung aussehen?**
 - Möglicherweise nach Anwendungsgrad der Software
 - nein 2x
- **Gibt es Ihrer Meinung nach noch weitere, möglicherweise relevante KI-Fokusse oder würden Sie die Fokusse anders unterscheiden?**
 - Vorhersage, Optimierung, autonomes Fahren, Datenanalysen (Data Mining)
 - Vielleicht eher direkt nach Medium unterteilen.
 - Automation
 - nein 3x
- **Würden Sie die KI-Fokusse anders unterteilen? Falls ja, wie würde Ihre Unterteilung aussehen?**
 - Verstehe die Kategorie "Rechenaufgabe" nicht. Gibt es Rechenaufgaben ohne Eingabe oder Ausgabe?
 - nein 3x
- **Gibt es Ihrer Meinung nach noch weitere, möglicherweise relevante Rechenquellen?**
 - SaaS, AaaS, PaaS
 - nein 3x
- **Würden Sie die Rechenquellen anders unterteilen? Falls ja, wie würde Ihre Unterteilung aussehen?**
 - nein 3x
- **Gibt es Ihrer Meinung nach noch weitere, möglicherweise relevante Antwort-/Reaktionszeiten?**
 - auf Anfrage
 - nein 3x

- **Würden Sie die gewünschten Antwort-/Reaktionszeiten anders unterteilen? Falls ja, wie würde Ihre Unterteilung aussehen?**
 - nein 3x
- **Gibt es Ihrer Meinung nach noch weitere, möglicherweise relevante spezielle Hardware Anforderungen?**
 - nein 3x
- **Würden Sie die Fälle, für die spezielle Hardware benötigt wird, anders unterteilen? Falls ja, wie würde Ihre Unterteilung aussehen?**
 - Datenausgabe und Visualisierung schwer verständlich als Kategorie
 - nein 3x
- **Gibt es Ihrer Meinung nach noch weitere, möglicherweise relevante Zuverlässigkeits- und Genauigkeitsgrade?**
 - keine, nicht nötig
 - nein 3x
- **Würden Sie die Zuverlässigkeits- und Genauigkeitsanforderungen anders unterteilen? Falls ja, wie würde Ihre Unterteilung aussehen?**
 - nein 3x
- **Gibt es Ihrer Meinung nach noch weitere, möglicherweise relevante Zeitpunkte, wann die KI im Entwicklungsprozess genutzt werden könnte?**
 - nein 3x
- **Würden Sie die möglichen Zeitpunkte der KI-Nutzung anders unterteilen? Falls ja, wie würde Ihre Unterteilung aussehen?**
 - nein 3x
- **Gibt es Ihrer Meinung nach noch weitere, möglicherweise primäre Aufgaben für KI-Lösungen?**
 - nein 3x
- **Würden Sie die primären Aufgaben von KI-Lösungen anders unterteilen? Falls ja, wie würde Ihre Unterteilung aussehen?**
 - nein 3x
- **Gibt es Ihrer Meinung nach noch weitere, möglicherweise relevante Datenquellen?**
 - nein 3x
- **Würden Sie die Datenquellen anders unterteilen? Falls ja, wie würde Ihre Unterteilung aussehen?**
 - nein 3x
 - eigene Daten

- **Sollte die benötigte Menge an Daten Ihrer Meinung nach anderweitig unterschieden werden?**
 - Konkrete Werte (Was ist Mittel, Angaben in GB etc...)
 - nein 2x

- **Gibt es Ihrer Meinung nach noch weitere, möglicherweise relevante Reifegrade?**
 - nein 3x
- **Würden Sie die Reifegrade anders unterteilen? Falls ja, wie würde Ihre Unterteilung aussehen?**
 - make, take, buy
 - nein 3x

- **Gibt es Ihrer Meinung nach noch weitere, möglicherweise relevante Häufigkeiten oder Zeitpunkte wie bzw. wann die Daten- und Modelle aktualisiert werden sollten/müssen?**
 - nein 3x
- **Würden Sie die Häufigkeit und Zeitpunkte der Daten- und Modellaktualisierung anders unterteilen? Falls ja, wie würde Ihre Unterteilung aussehen?**
 - nein 3x

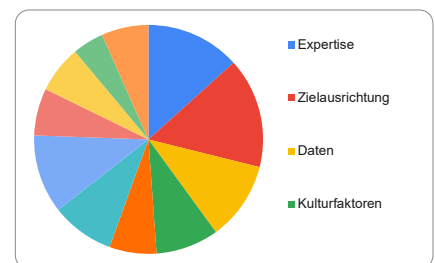
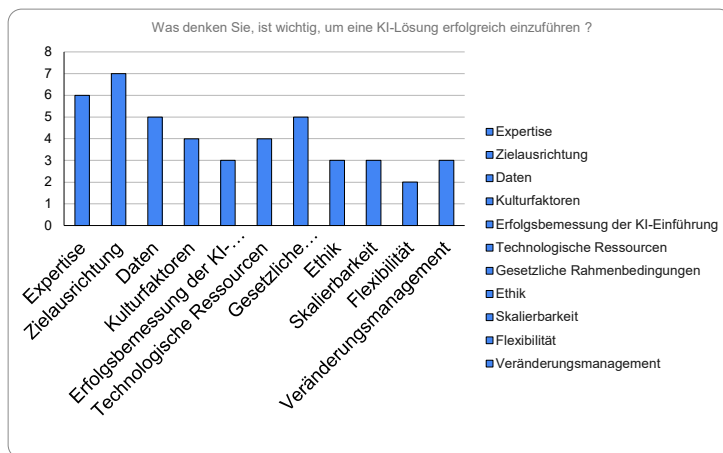
- **Gibt es Ihrer Meinung nach noch weitere, möglicherweise relevante Häufigkeiten oder Zeitpunkte wie bzw. wann die Daten- und Modelle aktualisiert werden sollten/müssen?**
 - nein 3x
- **Würden Sie die Häufigkeit und Zeitpunkte der Daten- und Modellaktualisierung anders unterteilen? Falls ja, wie würde Ihre Unterteilung aussehen?**
 - nein 3x

- **Gibt es Ihrer Meinung nach noch weitere, möglicherweise relevante Ausmaße an Auswirkungen auf Unternehmen?**
 - nein 3x
- **Würden Sie die Ausmaße an Auswirkungen auf Unternehmen anders unterteilen? Falls ja, wie würde Ihre Unterteilung aussehen?**
 - nein 3x

- **Gibt es Ihrer Meinung nach noch weitere, möglicherweise relevante Grade der Kommunikation zwischen Entwicklern und Fachabteilungen/Domänenexperten?**
 - nein 3x
- **Würden Sie den benötigten Grad der Kommunikation anders unterteilen? Falls ja, wie würde Ihre Unterteilung aussehen?**
 - nein 3x
- **Gibt es Ihrer Meinung nach noch weitere, möglicherweise relevante primäre Datentypen?**
 - nein 3x
- **Würden Sie die primären Datentypen anders unterteilen? Falls ja, wie würde Ihre Unterteilung aussehen?**
 - nein 3x
- **Gibt es Ihrer Meinung nach noch weitere, möglicherweise relevante Qualitätsprobleme, die Daten haben können?**
 - vollständig, unbeschädigte Daten
 - nein 3x
- **Würden Sie die potenziellen Probleme der Datenqualität anders unterteilen? Falls ja, wie würde Ihre Unterteilung aussehen?**
 - nein 3x
- **Gibt es Ihrer Meinung nach noch weitere, möglicherweise relevante Aspekte der Datensicherheit?**
 - nein 3x
- **Würden Sie die Aspekte der Datensicherheit anders unterteilen? Falls ja, wie würde Ihre Unterteilung aussehen?**
 - nein 3x

B.5 Survey 1: Open Question Analysis

Genannte Synonyme für mögliche neue Features (gruppiert je Zeile)								mögliches Feature	Aufkommen
	Experte	Wissen	Kompetenzen	Fachwissen	Fachwissen und Fertigkeiten	Expertenwissen		Expertise	6
	Grund zum Einsatz	Strategische Ausrichtung	erwartete Nutzen	KI-Strategie	Nützlichkeit	klare Geschäftsziele	klare Geschäftsziele	Zielausrichtung	7
	Trainingsdaten	Daten	Daten	hochwertige Daten	Datenverfügbarkeit und Qualität			Daten	5
	Mitarbeiter informieren	Kultur	Akzeptanz bei Kunden	Benutzerakzeptanz				Kulturfaktoren	4
	Funktionsfähigkeit testen	Performance	ROI-Bewertung					Erfolgsbemessung der KI-Einführung	3
	Technologien (Algorithmen, M...	Ressourcen	Ressourcen	Infrastruktur und Ressourcen				Technologische Ressourcen	4
	Gesetzliche Einschränkungen	digitale Datenspeicherung	Sicherheit	Datenschutz	rechtliche Überlegungen			Gesetzliche Rahmenbedingungen	5
	etische Einschränkungen	etische Aspekte	Ethische Überlegungen	Transparenz				Ethik	3
	Skalierbarkeit	Skalierbarkeit	Kontinuierliches Lernen					Skalierbarkeit	3
	Flexibilität	Flexibilität						Flexibilität	2
	Veränderungsmanagement	Änderungsmanagement	Kontinuierliches Verbessern					Veränderungsmanagement	3



This section briefly shows the analysis of the answers to the open questions. Here, statements were labeled with keywords and those keywords were grouped according to their topic.

Appendix: Survey 2

C.1 Survey 2: Questions & Structure

This section presents the second survey conducted in the scope of this thesis (see section 7.4). The survey was directly exported from LimeSurvey.

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Language:

English - English



Change the language

Introducing AI Solutions in Companies

We invite you to participate in this survey, designed for professionals and researchers who have been involved in the introduction or application of artificial intelligence (AI) within a company. Your insights are invaluable for advancing our understanding of how AI is being integrated into organizations, and your participation will contribute significantly to both academic research and practical applications.

If you have been part of multiple AI projects, please select the one you are most familiar with to guide your responses. By sharing your experiences, you'll not only help shape the future of AI research but also gain insights that could benefit your own work in the future.

Jack Rittelmeyer
Chair for Business Information Systems
University of Rostock

Confidentiality and Data Protection:

Please rest assured that all responses will be kept strictly confidential and will only be used for academic research purposes. Your data will be anonymized, ensuring that no personal information will be associated with your responses.

[Next](#)

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General AI Project Information

*Which of the following best describes your professional background?

❗ Choose one of the following answers

- ☐ Industry (practical background)
- ☐ Academia/Research (scientific background)
- ☐ Both
- ☐ Other:

Which type of AI technology was primarily used in the AI project you participated in?

❗ Check all that apply

- ☐ Machine Learning
- ☐ Deep Learning
- ☐ Natural Language Processing (NLP)
- ☐ Computer Vision

- ☐ Reinforcement Learning
- ☐ Support Vector Machines (SVM)
- ☐ Decision Trees
- ☐ Neural Networks
- ☐ Genetic Algorithms
- ☐ Expert Systems
- ☐ Fuzzy Logic
- ☐ Robotics
- ☐ Other:

In which industry was the AI project you participated in?

❗ Check all that apply

- ☐ Information Technology
- ☐ Finance
- ☐ Healthcare
- ☐ Education
- ☐ Manufacturing
- ☐ Retail
- ☐ Transportation and Logistics
- ☐ Telecommunications
- ☐ Agriculture
- ☐ Media and Entertainment
- ☐ Government

- ☐ Energy and Utilities
- ☐ Hospitality and Tourism
- ☐ Real Estate
- ☐ Other:

What was the size of the company where you introduced the AI application?

❗ Choose one of the following answers

- ☐ Micro-enterprise (1-10 employees)
- ☐ Small enterprise (11-50 employees)
- ☐ Medium enterprise (51-250 employees)
- ☐ Large enterprise (251-1000 employees)
- ☐ Very large enterprise (More than 1000 employees)
- ☐ No answer

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Project Classification

What was the main task of your AI application?

📌 Check all that apply

- ☐ To Process Input
- ☐ To Generate Output
- ☐ A General Computing Task
- ☐ Don't know
- ☐ Other:

How would you describe the IT-knowledge of the target end-user for your application?

📌 Check all that apply

- ☐ No IT-Knowledge
- ☐ IT-Savy
- ☐ IT-Expert

☐ Some AI Experience (not just ChatGPT)

☐ AI Expert

☐ No Human End-User

☐ Don't know

☐ Other:

Where did the computation of your application take place?

❗ Check all that apply

☐ In a Cloud

☐ In a Local Computing Center

☐ On an End-Device

☐ Hybrid (of previous answers)

☐ Don't know

☐ Other:

How fast had your application to deliver a solution?

❗ Check all that apply

☐ In Real-Time

☐ Near Real-Time

☐ In Several Hours

☐ Later

☐ Don't know☐ Other:

Was special hardware required for the development or use of the application? If yes, for which task was it required?

❗ Check all that apply

☐ Computing☐ Data Capture☐ Data Visualization☐ Data Output☐ No☐ Don't know☐ Other:

How precise and reliable had the results of your application to be? Was it defined by the influence of an external force (e.g. your competitors)?

❗ Check all that apply

☐ ~ 99,9 % Required☐ Defined by your Enterprise☐ Defined by your Domain (e.g domain specific regulations)☐ Defined by your Competitors☐ Don't know

☐ Other:

When was the AI part of your solution actually used?

❗ Check all that apply

☐ During Design-Time

☐ During Runtime

☐ Accompanying Runtime

☐ Hybrid (of the other options)

☐ Don't Know

☐ Other:

What was the primary purpose of your AI application?

❗ Check all that apply

☐ Forecasting

☐ Don't Know

☐ Assistance

☐ Decision Making

☐ Classification

☐ Anomaly Detection

☐ Other:

Where did you get the data for your AI application from?

📌 Check all that apply

- ☐ Open Data
- ☐ Don't Know
- ☐ Own Data
- ☐ Augmented Data
- ☐ Synthetic Data
- ☐ Commercial Collection (paid data)
- ☐ Other:

Please roughly estimate what amount of data did you need for your AI application?

📌 Choose one of the following answers

- ☐ Very High
- ☐ High
- ☐ Moderate
- ☐ Low
- ☐ Very Low
- ☐ Don't know
- ☐ Other:

Where did you start with the development of your AI application? Did you start individually from scratch, or were there already existing products/solutions you could use?

📌 Check all that apply

- ☐ Individual Development from Scratch
- ☐ Bought a finished Commercial-of-the-Shelf-Product (COTS)
- ☐ Bought Commercial Components
- ☐ Used Open Source Components
- ☐ Used an already existing Prototype
- ☐ Don't know
- ☐ Other:

How often do you need to update your application respectively the data and/or model it is trained on?

📌 Check all that apply

- ☐ Continuously
- ☐ In Case of Changes in Regulations
- ☐ In Case of New Documents / Data
- ☐ In Case of Changes in Customer Behaviour
- ☐ In Case of Quality Problems
- ☐ Don't know
- ☐ Other:

Did the introduction of the AI application change your companies processes, even your whole business model, or is it just an isolated solution on its own?

❗ Check all that apply

- ☐ Isolated Solution
- ☐ Single Process
- ☐ Workflow
- ☐ Work System
- ☐ Business Model
- ☐ Don't know
- ☐ Other:

During your application's development and implementation process, how much communication was needed between your domain experts/potential end-users and the developing team?

❗ Check all that apply

- ☐ Frequent & Detailed Communication (active collaboration)
- ☐ Regular Communication (some collaboration)
- ☐ Minimal Communication (minimum collaboration)
- ☐ Communication only in Specific Moments
- ☐ None
- ☐ Don't know

☐ Other:

What is the primary data type your AI application processes?

❗ Check all that apply

- ☐ Audio
- ☐ Video
- ☐ Raster Image
- ☐ Vector Image
- ☐ Transaction Records
- ☐ Time Series Data
- ☐ Don't know
- ☐ Other:

What were the most significant data quality problems that occurred during the development, introduction and use of your AI application?

❗ Check all that apply

- ☐ Incomplete Data
- ☐ Noisy Data
- ☐ Biased Data
- ☐ Duplicate Data
- ☐ Inconsistent Data

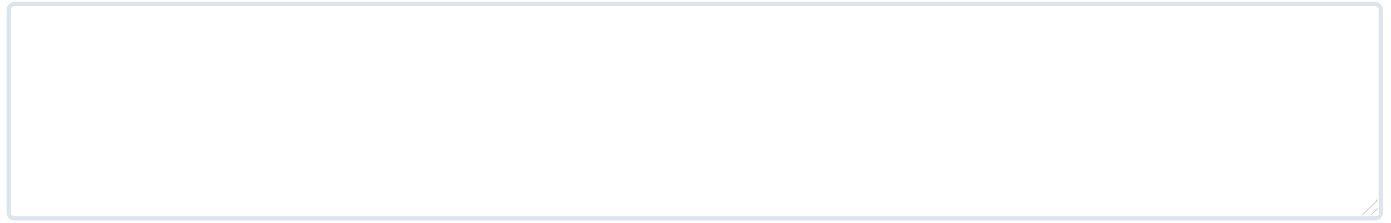
- ☐ Corrupted Data
- ☐ Outdated Data
- ☐ Don't know
- ☐ Other:

Were you confronted with data security problems during the development, introduction or use of your AI application? If yes, in which areas?

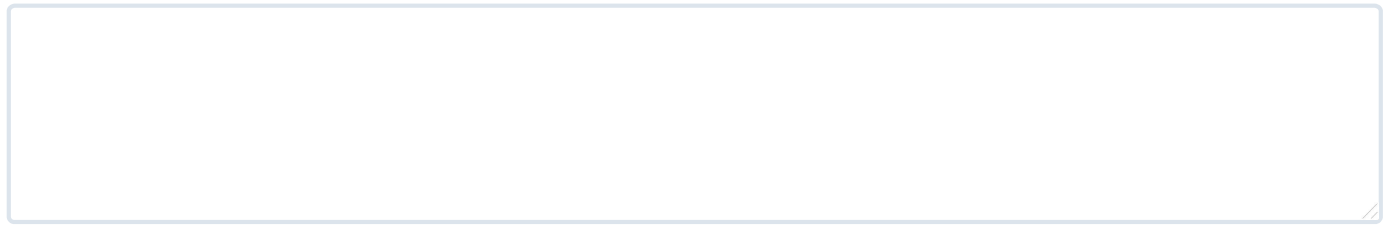
i Check all that apply

- ☐ Access Control
- ☐ Incident Management
- ☐ No
- ☐ Audit & Monitoring
- ☐ Data Integrity
- ☐ Don't know
- ☐ Data Privacy
- ☐ Data Encryption
- ☐ Compliance
- ☐ Other:

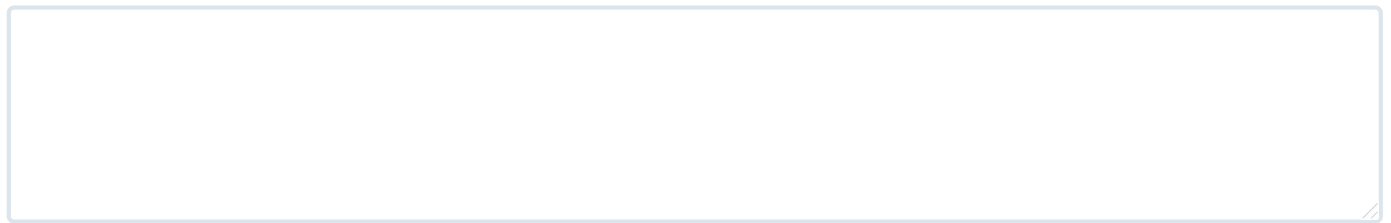
Were there any legal requirements specific to AI applications that were relevant to the development of your application or that you took into account? If so, please specify which.



Were there any ethical or cultural requirements specific to AI applications that were relevant to the development of your application or that you took into account? If so, please specify which.



What was required to implement your AI solution in general?



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Demographic Questions

What is your gender identity?

📌 Check all that apply

- ☐ Female
- ☐ Male
- ☐ Non-binary
- ☐ Prefer not to answer
- ☐ Other:

How old are you?

📌 Check all that apply

- ☐ Under 18
- ☐ 18-24 years
- ☐ 25-34 years

- ☐ 35-44 years
- ☐ 45-54 years
- ☐ 55-64 years
- ☐ 65+ years
- ☐ Prefer not to answer

What is the highest level of education you have completed?

❗ Check all that apply

- ☐ Secondary modern school
- ☐ Secondary school
- ☐ High school or equivalent
- ☐ Apprenticeship
- ☐ Master craftsman
- ☐ Bachelor's degree
- ☐ Master's degree
- ☐ Doctorate / PhD
- ☐ Habilitation
- ☐ Prefer not to answer
- ☐ Other:

What is your current employment status?

❗ Check all that apply

- ☐ Employed full-time
- ☐ Employed part-time
- ☐ Self-employed
- ☐ Retired
- ☐ Unemployed
- ☐ Student
- ☐ Prefer not to answer
- ☐ Other:

What is your current job role/title? (Please specify)

In which industry do you work?

i Check all that apply

- ☐ Information Technology & Telecommunication
- ☐ E-Commerce
- ☐ Finance, Real Estate & Insurance
- ☐ Healthcare & Pharmacy
- ☐ Research
- ☐ Education

- ☐ Retail
- ☐ Services
- ☐ Entertainment & Media
- ☐ Sport & Fitness
- ☐ Tourism & Gastronomy
- ☐ Transportation & Logistics
- ☐ Advertising & Marketing
- ☐ Economy & Politics
- ☐ Metal & Electronics
- ☐ Chemical & Raw Materials Industry
- ☐ Prefer not to answer
- ☐ Other:

How many years of experience do you have in your current field?

i Check all that apply

- ☐ Under 6 months
- ☐ 6-12 months
- ☐ 1-2 years
- ☐ 3-5 years
- ☐ 5-10 years
- ☐ 10+ years
- ☐ Prefer not to answer

☐ Other:

What is the size of your company?

📌 Check all that apply

- ☐ 1-10 employees
- ☐ 11-50 employees
- ☐ 51-100 employees
- ☐ 101-200 employees
- ☐ 200+ employees
- ☐ Prefer not to answer

In which country are you currently located?

📌 Choose one of the following answers

- ☐ Germany
- ☐ Switzerland
- ☐ Austria
- ☐ Sweden
- ☐ Italy
- ☐ Czech Republic
- ☐ Latvia
- ☐ Romania
- ☐ Spain

☐ United Kingdom

☐ USA

☐ Netherlands

☐ Other:

☐ No answer

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Final Question

Is there anything you want to add, comment on, or let us know about the overall topic or the survey?

[Previous](#)[Submit](#)

Conclusion and Next Steps:

Thank you for taking the time to complete this survey. Your contributions are crucial for advancing our understanding of AI integration in organizations, and we greatly appreciate your insights and experiences.

Questions or Concerns:

If you have any questions or concerns about this survey or how your data will be used, please feel free to contact us at jack.rittelmeyer@uni-rostock.de. We are happy to provide additional information or clarification.

Final Note:

Your input is not just valuable to us; it will also contribute to the broader scientific and business communities by helping to shape future AI initiatives. We hope the insights gained from this research will also offer you practical benefits in your own work.

Once again, thank you for your time and valuable insights.

Jack Rittelmeyer

C.2 Survey 2: Answers (CSV-Export)

This section should provide the answers collected via the second survey. However, because it was difficult to visualize all answers in a satisfactory way, an excel-file that includes the data is provided with the digital version of the dissertation.

[illegible]

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Statement of Authorship & Resume

I, Jack Daniel Rittelmeyer, hereby declare that I have written this dissertation with the title *"DEVELOPMENT AND EVALUATION OF A MORPHOLOGICAL BOX FOR ARTIFICIAL INTELLIGENCE SOLUTION INTEGRATION"* independently and have not used any sources or aids other than those stated.

All passages that are taken literally or analogously from publications are marked as such.

The thesis has not yet been published and has not yet been submitted for recognition or assessment in a similar or identical manner.

Rostock, the October 15, 2025

Jack Daniel Rittelmeyer

<u>Work Experience</u>	
07/2024 – today (Full-time)	Associate Researcher Center for AI in Mecklenburg-West Pomerania & Chair for Business Information Systems (BIS), University of Rostock • Connecting experts from science with small and medium-sized enterprises to enable and facilitate knowledge transfer • Planning, preparing, conducting and evaluating events like "Tag der KI" (AI Day) or a Big Data Workshop • Promoting our events on social media (Linked.in, Facebook) as well as on-site (e.g., flyers, posters)
02/2023 – 06/2024 (Part-time)	Project, IT & Social Media Manager AniMoon Publishing GmbH • Planned and executed marketing campaigns in a cross-functional team, creating engaging social media content with Adobe Photoshop and producing promotional videos, including trailers and synchronization clips with Adobe Premiere Pro for YouTube, Instagram, X, Facebook and TikTok. • Designed and launched the company's new online shop, improving user experience and functionality (www.ani-moon.de). • Prepared and delivered material for streaming platforms (Amazon Freevee, aniverse, ProSieben MAXX), including metadata, video-, audio-, image- and subtitle-files. • Co-Managed the localization project for "Haganai Next", including writing and editing German subtitles. • Designed a variety of merchandise and physical promotional material, including mock-ups, posters, buttons, roll-ups, and Blu-ray/DVD J-cards using Adobe InDesign and Photoshop. • Organized convention participation, managing booths at events like Leipzig Book Fair, AnimagiC and Dokomi.
02/2023 – 06/2024 (Part-time)	Associate Researcher Chair for BIS, University of Rostock • PhD-Topic: <i>Development of a Morphological Box for AI Solution Integration in Companies</i> (currently finalizing the thesis)
10/2020 – 01/2023 (Full-time)	• Conducted research on AI integration in enterprises, enterprise architectures, and digital marketing. • Published multiple peer-reviewed scientific articles at top academic conferences, adhering to varying strict style guidelines. • Supervised bachelor and master theses, held lectures, and served as Organizational Chair for the BIR 2022 conference.

01/2022 – 10/2022	Freelance IT Compliance Consultant Self-Employed Conducted GAP analyses and enhanced regulation management systems to meet compliance standards (MaRisk, BAIT).
09/2018 – 02/2019	Business IT Intern Siemens Plc Global Services IT (Poole, UK) - Analyzed IT helpdesk chatbot usage and recommended optimization strategies. - Implemented process improvements using Microsoft Flow and SQL queries.
<u>Education</u>	
04/2019 – 09/2020	M.Sc. Business Informatics University of Rostock Grade: 1.3 (Very Good) Thesis: <i>„Synergy Effects between Management Systems and Regulatory Requirements from an Enterprise Architecture Management Perspective“</i>
10/2015 – 03/2019	B.Sc. Business Informatics University of Rostock Grade: 1.8 (Good) Thesis: <i>„Towards a Mobile Augmented Reality Application to Check Meeting Room Availability“</i>
<u>Voluntary Work</u>	
02/2022 - 07/2022	Subtitle Writer and Editor emania Anime / Anime Kultur e.V. Authored and timed German subtitles for episode 6 – 13 of <i>“Shakugan no Shana: Second”</i>.
02/2022 – 07/2022	Co-Organizer Anime Messe Babelsberg 2022 Managed key event areas, including partnerships with the Japanese Embassy, DJG Berlin and Good Smile Company.
12/2015 – 09/2020	Financer & Member Student Council of the University of Rostock Organized the finances and several events using Slack and Trello.