Developing Purposeful AI Use Cases – A Structured Method and Its Application in Project Management

Abstract. An appropriate problem-solution-fit is essential to develop purposeful artificial intelligence (AI) applications. However, in domains with an unintuitive problem-solution-fit, such as project management (PM), organizations require methodological guidance. Hence, we propose a five-step method to develop organization-specific AI use cases: First, companies must consider five context factors, i.e. technology, data, organization, domain, and environment. Second, companies must identify existing domain problems and AI solutions. Third, our method facilitates abstraction to understand the underlying nature of the identified problems and AI solutions. Fourth, our problem-solution-matrix assists companies to match AI functions with the domain context. Fifth, companies derive necessary implications for the subsequent use case implementation. To construct and evaluate our method, we followed the design science research paradigm complemented by situational method engineering and based on 14 interviews. Our method addresses a relevant practical problem and contributes to identifying purposeful AI use cases in unintuitive application domains.

Keywords: Artificial Intelligence, Project Management, Use Case Development, Situational Method Engineering, Design Science Research.

1 Introduction

Advances in computational resources, the high availability of data, and advances in machine learning, among others, amplify the commercialization of artificial intelligence (AI) applications in a wide range of business areas. Exemplary AI applications range from medical diagnosis [1] over virtual assistants [2] to autonomous vehicles [2]. The business potential but also the pressure to lose competitive advantage drives organizations to put the identification of AI use cases at the core of their agendas. Thus, AI is no longer a primarily technical issue. For one thing, many companies lack the right understanding of AI. For another thing, developing use cases is not just a copying other organizations' use cases since AI use cases need to meet organization-specific context factors. While some application areas offer an intuitive problem-solution-fit (e.g., predictive maintenance in production), other application areas come along with major managerial challenges.

An exemplary application area with an unintuitive problem-solution-fit is project management (PM) with its temporary effort to build a unique result [3]. Since learning from data is at the center of current AI applications [4, 5], unique situations and the lack of project-specific data [6], contradicts the idea of using AI for PM. Rather, many successful decisions seem to relate to the project managers' knowledge [3]. However, the PM domain offers manifold opportunities for the application of AI which are mostly undiscovered in practice. Various approaches to solving the different PM problems exist [e.g., 6, 7], but previous work has only focused on specific applications in the field of AI to address particular problems of PM. Practitioners face the challenge to identify the right solution or to understand which solution suits their current problem best [6]. In other words, there exists a need to support organizations in bridging the gap between their organizational problems and potential AI solutions. On a technology-independent level, both practice and literature have already discussed the identification of use cases. However, the existing technology selection and evaluation literature [8–10] does not consider AI's characteristics sufficiently (detailed discussion in section 2.2). In addition, data's central role in AI applications requires special attention. To close this research gap, we pose the following research question: *How can a method support practitioners in developing purposeful AI use cases for the application in PM?* To answer this research question, we develop a method to identify organization-specific use cases for applying AI from both a problem and a solution perspective. Hence, the method engineering goal is to develop AI use cases throughout a domain's context purposefully. To develop our method, we applied situational method engineering (SME) [11] within the design science research paradigm (DSR) [12].

2 Theoretical Background

2.1 Artificial Intelligence in Project Management

In this section, we describe the application of AI in PM. In this context, we follow the broad and established AI definition of Russell and Norvig, who describe AI as intelligent agents [4]. PM does not seem to be an intuitive application domain for AI because data is not as structured and obvious as in other domains. However, both research and existing products indicate the use of AI in PM. Many of these existing tools and techniques are PM-specific but are not sufficient for successful PM. In addition, a project manager needs high knowledge and intuition about PM as well as the application domain [3]. Furthermore, the success of a project depends on the project managers performance and personality [3].

Therefore, we screened existing literature and available PM software solutions to provide an exemplary overview of AI use cases in PM. So far, literature particularly covers the use of machine learning for prediction. However, there are also AI applications considering budget, prioritizing requirements, or risk assessment. For example, Tronto et al. [6] predict the effort of projects based on cost drivers and software size variables. For predicting, they use an artificial neuronal network and a linear regression approach. Vargas [13] aims at predicting the PM cost of a given project. Nayebi et al. [14] developed a decision support system using natural language processing to improve effort estimation, scoping, and assignment of change requests in software projects. For further research see, for example, [7, 15, 16].

Existing research is slowly having an impact on product offerings. Today, most AI applications in PM are chatbots [17]. Here, the use of AI is at the input and output interface, but not in the PM task itself. Consequently, the AI application, instead of humans or rule-based software, triggers the PM task. For example, the project assistant bot *stratejos* (https://stratejos.ai) supports project teams by sharing daily tasks, creating new tasks, or requesting people to finish missing issues. Another example is the *redbooth bot* (https://redbooth.com), which illustrates daily tasks and issues the team is working on. However, applications already exist that execute PM core tasks. *PMOtto* (https://pmotto.ai) is a virtual assistant that advises on a task's time, cost, and resources based on Machine Learning. *Cloverleaf* (https://cloverleaf.me) is an AI-based platform that supports gaining insights into how the project team members work. For instance, Cloverleaf indicates where to focus on skill development. Furthermore, Cloverleaf understands how to position people in project teams and therefore helps to assemble the best possible project team for a project.

In summary, literature and existing products offer already some value-adding opportunities for the use of AI in PM. But organizations often lack the understanding for the AI solutions' benefits and thus, for creating a solution-problem-fit. Hence, we see the need for a method to match organization-specific problems and AI solutions.

2.2 Technology Evaluation and Selection

Technology selection and evaluation is a critical task for organizations to stay competitive [9, 18]. Technology selection is a process of identifying technologies and choosing the most appropriate of them [18, 19]. However, the rapid development of complex technology landscapes and the increasing complexity and dynamism in the business environment complicate the technology selection process [19, 20]. Existing technology selection approaches vary in their structure: Yap and Souder [10], Shehabudden et al. [20] and Collins and Williams [9] follow a filter approach to identify the appropriate technology through different criteria filter. Chan et al. [8] and Shen et al. [21] combine fuzzy concepts with hierarchical structure approaches for their technology selections models. The methods of Stillman [18] and Friedrich et al. [19] contain a step-by-step approach towards the appropriate technology. In addition to the technology selection literature, we identify the step-by-step method of Fridgen et al. [25] who conceptualize a method for developing blockchain use cases systematically.

Initially, identifying potential technologies and solutions is an important first step for many technology selection models [8, 10, 18, 21]. After the first step, technology selection literature often incorporates different context areas, such as technology, market, strategy, and customers [10, 18–20]. Both identifying technologies and analyzing context factors represent an important basis for technology selection. In contrast to the first two aspects, the understanding of technology is only explicitly mentioned in Fridgen et al. [22]. The major part of the considered methods incorporates criteria to evaluate the added value of the technology to be introduced [8, 9, 19–21]. The structured comparison of the evaluated solutions also plays an important role in all the considered methods. While the technology selection approaches concentrate on the right choice of technology, approaches in the field of AI concentrate on developing and implementing AI algorithms.

However, the existing technology selection methods would not adequately identify AI use cases for domains with an unintuitive problem-solution-fit such as PM. Technology selection focuses on considering context areas and meeting specific factors to create value for the organization. In addition, AI has characteristics that require explicit consideration for successfully using AI in organizations. The enormous expectations usually come from the fact that many organizations do not fully understand AI's business potential [23]. Consequently, it is very important to develop an understanding of AI before identifying use cases. Data is indispensable for AI applications and is increasingly becoming a central resource for organizations. Consequently, the triangle of application, data, and organization must fit when using AI. If a use case does not meet all of these criteria, there is a risk that the AI use case will not work in the organization. Ultimately, AI has a modular character [24, 25] that makes it very promising to transfer existing solutions to other domains and to recombine individual AI components to create completely new use cases. All these aspects need special attention when introducing AI in organizations.

3 Research Method

We follow the DSR paradigm to develop our artifact, i.e., a method that identifies AI use cases in PM. DSR is an approach to develop and evaluate artifacts that serve human or organizational purposes rigorously [26, 27]. Methods, as an acknowledged DSR artifact, specify how to perform goal-directed activities [27]. We complement the DSR paradigm with principles of SME [11]. SME provides techniques to create IS development methods fulfilling the requirements of a given situation [28]. Previous scholars have shown the value of embedding SME within the DSR paradigm to rigorously develop methods [29, 30]. In our study, we use the assembly-based method engineering approach, a procedure model for SME proposed by Ralyté et al. [31]. The assembly-based method engineering approach allows us to make use of existing technology evaluation and selection techniques (i.e., method chunks). Further, the iterative manner of the assembly-based method engineering allows us to incorporate additional insights from expert interviews.

In the course of our research project, we conducted, recorded, transcribed, and analyzed 14 semi-structured interviews [32]. The first ten interviews provided overarching insights into the practical relevance and related challenges of applying AI in PM motivating us to create a method that develops AI use cases in a domain with an unintuitive problem-solution-fit. The insights of the remaining four interviews especially encompass our method's evaluation to ensure its applicability. Moreover, we revisited the first ten interviews during evaluation to verify that our method is in accordance with interviewees' expectations. We used expert sampling [33] to identify interviewees with AI and PM expertise from different industries and company sizes. Table 1 provides an overview of the experts' background.

Table 1. Overview of Expert Interviews

#	Position	Area of Expertise	Experience in Years	Industry	Company Size	Interview Duration
E1	Senior Data Specialist	AI	<5	Energy	<50,000	56
E2	IT Project Manager	AI and PM	5-10	IT Consulting	<500	74
E3	Founder and CEO	AI	<5	Software Start-up	<50	46
E4	IT Solution Architect	AI	5-10	ICT	<100	105
E5	SVP and COO	AI and PM	>10	Logistic	>100,000	89
E6	Head of Program Management	PM	5-10	Engineering	<25,000	63
E7	Senior IT Consultant	PM	<5	IT Consulting	<500	69
E8	IT Program Manager	PM	>10	ICT and IT Consulting	>100,000	78
E9	IT Project Manager	PM	>10	Automotive	>100,000	65
E10	Senior Director	PM	>10	Logistic	>100,000	86
E11	Head of Strategy & Innovation	AI and PM	>10	AI Research & Development	< 50	59
E12	Data Analyst	AI	5-10	Software Start-up	< 50	49
E13	IT Project Manager	PM	<5	Engineering	<25.000	72
E14	IT Security Manager	AI and PM	<5	Public Sector	<100	54

In the first step of our method development, we defined the method engineering goals based on our assessment of AI's relevance and the shortcomings of existing technology selection and evaluation models to address AI specifics. In the second step, we identified method chunk requirements and overarching completion conditions. We set our completion conditions (CC) as follows: (CC1) The method assembly fulfills the targeted method engineering goals. (CC2) Each method chunk fulfills its requirements. (CC3) The method assembly considers a problem and potential perspective. In the third and fourth step, we selected and subsequently assembled method chunks until the method met all completion conditions. In the fifth step, we initially evaluated the method to demonstrate its inherent utility [26, 27]. Thereby, we followed the evaluation criteria of March and Smith [27], i.e., ease-of-use, feasibility, effectiveness, efficiency, and generality.

4 A Method for Developing Purposeful Artificial Intelligence Use Cases in Project Management

In this section, we describe our developed method to develop purposeful AI use cases in PM as an exemplary application domain. Our method consists of five steps, i.e., preparing, discovering, understanding, designing, and implementing. We use method chunks from established technology evaluation and selection models as well as from other methods focusing on emerging technologies' application. Moreover, our method considers expert opinions to cater to the practitioners' needs, such as understanding the technology, business value focus, use case evaluation, and implementation approaches, among others. Figure 1 summarizes the five method steps.

	Preparing	**Discovering**	**Understanding**	**Designing**	**Implementing**
Goal	Collecting and structuring information about five context factors	Collecting domain problems and existing AI solutions	Understanding problems and solutions through abstraction	Matching domain problems and AI solutions in a problem-solution-matrix	Deriving the prerequisites for the successful implementation of selected use cases
Output	Technology, data, organization, domain, and environment context	List of relevant domain problems and possible AI solutions	Abstract assignment of problems and solutions to problem and solution classes	Feasible list of use cases with a problem-solution-fit	Strategic and contextual implications for use case implementation

Figure 1. Method Overview for Developing AI Use Cases in the PM Application Domain

4.1 Preparing

The first method step (i.e., preparing) collects and structures relevant information about the organization-specific context. Thereby, we draw on technology selection literature [8–10, 18, 20, 21], the established Technology-Organization-Environment (TOE) framework [34], and AI adoption literature [23, 35] to derive relevant context factors for a detailed analysis. Technology selection is a critical process for organizations to stay competitive. By offering a generic theory for the diffusion of technologies, the TOE framework is suitable to get to know new technologies [36]. For example, Pumplun et al. [35] and AlSheibani et al. [23] describe AI adoption using the TOE framework and provide further context areas for using AI within an organization. We extend the TOE framework to include data and domain as additional context areas to account for AI's and domain's specifics. Hence, we distinguish five context areas: technology, data, organization, domain, and environment.

Technology. Organizations must provide an overall understanding of AI technologies. Further, organizations must consider the boundary conditions of existing strategies (business, IT, and AI, if applicable) for their technological implications as well as previous experience and current know-how within the organization regarding AI [35].

Data. Using machine learning, the successful implementation of AI is especially reliant on data [35]. For instance, training machine learning algorithms require large amounts of data to achieve adequate solution quality [37]. However, data availability, quality, and security are often limiting factors in AI projects [35]. Besides, machine learning models can only generate meaningful output if data matches the application [4]. Therefore, organizations must carefully consider these aspects and evaluate the available data (e.g., actuality, relevance, accessibility).

Organization. Considering the organization, aspects such as structures, resources, and culture play a decisive role [35]. It is important to ensure the alignment of emerging technologies such as AI with the organization's overarching strategy [19]. For instance, organizations must ensure, among others, top management support, an innovation-friendly culture, and adequate resources (e.g., budget, employee expertise, and availability).

Domain. With the method aiming at developing AI use cases within a specific application domain, organizations must assess the general domain characteristics. Thereby, organizations must gather relevant information and stakeholders to create a shared understanding (e.g., through joint teams with AI and domain experts). For AI use cases in PM, this may include the total number of projects, information on project types, content, and size, success, and failures report or current tool support.

Environment. The environmental context includes an assessment of industry requirements, competitors, customers, and regulation [35]. Thereby, organizations must identify facilitating and impeding factors for AI use cases development. These factors may include general industry trends for AI adoption, customer preferences for AI acceptance, and the regulatory impact on AI implementation (e.g., public funding, GDPR and ethical guidelines on AI's trustworthiness [38]).

4.2 Discovering

The goal of the second method step (i.e., discovering) is to collect specific domain problems and existing AI solutions. Thus, organizations can develop AI use cases from two perspectives: First, organizations may use AI to address existing problems in the application domain (problem perspective). Second, organizations may explore new AI solutions to open up new technological opportunities in the application domain (solution perspective).

Problem Perspective. In the PM case, following the problem perspective is a sensible approach to learn from past project failures for future projects [39]. However, the definitions of project success and failure differ in organizations as well as in literature [40]. Common success dimensions include the efficiency of the implementation process, the project's perceived value, and customer satisfaction [41]. Based on a common understanding of project failure, project managers must analyze their projects to identify past problems and impediments. This approach will initially result in very specific problems [39] which organizations can collate with PM failure literature [e.g., 39, 42–44].

Solution Perspective. The solution perspective identifies existing approaches and technological opportunities for AI use cases in the application domain. Companies must engage in a comprehensive market analysis [19] to collect existing AI solutions. Such an analysis may include available software products as well as state-of-art technological opportunities and research insights. Following this problem-agnostic approach, organizations gain a deeper understanding of potential AI solutions and can discover technological opportunities for additional improvements in PM [22].

4.3 Understanding

Organizations often lack profound knowledge of emerging technologies, which leads to exaggerated expectations [22]. Therefore, the third method step (i.e., understanding) further abstracts the identified domain problems and existing AI solutions to reveal their underlying nature. This understanding enables organizations to match problems and solutions in the subsequent method step. Moreover, it is important to understand the problems and solutions well to evaluate the application's outcome in the later development and deployment phase appropriately. Abstraction usually only changes the representation of a phenomenon (e.g., budget overrun in a specific project indicates a budget estimation problem) to reduce complexity [45]. Solving this abstraction is often easier than solving a specific phenomenon directly. Finally, one transfers the abstract solution into a specific solution for the original phenomenon (e.g., applying an AI-based budget estimation algorithm in a specific project with its characteristics). While an abstract solution can apply to several problems (e.g., several different projects with budget overruns), it is important to abstract purposefully to maintain the underlying nature of the phenomenon [46].

Application Domain Structure. Considering the domain understanding, organizations must find a way to structure the domain processes, activities, and expertise. For the PM application domain, we use the ten knowledge areas of the Project Management Body of Knowledge [3] as an expertise-focused de-facto PM standard. Organizations could also use process groups or PM phases to structure the application domain. However, we prefer the expertise-focus because it does not limit AI solutions to a specific project phase such as budget estimation at the beginning of a project or the ongoing prediction of budget needs. Of course, other application domains or organization-specifics may require their application domain structure (e.g., product development phases for AI uses in a production context).

AI Functions. Considering the AI understanding, we propose seven AI functions inspired by the human cognitive abilities for three major reasons. First, AI mimics problems of human thinking [4]. Second, AI is in part (e.g., artificial neural networks) inspired on the biological learning of humans [37]. Third, cognitive abilities are familiar to human decision-makers, facilitating the application of our method. For a discussion of cognitive abilities in PM see, among others, Mair et al. [47]. Consequently, we draw on psychology literature to distinguish the abstract tasks AI can support [e.g., 48, 49]. We list the seven AI functions, including a short definition, below.

- **Perceiving**, i.e., acquiring and processing data from the real world to produce information
- **Feature extraction and identification**, i.e., extracting and identifying specific objects from data
- **Reasoning**, i.e., separating data into (similar) entities to explain or understand its structure or its underlying relationships
- **Predicting**, i.e., estimating future events and conditions on a continuous scale
- **Decision-making**, i.e., choosing between known, discrete alternatives
- **Generating**, i.e., producing or creating something
- **Acting**, i.e., executing goal-oriented actions (e.g., movement, navigate, control)

AI Solution Types. In addition to the AI functions, different AI solution types exist. We refined the solution type approaches of Auth et al. [17] and Balada et al. [50] and distinguish four AI solution types depending on the role, extent, and value of AI usage: rule-based solutions, AI-enabled solutions, AI-based solutions, and full AI solutions. Rule-based solutions do not possess any AI component but rely on common rule-based programming. Rule-based solutions are particularly useful for automating standardized project tasks via simple workflow integration (e.g., robotic process automation). AI-enabled solutions use AI to support input and output interfaces. AI-enabled solutions usually comprise human-computer-interaction, often based on natural language processing (e.g., chatbots). AI-based solutions use AI to support processing the core task. Such solutions create new knowledge (e.g., budget estimation or risk management advice). Full AI solutions use AI for input and output as well as task processing. Full AI solutions may also consist of separate AI solutions (e.g., a chatbot that communicates AI-based budget estimations). Our method is primarily concerned with AI-based and full AI solutions because rule-based solutions to not include an AI component and AI-enabled solutions facilitate the process instead of addressing the core task. However, organizations can use this classification to guide the development of use cases for all four AI solution types.

4.4 Designing

The method's previous step resulted in a list of AI solutions and domain problems as well as a deeper understanding of the domain structure and AI functions. In the fourth method step (i.e., designing), one needs to match domain problems and AI solutions by consolidating the gathered information in the problem-solution-matrix (cf. Figure 2): In the PM case, we organize the knowledge areas in the matrix's columns and the AI functions in the matrix's rows. Depending on which human ability would be necessary to solve the problem or which human ability resembles the solution, an assignment to the AI functions can take place.

Problem-Solution-Constellations. After sorting the solutions and problems, three scenarios are possible: In the case of a problem-solution-fit**,** matrix elements include both problem(s) and solution(s). The organizations can compare the resulting use cases with the context factors and evaluate their added value. If there is only a problem in a matrix field, but no solution, the organization can conduct more intensive market research. The organization can search specifically for solutions in the area in which the problem occurred. If no solution exists, the organization can also evaluate whether developing the solution is possible. If there is only a solution in the matrix field, but no problem, the organization should check the following two possibilities. First, whether the organization has overlooked a problem. Second, if the organization has not overlooked a problem, whether the solution has the potential to improve current processes.

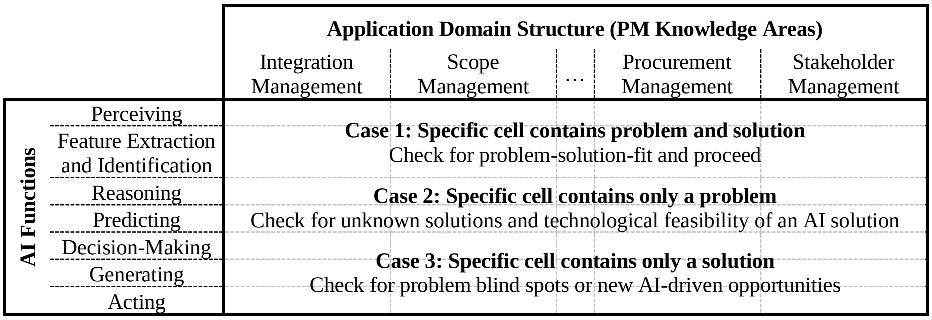

Figure 2. Problem-Solution-Matrix in the PM Domain

Comparison and Prioritization. As soon as a collection of use cases exists, the organization analyzes the context factors from the first method step (i.e., preparing) again, specifically for each use case. In this way, the organization can determine whether an implementation is possible at the current point in time or which obstacles and requirements exist to enable implementation. Based on this, the organization can prioritize the use cases. For this purpose, the organization must define criteria according to which it would like to evaluate the use cases. Common criteria from the literature refer to quality, cost, benefits, reliability, and compatibility [8, 20].

4.5 Implementing

The goal of the fifth method step (i.e., implementing) is to successfully take the hurdle from use case conception to use case implementation. Thus, organizations must put the theoretical considerations into practice and derive the prerequisites for successful use case implementation. Thereby, an organization must answer the question whether it wants to develop the AI application in-house, outsource the development, or purchase an existing solution from an external provider. Furthermore, organizations must consider the five context factors introduced in the first method step again during use case implementation. Regarding the technology context, the organization needs to consider, for example, how to integrate the AI application into the current infrastructure and how to develop a proof-of-concept. Closely related, the organization needs to consider the data context. For example, if the required data is not yet available, the organization must plan data acquisition or adapt its data strategy. In the organizational context, the organization needs to address, amongst others, employees' concerns. Regarding the domain context, the organization needs to decide how to change existing processes. As an example of the environmental context, the organization should verify data protection and ethical issues carefully.

5 Evaluation and Discussion

5.1 Discussing the Method's Application

Our method is not an isolated approach, but organizations must explicitly consider its integration within the organizational context. AI is not just a topic for labs or the IT department. The resulting interdisciplinary teams naturally bring together a problem and solution perspective and thus, complement each other. Since AI use cases can affect many employees, change management becomes an important issue for organizations. To cope with that, our method allows incorporating non-AI-experts at the very beginning of developing AI use cases to shape the use of AI in their domain.

Moreover, our method may appear to follow a sequential order of method steps. However, we suggest a more iterative implementation. Since our method leaves room for tailored execution, one can apply our method to different extents. For example, AI experts, domain experts, and executives start with a workshop to generate a first rudimentary and quick assessment of use case areas. Insights from a first iteration allow planning further iterations in more detail. Furthermore, practitioners can apply our method in other domains with unintuitive problem-solution-fits. First, the introduced AI functions are applicable domain-independently because they do not have any specific domain characteristics. Second, the structure of our method allows replacing PM by other domains characterized by an unintuitive solution-problem-fit.

5.2 Evaluating the Method's Utility

Following March and Smith [27], we evaluate our method with regard to five criteria (i.e., ease-of-use, feasibility, effectiveness, efficiency, and generality) and discuss the fulfillment of the CC. Although we have not yet applied our method in a real-world scenario, we assess the method's utility initially based on the later expert interviews.

Feasibility. Overall, experts confirm our method's comprehensibility and feasibility [E11-E14]. Moreover, experts agree that all method steps are complete. Despite the uniqueness of projects, E11 states no further obstacles to use AI solutions across different projects. E12, E13, and E14 emphasize the applicability of our matrix. In detail, E12 can combine our AI functions with different AI algorithms and E13, as a non-AI-specialist, can comprehend the AI functions.

Ease-of-Use. Practitioners do not need to make any long-term investments to use our method. But our method implies that the organization must deal intensively with the domain and AI. However, from our point of view, this is necessary to develop purposeful use cases. Due to the method's variability, the execution effort is controllable and scalable. According to the organization's demands, the process can range from a one-day workshop to a longer phase with few participants or a whole team.

Efficiency. The method's iterative character gives practitioners the possibility to terminate the current method stage to avoid sunk cost. Iteratively executing our method allows one to get deeper insights into their problems to get solutions as purposeful as possible. E11 confirms that it is important to get solutions for specific problems in a purposeful way. Furthermore, the abstraction part of the method allows covering a certain number of problems with one solution.

Effectiveness. Overall, experts confirm the relevance of a structured approach to use AI solutions [E11-E14]. E12 points out the method's relevance by describing his thought to create a similar method for his organization to create solutions in order to be able to develop solutions rapidly and purposefully. For example, scope estimations [E13] are an application area for AI in PM, which our method can identify. However, E13 states that a high abstraction bears the risk of project managers sorting problems differently in the matrix.

Generality. As stated in section 5.1, the method is independent of the domain and thus, provides general applicability in organizations. While we introduce our method in a PM context, for example, E12 transfers the method – especially the AI functions – to the medical sector. Furthermore, E14 transfers the method to a current IT security task and confirms the applicability of our matrix in this area.

Completion Conditions. Using our method, practitioners understand how to create AI use cases in PM. They can also organize AI knowledge and corresponding PM expertise (CC1). Furthermore, the experts confirm that each method chunk fulfills its requirements (CC2). Lastly, the method considers a problem and a potential view, since sorting is possible from both perspectives (CC3). Consequently, the initial evaluation of our method indicates that our method meets the CC.

5.3 Limitations and Future Research

Our study is subject to limitations that stimulate future research. First, we use 14 expert interviews to support the entire method development process and its subsequent evaluation. While the interviewees' statements support the method's relevance, future research should extend the number of interview participants to extend our method's evaluation. Second, we cannot present a real-world scenario to evaluate our method. However, building on our insights during method development and its initial evaluation, an application of our method seems promising. Hence, future research may address detailed questions like team composition and reasonable method iterations when executing our method [E11]. Third, the rate of change and technological advancements in AI require continuous evaluation and improvement of our method. Fourth, future research may validate the application of our method in other domains with an unintuitive problem-solution-fit.

6 Conclusion

Motivated by organizations' need to understand the nature of AI and its value-adding application, we provide a five-step method to develop purposeful AI use cases. In particular, such a method is necessary for application areas that have an unintuitive problem-solution-fit. In this study, we used PM as an exemplary application area in which it seems especially difficult to assess AI's application potential. Our paper's theoretical contribution extends existing research on technology selection and use case identification by AI-specific methodological guidance. Moreover, we provide arguments for the generalizability of our method beyond PM to cover other application domains with an unintuitive problem-solution-fit. Further, our method holds important managerial implications by providing initial scientific guidance for a structured and thoughtful identification of AI use cases. Therefore, our method helps to demystify AI, its domain-specific application, and purposeful use cases.

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