

METHODS AND MODELS FOR THE IDENTIFICATION AND EVALUATION OF AI USE CASES

Dissertation

zur Erlangung des Grades eines Doktors der
wirtschaftlichen Staatswissenschaften

(Dr. rer. pol.)

des Fachbereichs Rechts- und Wirtschaftswissenschaften

der Johannes Gutenberg-Universität Mainz

vorgelegt von

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in Mainz

im Jahre 2024

Tag der mündlichen Prüfung: 26.08.2024

Abstract

Artificial intelligence (AI) is considered to be one of the most important future technologies and is increasingly applied by both private and public organizations. As a multi-purpose data-driven technology, likely any organization may profit from AI's wide range of applications. However, the majority has not adopted AI yet and several initiatives to do so fail. This is especially true for organizations from the non-tech sectors but also small and medium-sized organizations. To adopt AI, several readiness factors should be present: IT, data and financial resources must be provided and aligned to AI's requirements while an innovative company culture is also beneficial. The strategic alignment of an AI solution is required as well, i.e., the AI use cases must fit with strategic and operative business goals as well as existing operations. Identifying purposeful AI use cases that fulfil those criteria already poses a severe hurdle for several organizations. This dissertation aims to support such organizations by providing procedural guidance and practical recommendations that help to identify and evaluate meaningful AI use cases. A procedure model providing detailed activities, instructions, techniques, tools and roles is proposed alongside an evaluation framework and modeling techniques supporting the identification and evaluation of AI use cases. The basic idea is to identify a set of AI use cases that are step by step evaluated and specified. To find business-driven ideas for AI use cases first, two strategies are proposed. A top-down approach that analyzes strategic business goals down to operative goals and associated processes is suitable to find ideas for AI use cases that promise short-term improvements for existing business solutions. A user-centered bottom-up approach instead focuses on the challenges and whole working environment of selected employees and derives AI enabled solutions to support them. This leads to ideas for AI use cases that are disruptive and offer great business improvements but are not feasible on the short to medium term. The feasibility of each AI use case idea is mainly explained by the availability and quality of required data as well as the insights when exploring the data. The AI use case ideas from the user-centered bottom-up approach are often not supported with required data. Thus, a lot of prior work is required to enable the use case goals. The top-down approach in contrast leads to AI use cases that are well aligned with existing data and thus promise a higher feasibility. Each AI use case should eventually be evaluated for its expected business impact against its feasibility before approaching the proof of concept phase. Here, an AI model is designed and evaluated for the real business improvement it would provide with currently available data. In addition, the AI model is tested against AI specific criteria such as explainability, transparency, legal and ethical aspects as well as the required integration into existing IT, data and human workflows. These findings are derived from a real-world case study where the procedure model was executed and evaluated within an organization. Nine business user groups were part of the project that aimed to identify and evaluate AI's potentials. The case study revealed the complexities and issues a non-tech organization faces when trying to introduce advanced data-driven technologies such as AI.

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List of Papers

Chapter 2:

Brunnbauer, Matthias¹; Piller, Gunther²; Rothlauf, Franz³ (2021). *idea-AI: Developing a Method for the Systematic Identification of AI Use Cases*.

Published in: Proceedings of the Americas Conference on Information Systems (AMCIS 2021), Virtual Conference, August 9-13, 2021.

Chapter 3:

Brunnbauer, Matthias¹; Piller, Gunther²; Rothlauf, Franz³ (2022). *Top-Down or Explorative? A Case Study on the Identification of AI Use Cases*.

Published in: Proceedings of the Pacific Asia Conference on Information Systems (PACIS 2022), Virtual Conference, July 5-9, 2022.

Chapter 4:

Brunnbauer, Matthias¹ (2023). *How Top-Down AI Introduction Leads to Incremental Business Improvement*.

Published in: Proceedings of the 56th Hawaii International Conference on System Sciences (HICSS 2023), Maui (USA), January 3-6, 2023.

Chapter 5:

Brunnbauer, Matthias¹. *Business, Data and Analytics: Specifying AI Use Cases with the Help of Modeling Techniques*.

Published in: Ěepa, V., Matulevičius, R., Laurenzi, E. (eds.) *Perspectives in Business Informatics Research. BIR 2024. Lecture Notes in Business Information Processing (529)*, Springer, Cham.

Chapter 6:

Brunnbauer, Matthias¹; Piller, Gunther²; Rothlauf, Franz³. *How Non-Tech Medium Enterprises Identify Promising AI Use Cases*.

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1 Introduction

1.1 Motivation

After OpenAI released its large language model ChatGPT (GPT-3.5) in November 2022, public attention for artificial intelligence (AI) technologies immensely grew. In fact, ChatGPT became the fastest-growing consumer application in history, reaching 100 million monthly active users within two months of its launch (Reuters, 2023). While some people see these technologies as a major threat, others emphasize their tremendous potential for business and the society. ChatGPT is a chatbot that responds to input (prompts) and provides appropriate responses. The level of these answers is very precise for some inputs, while the system fails for others (Borji, 2023). Thus, the technology has both strengths and weaknesses and should only be used for appropriate use cases. In addition to such flagship applications, there are thousands of other AI business cases and corresponding technological solutions. However, developing and deploying them in practice poses a wicked problem. In terms of AI adoption, the reality in several organizations looks grim: Many AI initiatives fail and the majority of organizations struggle to scale AI across their business (Reilly, Depa & Douglass, 2019). Consequently, AI as a technology requires in-depth knowledge in order to use it profitably.

1.1.1 Artificial intelligence and machine learning

In information systems (IS) research, a common definition states that AI is “the ability of machines to perform human-like cognitive tasks, including the automation of physical processes such as manipulating and moving objects, sensing, perceiving, problem solving, decision making and innovation” (Benbya, Davenport & Pachidi, 2020). Unlike non-AI systems, where the software systems are programmed based on human-made rules, AI systems are provided with an algorithm that enables them to learn such rules. As such, some or even all of the machine’s actions are not explicitly prescribed by humans. The ability of a machine to learn to perform tasks without being explicitly programmed to do so is called machine learning (ML), which is the core technology behind most modern AI systems.

Thereby, several technologies that are nowadays used for AI solutions are dozens of years old, e.g., random forests date back to 1995 (Ho, 1995), while support vector machines date back to the 1960s and 70s (Xu, Caramanis & Mannor, 2009). In the past, they have not always been able to reach their full potential due to smaller amounts of available data, but also due to a lack of computational power. With the increasing performance of hardware, the global availability of the internet and mobile devices but also digital platforms and communication, important prerequisites for modern AI systems were created in the 2000s. This is also true for deep learning (DL) technologies, an important subfield of ML, which led to remarkable technological improvements in the 2010s. DL uses multi-layer neural networks (NN), which have proven to be superior for problems in several domains (Sarker, 2021). Nevertheless, DL techniques are not always preferable, e.g., when the large amount of data required is simply not available. Other AI techniques such as random forests, support vector machines and others also provide good results for several AI use cases (Shaukat et al., 2020). Therefore, different AI techniques should always be considered in practice. Figure 1.1 provides an overview of AI, its subsets and relevant techniques (Mukhamediev et al., 2022).

ML systems are usually differentiated into several areas. Supervised ML systems are trained on a labeled dataset, i.e., the available data contains both the target variable (output) and the features (inputs). The ML training algorithm then learns a mapping function from the input to the output so that it can use this information for unseen data. This is typically applied to regression and classification problems. Some supervised ML algorithms can be used for both problem domains such as random forests, support vector machines and k-nearest neighbors. Unsupervised ML systems are given a dataset that does not contain the target variable but only several features. It then uses an algorithm to find meaningful patterns,

clusters or connections within such a dataset (James et al., 2023). Supervised and unsupervised techniques can also be combined which is called semi-supervised learning (Mukhamediev et al., 2022).

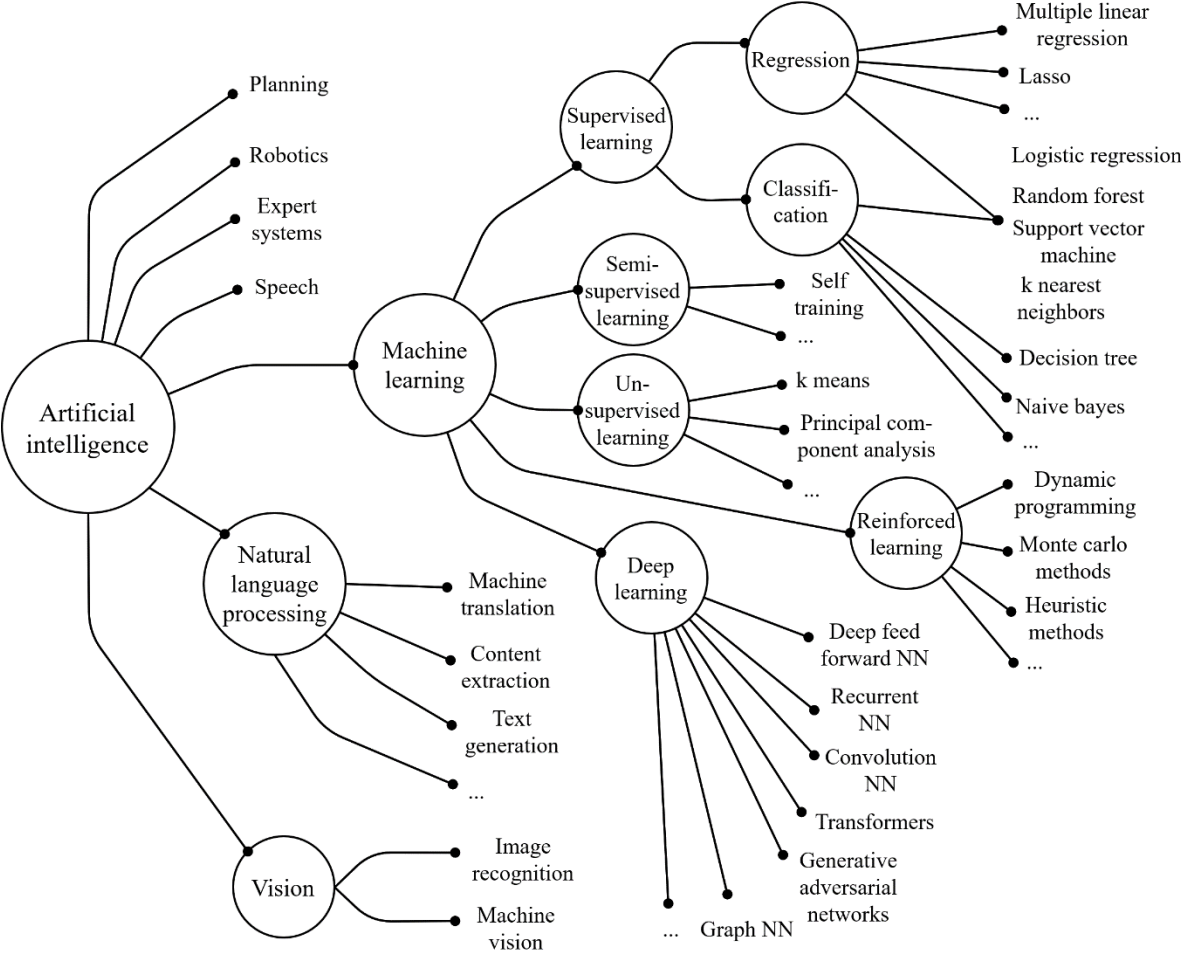


Figure 1.1. Subsections of AI and exemplary techniques

For AI systems, the availability of high-quality data in sufficient quantity is extremely important. Once a software learns based on the data it is given, this data combined with the training process and algorithm is essential to its ultimate performance. Since an AI system follows rules that are not or only partially prescribed by humans, both explainability and transparency are relevant factors, i.e., whether the results as well as the training data and process are understandable and publicly known (Rossi, 2018). The more complicated the internal workings of the AI model become, the less explainable an AI system will be. This issue is particularly relevant for AI systems that use DL techniques. AI systems must also consider ethical and legal requirements. Ethical aspects include questions such as whether AI systems should be allowed to make decisions about human life, health or similar aspects like in warfare and medicine. Legal frameworks that apply to AI solutions are currently developed, such as the EU AI Act within the European Union (EU, 2023). In addition, AI systems are often embedded in existing workflows: This includes IT, data but also employee or customer workflows. When designing an AI system, it must be adapted to these workflows, or the workflows must adapt to the AI system.

1.1.2 AI adoption in organizations

Both public and private institutions agree that AI is a very important technology by now and is likely to become more so in the future. In 2019, e.g., CIOs selected AI as the top game-changer technology underscoring its perceived relevance in the future (Howard & Rowsell-Jones, 2019). A 2023 survey in Germany found that 68% of the 605 participating organizations considered AI to be the most important

future technology (bitkom, 2023). Governments have also recognized the importance of AI and are increasing their funding as a result. Germany's Federal Ministry of Education and Research recently announced plans to nearly double public funding for AI research (BMBF, 2023). While it spent only €17.4 million in 2017 but already €280.4 million in 2022, the ministry aims for €483.3 million in 2024. In comparison, the U.S. government spent about US\$3.28 billion on AI research in 2022, about 2.5 times more than in 2017 (Stanford University, 2023).

Interdisciplinary research on AI is necessary because AI is a multipurpose technology that provides use cases for multiple business sectors and business functions. For example, several AI use cases are known for the construction sector (Regona et al., 2022), cybersecurity (Sarker, Furhad & Nowrozy, 2021), manufacturing (Kim et al., 2022), finance (Ahmed et al., 2022) and other industries. Thus, the diffusion of AI solutions in public and private organizations is growing and probably every organization can benefit from AI techniques. However, far from all organizations have successfully deployed AI. Studies vary because of their scope and other factors. These are recent figures:

- According to a global IBM survey of 7,502 companies, 35% are deploying AI while 42% are exploring it (IBM, 2022). In Germany, 34% are using AI while 44% are exploring it.
- A global survey by McKinsey of 1,684 companies states that 55% have deployed AI, but less than a third have done so in more than one business function (McKinsey, 2023).
- A survey in Germany states that 15% of 605 respondents are currently using an AI technology, while 28% are planning or discussing its use (bitkom, 2023).
- Another survey in Germany of 9,000 companies finds that 13% are currently using an AI technology, while 9% plan and 37% discuss its use (Schaller, Wohlrabe & Wolf, 2023).

These numbers show that there are wide variations across surveys, due to sample, respondents, regional and other effects. AI adoption also varies by the size and technological expertise of an organization. Organizations from non-tech sectors such as healthcare and public services lack behind in terms of their AI maturity (Guan et al., 2022). In addition, small and medium-sized enterprises (SME) integrate modern technologies such as AI less frequently than large organizations (Ghobakhloo et al., 2022).

1.1.3 Success factors and barriers for AI adoption

Within organizations, the typical AI success story is about improving (existing) business processes (Collins et al., 2021). Often, this can be achieved through increased automation of tasks or process steps, leading to lower costs, faster cycle times, or better decision making. In contrast, AI projects with overly ambitious goals are more likely to fail, which is why Davenport & Ronanki (2018) recommend focusing on the “low-hanging fruits” such as process automations first. A similar observation applies to SMEs: The main potential of AI is seen in the automation but also in the acceleration of existing business processes (Ulrich, Frank & Kratt, 2021). In part, these typical success stories can be explained by AI readiness factors, such as the AI process fit, as shown in Table 1.1. There are several categories and factors (Jöhnk, Weißert & Wyrski, 2021; Pumplun, Tauchert & Heidt, 2019). The more they are prevalent in an organization, the greater the chance of successful AI adoption. One category is the strategic alignment of an AI initiative with the overall business strategy and the digital transformation strategy. As such, organizations should align AI solutions with their business strategy and processes, ensure top management support and promote data-driven decision making. On top of that, they need the necessary resources, i.e., human resources, financial backing and IT infrastructure. Organizations need AI specific knowledge about relevant tools and techniques but also about AI ethics and realistic expectations towards AI. In addition, an innovative corporate culture where employees work in collaborative teams across business units to combine and nurture existing skills is beneficial. The final category deals with data which is the fuel for any AI solution. Organizations must provide enough data of adequate quality and ensure its accessibility for training, testing and eventual implementation of the AI solution. This requires a sufficient data infrastructure to enable automated data flows whenever applicable.

Category	AI readiness factors
Strategic alignment	<ul style="list-style-type: none"> • AI business potentials: Ensure that AI use cases are beneficial and suitable • Top management support: Outline strategic relevance and foster AI initiatives • AI process fit: Foster reengineering and implementation of required processes • Customer AI readiness: Internal/external customers must be prepared to use AI • Data-driven decision making: Fosters AI adoption as data and statistics are used
Resources	<ul style="list-style-type: none"> • Financial budget: Allocate budget for AI projects and teams • Personnel: Integrate AI specialists and business analysts with AI knowledge • IT infrastructure: Provide sufficient hardware and software for AI integration
Knowledge	<ul style="list-style-type: none"> • AI awareness: Ensure adequate expectations and understanding of AI • Upskilling: Foster employee training on AI and AI-related skills • AI ethics: Prevent biases, violations or discriminations due to AI use
Culture	<ul style="list-style-type: none"> • Innovativeness: Increase employees' willingness to change the status quo • Collaborative work: Let employees work in required teams and combine skills • Change management: Actively accompany required organizational changes
Data	<ul style="list-style-type: none"> • Data availability: Provide sufficient data for AI solutions • Data quality: Ensure high quality data for accurate AI outcomes • Data accessibility: Helps AI experts to efficiently design AI prototypes and solutions • Data flow: Ensure sufficient data infrastructure for automated data flows

Table 1.1. AI readiness factors based on Jöhnk, Weißert & Wyrski (2021)

The first factor within the strategic alignment deals with AI business potentials, i.e., AI use cases should provide a clear business value and business alignment. Hence, they should be evaluated for their true business impact and their alignment with the business strategy. However, AI use cases should also be assessed for their feasibility to avoid pursuing infeasible use cases. Accordingly, Westenberger, Schuler & Schlegel (2022) found that use case related issues are a major reason why AI projects ultimately fail: This is the case when the use case is too complex, allows only low error tolerance or simply does not provide clear business value. Unrealistic expectations are another reason according to the same study: Thinking too big and misunderstanding AI's capabilities are key risk factors. In contrast to the success factors, there are also barriers to AI adoption. For those organizations that are not AI leaders but have adopted AI in at least one business function, strategy, talent, data and adoption and scaling are cited as the key challenges to deriving value from AI (McKinsey, 2023). Similar challenges apply to SMEs with the lack of skills, implementation barriers, data issues, deficiencies in the IT infrastructure and financial constraints cited as key barriers (Ulrich, Frank & Kratt, 2021). The same survey also found that 28% of SMEs cited "no business case" as a barrier. As a result, small businesses often have not even identified meaningful AI use cases because they do not have the necessary in-house expertise, while medium-sized businesses can often afford external support to design and evaluate AI solutions (Bauer, van Dinther & Kiefer, 2020). The same study also concluded that frameworks that support the AI adoption process would be very helpful for SMEs with little AI expertise.

1.2 Research Goal

Given the importance of identifying and evaluating promising AI use cases in the beginning, there is little research on actual methods, procedures or models for doing so. Previous literature has conducted interview studies to elaborate on how organizations identify their AI use cases (Sturm, Fecho & Buxmann, 2021; Hofmann et al., 2020). This requires organizations that have already (successfully) identified, evaluated and potentially implemented AI solutions. However, the findings do not address the issues of non-tech organizations with little AI experience or SMEs. Previous studies emphasize the identification of AI use cases as an important aspect (Alsheibani et al., 2020; Brock & Wangenheim,

2019; Bughin et al. 2017; Davenport & Ronanki, 2018; Hofmann et al., 2020; Pumplun, Tauchert & Heidt, 2019; Tarafdar, Beath & Ross, 2019). However, they have not yet proposed detailed procedure models with detailed instructions on what an organization should actually do to start identifying AI use cases. Thus, this dissertation aims to develop a framework that supports SMEs with little AI expertise in identifying and evaluating appropriate AI use cases.

In particular, the dissertation aims to provide procedural guidance, i.e., methods with detailed activities, instructions, outputs, roles and tools (Braun et al., 2005), as well as useful modeling techniques that support the identification and evaluation of AI use cases. The goal is to develop a procedure model that can be applied by a small or medium-sized non-tech organization that is starting its AI adoption journey but faces the aforementioned barriers. As such, the dissertation addresses the research question:

How should a small or medium-sized organization with no experience in AI approach the identification and evaluation of AI use cases?

1.2.1 Conceptual framework

AI is a data-driven technology, so frameworks from related data-driven technologies can be useful. In fact, AI sometimes replaces previous data-driven solutions when it provides a superior algorithm or technique (Bughin et al., 2017). Thus, conceptual frameworks that have been used to develop, e.g., business intelligence, analytics or data mining solutions, could be adopted to identify and evaluate AI use cases. The most widely used model in practice is the Cross Industry Standard Process for Data Mining (CRISP-DM) which was developed in the late 1990s (Wirth & Hipp, 2000). It starts with a business understanding phase where the underlying business case is identified. The data understanding phase then specifies relevant data and collects and assesses its fit with the underlying business case. Basically, a data science use case is defined within these two phases. The third phase, data preparation, is aligned with the fourth phase, modeling. They iteratively design the underlying analytical model and evaluate its performance. The final evaluation takes place in the fifth phase and asks whether the original business objectives are being met. If that is the case, the model is deployed which is the sixth phase.

For the last two decades, CRISP-DM has been the de facto standard for data science projects and has been adapted for different purposes (Martinez-Plumed et al., 2019; Schröer, Kruse & Gómez, 2021). CRISP-DM has also previously been used as a framework for AI projects (e.g., Overgoor et al., 2019). It is now also being modified for specific industries to guide projects throughout the AI lifecycle (Bokrantz, Subramaniyan & Skoogh, 2023). Research is also beginning to adapt CRISP-DM to the needs of ML solutions (Studer et al., 2021).

In this dissertation, a new procedure model is developed and evaluated for its effectiveness in a practical setting. The procedure model aims to guide organizations that are not yet experienced with AI to identify and evaluate AI use cases. Its conceptual framework as shown in Figure 1.2 is derived from previous frameworks such as CRISP-DM and extends them to meet the needs of such organizations in combination with the requirements relevant to AI solutions. This requires detailed instructions on how to conduct an AI use case identification project in a real-world setting.

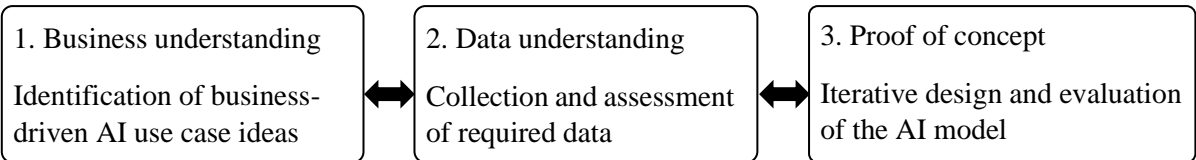


Figure 1.2. Conceptual framework to identify and evaluate AI use cases

The procedure model emphasizes the business understanding phase where the business-driven AI use cases are identified. The data understanding phase is specified to define and evaluate the required data. For these two phases, distinct evaluation criteria are developed to assess the business impact and the

feasibility of the AI use cases. The third and fourth phases of CRISP-DM are combined in the proof of concept (PoC) phase, where iterative data preparation and modeling allow the design of the required AI model. The PoC phase is also required to assess an AI use case in detail against AI specific criteria. All three phases are specified with specific activities, instructions, outputs, tools and roles. This includes certain modeling techniques that help to identify, evaluate and communicate the AI use cases in a practical setting. Finally, the methods and models are complemented with practical recommendations that can be applied by a non-tech SME that wants to start its AI adoption journey.

1.2.2 Findings

The main goal of this dissertation is to develop a new procedure model that helps non-tech SMEs new to AI to identify and evaluate AI use cases. Figure 1.3 shows a high-level view of the framework with its main entities for the three phases and the associated evaluation criteria. The complete procedure model and the definitions of the evaluation criteria are presented in detail in section 6.6.

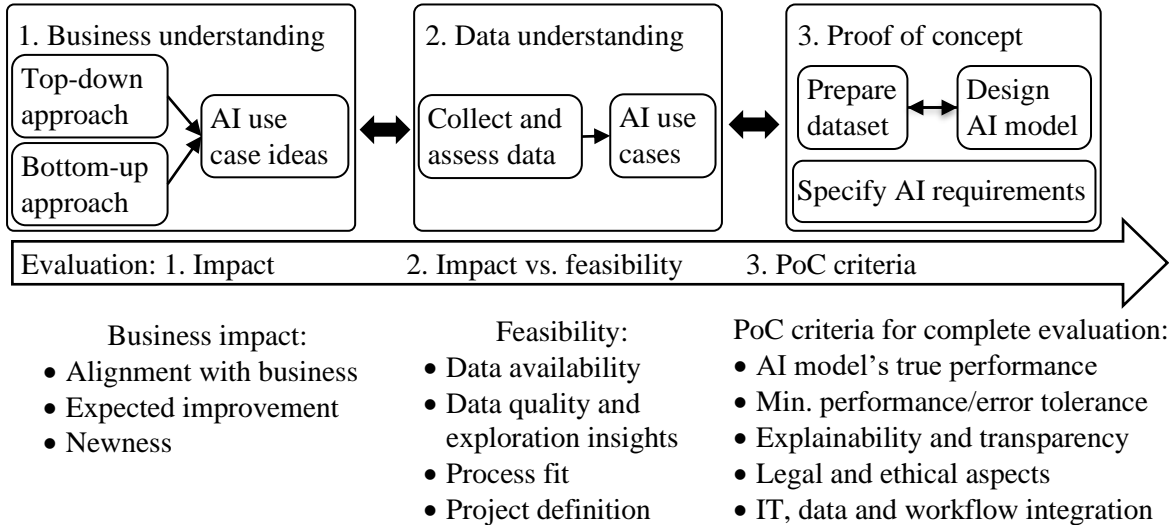


Figure 1.3. Framework to identify and evaluate AI use cases

To identify and evaluate the underlying AI business case in the first phase, two strategies were found and evaluated. The top-down strategy is derived from the typical AI success story to enhance existing business processes, while the bottom-up strategy is derived from AI’s potential to emulate human performance for complex tasks. The business impact evaluation criteria allow to assess the strategic alignment and expected impact. The data understanding phase allows to assess the availability, quality and suitability of the data for the desired analytical goal. It helps to define the feasibility of the AI use case which must be compared to the expected business impact. The proof of concept phase then designs the required AI model and assesses it for its actual performance as well as for AI specific requirements such as explainability, transparency, integration aspects as well as ethical and legal considerations.

Business understanding – top-down approach

A systematic top-down approach analyzes an organization or business unit top-down from the strategic business goals down to operative goals and relevant business processes. The latter are analyzed in more detail to find potential improvements enabled by AI. These AI use cases typically aim to improve existing solutions such as a business decisions or process steps. They are usually embedded in an existing process ensuring that the current solution is well understood and process data is available. From a modeling perspective, strategy maps and process analysis models, e.g., using BPMN, are useful tools. They also allow to evaluate the strategic alignment, business impact and process fit of each AI use case. The top-down approach leads to well-defined AI use cases with a narrow but realistic scope with a high business alignment.

Business understanding – user-centered bottom-up approach

A user-centered bottom-up approach allows for a deep dive into the business environment of selected employees. AI experts first explain AI's potentials, e.g., by providing typical AI use cases. Employees then explain their most relevant business-related challenges, needs and associated influencing factors. These can be summarized in a context map. By aligning them with relevant tasks, all information can be summarized in user journeys. These help AI experts and employees to explore ideas for potential AI-enabled improvements within the user journeys. This strategy leads to innovative and disruptive ideas that exploit the full technological potential of AI. They however often require entirely new data collection and processing steps, new process structures and are thus not feasible in the short term.

Business impact evaluation

All use case ideas from the business understanding phase should be evaluated for their strategic alignment, expected improvement and newness. This will ensure that the AI use cases provide a clear business value and will likely be supported by top management. Both aspects are key success factors for AI projects.

Data understanding and impact-feasibility evaluation

The AI use case ideas with highest priority should start the data understanding phase first, where the required data is specified and then collected. Both a data quality assessment and a data exploration reveal the feasibility of the AI use case idea. These two criteria are main limitations for non-tech SMEs as data has often not been uniformly collected, stored and processed consistently for automated analytics solutions. The insights from the data exploration also help to specify the expected business impact in more detail. To further evaluate the feasibility, the process fit of an AI use case idea can be assessed as well as its project definition, i.e., whether its objectives and relevant constraints are self-evident. The data understanding phase concludes with a comparison of the expected business impact against the feasibility of each AI use case.

Proof of concept and complete evaluation

AI use cases that are most feasible but also impactful move to the proof of concept stage. Here, the AI model is iteratively designed and evaluated. The actual performance is assessed against a minimum required performance or an error tolerance. In addition, AI specific criteria for the aspired solution are defined and evaluated. These include: Explainability, transparency, legal aspects, ethical aspects, IT integration, data integration and workflow integration. The complete evaluation is the last step before an AI use case would be piloted and thus adapted for its productive use.

1.3 Research methodology

The research goal is motivated by practical implications of the challenges of using AI in non-tech SMEs and thus a real-world problem. The design of innovative practical artifacts, i.e., constructs, methods, models or instantiations, to solve real-world problems is a central part of the design science research paradigm within IS research (March & Smith, 1995; Hevner et al., 2004). Thus, this dissertation follows the design science research process model as shown in Figure 1.4 (Peffer et al., 2007).

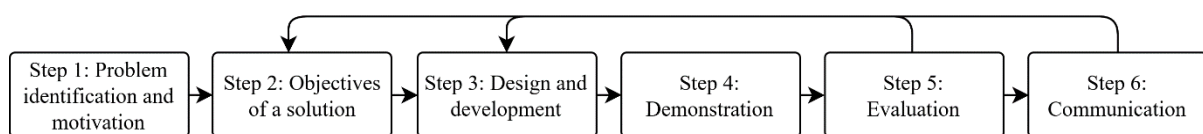


Figure 1.4. Design science research process model

Steps one and two have been outlined in the previous sections. The remaining steps are shown in more detail in Figure 1.5. To design and develop the procedure model, the dissertation builds on both practice-based and scientific literature to derive a procedure model that guides the identification and evaluation

of AI use cases. The demonstration step is the actual data collection phase where the procedure model is applied in a specific environment. In IS research, there are several methods to collect data with different distance and engagement between the researchers and the object of interest (Nandhakumar & Jones, 1997): The one with the shortest distance but highest engagement is the “consultancy” method where the researchers are in direct contact with the subject of interest and conduct a consulting project. The effectiveness of the research can be measured, e.g., by the willingness of the project sponsor of the case study to offer further contracts. This dissertation used the consultancy method for data collection and thus a case study where the researchers were part of a real-world project. Such case studies allow for a deep dive into the real-world complexities and challenges that an organization faces, e.g., when tackling a project such as identifying AI use cases without profound knowledge of the domain. This allows researchers to witness the entire process with detailed nuances and insights.

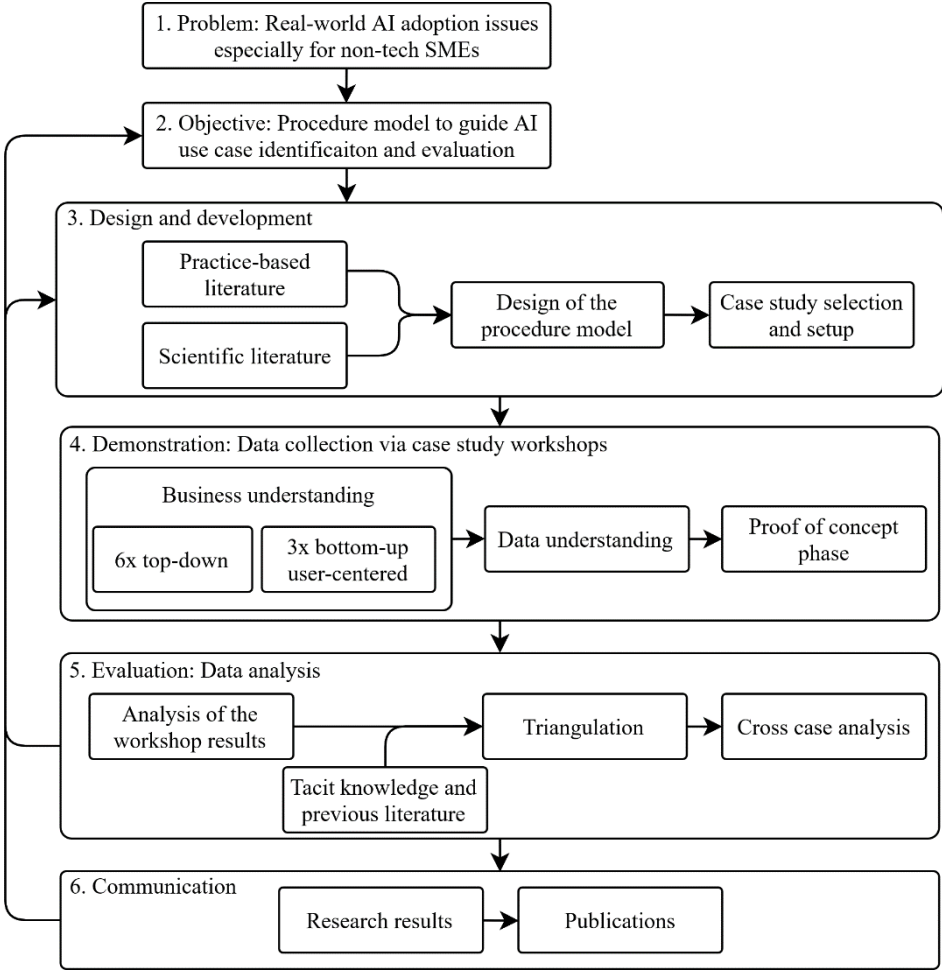


Figure 1.5. Research design

To ensure validity and reliability, the dissertation considers well-established concepts for case study research projects that include external validity, reliability and internal validity (Gibbert, Ruigrok & Wicki, 2008).

External validity refers to the degree of generalizability (Gibbert, Ruigrok & Wicki, 2008). Case studies usually do not allow for statistical generalization because the number of cases is too small. This is also the case for this dissertation, so analytical generalization is used by comparing and generalizing the results of multiple groups using the same case study approach (Gibbert, Ruigrok & Wicki, 2008). These groups may also come from the same organization, i.e., a “nested” approach (Yin, 1994), which is the case for this dissertation. A total of nine business user groups as shown in Table 1.2 would complete the case study, so a continuous cross-case analysis was conducted to evaluate the effectiveness of the proposed procedure model. The groups are part of a public organization specializing in construction and

real estate management and have not used AI solutions before. They also have not identified AI use cases before and are thus a novice in terms of their AI adoption (Schuster, Waidelich & Volz, 2021). The headquarters with about 200 employees receives and coordinates project requests from various customer segments, such as the military and local government. They seal the most basic project characteristics with their customer and then transfer the project to subsidiaries which are responsible for detailed design and construction planning. The research project aimed to identify and evaluate the potential of advanced data-driven technologies such as AI up to the proof of concept stage. The use cases were to be designed for several business user groups within the headquarters and the subsidiaries. The project was initially scheduled to run for one year. After delivering valuable insights and promising results, the project was extended for another year and a quarter afterwards. As such, the research proved to be effective and allowed for the inclusion of additional business user groups to sharpen the results. The nine groups were acquired step by step by an internal project lead of the project sponsor. The groups were advised by the research team (consultants): One project lead, two data scientists and an AI expert who were at times consulted by another AI expert.

Groups, approach		Division	Participants and job roles
1.	Top-down	Headquarters division customer A	Head of division (1) Project coordinator (2)
2.		Headquarters division customer B	Head of division (1) Project coordinator (1)
3.		Controlling division (headquarters)	Head of division (1) Controller (2)
4.		Project managers customer A	Project manager (2)
5.		Project managers customer B	Project manager (2)
6.		Supply engineering	Head of division (1) Practitioner (1)
7.	User-centered bottom-up	Headquarters division customer A	Project coordinator (2)
8.		Headquarters division customer B	Project coordinator (2)
9.		Project managers customer A	Project manager (3)
All groups supported by internal (1) and external (1) project lead, data scientist (2), AI expert (1)			

Table 1.2. Case study groups and participants

Reliability refers to the absence of random error such that other researchers would reach similar conclusions when performing the same procedure model (Gibbert, Ruigrok & Wicki, 2008). This dissertation collected its data through structured workshops with business user groups in their real working environment. All workshops followed the same procedures. For each of the nine groups, one half-day workshop was held for the business understanding phase and another half-day workshop for the data understanding phase. Both were followed by one or more shorter follow-up meetings to specify, discuss and evaluate the results. For the AI use cases that were progressed to the PoC stage, meetings were held to specify the PoC requirements and design and evaluate the AI models. The procedure model describes the outputs of these phases as well as intermediate outputs which is the main data that was analyzed. In addition, secondary data about the organization itself was collected, e.g., internal reports, and the researchers collected and noted a lot of implicit and tacit knowledge throughout the project. To ensure reliability, the activities of the procedure model and the evaluation criteria are published in detail. This allows other researchers to set up a similar real-world case study and to test the conclusions drawn

in this dissertation. However, each real-world case study got its unique organizational setting, so an equivalent replication would not be possible.

Internal validity refers to the logical chain within the data analysis, i.e., how certain variables lead to certain results and conclusions (Gibbert, Ruigrok & Wicki, 2008; Yin, 1994). In this dissertation, the data and results from the case study are assessed with a thorough evaluation scheme that allows to quantify most of the findings, especially for the business and data understanding phases. This allows to comprehend the conclusions in a transparent manner. In addition, the conclusions are compared with related practice-based literature to strengthen the conclusions and recommendations to practice. As such, the results are triangulated with existing literature to ensure their validity. Internal validity is thus ensured with the fifth phase shown in Figure 1.5, the evaluation phase. It asks whether the objectives of the solution have been met. The main objective of the evaluation is to assess the effectiveness of the proposed procedure model to identify and evaluate AI use cases (Prat, Comyn-Wattiau & Akoka, 2015).

The sixth phase within the research design, communication, calls for an appropriate presentation of the research findings. This dissertation includes five papers as described in the next section.

1.4 Structure of the thesis

This dissertation is structured into seven Chapters that report on the emerging results and implications from the real-world case study. Chapter 2 presents the underlying procedure model and how it was developed. Chapters 3 and 4 present the results of seven business user groups performing the procedure model. They evaluate the effectiveness of the top-down and user-centered bottom-up approaches from two different perspectives. Chapters 5 and 6 were developed after the case study was completed and are therefore informed by all the data that emerged from the case study. They include data from two additional groups and the proof of concept phases, so that the practical results of the case study can be further evaluated.

Chapter 2 focuses on the methodological framework to identify AI use cases. It presents relevant practice-based and scientific literature which was combined and extended to a new framework for identifying and evaluating of AI use cases. The new procedure model is called “idea-AI” and proposes a business understanding phase followed by a data understanding phase. Two strategies are proposed for business understanding: The top-down and the explorative user-centered approach. They, as well as the data understanding phase, are detailed with certain activities, outputs, instructions, tools and roles required to identify AI use cases. The paper briefly reports on initial results from the case study.

RQ 1: Which procedure model is useful to guide the identification and evaluation of AI use cases?

Chapter 3 extends the findings from Chapter 2 with additional results from the real-world case study and by applying an evaluation framework. Seven business user groups completed the procedure model idea-AI: Four followed the top-down approach while three followed the explorative user-centered bottom-up approach. The paper discusses distinct evaluation criteria: The alignment with business and the richness of influencing factor assess the business understanding results, while data availability and feasibility from a data perspective assess the data understanding results. To assess the eventual AI use cases, their newness and alignment with AI are evaluated.

RQ 2: What is the effectiveness of the top-down and explorative user-centered approaches to identify and evaluate AI use cases?

Chapter 4 focuses on the practical implications of the case study results. In particular, the paper examines the expected benefits when introducing AI use cases with the procedure model. To this end, the paper discusses relevant AI readiness factors and distinguishes between a short-term and long-term view towards AI adoption. To assess the expected practical benefits, a different evaluation framework is applied. It emphasizes the expected business impact, which is measured by the alignment with

business, expected improvement and the newness of the AI use cases. This is compared with the feasibility, i.e., the data availability, the process fit and the project definition. The paper closes with practical recommendations for organizations that want to apply the top-down or user-centered bottom-up approaches to identify AI use cases.

RQ 3: Which short-term and long-term business improvements are to be expected from the identification of AI use cases?

Chapter 5 focuses on appropriate conceptual models that can support the identification, specification and evaluation of AI use cases. The paper proposes modeling techniques that aid the entire process from AI use case identification until the proof of concept: First, a business view with two different strategies, i.e., top-down and user-centered, is used to identify the business case. Strategy maps and process models are proposed for the top-down strategy, while context maps and user journeys would support the user-centered approach. Next, a data view and an analytics view help to design, present and communicate the results from the data understanding and proof of concept phases. The paper closes with a discussion on the efficient use of the conceptual models in a practical setting.

RQ 4: Which modeling techniques are useful to support the identification of AI use cases and how to apply them efficiently in a practical setting?

Chapter 6 extends the practical implications by presenting and discussing the full results of the case study. The paper proposes the complete procedure model from the business-driven AI use case identification, data specification and assessment until the proof of concept stage with the design of the AI model. In addition, the tacit knowledge and findings from the real-world case study are integrated into the practical recommendations. They are customized for a medium-sized organization from the non-tech sector that is not yet experienced with AI and does not employ AI experts yet. The recommendations cover aspects such as becoming familiar with AI's basics at first, why to set up a project with external consultants, how to select a suitable and cost-efficient approach and how to best communicate the research project's objectives.

RQ 5: How should a non-tech medium-sized enterprise with no AI-related experience start the AI adoption process?

Chapter 7 summarizes and discusses the dissertation's findings before drawing the final conclusions.

The papers presented in the following Chapters are adjusted to meet the layout of this dissertation and to ensure an appropriate reading flow and consistency.

2 idea-AI: Developing a Method for the Systematic Identification of AI Use Cases

Matthias Brunnbauer, Gunther Piller and Franz Rothlauf

Abstract

Artificial intelligence offers various paths to value for organizations. However, many organizations struggle to identify its actual potential in order to solve or improve business problems. Following the design science research paradigm, this paper suggests idea-AI as a method supporting organizations to systematically identify and assess artificial intelligence use cases. Following CRISP-DM, idea-AI uses a business understanding and a data understanding phase. For the business understanding phase, idea-AI suggests two approaches to identify suitable use cases: a systematic top-down approach and an explorative user-centered approach. For both approaches, appropriate activities, roles, instructions, tools and outputs are suggested. Finally, idea-AI is tested and evaluated within a case study in the construction sector.

Published in:

Proceedings of the 27th Americas Conference on Information Systems, 2021

2.1 Introduction

Artificial intelligence is a phenomenon originating several decades ago but received a huge thrust in recent years due to a heavily increasing amount of available data and computational power. Especially the growing field of machine learning, i.e. algorithms that are able to build models using available data, is a key factor for the increasing spread of AI (Borges et al., 2021). Hereby, AI enables organizations several paths to create value, e.g. by engaging customers and employees, process automation, decision support or delivering new products and services (Borges et al., 2021; Davenport & Ronanki, 2018). However, many organizations still struggle to identify benefits AI may offer them. A study among 1,614 organizations worldwide reveals that 30% of them are not using nor testing AI yet, whilst only 20% have implemented AI with impact (Brock & Wangenheim, 2019). Another survey covering more than 3,000 business executives, managers and analysts worldwide, states that 36% of the organizations have neither understood nor adopted AI yet, whilst only 19% have done so (Ransbotham et al., 2017).

To adopt AI, an organization needs several strategic, technological, methodological, data but also project management capabilities (Brock & Wangenheim, 2019). Data science competences and business domain proficiency, i.e., the knowledge about the tasks, workflows, and logic of business processes and where AI may improve them, are key skills (Tarafdar, Beath & Ross, 2019). Hence, organizations with no adoption or much understanding of AI struggle to identify business cases for AI (Ransbotham et al., 2017). Thus, there is a gap between the potential business impact due to AI and its actual usage. But how to assist those organizations?

A major opportunity lies in the support to identify and assess suitable AI use cases. Several researchers stress the importance of a well-defined AI use case as the base of an AI initiative. Tarafdar, Beath & Ross (2019) claim the development of “clear, realistic use cases” as one of four key practices in order to successfully operationalize AI. Davenport & Ronanki (2018) propose to start with “understanding the technology” and then to match the technological potential with a relevant business problem to derive a potential AI project. Brock & Wangenheim (2019) acknowledge that AI is ultimately not about the technology itself but about the business opportunities and capabilities it offers. Thus, they propose that organizations yet unfamiliar with AI should start with small AI projects first. Pumplun, Tauchert & Heidt (2019) stress the importance of well-defined business cases and hypothesize it to be an important factor for the adoption of AI. However, concrete methods and guidance for identifying and defining promising AI use cases are rarely addressed in the literature. Most studies focus on general recommendations for organizations on how to start with AI.

Consequently, the goal of this paper is to develop *idea-AI* as a systematic approach for the *identification* and *assessment* of AI use cases. In addition, *idea-AI* provides guidance in terms of activities, roles, techniques, tools and outputs to help organizations yet unfamiliar with AI to identify promising use cases. In order to develop *idea-AI*, we follow the design science research paradigm (Peppers et al., 2006).

Existing work on approaches that support the development of data-related use cases was examined. This previous research does not provide guidance for identifying AI use cases through systematic methods or processes. However, it does provide useful concepts and building blocks. We use these for constructing *idea-AI*. The method is then applied and evaluated within a case study in the construction sector. The paper closes with a discussion of the results and future research directions.

2.2 Data science process models

Data science process models help to structure data science projects in organizations (Martinez-Plumed et al., 2019; Park, Sugumaran & Park, 2018; Saltz, Shamshurin & Crowston, 2017). Such models support users to systematically apply AI methods by describing the relevant phases, activities, techniques and the artefacts and relevant roles. The most frequently used model is the Cross Industry Standard Process for Data Mining (CRISP-DM), a cyclical process model that consists of six phases (Martinez-Plumed et al., 2019). In the first phase (*business understanding*), CRISP-DM assesses the current business situation

and derives business objectives. The requirements from a business perspective are defined and converted into analysis questions that can be addressed by data science methods. In the second phase (*data understanding*), initial data required to solve the identified business problem is collected, assessed and explored. Both phases are closely linked since any data science but also AI solution will require data that is processed to achieve a specified goal. If the required data is not available or of poor quality, the business problem might not be solvable. Martinez-Plumed et al. (2019) found that CRISP-DM works well for situations where a business goal can be easily transferred into a data science goal. The third (*data preparation*) and fourth (*modeling*) phase of CRISP-DM comprise elementary steps required for an AI project. Specifically for the application of CRISP-DM for ML projects, Studer et al. (2020) propose a slightly adjusted model. Business and data understanding are still addressed first to define business objectives, which are translated into ML objectives and evaluated based on their feasibility and data quality. Figure 2.1 summarizes the first two phases of CRISP-DM including the main tasks.

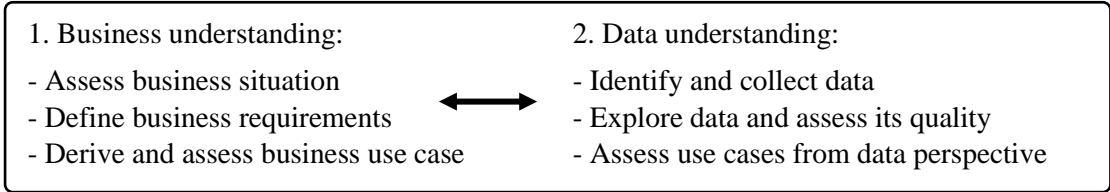


Figure 2.1. CRISP-DM’s first two phases – business and data understanding

Thus, CRISP-DM’s first two phases define a suitable approach for the identification of AI use cases. The business need and problem to be solved is defined and assessed in the first phase, while the required data perspective is assessed next. Consequently, CRISP-DM is already used within AI and ML projects. For example, Overgoor et al. (2019) report the development of three AI applications within marketing. However, CRISP-DM does not systematically guide practitioners how to identify a business question that could be solved or improved by AI methods. CRISP-DM offers general directions, but no specific methods or artefacts for the identification of AI use cases.

To construct idea-AI as a new approach for the identification and assessment of AI use cases, we recall the general constituents of methods. Braun et al. (2005) analyzed several method definitions and examined central attributes as well as fundamental elements of a method. Table 2.1 summarizes and defines both. We will follow these principles when formulating idea-AI.

	Denomination	Definition
Attributes of a method	Goal orientation	Methods are executed in order to achieve defined goals
	Systematic approach	Methods must possess a structure with concrete work steps or tasks
	Principles	Methods contain specifications closely related to design principles
	Repeatability	Methods should be intersubjectively repeatable
Elements of a method	Activities	Construction tasks creating certain results
	Roles	Entities executing the activities
	Output (Results)	Defined documents to record the results
	Instructions	Detailed instructions for development of outputs
	Tools	Support the application of one or more techniques

Table 2.1. Attributes and elements of a method (Braun et al., 2005)

2.3 idea-AI

We operationalize the phases of idea-AI. We start with formulating the general framework of idea-AI and continue with a specification of its phases.

2.3.1 Underlying framework

In elaborating approaches to identify data-related use cases, both Vanauer, Bohle & Hellingrath (2015) and Sturm, Fecho & Buxmann (2021) distinguish between a business-driven (purpose-driven) and a data-driven starting point. The business-driven approach starts with an organizational exploration, i.e., to identify which of the currently existing processes could be improved by utilizing data or if there are potentials to form entirely new offerings or routines. Afterwards, relevant data is explored and assessed. The data-driven approach starts with the identification of usable data and then tries to identify associated analysis possibilities.

However, many organizations already struggle to get a handle on their data before starting a data-driven initiative (Kiron, 2017). Thus, for organizations that are not yet experienced with AI and data-driven technologies, the business-driven approach is usually the preferred approach. This is also in line with the order of CRISP-DM's phases. Therefore, idea-AI also follows a business first approach. In addition, we suggest two different ways to identify AI use cases: a systematic top-down approach and an explorative user-centered approach. The first approach structures and connects an organization's business goals with relevant processes and specifies tasks and decision points within these processes in order to identify aspects to be improved by AI. The second approach directly addresses the business users' needs and analyzes them in detail to examine which can be supported by applying AI methods. Figure 2.2 summarizes the framework.

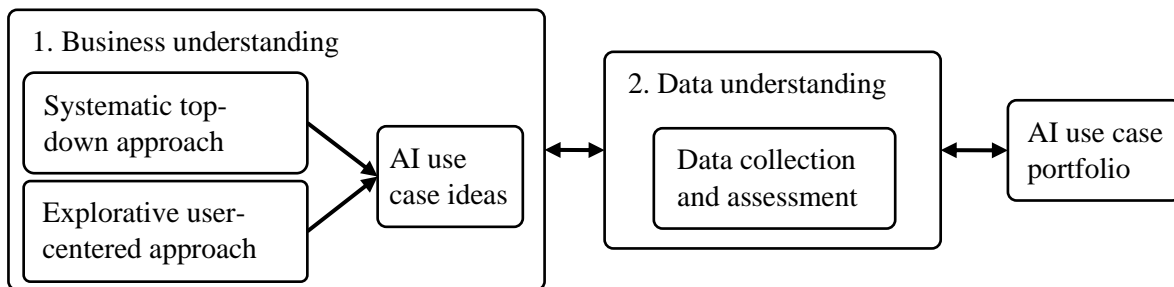


Figure 2.2. Framework of idea-AI

2.3.2 Operationalization of idea-AI

The actual identification of AI use case ideas is performed in the business understanding phase. Thus, relevant frameworks for the approaches are examined next and transferred into a method. The objective is to define AI use cases by specifying analysis questions that can be addressed by AI methods. The data understanding phase evaluates them from a data perspective resulting in an AI use case portfolio as shown in Figure 2.2.

To execute the method, clearly defined job roles are required. We propose a core team consisting of the project leader, an AI expert and at least one data expert and one data scientist participating at every method step. The project leader represents the project sponsor and should be familiar with the organizational structure and the overall business objectives of the organization. The data expert has an overview of the data available in the organization while the data scientist is familiar with current methods of data mining and ML.

Systematic top-down approach

Balanced scorecards and strategy maps are well-known and common concepts to gain a strategic view upon an organization (Kaplan & Norton, 2000). These concepts, among requirements and conceptual

modeling techniques, are used by the Business Intelligence Model (BIM) (Jiang et al., 2011). This model conceptualizes business strategy by linking business goals, operations, processes and key performance indicators (KPIs) with each other as well as with enterprise data. Hereby, it results in a top-down business schema that helps to identify currently existing processes or challenges that could be improved by a specific utilization of data. An extension of the BIM is the Conceptual Modeling Framework for Business Analytics (CMFBA) (Nalchigar & Yu, 2017, 2020). It defines three distinct layers, the business view, the analytics design view and the data preparation view. The business view “aims to facilitate the elicitation and clarification of analytics requirements in business contexts, to support the analysis of those requirements, and to ensure the alignment of business and analytics strategies” (Nalchigar & Yu, 2017). Matching CRISP-DM’s requests with conceptual modeling techniques is discussed by Lukyanenko et al. (2019), arguing that conceptual models like the BIM can represent specific objectives and goals for a ML project. Park, Sugumaran & Park (2018) stress that the CMFBA has its strength in aligning data analytics goals with strategic goals. Thus, both models allow specifying decision points or process steps that can be addressed by AI or ML methods.

Hence, idea-AI operationalizes the business view of the CMFBA and the BIM by first identifying, linking, and prioritizing a business unit’s strategic and operative goals resulting in a strategy map. Then the goals are linked to relevant business processes to extend the strategy map. The prioritized processes have to be analyzed in detail to examine which specific tasks, process steps or decisions are data driven. Ultimately, one must identify which of these could be improved or supported by AI methods before formulating precise AI use case ideas. Detailed instructions including useful tools are listed in Table 2.2.

Activities and roles	Output	Instructions	Tools
(1) Understand business unit’s goals •Core team •Practitioners •Heads of business units	•Strategy map	•Explain project goals and potential benefits to business unit •Send template to capture business unit’s strategic and operative goals, processes, KPIs and related challenges •Structure, link and prioritize goals	•Template for goals and processes •Workshops •Prioritization techniques
(2) Identify relevant processes •Core team •Practitioners •Process manager	•Strategy map’s goals linked to processes	•Identify relevant business processes to accomplish goals with high priority •Map processes to the strategy map and add KPIs to processes and sub-processes •Prioritize the processes from business but also data perspective	•Tools from (1)
(3) Specify tasks and decision points •Participants from (2)	•Process models •Data-driven process steps and decisions	•Analyze and model the prioritized processes in detail •Identify information and data needed and generated throughout the process •Specify important and data-driven decision points, process steps and tasks	•Workshops •Process modelling tool
(4) Derive AI use case ideas •Participants from (3)	•AI use case ideas	•Identify tasks or decision points to be supported or improved by AI methods •Specify AI use case ideas •Collect and map context information	•Tools from (3)

Table 2.2. Systematic top-down approach

Explorative user-centered approach

Often, the adoption of AI in organizations is motivated by business needs (Borges et al., 2021). The specific business needs should be well known by the business users themselves. The challenge is to

identify which of those needs can be improved or supported by AI methods. Thus, an explorative approach directly focusing on business users' needs is a different perspective on the identification of AI use cases. Therefore, in addition to the systematic top-down approach, we propose an explorative user-centered approach.

User-centered approaches have been used to identify potentials of new technologies. For example, utilizing a human-centric approach to identify digital innovation potentials in healthcare, Przybilla et al. (2018) observe user needs, followed by an initial idea generation and first evaluation before defining the actual user requirements. In order to identify blockchain use cases within organizations, Fridgen et al. (2018) developed a method including ideation phases involving practitioners and utilizing creativity techniques. Addressing creativity techniques, Kolbjørnsrud, Amico & Thomas (2016) report that one third of the managers in their survey considered creative thinking and experimentation to be a key skill to stay successful as AI takes over more and more tasks. Hereby, they acknowledge the Design Thinking (DT) methodology, which was also utilized by Przybilla et al. (2018), as one of five key practices.

DT starts with the gathering of information about user needs followed by idea generation and testing whilst emphasizing iterative cycles of exploration focusing on deep user research to develop insights (Liedtka, 2015). Hereby, a holistic understanding of user needs is mandatory. Micheli et al. (2019) summarize the attributes of DT of which the following are mainly referred to: Creativity and innovation, user-centeredness and involvement, problem solving, iteration and experimentation, and interdisciplinary collaboration. Liedtka (2015), Micheli et al. (2019) and Kumar (2009) summarize essential DT tools.

Activities and roles	Output	Instructions	Tools
(1) Emphasize, define <ul style="list-style-type: none"> •Core team •Heads of business unit •Practitioners •Design thinking expert 	<ul style="list-style-type: none"> •Needs overview •Design challenge 	<ul style="list-style-type: none"> •Explain project goals and potential benefits to business unit •Capture and discuss business users' needs, collect additional information •Explain basic AI techniques and potentials •Derive and discuss the design challenge 	<ul style="list-style-type: none"> •Workshops •Visualization, e.g., whiteboard •Brain dump and voting techniques
(2) Observe needs and influences <ul style="list-style-type: none"> •Core team •Practitioners •Design Thinking expert 	<ul style="list-style-type: none"> •Specified user needs •Context map 	<ul style="list-style-type: none"> •Interview practitioners about their needs, tasks and related challenges in detail •Identify both relevant internal and external influences, data and information •Structure needs, influences, qualitative and quantitative data and information 	<ul style="list-style-type: none"> •Ethnographic methods, e.g., interviews •DT templates for context map
(3) Define personas and user journeys <ul style="list-style-type: none"> •Participants from (2) 	<ul style="list-style-type: none"> •Personas •User journeys 	<ul style="list-style-type: none"> •Select and describe personas by discussing most relevant needs and tasks •Select and describe typical user journey including tasks, needs and information 	<ul style="list-style-type: none"> •Workshops •DT templates for personas, user journeys
(4) Generate ideas <ul style="list-style-type: none"> •Participants from (3) 	<ul style="list-style-type: none"> •Rated and prioritized ideas •AI use case ideas 	<ul style="list-style-type: none"> •Define brainstorming questions •Generate (if possible, data-driven) ideas •Cluster, specify and prioritize the ideas •Define AI use case ideas •Collect and map context information 	<ul style="list-style-type: none"> •Workshops •Brainstorming techniques •Voting techniques

Table 2.3. Explorative user-centered approach

Thus, the explorative user-centered approach of idea-AI suggests starting with the identification of business user needs. This is followed by an explanation of basic AI techniques and potentials to the business users and the definition of a design challenge asking for, e.g., data-driven AI potentials to address certain business problems. Next, user needs and relevant internal and external influencing

factors must be discussed in detail resulting in a context map and specified user needs. Afterwards, personas are defined including the business users' needs and tasks that have to be transferred into user journeys. Both are built by collecting and summarizing qualitative and quantitative data about the users and their working environment. Finally, data-related solutions are identified via brainstorming techniques before specifying the AI use case ideas. The activities are summarized in Table 2.3.

Use case formalization and data understanding

Both the systematic top-down approach as well as the explorative user-centered approach return AI use case ideas which must be consolidated. Hereby, interdependences between the ideas must be identified and specified first. Additionally, it is useful to discuss the connection of the goals and processes from the strategy map with the AI use case ideas identified by the explorative user-centered approach. That aids the assessment of all ideas from a business perspective, as each one can be linked to a prioritized overview of goals and processes. The prioritizing is usually performed by the project sponsor and heads of business unit.

The data understanding phase starts with the specification of required data for each use case idea. After the data has been structured, it has to be collected before describing and defining requirements towards the data (Studer et al., 2020). Then, an explorative data analysis must be performed in order to assess the data quality. Pipino, Lee & Wang (2002) introduce the most important data quality dimensions and how to conduct an assessment. Ultimately, the results of the assessments must be presented to discuss if the expected business improvements are realistic, thus re-prioritizing the use cases if required. This results in an updated portfolio of AI use cases. The resulting activities are summarized in Table 2.4.

Activities and roles	Output	Instructions	Tools
(1) Formalize AI use cases •Core team •Practitioners	•Consolidated list of AI use case ideas	•Summarize AI use case ideas and related data and information •Discuss interdependences and required additional information	•Group discussion •Template for AI Use case
(2) Present and prioritize •Participants from (1) •Heads of business unit	•Portfolio of prioritized AI use case ideas	•Present identified AI use cases •Link all use cases to strategy map •Assess use cases from business perspective •Prioritize use cases accordingly	•Tools from (1) •Elevator pitch •Voting techniques
(3) Specify required data •Participants from (1) •Data engineer	•Data Maps •Collected data	•Derive required data from previous steps •Discuss additionally required data •Map and structure required data •Collect the required data	•Interviews •Workshops •Tools for data visualization
(4) Assess data quality and explore the data •Participants from (3)	•Data quality assessment	•Describe and define requirements on data •Assess data quality •Perform explorative data analysis	•Data extraction and analysis tools
(5) Present and prioritize •Participants from (4)	•Updated Portfolio of AI use cases	•Present explorative data analysis and assessment •Discuss prioritization of AI use cases	•Group discussion •Voting techniques

Table 2.4. Use case formalization and data understanding phase

2.4 idea-AI in practice: Case study and evaluation

We used idea-AI in an organization that specializes in construction and real estate management. The headquarters employ about 200 employees while eight independent subsidiaries are responsible for

detailed construction planning and execution. The headquarters aimed at incorporating data-driven technologies such as AI to enhance operations and predictive knowledge. They had no AI use cases implemented beforehand. The aim of the project was to identify a catalog of AI use cases with high potential. After project initialization a core team was defined. It consisted of the project lead who represented the project sponsor and the research team: One AI project lead, two data scientist and an AI expert. Afterwards, middle managers and selected practitioners of the different business units were brought into the project. Two business units from the headquarters were split into groups and performed either the top-down or the explorative user-centered approach.

The research team ensured that the method was executed step-by-step and conducted an evaluation of the results and method components. We combined brief meetings and joint workshops. To evaluate idea-AI, we conducted an evaluation after each workshop (Thoring, Müller & Badke-Schnaub, 2020) asking whether the objectives as well as the method steps to achieve the objectives of the workshop were transparent and understandable. Additionally, we asked for a rating of the achieved results, i.e., the outputs of each workshop, and collected feedback on the extent to which the activities that were being carried out were considered relevant.

2.4.1 Business understanding

Systematic top-down approach

To execute the systematic top-down approach, templates were sent to the practitioners asking for information on their business role, related strategic and operative goals, processes, tasks and related challenges. On this basis, a first version of the strategy map was developed. Within a workshop, the goals of the business unit were further specified, structured and assessed. Afterwards, relevant processes and tasks to achieve the goals were specified and linked to the strategy map. Where available, KPIs were added. During the prioritization of the processes, we stressed the importance of potential data-driven process steps or decision points, thus introducing data aspects for the first time here. Next, the processes with highest relevance for the prioritized goals were analyzed in detail. All processes were modelled using the Business Process Modelling Notation to gain a detailed understanding of relevant process steps, tasks and decision points, their interdependences as well as relevant stakeholders, data and information. Afterwards, we discussed which process steps or decision points could potentially be supported or improved by data-driven analysis, e.g., AI methods. Potential AI use case ideas were formulated, specified and briefly assessed. Next, they were equipped with all findings throughout the workshop, i.e., addressed processes and operative goals, incoming and generated data and information, involved stakeholders and current solutions towards the process step or decision point. This resulted in a catalog of use case ideas that are listed in Table 2.5.

Business unit 1	Business unit 2
<ul style="list-style-type: none"> • Forecast of annual project cost for next six years • Causal relations of deviations of current project costs from estimates • Risk factors for deviations from planned annual project volume 	<ul style="list-style-type: none"> • Patterns and causal relations for annual project costs and their deviation from plan • Forecast of annual project cost for next two years and evaluation of risk to deviate from plan • Forecast of annual construction costs for the project portfolio for the next two years • Frequent patterns leading to project risks with respect to cost, quality and time

Table 2.5. Exemplary AI use case ideas derived from the systematic top-down approach

The activities and desired outcomes were transparent and clear to the practitioners. The project participants emphasized the importance of the templates to build the strategy map. This artefact was considered to be a good starting point for the project. It helped the practitioners to reflect their own goals, the business unit's goals and required processes. They stated that the hierarchical mapping and

the discussion of goals and processes, i.e., the critical reflection on “What do we want to accomplish and why?” and “What do we do and why?” improved their own business understanding. Thus, the strategy map provided a common understanding of priorities for goals and processes. It also offered a solid basis for the prioritization of the AI use case ideas. The discussion of the strategy map allowed to jointly identify the main KPIs related to cost, time, and quality aspects. For the project, the main indicator of project success was cost. Since the availability of data on cost was high, cost analyses and forecasting had high priority.

Explorative user-centered approach

The explorative user-centered approach was carried out with DT workshops. In these workshops, the needs of the practitioners were discussed. Furthermore, technological opportunities of AI as well as general design challenges defined by the project sponsor were presented. Most relevant was “which specific analyses can improve our operative project business?”. All practitioners shared their initial ideas and thoughts using a brain dump technique to ensure a common understanding of the design challenge. The next steps were in-depth interviews about the business users’ needs and relevant influencing factors. The findings were summarized in a needs overview and a context map. Afterwards, personas that had to address specified problem areas were determined. Matching them with information from the context map led to a detailed description of user journeys. Different problem statements were then derived from the user journeys and transferred into brainstorming questions. Their goal was to create data-driven ideas on how to improve or solve aspects within the user journeys.

The explorative user-centered approach found several ideas, e.g., the detection of patterns that are related to order clarity affecting project progress and the provision of early warnings. The holistic collection of needs and relevant influences gathered a lot of additional information that proved to be very valuable. While the systematic top-down approach included almost no data and information on external factors, like industry and technology trends, the context map did. As an example, macroeconomic trends in the construction industry and subcontractor availability were seen as an important input for forecasts of project costs and risks. Additionally, it was possible to identify influencing factors that are primarily based on practitioners’ long-time job experience. For example, the simultaneous assignment of specialists to multiple construction projects was viewed as a relevant risk factor that should be factored into project cost and risk forecasts.

At the end of the business understanding phase, the AI use case ideas were summarized with all identified information. Both practitioners as well as heads of business units evaluated the portfolio of AI use case ideas positive. Besides the benefits of both approaches discussed, their combination was also considered very valuable. The two main arguments were: They “lead to a more detailed and holistic understanding of the identified AI use cases” and they “ensure their acceptance among the managers and practitioners”.

2.4.2 Data understanding

The data understanding phase builds upon the AI use case ideas gathered in the business understanding phase. We first identified and discussed data records that express the relevant information, data and influencing factors. We then discussed which further data is necessary to address each use case and summarized the results in use case specific data maps. If a required information or influencing factor could not be expressed by available data records, the stakeholders discussed whether it can be derived from other data. For example, the complexity of planning of construction activities was considered to be important, but not covered by existing data. Thus, the stakeholders developed a measurement for the planned expenditures, which was based on the ratio of planned brickwork costs in comparison to the planned costs for technical equipment. For each use case idea, approximately 40 data records were identified. The data map then structured the data, e.g., according to project specific data, company specific data, macro-economic data, and other external data.

In a next step, the data was prioritized. Here, stakeholders discussed the potential influence of a data record on the target variable of an AI use case idea, e.g., the forecast of annual project costs. Second, the required effort to provide each data record was discussed. For example, data on cost aspects was available quickly, while it was rather complex to develop measures for the composition of a project team. Thus, the data records were ordered with respect to their relevance and then assessed towards their quality (Pipino, Lee & Wang, 2002). The data exploration then aimed to identify correlations between the target variable and the potential input data. These steps were complemented by regular meetings with the practitioners, where the AI use cases were specified step-by-step. For example, to make accurate forecasts on annual project costs some knowledge on the expected start date of construction is necessary.

In summary, the information and influence factors noted in the AI use case ideas benefited the data understanding phase. The data map served as a useful tool to record and structure the data. During the data assessment and data exploration, specifications towards the use case ideas showed up. A regular exchange between the data scientist and the practitioners was required. The data understanding phase enhanced the understanding of the use cases. This verified that specifying AI use cases within the business understanding phase is not sufficient, but an assessment of the data perspective is required.

2.5 Summary and conclusion

Many organizations struggle to identify the potentials that AI might offer them. Thus, systematic approaches to help them identifying and assessing suitable AI use cases are required. We suggest idea-AI as a new method. It is based on CRISP-DM which offers a useful and well-established framework for data science projects. For the business understanding phase, we suggest two approaches. First, a systematic top-down approach that maps and links business goals and processes to identify process steps or decision points to be addressed by AI methods. Second, an explorative user-centered approach focusing on the business users' needs that aims to match the needs with the potentials of AI methods. The latter approach utilizes the design thinking methodology to ensure user-centricity. We operationalize the approaches and propose useful activities, outputs, techniques, tools and required job roles for their execution. Finally, we operationalize CRISP-DM's data understanding phase, which is necessary to assess AI use cases from a data perspective.

The main contribution of this work is the construction of a new procedure model, a method named idea-AI, that combines and extends existing frameworks and models. These are discussed and transferred to a new context. Thus, the existing knowledge base is examined and broadened with a new IT artefact. Our research is mainly motivated by practical observations and aims to support organizations yet unfamiliar with AI to identify and assess the potentials of AI methods. Thus, the practical contribution lays in a systematic approach supporting these organizations to develop an AI use case portfolio that serves as a base to decide which AI use cases to follow and pilot first.

The execution of idea-AI heavily relies on the project setting within an organization. Further research could address this limitation by emphasizing project management aspects. Different resulting AI use cases are expected. For example, for the data understanding phase, the difference between requiring a few records of structured data versus large amounts of unstructured data creates different challenges. Further testing and evaluation of idea-AI is thus required.

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3 Top-Down or Explorative? A Case Study on the Identification of AI Use Cases

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Abstract

Despite the huge potentials granted to AI to improve business, several organizations already struggle to identify purposeful AI use cases. To guide organizations to systematically identify and assess AI use cases, two trajectories emerge: a top-down approach aiming to improve current processes, offerings or decisions by AI. And an explorative approach that broadly explores business problems and AI's technological potentials to identify AI-enabled solutions. We apply both approaches in a case study and report on the results and evaluation. The top-down approach identifies AI use cases that are highly aligned with existing business and data. They aim to improve current solutions while no entirely new ideas were found. The explorative approach leads to AI use case ideas aiming for analyses that were not addressed before. They mostly create new ideas with a broader business perspective but are often infeasible due to low data availability.

Published in:

Proceedings of the 26th Pacific Asia Conference on Information Systems, 2022

3.1 Introduction

Artificial intelligence has seen enormous attention in recent years in practice and academia especially due to the advancements of machine learning techniques: Increasing computational power and the growth of available data are main reasons for the rise of AI and ML (Borges et al., 2021). The potentials of AI are manifold, ranging from improved processes to new products and services up to entirely new business models (Borges et al., 2021; Davenport & Ronanki, 2018). The growing importance of AI is also recognized by CIOs who picked AI as the top game-changer technology (Howard & Rowsell-Jones, 2019). Borges et al. (2021) found that AI adoption is mostly motivated by business needs and in part by AI's technological possibilities. Surveys that analyzed AI use cases found that AI is mostly deployed to support an organization's existing business (Brock & Wangenheim, 2019). However, by far not all organizations have adopted AI successfully yet and several AI initiatives fail (Ransbotham et al., 2019). Various studies state that around 10-20% of the surveyed organizations have not yet adopted or tested AI at all (Alsheibani, Cheung & Messom, 2019; Brock & Wangenheim, 2019; Magoulas & Swoyer, 2020; Ransbotham et al. 2019). One of the main adoption barriers is the lack of suited AI use cases with clear business benefit (Alsheibani, Cheung & Messom, 2019; Bughin et al. 2017; Loukides, 2021; Magoulas & Swoyer, 2020; Ransbotham et al. 2017; Someh, Wixom & Zutavern, 2020). Moreover, both Alsheibani, Cheung & Messom (2019) and Ransbotham et al. (2017) found that the barrier "unclear or no business cases for AI" differs according to the knowledge and current usage of AI: Organizations that have not yet adopted AI or do not understand it well are significantly more likely to cite "unclear or no business case". Thus, identifying suitable AI use cases is a key challenge for organizations not familiar with AI. Additionally, Westenberger, Schuler & Schlegel (2022) identified use case related issues as a factor for eventual AI project failure: Missing value, high complexity and low error tolerance of an AI use case imply high risks. Also within the academic field several authors stress the importance to identify purposeful AI use cases as a base for a successful AI initiative (Alsheibani et al., 2020; Brock & Wangenheim, 2019; Bughin et al. 2017; Davenport & Ronanki, 2018; Hofmann et al., 2020; Pumplun, Tauchert & Heidt, 2019; Tarafdar, Beath & Ross, 2019).

However, there is only little research that proposes and evaluates approaches how to identify AI use cases. Both Hofmann et al. (2020) and Sturm, Fecho & Buxmann (2021) conducted expert interviews and found two trajectories to identify AI use cases. For the first trajectory, AI use cases emerge through an analysis of existing processes and routines. The aim is to identify business aspects where AI delivers better solutions. The second trajectory explores AI's technological potentials together with relevant business problems. The aim is to identify new solutions, e.g., offerings or processes, enabled by AI. In line with those two trajectories, Brunnbauer, Piller & Rothlauf (2021) propose a method named "idea-AI" that subsumes the trajectories by proposing two approaches: "Top-down" that aims to identify process steps, tasks or decisions to be improved by AI and "explorative user-centered" that broadly explores potential AI solutions by analyzing business users' challenges. Both are complemented by a data understanding phase. All approaches and phases include detailed activities, techniques, tools, outputs and roles that can be executed by practitioners.

Hofmann et al. (2020) and Sturm, Fecho & Buxmann (2021) derive their trajectories from expert interviews and did not yet test them in a practical setting. Brunnbauer, Piller & Rothlauf (2021) briefly report on practical insights. Thus, the proposed methods have not been sufficiently evaluated in real world scenarios so far. As they aim to support practitioners to identify purposeful AI use cases, the evaluation of their effectiveness in practical settings is essential. To evaluate methods, case studies are regularly used in the IS discipline (Peffer et al. 2012).

Our research opportunity allows us to perform a case study with an organization that aims to identify the potentials AI offers them. As different trajectories are proposed by previous literature, we test and evaluate their differences. In particular, the goal of this paper is to evaluate the effectiveness of the top-down approach and the explorative user-centered approach followed by a data understanding phase as suggested by Brunnbauer, Piller & Rothlauf (2021). These approaches subsume different trajectories

found by previous research and contain detailed instructions on how to perform them in a practical case study setting. We apply them with distinct groups within an organization. For the evaluation, we apply different evaluation criteria to assess and compare the results from a business perspective, a data perspective and further use case characteristics.

From a Design Science Research perspective (Hevner et al., 2004; Peffers et al., 2006), we demonstrate and evaluate a given artifact in a real world setting using a case study. The paper is organized as follows: In the next section we introduce current approaches that relate to our research. We then describe the artifact that we apply in our case study which is introduced afterwards. Then, the evaluation criteria for our real-world case are described. Afterwards, we present the results of the case study and summarize our findings.

3.2 Approaches for the identification of AI use cases

Different approaches to identify AI use cases were proposed in recent years. We present literature that aims to identify AI use cases and literature from related research directions, e.g., business analytics. We summarize the commonalities between the approaches and explain which approaches we apply.

Hofmann et al. (2020) apply Design Science Research and conduct expert interviews to derive a method to identify purposeful AI use cases. They propose five phases: Preparing, discovering, understanding, designing, implementing. For each phase the goal, the output and key components are specified. In the preparation phase general requirements for use cases are derived from the Technology-Organization-Environment (TOE) framework (Baker, 2012). The next two phases lead to the identification of relevant business domain problems and potentially suited AI solutions. Two trajectories to identify specific domain problems are identified: Organizations can use AI to address existing problems and improve current solutions. Or an organization explores how the technological potentials of AI may help them to find entirely new solutions to improve business. In the designing phase an AI use case is identified if a business domain problem and a potential AI solution can be matched. AI use cases are equipped with context factors from the first phase and are then prioritized. In the implementing phase, strategic and contextual implications for use case implementation are formulated. The method is evaluated through 14 expert interviews.

Sturm, Fecho & Buxmann (2021) carry out interviews with 24 experts and derive two approaches to identify AI use cases: purpose-driven and data-driven, both followed by an evaluation phase. The purpose-driven approach identifies business problems through an organizational exploration and then explores usable data. Two trajectories for organizational exploration are identified. Established routines or offerings, e.g., existing processes, can be revisited to identify ones where AI may offer better solutions. The other trajectory tries to explore new problem domains where AI might deliver benefits and which were not addressed before – either because they were out of an organization’s scope or other data-driven solutions were not sufficient. The data-driven approach identifies potential problems that build on available data. Then the organizational context and value is explored. The framework is evaluated with five IS researchers and three student assistants.

Studer et al. (2021) propose CRISP-ML(Q), a practice-driven standard process model to build machine learning applications. They adapt the CRISP-DM model (Wirth & Hipp, 2000) which is the de-facto standard for data mining and related data-driven projects (Martinez-Plumed et al., 2019). CRISP-DM is an iterative process model that consists of six phases: Business understanding, data understanding, data preparation, modeling, evaluation, deployment. In CRISP-ML(Q) the scope and success criteria for potential use cases are identified in the business and data understanding phase. Additionally, the feasibility of use cases is addressed from a technical and data perspective. Their model describes the goals and main questions to be considered in these phases and has not been evaluated in a practical setting yet.

Brunnbauer, Piller & Rothlauf (2021) apply Design Science Research to derive a method named “idea-AI” to identify AI use cases. It is based on CRISP-DM and proposes a business understanding and a data understanding phase. The business understanding phase differs two approaches to find AI use cases: a systematic top-down approach and an explorative user-centered approach. The top-down approach is derived from business engineering approaches that aim to identify business analytics solutions (Barone et al., 2010; Nalchigar & Yu, 2018). Current business goals, processes, tasks and decision points are analyzed in order to identify potentials for improvements with AI. The explorative user-centered approach utilizes Design Thinking (Hehn et al., 2020; Micheli et al., 2019) and explores potential AI solutions by analyzing problems formulated by business users. For both approaches detailed activities, tools, techniques, roles and outputs are proposed. The data understanding phase allows to evaluate the use case ideas from a data perspective. Further evaluation criteria are not proposed and a brief practical evaluation is presented.

Besides explicit approaches for AI use case identification, other research discusses their identification qualitatively. Davenport & Ronanki (2018) and Andrews (2018) argue that organizations first have to understand the technological potentials that AI offers. Afterwards, suitable use cases can be explored by determining which business areas could profit most from AI. Use cases should be evaluated for their short and long term value, strategic alignment and their feasibility. Andrews (2018) additionally states that AI is often used for automation, e.g., to improve current processes, but that a second trajectory is often overseen: AI can emulate human performance, thus AI use cases can emerge from exploring critical business points requiring human expertise. Bughin et al. (2017) stress that AI use cases should be aligned to actual business needs and be connected to an organization’s strategy. They propose a business-driven approach to identify use cases and emphasize that a realistic view on the technological potentials of AI is required.

In related research areas, academics also discussed approaches to identify use cases for data-driven solutions. Vanauer, Bohle & Hellingrath (2015) discussed approaches to identify big data solutions. They propose an ideation phase that differs between two trajectories: a business first approach aiming to improve current operations by analyzing existing goals and processes. The second trajectory is a data first approach that aims to create sellable services by exploring available data. Barone et al. (2010) and Horkoff et al. (2014) propose the business intelligence model (BIM) supporting organizations to identify business intelligence solutions. The relations between an organization’s goals, processes and related factors, e.g., performance indicators and influencing factors and required data are analyzed. A subsequent model proposed by Nalchigar & Yu (2018) aims to identify business-driven analytics solutions and uses three hierarchically aligned layers: Business design, analytics design, data preparation. The business design layer results in analysis question goals, which aim to improve certain business decision or tasks.

In summary, current literature considers a well-defined business objective and the organizational purpose of the AI use case highly important. Understanding AI as the underlying technology is emphasized as well as an assessment of the availability and quality of required data. Most studies propose a business-driven approach to identify AI use cases starting with an organizational exploration. To do so, one trajectory suggests to identify established processes and offerings where AI can deliver improvements (Hofmann et al., 2020; Nalchigar & Yu, 2018; Sturm, Fecho & Buxmann, 2021). Another trajectory suggests to broadly explore new solutions enabled by AI by matching business users’ specific domain knowledge with AI’s technological potentials (Andrews, 2018; Davenport & Ronanki, 2018; Hofmann et al., 2020; Sturm, Fecho & Buxmann, 2021). The method idea-AI proposed by Brunnbauer, Piller & Rothlauf (2021) subsumes both trajectories and delivers detailed instructions to execute them in an organization. However, the approaches so far have not been sufficiently tested and evaluated to assess their effectiveness in real world settings.

3.3 idea-AI: Identification and assessment of AI use cases

In Figure 3.1 we present the method we demonstrated and evaluated based on Brunnbauer, Piller & Rothlauf (2021). It contains a business understanding phase with two distinct approaches followed by a data understanding phase. Brunnbauer, Piller & Rothlauf (2021) did not discuss whether the top-down approach and the explorative user-centered approach are exclusive or complementary. We treat them as discrete alternatives with the same objective: Identifying AI use case ideas from a business perspective. The AI use case ideas define the associated business goal and the business objective to be addressed by AI techniques. They contain the target variable to be analyzed and potentially required influencing factors. They can also comprise further information, e.g., on involved stakeholders. Within the data understanding phase, data for the required information is defined, collected and assessed. The feasibility of each AI use case idea is evaluated from a data perspective. In case an implementation is feasible, an AI use case is formulated.

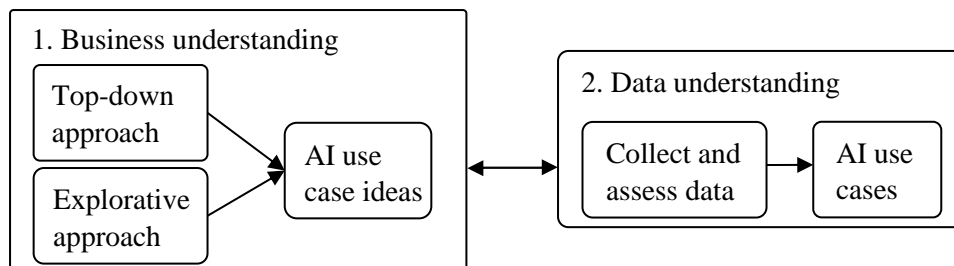


Figure 3.1. Adopted framework to identify AI use cases

To execute the approaches, distinct roles within the project team are required. Brunnbauer, Piller & Rothlauf (2021) describe a core team consisting of the project leader, an AI expert and at least one data expert and a data scientist. It is complemented by business domain experts from selected business divisions, i.e., business users and the business division heads, e.g., middle managers. Engel, Ebel & van Giffen (2021) propose similar roles: Data scientists and data engineers, product owners and business domain experts. We also propose the AI expert familiar with AI's technological potentials in line with Brunnbauer, Piller & Rothlauf (2021). External consultants may be required for organizations yet unfamiliar with AI.

The approaches are summarized in the next sub-sections. We denominate the overall activities and more detailed instructions that we used in our case study and name the resulting outputs. Brunnbauer, Piller & Rothlauf (2021) additionally named tools, e.g. workshops formats, for each activity.

3.3.1 Business understanding – top-down approach

The top-down approach is summarized in Table 3.1. It is closely related to the modeling of a business view as proposed by Barone et al. (2010), Horkoff et al. (2014) and Nalchigar & Yu (2018). A strategy map, which is a well-known business concept, is the first output (Kaplan & Norton, 2000). After identifying an organization's or business unit's strategic and operative goals, relevant processes are identified in the second step. After prioritization, these processes are analyzed in more detail to derive data-driven process steps, tasks and decision points. Process specific information, e.g., required and generated data, involved stakeholders and process outputs are recorded. Discussing which tasks or decisions may be improved or supported by AI solutions leads to the initial formulation of use case ideas. The target variables are defined. Afterwards, potential influencing factors are identified. Eventually, each use case idea is formalized such that they can be structured and compared for possible interdependencies. The use case ideas are prioritized according to the assumed business improvement and a first emphasis on potentially available data.

Activities	Output	Instructions
(1) Understand business unit's goals	• Strategy map	<ul style="list-style-type: none"> • Explain project goals and potential benefits to business unit • Identify and discuss business unit's strategic and operative goals, KPIs and related challenges • Structure, link and prioritize goals
(2) Identify relevant processes	• Processes within Strategy map	<ul style="list-style-type: none"> • Identify relevant business processes for goals with high priority • Map processes to the Strategy map and add KPIs to them • Prioritize processes from business perspective
(3) Specify tasks and decision points	• Process models incl. process steps and decisions	<ul style="list-style-type: none"> • Analyze and model the prioritized processes • Record information and data needed and generated throughout the process • Specify data-driven decision points, process steps and tasks
(4) Derive AI use case ideas	• Initial AI use case ideas	<ul style="list-style-type: none"> • Identify tasks or decisions to be improved by AI solutions • Derive initial use case ideas including target variables • Collect and map relevant influencing factors
(5) Prioritize AI use case ideas	• Prioritized AI use case ideas	<ul style="list-style-type: none"> • Specify use case ideas: Goal and objective, target, influences • Summarize, structure and compare use case ideas • Prioritize use case ideas mainly from business perspective

Table 3.1. Top-down approach based on Brunnbauer, Piller and Rothlauf (2021)

3.3.2 Business understanding – explorative user-centered approach

The explorative user-centered approach is summarized in Table 3.2.

Activities	Output	Instructions
(1) Emphasize and define	<ul style="list-style-type: none"> • Needs overview • Design challenge 	<ul style="list-style-type: none"> • Explain project goals and potential benefits to business unit • Explain basic AI techniques and potentials to business users • Capture and discuss business users' needs • Derive and discuss the design challenge
(2) Observe needs and influences	<ul style="list-style-type: none"> • Specified user needs • Context map 	<ul style="list-style-type: none"> • Interview practitioners about needs, tasks and related challenges • Identify relevant internal and external influencing factors • Structure needs and influencing factors in a context map
(3) Define personas and user journeys	<ul style="list-style-type: none"> • Personas • User journeys 	<ul style="list-style-type: none"> • Select and describe personas by specifying user needs and tasks • Describe typical user journeys including tasks, user needs and relevant influences
(4) Generate AI use case ideas	• Initial AI use case ideas	<ul style="list-style-type: none"> • Define brainstorming questions addressing user needs and tasks • Generate AI-enabled solution ideas • Cluster and prioritize ideas to derive initial use case ideas • Define target variables and add relevant influencing factors
(5) Prioritize AI use case ideas	• Prioritized AI use case ideas	<ul style="list-style-type: none"> • Specify use case ideas: Goal and objective, target, influences • Summarize, structure and compare use case ideas • Prioritize use case ideas mainly from business perspective

Table 3.2. Explorative user-centered approach based on Brunnbauer, Piller & Rothlauf (2021)

Business users' challenges and problems are explored together with the technological potentials of AI, i.e., basic AI techniques and solutions are explained to the business users, in the first step. To identify relevant business problems and subsequent use case ideas, Design Thinking (DT) can be utilized. DT can be used to explore relevant user problems and lead to requirements for user-centered solution ideas (Engel, Ebel & van Giffen, 2021; Hehn et al., 2020; Kumar, 2009; Liedtka, 2015; Micheli et al., 2019).

A DT expert can be included into the project team. After introducing AI's potentials, business domain experts explain their problems and needs in detail. Throughout the discussion, a design challenge is formulated, e.g., how certain business problems can be supported or improved by AI. Then business users' tasks and challenges related to the design challenge are defined and analyzed. Relevant influencing factors are collected and summarized in a context map. That information is joined within personas and user journeys that help to derive data-driven aspects within the business users' problems. An ideation phase aims to develop AI use case ideas. These are prioritized and equipped with relevant information on the target variable and possible influencing factors. The approach ends with a prioritization of the use case ideas' assumed business improvement and a first emphasis on potentially available data.

3.3.3 Data understanding

The data understanding phase is summarized in Table 3.3. High data availability and quality are key organizational AI readiness factors (Jöhnk, Weißert & Wyrski, 2021). They are also vital for individual AI use cases (Brethenoux & Karamouzis, 2019; Vial et al., 2021; Westenberger, Schuler & Schlegel, 2022). Defining and collecting required data, followed by a data quality assessment are the first activities. Studer et al. (2021) propose to describe the collected data on a meta-level including its statistical properties and then to define requirements on it. Afterwards, the data quality can be verified. Data maps can be used to structure required data into different categories and assign certain criteria, e.g., data source and availability. Regarding data quality assessment, Batini et al. (2009) and Pipino, Lee & Wang (2002) discuss several data quality criteria. We propose a further data exploration to identify correlations between target variables and assumed influencing factors. An initial test of adequate AI techniques with selected data of high quality can be performed (Brethenoux & Karamouzis, 2019). The combination of data availability, data quality assessment and data exploration leads to an estimation of the feasibility from a data perspective for each AI use case idea. In line with Brethenoux & Karamouzis (2019), we propose to formulate feasible AI use cases only. Low feasibilities are an indicator that prior projects are necessary to collect data or to enhance data quality. Eventually, the identified AI use cases are prioritized leading to a portfolio of AI use cases.

Activities	Output	Instructions
(1) Collect required data	<ul style="list-style-type: none"> •Data maps •Collected data 	<ul style="list-style-type: none"> •Derive and define required data •Map, structure and afterwards collect required data •Define proxies for missing data whenever possible
(2) Assess data quality	<ul style="list-style-type: none"> •Data quality assessment 	<ul style="list-style-type: none"> •Describe data on meta-level and for statistical properties •Define requirements on collected data •Assess and verify data quality •Prioritize use case ideas from data quality perspective
(3) Perform data exploration	<ul style="list-style-type: none"> •Feasibility from data perspective 	<ul style="list-style-type: none"> •Perform data exploration on target and influencing variables •Observe correlations and connections and perform initial tests for suitable AI techniques with selected data •Determine feasibility from data perspective
(4) Present and prioritize	<ul style="list-style-type: none"> •Portfolio of AI use cases 	<ul style="list-style-type: none"> •Summarize all information in an AI use case template •Present, structure and prioritize AI use cases

Table 3.3. Data understanding phase based on Brunnbauer, Piller & Rothlauf (2021)

3.4 Case study setting

We tested and evaluated the approaches described in the previous section within a case study, which is often used in IS research to evaluate the performance of procedure models or methods (Peffer et al. 2012). We carried it out with a public organization specialized on construction and real estate management projects. Within the headquarters and eight independent subsidiaries, they employ about

1,000+ employees. They currently run a project to implement a data warehouse and aim to identify potentials of advanced analytics, machine learning and AI to improve operations and products. So far, they have not implemented any AI or machine learning applications nor tried to identify purposeful use cases. The main objective of the organization is to execute commissioned construction projects in time and on budget with the agreed quality. Their operative goals and dedicated key business processes are all aligned towards this overall objective. The organization is structured into several divisions that service different customer segments. Each division has its own unit in the headquarters and operative project management units in different subsidiaries. The headquarters units receive project inquiries from their customers and coordinate them. They clarify the main requirements towards construction projects by roughly defining the buildings' properties in conjunction with an initial time and cost schedule. The project requests are then passed on to the operative project management units for detailed construction planning and execution.

Our case study covered seven groups as summarized in Table 3.4. They comprise headquarters divisions that serve the two major customer segments and corresponding project management units. With the first four groups the top-down approach was used during the business understanding phase. For both headquarters divisions, the division heads and project coordinators participated as the business domain experts. For the project management units, two project managers participated. With groups 5-7 the explorative user-centered approach was applied. Two project coordinators for the headquarters divisions, and three project managers for the project management division participated as the business domain experts. All seven groups were served by two external data scientists, an external AI expert who advised each group and an external project lead. In addition, an internal project lead of the organization advised all groups. All groups executed the data understanding phase afterwards.

Group #	Division	Participants (number)	Approach
1.	Headquarters division A	Head of division (1), project coordinator (2) Data scientist (2), AI expert (1), project lead (1)	Top-down
2.	Headquarters division B	Head of division (1), project coordinator (1) Data scientist (2), AI expert (1), project lead (1)	
3.	Project management division A	Project manager (2) Data scientist (2), AI expert (1), project lead (1)	
4.	Project management division B	Project manager (2) Data scientist (2), AI expert (1), project lead (1)	
5.	Headquarters division A	Project coordinator (2) Data scientist (2), AI expert (1), project lead (1)	Explorative user-centered
6.	Headquarters division B	Project coordinator (2) Data scientist (2), AI expert (1), project lead (1)	
7.	Project management division A	Project manager (3) Data scientist (2), AI expert (1), project lead (1)	

Table 3.4. Case study setting

With each group, we conducted an initial kick-off session to explain the characteristics of the case study. We then conducted workshops with each group following the instructions described in the previous section. We began with a half-day business understanding workshop with each group. Shorter follow-up sessions were held as needed, e.g., to prioritize and recap the use case ideas, but also for evaluation. We noted the outputs of each activity in order to collect data for each group. For the business understanding phase, data collection for the use case ideas is the main result. Each use case idea is possibly solved by AI methods and relates to a business goal considered relevant by a group. It addresses a target variable, is equipped with potential influencing factors and further contextual information, e.g.,

on relevant stakeholders. We also collected data for the accordance of the use case idea’s goals with the organization’s business goals which is relevant for evaluation. For the data understanding phase, we again held one main half-day workshop with each group. We noted the required data which was divided into collected and missing data. The data assessment and data exploration were accompanied by shorter follow-up meetings as required. They led to the eventual formulation of AI use cases or their dismissal.

3.5 Evaluation goals and criteria

For the evaluation we apply the Framework for Evaluation in Design Science Research (FEDS) as proposed by Venable, Pries-Heje & Baskerville (2016). The approaches are executed in a real-world scenario with real users in their real context. The “human risk and effectiveness strategy” denominated by Venable, Pries-Heje & Baskerville (2016) is in line with our evaluation approach because it is focused on a naturalistic and summative evaluation. Our evaluation is also in line with the “practice-based evaluation of effectiveness approach” described by Prat, Comyn-Wattiau & Akoka (2015). This is the case because we aim to determine the method’s effectiveness which is defined as “the degree to which the artifact achieves its goal in a real situation” (Prat, Comyn-Wattiau & Akoka, 2015).

For all evaluation criteria, we compare the results of the top-down approach and the explorative user-centered approach. Brunnbauer, Piller & Rothlauf (2021) did not propose distinct evaluation criteria. We thus propose several evaluation criteria and differentiate between results of the business understanding phase and the data understanding phase. Additionally, we define distinct criteria to evaluate the identified AI use cases. We propose six evaluation criteria as summarized in Table 3.5. We utilize a 3-point Likert-scale for each evaluated component of each evaluation criteria with the qualitative measurements “High” (+), “Medium” (o) and “Low” (-). In addition, an overall rating per group and evaluation criterion is assigned. It serves to compare the results from the top-down approach and the explorative user-centered approach as a whole. It is determined by calculating the mean value of the individual ratings and rounding it to the nearest whole number. For the criterion “richness of influencing factors” the number of identified influencing factors is considered as well.

	Evaluation criterion	Evaluated component	Description	Measurement
Business understanding	Alignment with business	Use case idea	Alignment of use case idea’s goal to organization’s strategy and goals	3-point Likert-Scale for all criteria: High + Medium o Low -
	Richness of influencing factors	Influencing factors	Number and assumed relevance of potential influencing factors	
Data understanding	Data availability	Use case idea	Availability of data for target variables and influencing factors	
	Feasibility from data perspective	Use case idea	Data quality and correlations with target variables	
Use case characteristics	Alignment with AI	Use case	Expected utilization of AI methods	
	Newness	Use case	Novelty of use case	

Table 3.5. Evaluation criteria and evaluated components

The business understanding phase leads to use case ideas that address an underlying business problem. The AI expert and project lead evaluate each use case idea’s “alignment with business”. Prat, Comyn-

Wattiau & Akoka (2015) define it as “the congruence of the artifact with the organization and its strategy” which relates back to Henderson & Venkatraman (1999). Ransbotham et al. (2019) and Bughin et al. (2017) also stress the importance to align AI strategy and AI use cases with an organization’s overall strategy. We consider the assumed effect of the use case idea to the organization’s strategic goals as specified within its strategy maps. If the assumed effect is direct and positive, a high rating is assigned. If it is positive but not direct, e.g., if the use case idea aims to improve an instance which is not directly related with cost, time or quality goals, a medium rating is assigned. If there is no assumed positive effect, a low rating is assigned.

The evaluation criterion “richness of influencing factors” refers to the identified parameters that potentially influence or correlate to the analysis objective of the AI use case idea. These can cover e.g., information on stakeholders and their actions, resource-related considerations, information on external factors like economic and regulatory aspects and many more. The assumed relevance of influencing factors heavily depends on the underlying business problem and the aspired solution. The same accounts for the number of required influencing factors. An experienced business domain expert and an AI project manager should thus conduct this evaluation. Every identified influencing factor is evaluated for its assumed relevance. Additionally, an overall rating is assigned: If the number and relevance of identified influencing factors is both high, a high rating is assigned. In case either the number or relevance is not sufficient, a medium rating is assigned. And if neither is sufficient, a low rating is assigned.

For the data understanding phase, the criterion “data availability” assesses which of the relevant data for the target variables and the corresponding influencing factors of a use case idea is available. When checking the availability of data records, we recommend discussing potential proxies for missing data. For example, if data on the complexity of a construction project is missing, the ratio of planned costs for brickwork in relation to costs for technical equipment could be an alternative. For a high rating, data representing the target variable and data for the most promising influencing factors must be available. If several interesting influencing factors are not covered with data, a medium rating is assigned. A low rating is assigned if data for the target variables is insufficient. This criterion is evaluated by the data scientists and the AI expert.

The assessment of data quality (Batini et al., 2009; Pipino, Lee & Wang, 2002) and the correlation of data for potential influencing factors with corresponding target variables are covered by the criterion “feasibility from data perspective”. Prat, Comyn-Wattiau & Akoka (2015) denominate the criterion “technical feasibility” which evaluates “from a technical point of view, the ease with which a proposed artifact will be built and operated”. The AI expert and the data scientist assess whether the execution of the aspired use case idea is likely feasible. For a high rating, available data should be of high quality and correlations between target variables and influencing factors must be observable. A medium rating is assigned in case either data quality is low or if only few correlations are present. In case both parameters are low, the rating is also set to low.

The next criterion evaluates the “alignment with AI” of a use case and must be evaluated by the AI expert. Prat, Comyn-Wattiau & Akoka (2015) describe the criterion “alignment with IT innovation” which evaluates “the degree to which the artifact uses innovative IT”. In our case AI is the innovative technology which however might not be appropriate for each use case. Chui et al. (2018) for example categorize the applied data analysis technique from traditional non-AI methods, e.g. descriptive statistics, to advanced AI techniques, e.g. deep learning. Some approaches to identify AI use cases neglect use cases that are better solved by non AI techniques (Hofmann et al., 2020; Sturm, Fecho & Buxmann, 2021). We propose to consider all use cases because an organization might benefit from ones with a low AI alignment as well. A low rating is assigned if simple techniques, e.g., descriptive statistics, human-made rules or reporting techniques are adequate. A high rating is assigned in case AI techniques will likely be utilized. If AI is at least required in part, a medium rating is assigned.

The final criterion “newness” evaluates the degree of each use case’s novelty, i.e. whether a use case’s objective is already addressed by a current solution. Chui et al. (2018) observed that 69% of AI use cases

they had analyzed aim to improve current data-driven solutions. For each use case the AI expert and project lead assess whether a current solution is present. If no such solution has been implemented before, a high rating is assigned. If a use case aims to improve a current solution by applying AI, a low rating is assigned. A medium rating is assigned if a solution has been tested but is not implemented.

3.6 Results

In this section we present the results of our case study and the detailed evaluation. We differentiate between business understanding, data understanding and the evaluation of the use case characteristics.

3.6.1 Business understanding

The business understanding phase led to several use case ideas for each group. Their number and evaluation of alignment with business are summarized in Table 3.6.

Alignment with business	Top-down approach				Explorative approach		
	#1	#2	#3	#4	#5	#6	#7
+ (high)	4	5	4	3	/	/	/
o (medium)	/	/	/	/	6	5	11
- (low)	/	/	/	/	2	/	3
Overall rating	+	+	+	+	o	o	o

Table 3.6. Number of use case ideas and their alignment with business

The prioritization of goals, processes and important tasks and decision points has been carried out without difficulty for groups 1-4 which used the top-down approach. They derived several data-driven tasks and decision points and formulated between three to five use case ideas. All of them were directly aligned with a business goal. A direct and positive effect on that goal was assumed, such that alignment with business was rated high for all. Most of the identified use case ideas eventually aim to improve predictions for project schedules or building costs. Both groups 1 and 2 for example aimed to predict annual construction costs for individual projects for the next three years.

In contrast, the explorative user-centered approach taken by groups 5-7 led to a more holistic understanding of the units' whole business environment. The formulated design challenge was: "How may we improve project success regarding time, cost and quality aspects?" The explorative user-centered approach resulted in five to fourteen use case ideas per group. They mainly aimed to analyze the impact of potential influencing factors on various project success criteria. For example, changes in customers' demands requiring adjustments in the planning or even construction phase were considered highly important in a use case idea by group 6. However, these changes have so far neither been uniformly defined nor directly captured by data. Furthermore, they could be related to current business goals in an indirect way only. The other use case ideas from group 6 but also some from groups 5 and 7 were in a similar category. Overall, the alignment with business for the explorative user-centered approaches was rated medium.

Next, we present the total number and individual evaluation per influencing factor as well as the overall evaluation per group in Table 3.7. For the top-down approach, ideas for influencing factors were discussed in the lens of the use case ideas. They most often included data that existed in the core processes related to the use case ideas and information on involved stakeholders. Thus, they were well defined. In total 8-14 influencing factors were obtained per group that we mainly considered of high importance.

The explorative user-centered approach asked the business users to explain their business-related problems which relate to the design challenge in detail. This eventually led to the identification of 28-

31 potential influencing factors. Most influencing factors that were identified through the top-down approaches were covered by the explorative user-centered approaches which was not the case vice versa. The explorative user-centered approach also led to many ideas for influencing factors beyond existing business processes and included, e.g., developments in the business ecosystem of the construction industry. Most were considered quite important, although they were neither discussed nor used before and thus oftentimes not defined. Still, they led to a very deep understanding of the business contexts, especially compared to the top-down approach. Overall, the criterion was thus rated high for the explorative user-centered approaches, but only medium for the top-down approaches due to the smaller scope of influencing factors.

Richness of influencing factors	Top-down approach				Explorative approach		
	#1	#2	#3	#4	#5	#6	#7
+ (high)	7	9	7	5	19	17	21
o (medium)	5	5	2	3	12	11	9
- (low)	/	/	/	/	/	/	/
Overall rating	o	o	o	o	+	+	+

Table 3.7. Number (in total) and evaluation of potential influencing factors

To compare typical results from the two approaches, we present one use case idea and potential influencing factors from groups 1 and 7 in Table 3.8. While group 1 aims for an analysis to directly predict construction costs, group 7 aims to detect cause-effect relationships. They aim to identify patterns for team set-ups that lead to efficient project execution in terms of time or cost. This use case idea can indirectly lead to improved cost predictions. The potential influencing factors from group 7 covered almost all of those of group 1. Additionally, group 7 formulated further possible criteria like current staff utilization or the order and demand situation in other division. They also emphasized external aspects and events, e.g., the risk of bottlenecks within a commissioned external company, their expertise level and past performance.

	Group 1: Top-down approach	Group 7: Explorative approach
AI use case idea #1	Predict annual project specific construction costs for 3 years (direct effect on cost predictions)	Detect cause-effect relationships of team set-ups on project efficiency (indirect effect on cost predictions)
Potential influencing factors	<p>Twelve in two categories, e.g.:</p> <ul style="list-style-type: none"> •Project characteristics: Size, type, client, past construction costs, ... •Stakeholders: Commissioned services and schedule, number of external companies, ... 	<p>Thirty in five categories, e.g.:</p> <ul style="list-style-type: none"> •Project characteristics: Size, type, client, complexity, budget, ... •Project team: Number and expertise of internal and external team members, ... •Company related: Staff capacity utilization, staff fluctuation rate, order and demand situation in other divisions, ... •Market situation: Economic indicators, ... •External events: Bottlenecks at contractors, dismissal of contractors, ...

Table 3.8. Business-related comparison of top-down group 1 and explorative group 7

3.6.2 Data understanding

After the formulation of several use case ideas, these are assessed for data specific criteria. The results of data availability are summarized in Table 3.9. For most use case ideas from the top-down groups 1-4, the target variables and the possible influencing factors could be supported with the necessary data. For example, for the use case idea from group 1 in Table 3.8, data back to the early 2000s was available for several hundred projects. The same was true for most other use case ideas from these groups, leading to a high overall rating for data availability.

Data availability	Top-down approach				Explorative approach		
	#1	#2	#3	#4	#5	#6	#7
+ (high)	3	3	3	2	/	/	/
o (medium)	1	2	1	1	1	/	4
- (low)	/	/	/	/	7	5	10
Overall rating	+	+	+	+	-	-	-

Table 3.9. Evaluation of data availability for each use case idea

For groups 5-7, which followed the explorative user-centered approach, most of the use case ideas were not well supported by data. Only 5 out of 27 use case ideas received a medium rating for data availability. For example, for the use case idea from group 7 in Table 3.8 data on project success could be derived. For the team set-ups, data on internal team members was available due to time tracking information. Data on external parties was scarce and sketchy though. An often suggested influencing factor was the expertise level of internal project team members as well as the external contracted companies. These were however not systematically captured. The same accounted for data on bankruptcies or dismissals of contracted companies. For other use case ideas, even less data was available.

After collecting the available data, it is assessed for data quality and correlations to corresponding target variables. The results of the feasibility from data perspective are presented in Table 3.10.

Feasibility from data perspective	Top-down approach				Explorative approach		
	#1	#2	#3	#4	#5	#6	#7
+ (high)	/	/	/	/	/	/	/
o (medium)	3	4	2	1	/	/	2
- (low)	1	1	2	2	8	5	12
Overall rating	o	o	o	-	-	-	-

Table 3.10. Evaluation of feasibility from data perspective for each use case idea

Each top-down group had at least one use case idea where no significant correlations between target variables and potential influencing factors could be found. The corresponding feasibility was rated low. For all others, a medium rating was assigned. For example, the use case ideas from group 1 in Table 3.8 faced issues for small construction projects. The data on timelines of past projects was occasionally missing and sometimes contained data with flawed logic, e.g., projects assigned a progress of 0% even though payments had already been made to contracted companies. Data exploration also revealed that only a part of the assumed correlations could be confirmed. Eventually, it mostly led to a medium overall rating for feasibility.

For groups 5-7, lots of required data was not available or of low quality – especially for the large amount of identified influencing factors. Consequently, significant correlations with the target variables could

only be found in very few cases. This led to a low overall rating for the feasibility from a data perspective for all groups. For the use case idea of group 7 in Table 3.8, some promising correlations between target and assumed influencing factors were found. Hence, it has been one of two use case ideas with a medium rating.

3.6.3 Use case characteristics

Assessing the use case ideas from the business understanding phase in terms of their feasibility from a data perspective leads to AI use cases. In our case study only use case ideas that were at least rated medium for their feasibility were adequate to formulate use cases that could potentially be implemented. Several use case ideas – although often interesting and promising – had to be discarded for the time being because no data of the required quality is currently available. These ideas require further work on data collection and analysis. Eventually, most use cases have emerged from the top-down approach with ten out of twelve. We now present the number of identified use cases and their alignment with AI as summarized in Table 3.11.

Alignment with AI	Top-down approach				Explorative approach		
	#1	#2	#3	#4	#5	#6	#7
+ (high)	2	1	/	1	/	/	2
o (medium)	/	1	1	/	/	/	/
- (low)	1	2	1	/	/	/	/
Overall rating	o	o	o	+	/	/	+

Table 3.11. Number of use cases and their alignment with AI

The ten use cases identified by the top-down approach received very different ratings regarding their AI alignment. For example, group 4 looks at a comparison and prediction of planned against actual project budgets over time, leveraging internal and external influencing factors. Alignment with AI was rated high, as forecasting and an analysis of the importance of various influencing factors over time require advanced AI methods. In total, four top-down use cases are well aligned with AI. For groups 1 and 2 for example, these use cases aimed for a detailed prediction for project specific construction costs. Four other use cases require descriptive statistics or simple reporting techniques only, resulting in a low rating.

For the explorative user-centered approaches, the inputs of groups 5 and 6 were not sufficient to derive well defined use cases that are supported by the necessary data from the initial use case ideas. The explorative user-centered approach led to two use cases from group 7. One use case aims to detect cause-effect relationships of different project team constellations on project efficiency to identify risk situations at an early stage. Cause-effect relations can leverage pattern mining and association rule-based methods. Therefore, AI alignment is set high here. The second use case from group 7 is similar to the use case from group 4. They were evaluated identically and showed that both approaches can eventually also lead to similar use cases. Overall, AI alignment was rated high for the explorative user-centered approach, but medium for most top-down groups.

We also evaluated the newness of the use cases. Their number and evaluation are shown in Table 3.12. Eight out of ten top-down use cases aim to improve solutions that are already in use within the organization. This mainly leads to low ratings for newness. Only two use cases identified by groups 3 and 4 aim for a partially new analysis. For example, the comparison of planned against actual project budgets by group 4 saw similar analysis single-handedly performed by some project managers before. Systematic approaches based on predictive models for budget planning were not used so far. Thus, newness is rated medium. The use case from group 7 which is similar to group 4 is also rated medium for newness. The other use case, i.e., detection of cause-effect relationships, is rated high for newness

because no data driven analysis or similar solution are in use. The overall rating for newness is high for the explorative user-centered approach, also regarding the vast initial amount of new use case ideas, while it is medium or low for the top-down groups.

Newness	Top-down approach				Explorative approach		
	#1	#2	#3	#4	#5	#6	#7
+ (high)	/	/	/	/	/	/	1
o (medium)	/	/	1	1	/	/	1
- (low)	3	4	1	/	/	/	/
Overall rating	-	-	o	o	/	/	+

Table 3.12. Number of use cases and their newness

3.7 Summary and conclusion

Organizations not yet familiar with AI struggle to identify the potentials that AI offers them. To date, only little research is present guiding them to systematically identify AI use cases. Most studies propose a business-driven approach that first performs a business exploration and is followed by data exploration. To identify business-driven AI use cases, two trajectories emerge. Organizations can analyze existing processes, routines and offerings and identify improvements enabled by AI. A top-down approach that analyzes business goals and associated processes, tasks and decisions can be utilized. The other trajectory proposes a broad exploration of relevant business problems and the technological potentials of AI to find new solutions. A business user centered explorative approach allows to match business problems and potential AI solutions. Afterwards, the feasibility from a data perspective of each AI use case idea can be assessed.

This paper evaluates the effectiveness of a top-down approach and an explorative user-centered approach to identify AI use cases. These approaches differ two possibilities within a business understanding phase that is succeeded by a data understanding phase. The results from business understanding are evaluated with four distinct criteria that assess the alignment with business, richness of influencing factors, data availability and the feasibility from a data perspective. An AI use case is formulated if it is considered relevant for business and feasible. The resulting use cases are evaluated for their alignment with AI and their newness. A case study is applied to demonstrate the top-down approach and the explorative user-centered approach in a naturalistic setting.

The top-down approach was eventually more fruitful to obtain use cases which were also feasible from a data perspective. It led to results that are highly aligned with business but also with data. It therefore allowed to identify AI use cases that promise rather immediate business impact and can soon be piloted. The relevant information and data could be well defined. However, the top-down approach will likely lead to AI pilot projects that aim to improve a current solution. No entirely new ideas are to be expected and the variety of use case ideas is limited.

The explorative user-centered approach in comparison led to much more use case ideas covering a broader context of the organization’s business. A rich set of potential influencing factors was found. It helps to identify entirely new ideas for interesting business analyses. However, the results cannot necessarily be implemented quickly. Many promising use case ideas required information where data has not been specified nor systematically collected before. Thus, they were not doable and first require a detailed specification and collection of data for required information. This side-effect triggered initiatives for data-related projects aiming to collect more data and contextual information related to the broad range of use case ideas.

Previous research found that most AI projects aim to improve current business solutions (Brock & Wangenheim, 2019; Bughin et al., 2017). Our results confirm that several use cases aim for an improvement of a current business solution by advanced techniques such as AI. However, this is mainly due to the satisfying amount of available data for use cases that are highly aligned with current business. When trying to identify use cases that allow for entirely new analyses, data issues hindered their continuation. These ideas would have likely led to project failure. They should however not be neglected because previous research also states that AI's true potential does not lie in doing the same thing better, but in doing things entirely new (Ransbotham et al., 2019). Prior efforts, e.g., to fix data related issues and to gradually build up AI competencies, are however required. This is well in line with AI readiness and success factors identified by previous literature (Alsheibani et al., 2020; Jöhnk, Weißert & Wyrki, 2021; Pumplun, Tauchert & Heidt, 2019). The use cases identified in our case study eventually aimed for small instead of wide-ranging improvements. This finding matches well with the recommendation to start with small and feasible AI projects first (Brethenoux & Karamouzis, 2019; Davenport & Ronanki, 2018).

These implications are derived from a case study with one organization that had no experience with advanced data driven technologies such as AI before. Thus, an important aspect for future research is to execute the approaches with other organizations. A distinction can be made for different industries, but also according to an organization's current status of AI adoption (Alsheibani, Cheung & Messom, 2019; Ransbotham et al., 2017). Practical insights from related approaches to identify AI use cases are desirable as well, e.g., data-first approaches (Sturm, Fecho & Buxmann, 2021). Further explorative studies observing approaches used by practitioners to identify AI use cases could distinguish between industries and current AI adoption as well. Currently, there is no evidence which approaches are best suited for AI novices in comparison to previous AI adopters. Our case study focused on an AI novice at an early stage of the AI adoption process, i.e., where organizations evaluate which potentials for business improvement AI might offer them at all (Bughin et al., 2017; Henke et al., 2016). In combination with other research on AI adoption and required capabilities, e.g., Alsheibani, Cheung & Messom (2019) and Brock & Wangenheim (2019), the approaches offer a starting point for an AI initiative.

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4 How Top-Down AI Introduction Leads to Incremental Business Improvement

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Abstract

Artificial intelligence offers the opportunity for radical improvements such as completely new business solutions. It also enables the improvement of existing business. This paper reports on a case study that tests two strategies to identify AI use cases: Top-down and user-centered bottom-up. The use cases are differentiated according to whether they promise incremental or radical business improvements and whether they are realizable in the short or long term. The top-down strategy identifies use cases that promise short-term but incremental improvements. They relate to existing business, but no disruptive ideas emerge. The bottom-up strategy allows for a broader understanding of AI's potentials to improve business. Completely new and disruptive ideas emerge but require huge upfront effort. Organizations best start with AI pilot projects that are feasible in the short term: Either by first applying a bottom-up strategy that is supplemented and evaluated with the top-down strategy, or top-down only.

Published in:

Proceedings of the 56th Hawaii International Conference on System Sciences, 2023

4.1 Introduction

“Don’t start with moon shots” is the subtitle of a research paper that examines the practical use of artificial intelligence in organizations (Davenport & Ronanki, 2018): Their survey of 152 AI projects shows that projects that aim for very ambitious goals are less likely to succeed than projects that aim for the "low-hanging fruit," such as a simple improvement within an existing business process. Failure is also not uncommon in AI projects: a survey of more than 2,500 executives shows that 40% of organizations that have made significant investments in AI have not yet realized any business benefits from AI (Ransbotham et al., 2019).

An important subfield of AI deals with machine learning models, which promise real benefits for businesses in a number of ways: They can support decision-making, improve customer and employee engagement, increase automation, and deliver new products and services (Borges et al., 2021). The possibilities of AI offer different industries various chances to improve business (Collins et al., 2021; Plastino & Purdy, 2018). In addition, AI was selected by CIOs as the top game-changer technology in 2019 (Howard & Rowsell-Jones, 2019). The use of AI thus promises multiple paths to create value for organizations, which is why a strategic view of its adoption is recommended (Borges et al., 2021).

Improving the business model by adopting new ideas and technologies is essential for organizations (Chesbrough, 2010). This is often accompanied by a process of trial and error in which organizations gradually learn both the technological potential and the skills required to exploit that potential (Sosna, Trevinyo-Rodríguez & Velamuri, 2010). Technological innovations can enable various improvements to the business model (Tecece, 2010): Depending on the expected added value, a distinction can be made between small, incremental and radical, disruptive improvements (Simmert et al., 2019).

AI should offer the potential for disruptive innovation to create new processes or entirely new business models (Lee et al., 2019). Some organizations have already experienced radical changes through the use of AI (Bughin et al., 2017). Others, such as Airbnb, Amazon and Uber, managed to challenge and disrupt existing business models by following data-driven and digital strategies (Iansiti & Lakhani, 2020). The targeted use of AI - alongside other technologies - is an important prerequisite for the success of such disruptive business models (Sousa & Rocha, 2019). Most organizations however report incremental business improvements only from AI adoption (Brock & Wangenheim, 2019). In most cases, the use of AI leads to increased automation of the relevant business processes (Collins et al., 2021; Davenport & Ronanki, 2018). AI thus offers the opportunity for both incremental and radical business improvements and innovations. The actual extent will largely depend on each individual AI use case.

Factor	Description
Strategic alignment	<ul style="list-style-type: none"> • Identify AI-business potentials • Ensure top management support • Ensure AI-process fit • Ensure AI readiness among customers and employees • Foster data-driven decision making
Resources	<ul style="list-style-type: none"> • Build team with AI specialists, business analysts, data scientists • Ensure financial backup and provide required IT infrastructure
AI knowledge	<ul style="list-style-type: none"> • Ensure awareness and basic understanding of AI as a technology • Upskill employees with AI skills • Ensure AI ethics
Culture	<ul style="list-style-type: none"> • Ensure innovate company culture and facilitate change management • Integrate required business divisions
Data	<ul style="list-style-type: none"> • Provide access to high quality data • Provide sufficient data infrastructure

Table 4.1. AI readiness factors based on Jöhnk, Weißert & Wyrтки (2021)

Researchers aim to help organizations achieve business value from AI and provide a range of guidance, e.g., by identifying readiness factors and barriers to AI adoption (Alsheibani, Cheung & Messom, 2018, 2019; Jöhnk, Weißert & Wyrcki, 2021; Loukides, 2021; Pumplun, Tauchert & Heidt, 2019; Someh, Wixom & Zutavern, 2020). Their results agree very well. Table 4.1 summarizes the key readiness factors of AI adoption into five categories (Jöhnk, Weißert & Wyrcki, 2021).

As far as AI project failure is concerned, unrealistic expectations are risky, i.e., misunderstanding AI's capabilities or thinking too big. Use case related issues are also important: If the added value is not obvious, the use case is too complex, or only allows for low error rates, an AI project is likely to fail (Westenberger, Schuler & Schlegel, 2022). Consistent with these findings, several researchers emphasize the definition of clear, realistic use cases as a key aspect of a successful AI initiative (Alsheibani et al., 2020; Brock & Wangenheim, 2019; Bughin et al., 2017; Davenport & Ronanki, 2018; Pumplun, Tauchert & Heidt, 2019; Tarafdar, Beath & Ross, 2019).

Researchers also discuss ways to create value for organizations that want to launch an AI initiative. In the short term, research calls for the definition of small, realistic use cases (Brethenoux & Karamouzis, 2019; Davenport & Ronanki, 2018; Weber, Limmer & Weking, 2022) even if they only provide incremental business improvements. In the long term, the potential of AI is seen "not in doing the same thing better, faster and cheaper, but doing new things altogether" (Ransbotham et al., 2019). So, there is a distinction between AI use cases with rather short-term but incremental impact and those with long-term, disruptive potential.

There are several approaches to identifying AI use cases. They do not explicitly distinguish between a short-term and a long-term view. However, two studies found that organizations distinguish between improving current business solutions with AI and exploring entirely new solutions (Hofmann et al., 2020; Sturm, Fecho & Buxmann, 2021). In another study, different approaches, top-down and explorative user-centered (bottom-up), are proposed to identify AI use cases (Brunnbauer, Piller & Rothlauf, 2021). To date, none of the approaches have been evaluated for their suitability in identifying AI use cases with short or long-term potential.

The aim of this paper is to investigate how an organization can identify suitable AI use cases that are more focused on short-term incremental improvement or long-term disruptive business improvement. To do so, a case study will test two different approaches: a top-down and a bottom-up approach. To evaluate this distinction, the case study results are assessed against several criteria. Finally, practical advice from previous research is combined with these results. These lead to the formulation of practical recommendations for organizations starting an AI initiative to improve their business.

4.2 Foundations: Starting with AI

Getting back to the "moon shots", one must elaborate what current research suggests for launching an AI initiative. General recommendations will be discussed from a short-term and long-term perspective. This is also done for procedure models to identify AI use cases.

4.2.1 Short-term versus long-term view

In this section, general recommendations are analyzed and differentiated into a short-term and a long-term perspective. Different characteristics of an AI initiative and its use cases are discussed. Table 4.2 summarizes the key findings from various studies. They are divided into four characteristics: Project scope, added value, type of improvement, data perspective. In addition, general objectives are discussed.

The first recommendation relates to the scope of the AI initiative and individual AI pilot projects. The research suggests starting with a small portfolio of projects and then gradually scaling up (Andrews, 2018; Brethenoux & Karamouzis, 2019; Brock & Wangenheim, 2019; Davenport & Ronanki, 2018; Lee et al., 2019; Someh, Wixom & Zutavern, 2020; Tarafdar, Beath & Ross, 2019; Weber, Limmer & Weking, 2022).

Dimension	Short-term view	Long-term view
Project scope	<ul style="list-style-type: none"> • Identify and pilot few AI use cases with a small and realistic scope 	<ul style="list-style-type: none"> • Scale up step by step with new AI use cases, more business divisions, people and data
Added value	<ul style="list-style-type: none"> • Find AI use cases that offer quick wins, even if incremental or only for learning 	<ul style="list-style-type: none"> • Find AI use cases with disruptive potential and highest impact on current and future business
Type of improvement	<ul style="list-style-type: none"> • Improve current business solutions, e.g., existing processes, decisions, offerings 	<ul style="list-style-type: none"> • Try to find entirely new AI-enabled solutions, e.g., new products, processes or services
Data perspective	<ul style="list-style-type: none"> • Build on currently available data and identify prospectively required data 	<ul style="list-style-type: none"> • Systematically build up the required data infrastructure
General objectives	<ul style="list-style-type: none"> • Integrate AI into your business strategy • Get familiar with AI as the technology • Evaluate current AI readiness and AI's current potential regarding readiness 	<ul style="list-style-type: none"> • Exploit AI's full potentials • Recruit and engage with the required AI talent • Build up AI infrastructure and fulfill AI readiness factors

Table 4.2. Short-term and long-term recommendations when starting an AI initiative

Organizations should initially view AI as a way to solve and improve clearly defined business problems. Therefore, smaller projects are preferable at the beginning. One paper even argues that projects at the beginning could only serve learning purposes (Andrews, 2018). In the best case, running AI pilots helps strengthen the necessary AI skills of employees, which in turn leads to better practices in the long run (Tarafdar, Beath & Ross, 2019).

From a value creation perspective, organizations should initially target projects with quick wins (Someh, Wixom & Zutavern, 2020). It is recommended to start with projects that have a certain and short-term impact on the business (Brethenoux & Karamouzis, 2019). In this way, a variety of AI technologies can be tested for their suitability for selected pilot projects. The findings from small AI projects, which provide varying benefits, must first be evaluated before larger projects are initiated. The findings should help to self-assess current AI readiness, e.g., in terms of strategic direction, required resources, AI knowledge, culture, and data (Jöhnk, Weißert & Wyrтки, 2021).

In terms of the type of improvement, AI offers the potential for incremental, but also disruptive business improvements. In the short term, trying to improve existing processes, products, or decisions with AI is likely to be easier than developing entirely new processes or offerings. Accordingly, most AI use cases improve current business solutions that are already based on simpler analytics techniques (Bughin et al., 2017). AI projects that target entirely new offerings or processes may require new data, skills, and culture - in other words, improved AI infrastructure and AI readiness. These need to be built first.

A separate data perspective is also required, as high-quality data is essential to any AI solution (Engel, Ebel & van Giffen, 2021; Vial et al., 2021). Defining and capturing entirely new information and data, as well as upgrading the necessary data infrastructure, pose a major problem. In the short term, it may therefore make more sense to build on available and existing data. For more complex AI projects that seek entirely new solutions, prior or concurrent projects on data-specific problems might be required.

In summary, the biggest increases in value from AI may come from doing entirely new things, which is however not a good starting point for organizations new to AI (Ransbotham et al., 2019). Realizing the disruptive potential of AI through larger and riskier AI projects may happen eventually, but more likely not at the beginning (Brock & Wangenheim, 2019). Therefore, organizations should start integrating AI into their business strategy in the short term and familiarize themselves with the technology. Its potential to improve current business solutions with currently available data, capabilities and infrastructures needs

to be assessed. Flagship projects should be undertaken to demonstrate the potential of AI and convince key internal stakeholders. In the long term, larger and breakthrough projects can be undertaken. In addition, the required AI readiness needs to be improved.

4.2.2 Approaches to identify AI use cases

In this section, current approaches to identify AI use cases are analyzed from the perspective of whether they target short-term or long-term AI use cases. They are summarized in Table 4.3.

Study	Contribution	Short-term view	Long-term view
Sturm et al. (2021)	Method to identify problems to be solved with ML-based AI: Business-driven with two trajectories	First trajectory proposes to “replace existing solutions”	Second trajectory proposes to “explore new problem domains”
Hofmann et al. (2020)	Five step method to identify purposeful AI use cases: Prepare, discover, understand, design, implement	Improve current business solutions (“problem perspective”)	Broadly explore new solutions enabled by AI (“opportunity perspective”)
Brunnbauer et al. (2021)	Method to identify AI use cases with two different approaches: Top-down and explorative bottom-up	Top-down: Identify existing business aspects to be improved by AI	Explorative, bottom-up: Match AI’s potentials with business user problems

Table 4.3. Approaches to identify AI use cases

Expert interviews are conducted in two studies to explore how organizations find AI use cases (Hofmann et al., 2020; Sturm, Fecho & Buxmann, 2021). Both studies find two paths: The first path leads to AI deployment opportunities via an analysis of existing processes and routines. The goal is to identify business aspects where AI provides better solutions.

It is thus in line with the proposal to identify current business aspects that can be improved by AI and is more short-term oriented. The second path explores the technological potential of AI to solve relevant business problems. The goal is to find completely new solutions enabled by AI, which corresponds to the long-term view.

Another method subsumes these two paths and proposes two approaches (Brunnbauer, Piller & Rothlauf, 2021, 2022): Top-down aims to identify process steps, tasks, or decisions that can be improved through AI. On the other hand, user-centered bottom-up explores potential AI solutions by analyzing business user problems. Both are equipped with detailed activities, techniques, tools, outputs and roles that can be executed by an organization. Both are complemented by a data understanding phase. The two approaches are presented in more detail below.

4.3 Top-down and bottom-up approach

The top-down and bottom-up approaches both aim to identify AI use case ideas (Brunnbauer, Piller & Rothlauf, 2021). The main activities are summarized in Figure 4.1.

4.3.1 Top-down approach

The top-down approach maps and prioritizes business goals and processes to identify data-driven entities to address with AI (Barone et al., 2010; Nalchigar & Yu, 2020). It requires the involvement of business division leaders or senior managers who are familiar with the overall business goals. It includes five key activities that guide a business unit step by step. First, a strategy map is created that includes strategic and operative business goals, including relevant key performance indicators (Kaplan & Norton, 2000). Next, relevant business processes related to the business goals are identified and prioritized. Then, key

processes are modeled and analyzed in detail to identify data-driven process steps, tasks, decisions, or process outcomes. Then, subject matter experts and AI experts work out which aspects can be addressed or improved through AI techniques. AI use case ideas are formulated and provided with relevant contextual information. Finally, they are prioritized.

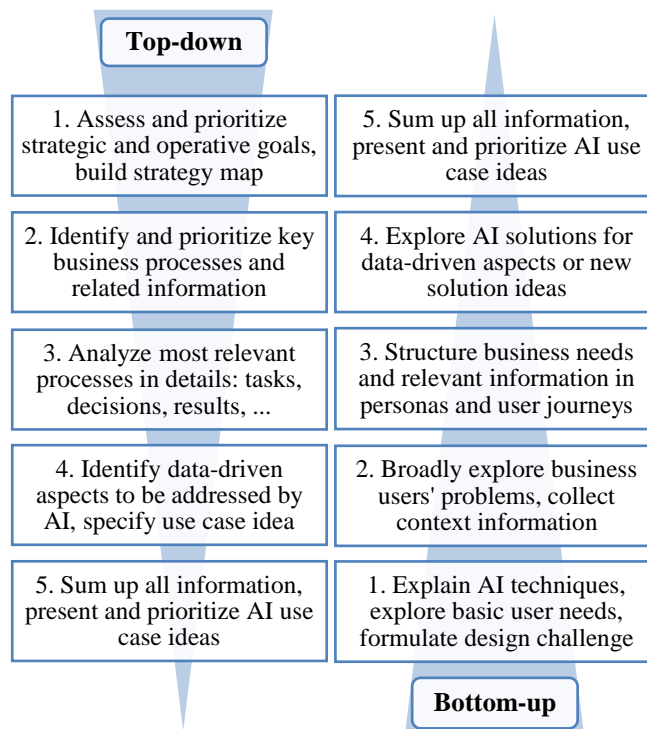


Figure 4.1. Top-down and user-centered bottom-up approaches

4.3.2 User-centered bottom-up approach

The bottom-up approach analyzes employees' business-related problems and challenges and seeks to identify AI-enabled solutions. It comprises five activities and uses a design thinking approach that focuses on the participating business users (Engel, Ebel & van Giffen, 2021; Hehn et al., 2020; Kumar, 2009; Liedtka, 2015; Micheli et al., 2019). The approach begins with an explanation of basic AI techniques. Business users then explain their business-related problems and needs, which leads to the definition of a design challenge. Next, the relevant contextual information is summarized in a context map. The data is then structured into personas and user journeys before an ideation phase begins. The AI experts and the business users develop ideas to improve certain aspects within the user journeys by using AI techniques. The resulting AI ideas for use cases are summarized and finally prioritized.

4.3.3 Data understanding phase

Both approaches are followed by a data understanding phase. Relevant information and data for each use case idea are defined and collected. They are then evaluated for their data quality and their suitability to enable the intended solution of the use case idea. This allows the feasibility of a use case idea to be evaluated from a pure data perspective.

4.4 Case study and evaluation criteria

Now the case study is presented to test and evaluate the top-down and bottom-up approaches in practice. Then the evaluation criteria are explained. They are used to evaluate the effectiveness (Prat, Comyn-Wattiau & Akoka, 2015) of the approaches to identify AI use case ideas with a short- or long-term potential.

4.4.1 Case study setting

The project partner is a public institution specializing in construction and real estate management projects. Together with numerous external service providers, it manages several hundred construction projects each year. Its main objective is to execute contracted construction projects on time and within budget, with the agreed quality. The organization consists of several divisions serving different customer segments. Each division has its own unit in the headquarters and operational project management units. The headquarters receives project requests and clarifies key requirements, i.e., building characteristics and an initial schedule and cost plan. The projects are then passed on to the operational project management units. These are responsible for detailed construction planning and execution.

The organization does not use AI applications yet. There also have been no projects to identify AI use cases before. The data infrastructure is currently being further developed by introducing an enterprise-wide data warehouse. Building on this project, more in-depth data analyses are to be carried out in the future. These are also to be supported by AI-based applications.

The case study covers seven groups as summarized in Table 4.4. They include divisions from the headquarters and corresponding project management units serving the two major customer segments. The top-down approach was used for the first four groups. For groups 1 and 2, division heads participated along with project coordinators. For groups 3 and 4, two project managers participated in each. For the other three groups, the bottom-up approach was used. Two project coordinators participated in each of groups 5 and 6, and three project managers participated in group 7. All groups then conducted the data understanding phase. They were all supported by two external data scientists, one AI expert and an external project lead alongside an internal project leader.

Group #	Division	Participants (number)	Approach
1.	Headquarters division A	Head of division (1), project coordinator (2) Data scientist (2), AI expert (1), project lead (1)	Top-down
2.	Headquarters division B	Head of division (1), project coordinator (1) Data scientist (2), AI expert (1), project lead (1)	
3.	Project management division A	Project manager (2) Data scientist (2), AI expert (1), project lead (1)	
4.	Project management division B	Project manager (2) Data scientist (2), AI expert (1), project lead (1)	
5.	Headquarters division A	Project coordinator (2) Data scientist (2), AI expert (1), project lead (1)	User-centered bottom-up
6.	Headquarters division B	Project coordinator (2) Data scientist (2), AI expert (1), project lead (1)	
7.	Project management division A	Project manager (3) Data scientist (2), AI expert (1), project lead (1)	

Table 4.4. Case study setting

4.4.2 Evaluation criteria

Various evaluation criteria are used to assess the results of the approaches. They are summarized in Table 4.5. For each criterion, a 3-point Likert-scale with qualitative ratings of “High,” “Medium” and “Low” is used. The criteria are explained below.

Regarding the added value component, three criteria are applied. First, the “alignment with business” of each use case idea is evaluated. It is defined as “the congruence of the artifact with the organization and its strategy” (Prat, Comyn-Wattiau & Akoka, 2015). If there is a direct and positive link to a clearly

defined business goal, a high rating is assigned. If there is an indirect but positive effect, a medium rating is assigned. If no positive effect is assumed, a low rating is assigned.

Additionally, the “expected improvement” of a use case idea is evaluated. If a use case idea does not add value, e.g., if its purpose is pure learning (Andrews, 2018) or experimentation, a low rating is assigned. If a current solution is slightly improved by AI, e.g., part of a process, a decision, or part of an offering, a medium rating is assigned. It represents an assumed incremental improvement. If a completely new process or process segment, an entirely new offering or solution is expected, a high rating is given. It represents a major, potentially disruptive improvement.

Next, “newness” is evaluated, i.e., whether the objective of a use case is already covered by a current solution. If no such solution exists, a high score is assigned. If a use case aims to improve an existing solution, a low rating is assigned. A medium rating is assigned if a similar solution for a similar purpose has at least been discussed or tested.

Dimension	Criterion	Description	Measurement
Added value	Alignment with business	Alignment of use case idea’s goal to organization’s strategy and goals	3-point Likert-scale for all criteria: <ul style="list-style-type: none"> • High • Medium • Low
	Expected improvement	Expected value addition if the use case idea can be realized	
	Newness	Novelty of the use case idea in comparison to existing solutions	
Feasibility	Process fit	Alignment of the use case idea with existing business processes	
	Project goal definition	Clarity about use case idea’s objective, target and potential input parameters as well as relevant context information	
	Data availability	Availability of data for target variables, potential input parameters and context information	

Table 4.5. Evaluation criteria

For the feasibility, the compatibility with existing business processes, i.e., the “process fit” of the targeted AI use case (Jöhnk, Weißert & Wyrski, 2021), is evaluated. If a use case idea is related to existing processes or can even be integrated into them, a high rating is assigned. A medium rating is assigned if it is partially related to existing processes. A low rating is assigned if no existing process can be linked to it.

Since incomplete or inaccurate project definition is a key risk factor for project failure (Sweis, 2015), the first criterion, “project goal definition”, assesses an important part of the project scope. Each identified use case idea is evaluated on the clarity of the use case idea’s objective, as well as key target and input parameters and contextual information. To receive a high rating, all criteria must be well defined. A low rating is assigned if the goal cannot be defined precisely. If the goal can be well defined but other relevant factors cannot, a medium rating is assigned.

The last evaluation criterion assesses “data availability”. If most of the required data are available, especially for the target variables, a high rating is assigned. If data are missing for some relevant contextual information or influencing factors, a medium rating is assigned. If the target variables cannot be well supplied with data, a low rating is assigned.

4.5 Results and evaluation

The case study resulted in the identification of 16 use case ideas by the four groups that followed the top-down approach, while the other three groups identified 27 ideas bottom-up. This section presents their evaluation as shown in Table 4.6. In addition, selected use case ideas from both approaches are presented.

	Top-down approach			Bottom-up approach		
Number of identified AI use case ideas	16			27		
Ratings	High	Medium	Low	High	Medium	Low
Alignment with business	16	-	-	-	22	5
Expected improvement	1	15	-	10	17	-
Newness	-	6	10	19	8	-
Process fit	13	3	-	-	20	7
Project definition	10	6	-	2	17	8
Data availability	11	5	-	-	5	22
Number of specified AI use cases	10			2		

Table 4.6. Evaluation results of each identified AI use case idea

All top-down use case ideas are highly aligned with business and mostly well aligned with existing processes. Thus, the data for the assumed influencing factors are mostly well available due to the previously collected process data. However, since 10 of the 16 ideas are aimed at improving existing solutions, the degree of novelty is predominantly rated as low. Thereby, most of the top-down use case ideas are expected to result in an incremental improvement, e.g., for a single part within a process, if implemented. Therefore, they are classified as medium in terms of expected improvement.

For example, two groups specified a use case idea for predicting project-specific annual construction costs. There is a clearly defined process and a current solution for this purpose, but it is time-consuming and not automated. The envisioned AI solution should therefore support the prediction and can build on data that has been collected as part of the process for nearly two decades. If implemented, it would save time and ideally provide similar or better predictions. Another use case is aimed at predicting the staff-hours required within selected project phases for selected internal departments. Various approaches are used throughout the organization for this purpose, mainly based on employees' experience. Accordingly, this use case idea also aims for a more standardized and automated approach. Most top-down use case ideas are similar to these two.

However, one use case idea of the top-down approach received a high rating for the expected improvement. It aims to implement an early warning system that automatically categorizes project risks in terms of time and cost targets. This is currently done purely on the basis of the professional experience of the project managers, but not systematically. It is only partially aligned with a process and requires the prior implementation of new process and data structures to be standardized. The possible influencing factors are diverse and were difficult to identify and define. While the project definition is clear in terms of the objective, it is not for possible influencing factors. This leads to a medium rating for the project definition. The same is true for data availability.

The bottom-up approach led to a greater variety of use case ideas. Most are aimed at identifying cause-effect relationships between project success criteria and various influencing factors, such as specific project constellations. These, if implemented, could lead to better determination of team setups, cost predictions and more. The use case ideas would serve current business goals more indirectly, leading primarily to a medium rating for alignment with business. The majority of use case ideas have not been

addressed before. The high ratings for newness correspond with medium and few low ratings for process alignment. The use case ideas are loosely or not all aligned with existing processes. In addition, this leads to predominantly low ratings for data availability. The required information is often neither defined nor has data been previously collected. In terms of expected improvement, some use case ideas would require entirely new process structures that completely replace or complement existing business aspects. This makes them unsuitable for short-term pilot projects, but on average they promise greater improvements than the top-down use case ideas.

A well-defined use case idea from the bottom-up approach aims to identify cause-effect relationships of typical project constellations that lead to different project efficiencies. Different project team constellations could be derived by collecting data on internal time tracking and external parties involved. Project success to date, the target variable, could also be measured for the parameters of cost and time. However, data was not collected consistently across the organization. This results in some missing data, data inconsistencies and thus a medium rating. The targeted analyses are loosely based on existing processes, e.g., internal evaluation of time tracking data, and are predominantly not supported by existing solutions. Implementation is considered highly valuable due to several anticipated improvements, e.g., better team setups, improved resource planning, improved knowledge of contractor performance. However, implementation would first require more accurate data and thus clearly defined processes.

Other typical bottom-up use case ideas involve novel influencing factors that may be related to project success. For example, one use case idea aims to quantify the impact of successful commissioning on project timelines. The idea is to analyze which factors within the commissioning processes are more or less likely to lead to successful commissioning. For the most part, these use case objectives are new and therefore loosely based on existing commissioning processes and resulting data. However, when it comes to the detailed definition of the actual influencing factors that lead to (in)successful contract award, these are not known and defined. As a result, the project definition is rated as medium. If the idea is implemented, it can be assumed that it is more likely to lead to incremental improvement and help to identify commissioning delays earlier.

Overall, all use case ideas are considered to deliver at least an incremental business improvement. However, the approaches predominantly resulted in different types of use case ideas. Although comparable to some extent, the ideas that resulted from the top-down approach were better defined and related to the existing business. After the data understanding phase, 10 of the 16 use case ideas from the top-down approach were eventually pursued. In the bottom-up approach, due to the lack of high-quality data and vague project definitions, 2 of the 27 use case ideas resulted in AI use cases. The others were shelved for the time being.

4.6 Discussion and recommendations

The case study findings lead to recommendations on how to identify AI use cases with either short-term incremental impact or long-term disruptive potential. These are combined with recommendations from previous literature on starting an AI initiative.

4.6.1 Find short-term feasible AI ideas top-down

To identify purposeful AI use case ideas with short-term feasibility, analyze existing business processes and offerings. Systematically identify which aspects within the processes or offerings are data-driven and may be improved with advanced analytical techniques such as AI. To do this, apply a top-down approach to gather the most relevant processes, offerings and data aligned to them. If possible, define a key performance indicator that the use case should improve (Engel, Elshan & Ebel, 2021). The use of a strategy map (Kaplan & Norton, 2000) proved very useful in the case study. It also served to estimate the expected improvement.

Attempting to improve the existing business by introducing AI has many advantages: Business alignment is ensured and the underlying business problems are well known and understood. Data has most likely been collected systematically over a period of time. As a result, the AI use case ideas that emerge from the top-down approach can be well defined. They are mostly aimed at improving certain parts of an existing process, which is in line with previous research (Davenport & Ronanki, 2018; Tarafdar, Beath & Ross, 2019). However, these use case ideas do not address entirely new problems. Therefore, one should not expect highly disruptive use case ideas, but those that are likely to lead to incremental business improvements.

4.6.2 Find disruptive AI ideas bottom-up

To identify AI use case ideas that are disruptive and novel, apply a bottom-up strategy. They are less feasible in the short-term but promise significant business improvements. To find such use cases, combine the technological potential of AI with the in-depth business domain knowledge of your employees. The use of human-centered and creative concepts such as design thinking techniques proved useful in the case study. It provided valuable insights from a different business perspective than the top-down approach. It helped to understand the business-related problems of employees in relation to their customers, products and processes. Combined with actual AI technologies, this led to a variety of AI use cases that involved completely new approaches to analysis.

The active involvement of employees is beneficial from various perspectives. First and foremost, employees actively participate in the development of the AI solution. This can increase user acceptance, which is a critical factor for IS project success (Nguyen, Nguyen & Cao, 2017) and an important AI readiness factor (Jöhnk, Weißert & Wyrcki, 2021). Additionally, AI offers the potential to emulate and learn from human performance (Andrews, 2018). Therefore, use cases with long-term business impact can also evolve by analyzing critical decision-making and interactions of humans, either employees or customers.

However, the use case ideas from the bottom-up approach would often require entirely new processes and procedures. In many cases, upfront projects would be required. The bottom-up approach thus found use case ideas with higher expected improvement than the top-down approach. However, it was not suitable for identifying use cases that could be implemented in the short term.

4.6.3 Start bottom-up and assess top-down

If an organization chooses only one approach, the top-down strategy is recommended as it leads to more feasible results. If using both approaches, use the bottom-up approach first: Involve selected employees and broadly explore potential AI solutions to improve current business and to construct ideas for new offerings and processes. Then conduct the top-down approach: Include top management and department heads or middle managers and try to find further ideas. With the help of the strategy map, critically assess each use case idea in terms of its business alignment and process fit. Also evaluate the expected business improvement, current data availability, and project definition. Keep in mind that unrealistic expectations, e.g., overly complex use cases, are risk factors for AI project failure (Westenberger, Schuler & Schlegel, 2022). Thus, explicitly prioritize AI use cases that can be implemented in the short term, even if they promise only incremental business improvements. You will have to postpone most use case ideas for the moment – especially the ones from the bottom-up approach.

In the case study, the use case ideas with high business alignment and process fit were not only more feasible to implement but were also preferred by top management. The top-down strategy thus positively affected top management support which is an important AI readiness factor (Jöhnk, Weißert & Wyrcki, 2021). Accordingly, a critical self-assessment of current AI readiness is recommended (Alsheibani, Cheung & Messom, 2018; Jöhnk, Weißert & Wyrcki, 2021; Pumplun, Tauchert & Heidt, 2019) followed by improving weak points. In addition, management should integrate AI adoption into the digital transformation strategy (Ransbotham et al., 2019).

4.7 Summary and conclusion

AI is considered a disruptive technology that has the potential to transform all industries. However, most organizations have seen only incremental or no business benefit from AI projects. Current literature suggests several recommendations how organizations can start an AI initiative. It is suggested to distinguish between a short-term and a long-term perspective. In the short-term perspective, organizations should aim for short, realistic AI pilot projects with a clearly defined business objective. Accordingly, they should understand the technological potentials of AI and increase their AI readiness. If successful, they should gradually expand their portfolio of AI projects: By tackling larger and riskier projects, they can optimize existing business while developing entirely new offerings and processes.

This paper analyzes approaches to identifying AI use cases with either a short-term, more incremental impact or with a long-term, but more disruptive impact. To this end, a top-down and a bottom-up approach are tested in the context of a case study. The bottom-up approach leads to more ideas for use cases, but they are not easy to define. They usually target completely new analyses and therefore promise significant business improvements. However, they lack both high process fit and data availability. Therefore, they cannot be implemented in the short term and require prior projects. Instead, they offer a long-term perspective that must be included in the medium- to long-term AI strategy.

The top-down approach, on the other hand, leads to fewer but well-defined use cases. They are strongly aligned with the existing business and processes and backed up with data. They are much more suitable for piloting in the near future and therefore offer short-term potential. On the other hand, they mainly aim to improve specific aspects within existing processes or offerings. Therefore, they tend to promise more immediate, but only incremental, business improvements.

When starting an AI initiative, a top-down approach is highly recommended, as it is better to start with small, clearly defined AI use cases. Only after an organization has gained AI experience while increasing its AI readiness, it should scale up its AI project portfolio. When performing both approaches, starting bottom-up to find a large variety of ideas seems beneficial. Afterwards, the top-down approach complements the list of use case ideas and is used to evaluate each of them.

In terms of future work, especially approaches to identify long-term, disruptive AI use case ideas should be further evaluated. The bottom-up approach tested in the case study could be an alternative, but its results could not yet be evaluated in the long term. Therefore, it would be beneficial to follow organizations with the process of AI adoption over several years.

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5 Business, Data and Analytics: Specifying AI Use Cases with the Help of Modeling Techniques

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Abstract

While artificial intelligence promises a wide range of potential for businesses, its adoption poses major problems for some organizations. This paper presents a modeling framework that aims to specify AI use cases. It models three views: Business, data and analytics, that are adopted for the requirements of AI. The framework was applied in a real-world case study leading to several AI use cases and two proof of concepts. While the business view is a useful tool to derive ideas for AI use cases in general, the data and analytics views are very specific to each use case. The framework serves as a means to an end to communicate the project goals, deliver practical guidance and to capture the main results. As its application is time consuming and challenging, this paper closes with guidelines for its efficient use in practice.

Published in:

Řepa, V., Matulevičius, R., Laurenzi, E. (eds.) Perspectives in Business Informatics Research. BIR 2024. Lecture Notes in Business Information Processing (529), Springer, Cham.

5.1 Introduction

Artificial intelligence recently received huge public attention due to the performance of large language models such as Open AI's GPT models. In general, AI systems take over tasks that are considered to require some level of human intelligence, e.g., perceiving, deciding, creating, automating or innovating (Benbya, Davenport & Pachidi, 2020). AI covers a variety of technologies from, e.g., robotic process automation, robots, expert systems, natural language processing, computer vision to deep learning and machine learning techniques. The latter is the most important subfield of AI and is divided into supervised, unsupervised, semi-supervised and reinforcement learning (Enholm et al., 2022). Supervised ML systems account for the majority of AI systems. AI systems can only be as good as the data they are fed with. They may improve their performance over time with increasing available data. Other important AI characteristics deal with its black box character, i.e., the outputs cannot be fully comprehended, and AI's experimental character, i.e., being non-deterministic but rather probabilistic (Engel, Ebel & van Giffen, 2021). Despite the huge potentials, e.g., AI has been named the top game changer technology by CIOs in 2019 (Howard & Rowsell-Jones, 2019), by far not all organizations that experiment with AI have gained any business value. Several AI initiatives entirely fail or do not meet their goals (Ransbotham et al., 2019). One risk factor is an inaccurate definition of the underlying AI use case (Westenberger, Schuler & Schlegel, 2022). Thus, supporting organizations to find and evaluate purposeful AI use cases is an important step in the early stage of AI adoption.

The typical AI use case leading to a success story is the improvement of existing business processes, e.g., by automating a process step or supporting decision making (Davenport & Ronanki, 2018; Collins et al., 2021). Often, there are certain data-driven decisions, tasks or process steps that are not yet supported by AI techniques or not even automated or digitalized at all. These could be aided, e.g., by automating or providing superior algorithms, through the wide range of AI's technological capabilities. As such, modeling and analyzing existing business processes is a potential starting point to identify AI use cases. For example, a bank found that its process for granting a loan to a customer was either too slow, long or complicated (Mayer, Strich & Fiedler, 2020). Thus, it aimed to improve the process and hired an external AI provider to train a ML system to automatically decide whether to grant a loan. Besides process automation, AI can also emulate humans' tasks or decisions by learning from human performances (Andrews, 2018). This may eventually also lead to more efficient processes. For example, analyzing lawyers' manual workflow for litigation analytics enabled a startup to specify an AI use case aiming for a more automated analysis of judgment files (Zhang et al., 2020). Therefore, a user-centered approach that analyzes customers' or employees' challenges, needs, working systems or interactions could also be used to identify ideas for AI use cases.

Both the analysis of existing business processes as well as humans' business challenges and needs can be supported by modeling techniques. In general, models promise support to generate and evaluate ideas for technological improvements, e.g., by providing procedural guidance, best practices and templates to design and store relevant results. To date, there is little research on distinct modeling techniques that aid the identification and evaluation of AI use cases in a practical setting. Our research opportunity allowed us to conduct a real-world case study aiming for the identification of AI use cases. This paper reports on the case study requirements, the modeling techniques we applied as well as the results and lessons learned from the case study. We discuss the usefulness of the modeling framework and practical advice for its use. As such, this paper addresses the following questions:

- i. Which modeling techniques are useful to identify and evaluate AI use cases and how are they adjusted to meet the requirements of AI?
- ii. How effective are these modeling techniques in a practical setting and how to apply them in an efficient manner?

5.2 Case study setting and related requirements

5.2.1 Case study setting

The project partner is a public organization that specializes on construction projects and real estate management. They aim to introduce advanced analytical solutions, e.g., utilizing AI techniques, to

support processes, decisions, and products on the mid- to long-term. They do not employ data scientists or AI experts yet. As an AI explorer (Uba, Lewandowski & Böhm, 2023), they have not identified AI use cases before and searched for external consulting to design use cases from scratch until the proof of concept (PoC) stage. The organization consists of a headquarters of about 200+ employees and eight independent subsidiaries. Several customer groups commission dozens of construction projects each year. The headquarters coordinates the incoming projects and transfers them to one of the eight subsidiaries. These are responsible for detailed design and construction planning. They use both internal and external workforce, although the share of external service providers continuously grew over the last years. We collaborated with nine business user groups each consisting of 2-3 practitioners from distinct business units. They were supported by the project sponsor's person in charge and the research team, i.e., one project lead, an AI expert and two data scientists.

5.2.2 Case study requirements

For the case study, we need a structured approach that leads to the aspired results: AI use cases until the PoC phase. Such an approach typically requires three overarching stages (Andrews, 2018; Maass & Storey, 2021): Identify a business case first, then collect, analyze and prepare the required data and eventually design the AI model for the PoC. This is also in line with CRISP-DM (Martinez-Plumed et al., 2019), the most used procedure model to guide data science projects. The basic concept is to identify a set of use case ideas first. They are specified step by step and continuously evaluated for their expected business impact and feasibility (Brethenoux & Karamouzis, 2019) as well as further AI specific criteria. Infeasible or insignificant use cases are dropped. For each stage, we specified the constituents of the evolving AI use case as shown in Figure 5.1.

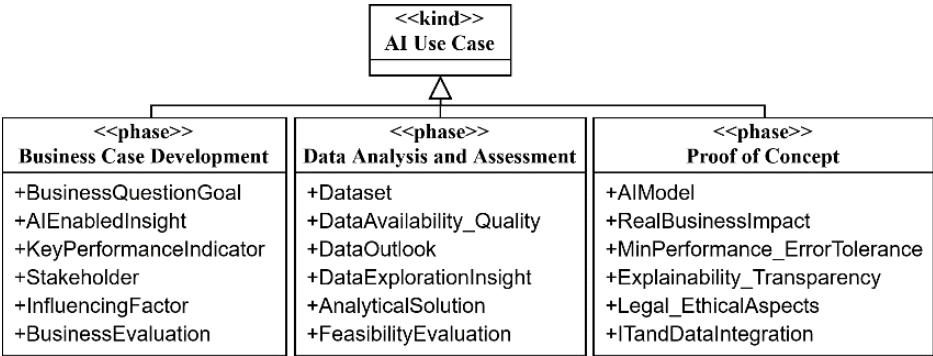


Figure 5.1. Development of an AI use case until the proof of concept

AI use cases aim to alter a business-related aspect by utilizing AI techniques. They are mainly motivated by business needs (Borges et al., 2021), so the first phase specifies the underlying business case. The addressed business question goal must be formulated together with potential AI enabled insights to solve it. To make improvements measurable, key performance indicators (KPI) related to the business question goal should be used. The business case should outline the relevant stakeholders and influencing factors. It should be evaluated for its potential business impact, i.e., for its expected business improvement, alignment with business and newness.

AI solutions can only be as good as the underlying data allows, so the second phase builds a data view. This requires an idea of the aspired analytical solutions that relevant datasets should be identified and collected for. The availability and quality of such data must be evaluated and is the key aspect to assess the use case's feasibility. An outlook whether more and better data will be provided in future is also useful as AI solutions can be improved over time with more and better data. Furthermore, data exploration insights allow for a more qualified statement on the expected business impact. The latter must be compared with the feasibility. For the feasibility, the alignment of the aspired analytical solution with existing processes can also be evaluated as well as the project definition.

In the third phase, the PoC outlines the impact and feasibility aspects in more detail. An AI model must be designed and fed with the currently available data to measure the real business impact. This must be

compared with the minimum required performance (Davenport & Seseri, 2020) respectively an error tolerance. The PoC must consider further AI specific aspects (Engel, Elshan & Ebel, 2021) such as explainability and transparency (Haresamudram, Larsson & Heintz, 2023) to confront AI’s black box character. Legal and ethical aspects must also be taken into account, especially if the AI use case concerns the people or sensitive topics (Felzmann et al., 2019). In addition, AI solutions are usually embedded within existing workflows (Salwei & Carayon, 2022), wherefore the process fit can be assessed beforehand. For the PoC, requirements for IT and data integration should be formulated as well as the integration into existing working processes of employees and customers.

5.3 Related work and choice of the conceptual model

Our first phase aims to develop the business case. Conceptual modeling techniques can thereby help to elicit relevant business goals (Amyot et al., 2010; Jiang et al., 2011) that may lead to business cases. By modeling business goals and their relations top-down, one can identify goals that may be improved by applying new technologies. Such a business view is also used by the Conceptual Modeling Framework for Business Analytics (CMFBA) (Nalchigar, Yu & Ramani, 2016). It supports the identification, specification and requirements analysis of data analytics systems in particular (Nalchigar & Yu, 2018). The CMFBA also proposes an analytics design view that helps to choose the required analytical solution. It is closely related to a data preparation view that models the required data preparation steps for the aspired analytical solution. This is well in line with our second and third phase to specify the data view and the PoC.

Thus, we apply an extended approach that is adjusted for the requirements of AI and matches the elements within Figure 5.1. We add a continuous evaluation throughout the views and the emerging use cases. We specify the evaluation criteria as explained when outlying the constituents of an AI use case. While the business view focuses on the business impact criteria, the data view additionally delivers feasibility criteria. These criteria can be quantified, e.g., using a 3-point Likert-scale. The use cases can then be mapped within an impact-feasibility-matrix for comparison (Brethenoux & Karamouzis, 2019). For the PoC criteria, the requirements are analyzed in more detail as explained before. Figure 5.2 presents the overall process model.

Besides related modeling techniques, related work also provides procedural guidance to manage AI projects in a real-world setting (Brunnbauer, Piller & Rothlauf, 2021, 2022; Studer et al., 2021; Hofmann et al., 2020). They provide useful instructions to perform an AI project and can be combined with modeling techniques.

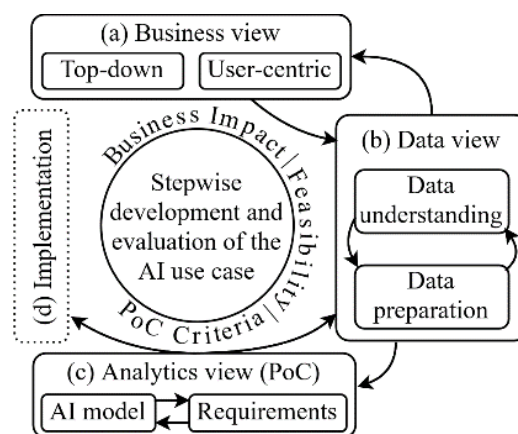


Figure 5.2. Overall process model

5.3.1 Business view

We specify the business view as shown in Figure 5.3 by adding two strategies to identify business question goals and associated AI enabled insights. The top-down strategy initially models an organization or business unit as proposed by the CMFBA, i.e., analyzing hierarchically aligned business goals (Nalchigar, Yu & Ramani, 2016; Barone, Topaloglou & Mylopoulos, 2012; Barone et al., 2010).

As successful AI use cases often improve existing business processes, we include their analysis, e.g., using BPMN models (Chinosi & Trombetta, 2012). The aim is to identify business question goals related to tasks, decision points, events, process results or business goals that might be improved with AI techniques. The process models should explicitly contain both incoming and generated data and information.

The user-centered strategy focuses on the business users. To learn about their business environment, challenges and needs, user-centered approaches are a useful tool, e.g., applying design thinking principles (Hehn et al., 2020; Micheli et al., 2019; Thoring & Müller, 2011). Doing so, we design two models: First, a context map to gain a general understanding of relevant influencing factors of the business users' working environment. Second, user journeys that include different aspects a business user faces (Temkin, 2010; Ludwiczak, 2021): We apply relevant user tasks, related challenges, needs, touchpoints and relate them to influencing factors from the context map. When trying to match the relevant challenges, tasks or influencing factors with AI's technological possibilities, the business question goals and aspired AI enabled insights can be derived.

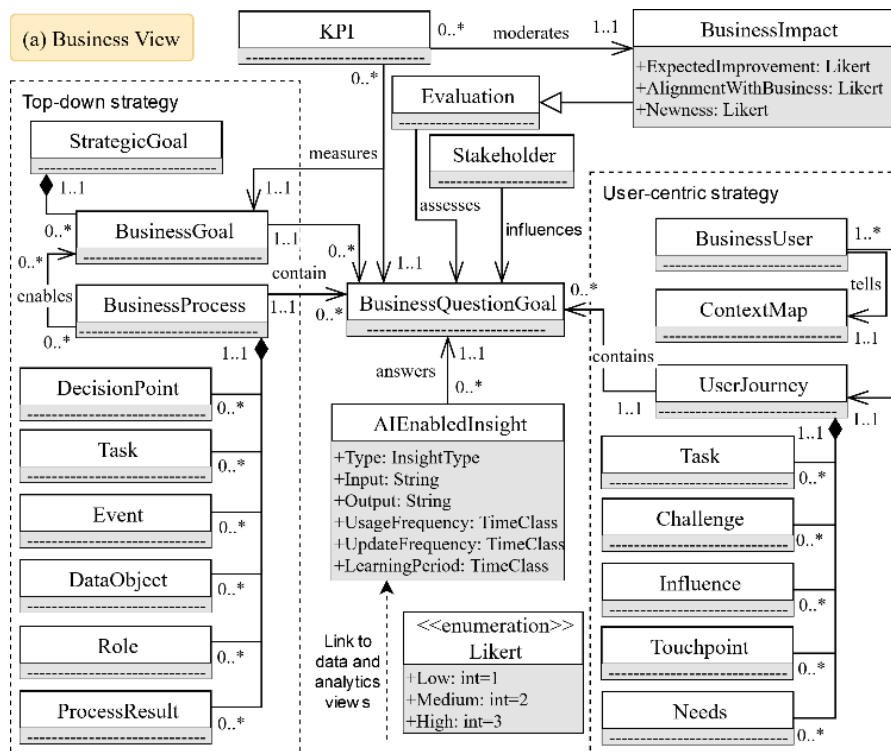


Figure 5.3. Meta model of the business view

5.3.2 Data and analytics views

We then use data understanding and data preparation tasks for the data view, see Figure 5.4 which also covers the analytics view. The CMFBA data preparation view does not cover data understanding tasks. We add them, i.e., the definition, collection, description, assessment and exploration of required data. Relevant data can be identified via currently used data within related processes and tasks as well as the influencing factors identified in the business view. In most cases high quality data is scarce but abundant. Thus, checking for external data, e.g., purchased data, can be required. Afterwards, the available data is collected while the missing data is noted. The collected data should be described, i.e., its source, owner, type, scope, update frequency, its values as well as their practical meaning. Afterwards, the data quality assessment evaluates the completeness, validity, interpretability and accessibility of available data (Wang & Strong, 1996). Then the data exploration follows to assess the usefulness of the data for the aspired AI enabled insight. For such an exploration, data processing tasks are required, i.e., operators which perform single data processing tasks using certain mechanisms (Trujillo & Luján-Mora, 2003), e.g., join or filter, and potentially necessary algorithms (Nalchigar & Yu, 2018). The data understanding tasks lead to the required datasets. These (raw) datasets are then processed to datasets required for the

analytics goal (Nalchigar & Yu, 2018).

The analytics view helps to choose and design the required AI models. These are iteratively fed with the prepared datasets and evaluated. Data preparation tasks are thus highly iterative, so they are shared among the data view and the analytics view in Figure 5.4. The results of the AI model allow for a realistic estimation of the current business impact. To support the choice of suitable algorithms, the CMFBA provides an algorithm catalogue (Nalchigar & Yu, 2018). For AI specific technologies and exemplary algorithms, an overview can be found in Mukhamediev et al. (2022) which is summarized in Figure 5.5.

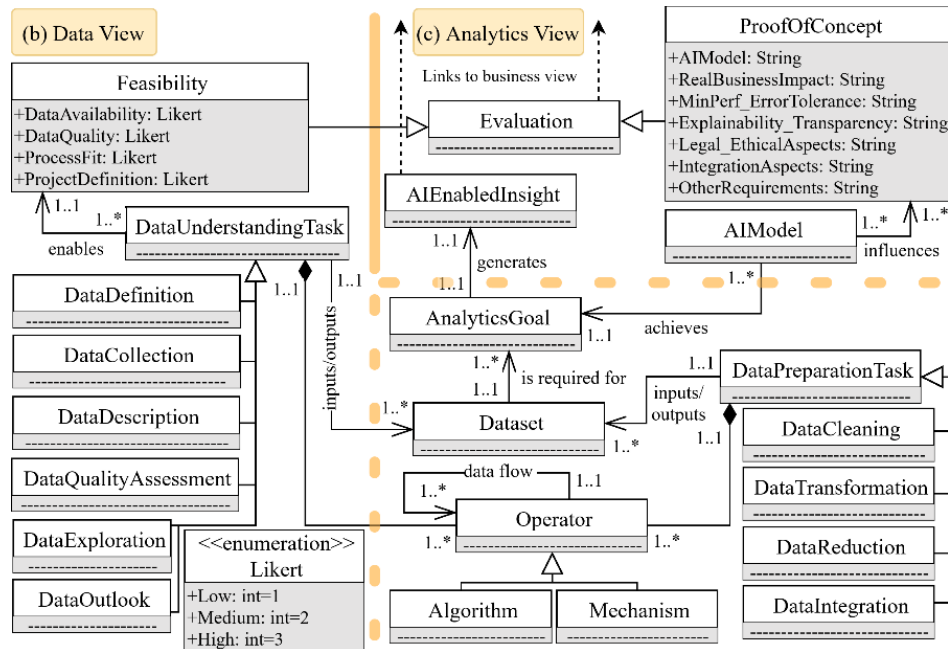


Figure 5.4. Meta model of the data and analytics views

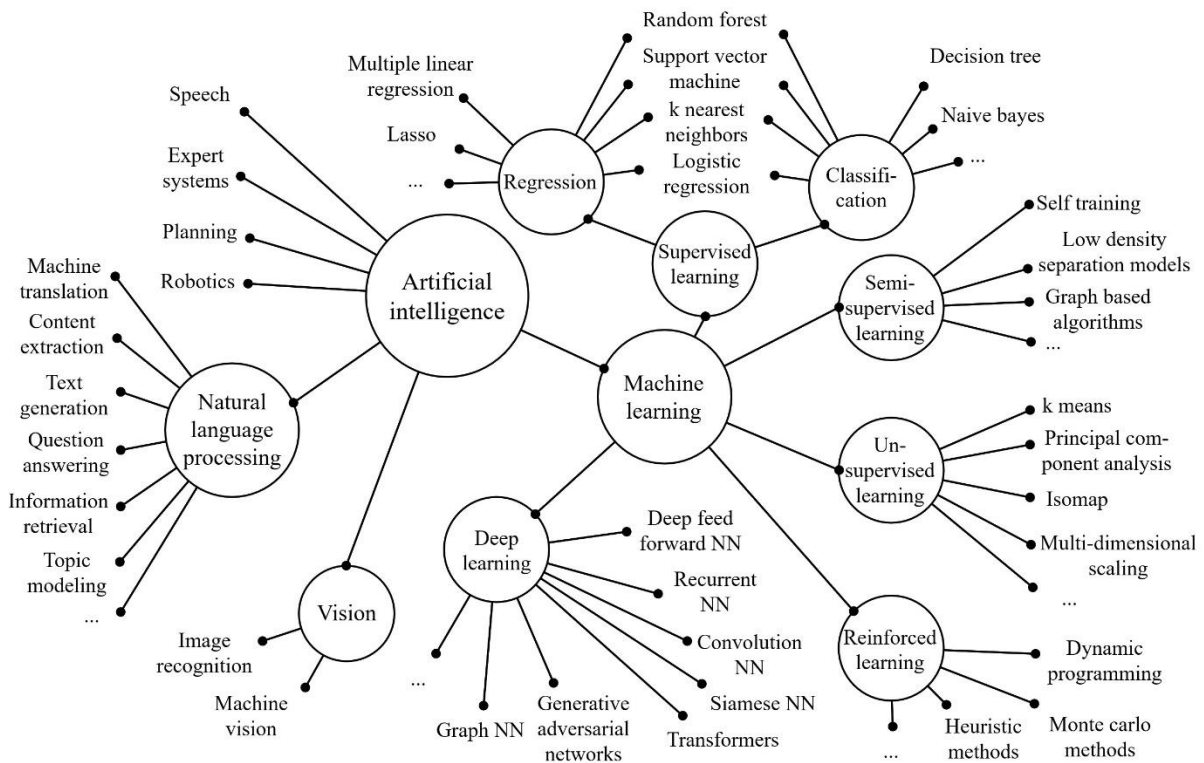


Figure 5.5. AI technologies and exemplary techniques based on Mukhamediev et al. (2022)

5.4 Application in a real-world case study

5.4.1 Business view by top-down strategy

A part of the business view is presented in Figure 5.6 for a headquarters division.

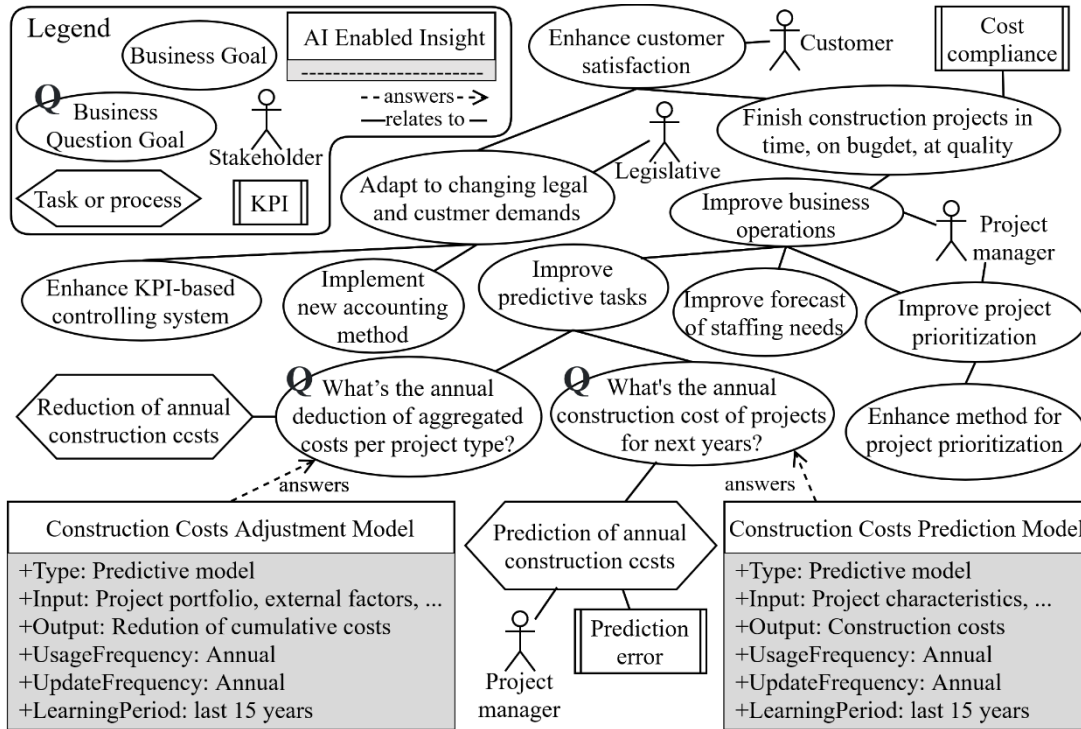


Figure 5.6. Excerpt of the business view for a headquarters division

They aim to enhance customer satisfaction who wish to get the construction projects finished in time and on budget. Customers demand precise forecasts of construction costs, so the organization aims to improve their predictive tasks. The business question goal that asks for the volume of project specific annual construction costs was formulated by three different groups proving its business relevance. The related process is modeled in Figure 5.7. Thanks to the process model, another business question goal could be derived. When the headquarters aggregate individual values to the project portfolio value, they must reduce the sum. This is due to unpredictable events that cannot be linked to single projects, e.g., project cancellations. However, there is little knowledge on the required reductions concerning different project types and so forth. Hence, the business question goal ‘What’s the annual deduction of aggregated costs per project type?’ emerged.

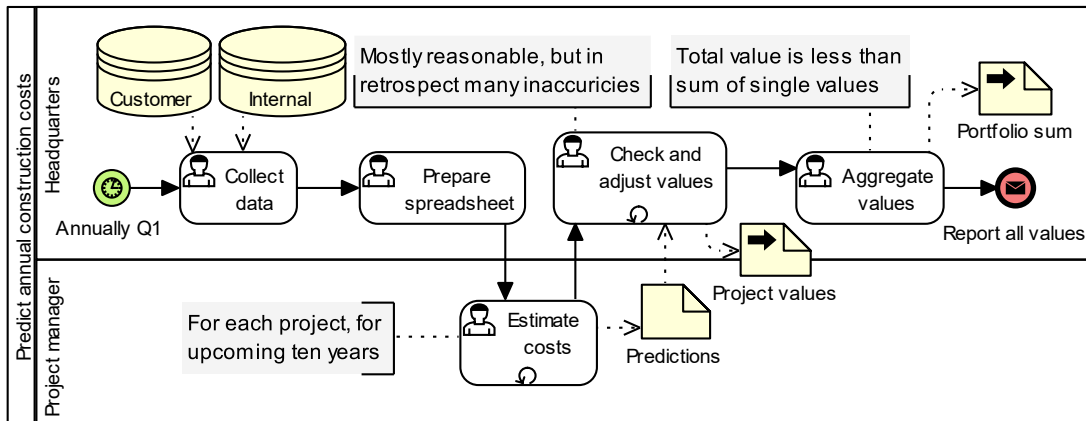


Figure 5.7. Process model for the prediction of annual construction costs

5.4.2 Business view by user-centered strategy

In Figure 5.8, the context map shows a part of the important influencing factors for a project manager. Construction projects are affected by their inherent characteristics and internal and external organizational factors. For the latter, mainly factors related to external architects and engineers, customers and the legislative are relevant.

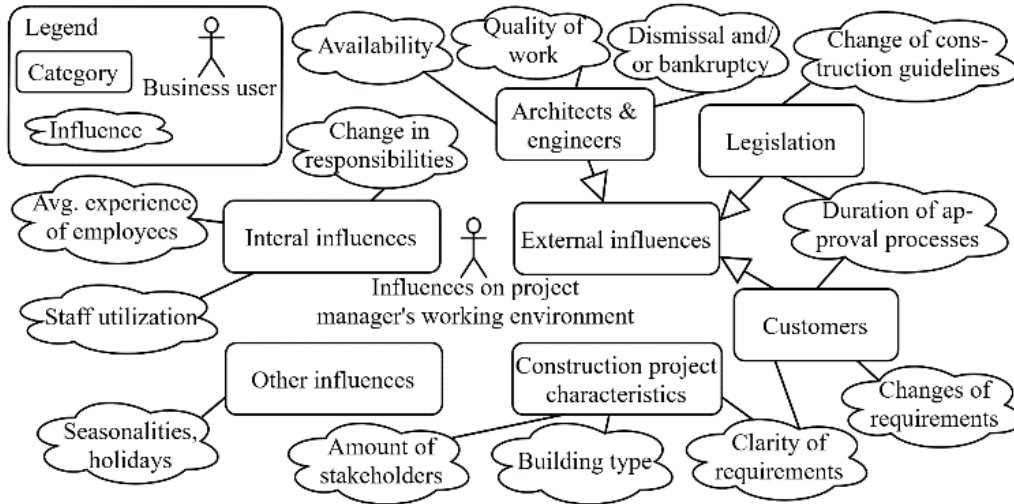


Figure 5.8. Excerpt of a project manager's context map

In Figure 5.9, a greatly shortened version of the user journey of a project manager is presented. The user journey concerns the typical lifecycle of a construction project from assignment until completion. Projects are assigned by the headquarters. Project managers then check the project's requirements, the available resources and set up the project constellation. As soon as the project is set up, they control and communicate its progress until the project is delivered to the customer. There are several related challenges, influences, and associated needs. Project managers especially seek assistance for their daily routines, i.e., planning and allocating resources as well as managing risks. This led to the definition of several ideas for AI use cases.

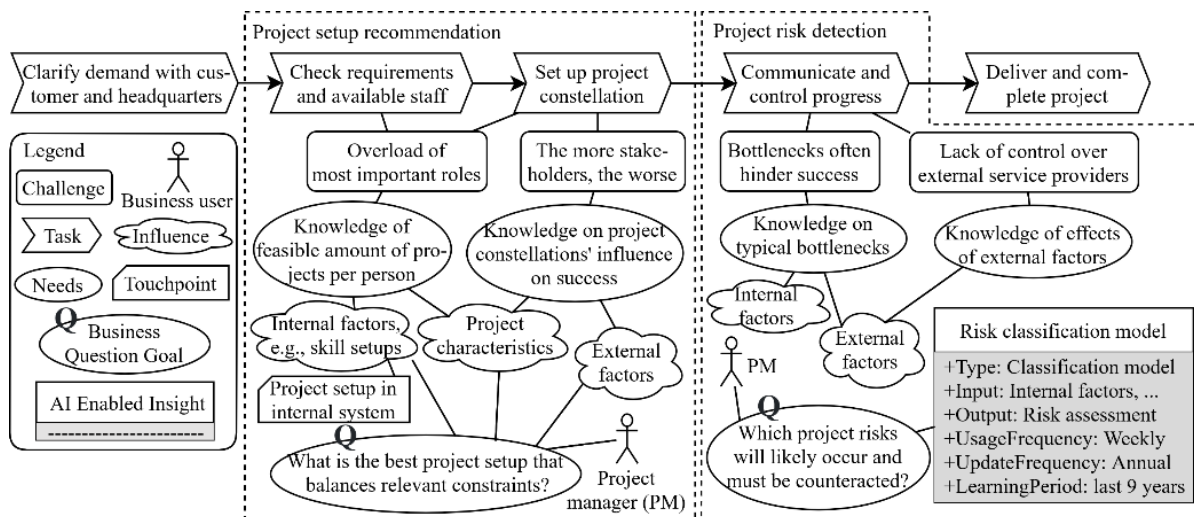


Figure 5.9. Excerpt of a project manager's user journey

Two exemplary business question goals are shown. Project managers need to know the most suited project setup, e.g., concerning the team setup, for an upcoming construction project. This requires insights such as a project setup recommendation that accounts for, e.g., the project's expected staff demand compared with current staff resources and employees' experience and skill setup for certain project types. Another business question goal asks when countermeasures must be initiated to tackle

project risks such as typical bottlenecks. To do so, an insight on the severity and likelihood of such risks is required. Both question goals could potentially be supported by AI enabled solutions. For example, unsupervised ML algorithms could detect typical bottlenecks and project risk patterns in past projects. These could be utilized to recognize and assess similar risks for current projects earlier on.

5.4.3 Data view for the prediction of annual construction costs

In this section, we present the data view for one selected AI use case: The prediction of annual construction costs as shown in both Figure 5.6 and Figure 5.7. For this use case, we first defined relevant data which is mainly informed by the data and information from the process models. We then identified required datasets for past and current projects, e.g., regarding projects’ master data, previous construction costs back to 2005, internal and external incidental building costs as well as project progress data. These are briefly sketched in Figure 5.10 together with the most basic data processing steps and additional information, e.g., a brief data description for one dataset.

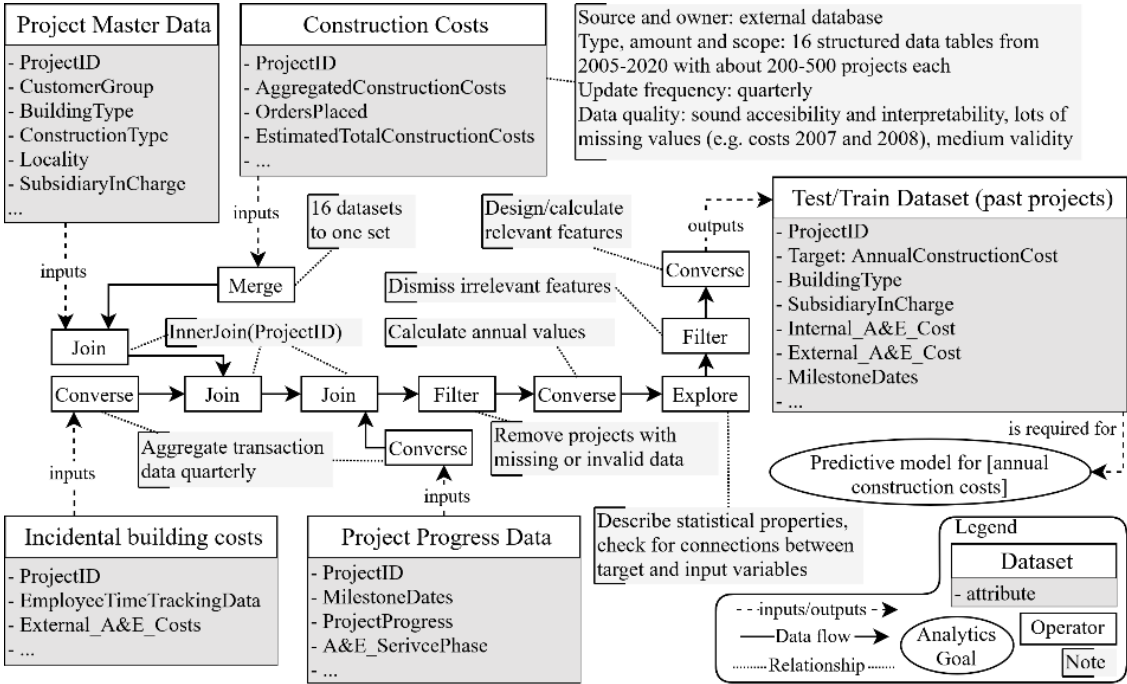


Figure 5.10. Excerpt of the data view for the prediction of annual construction costs

The data quality assessment revealed tremendous issues for several projects, especially small ones. At times, no construction costs were stored, e.g., entirely for the years 2007 and 2008. The project progress data at times did not match the cost related data, e.g., if no incidental building costs are recorded although a project already passed several milestones. For the data exploration, project data was matched on the level of an individual construction project. Interestingly, although large amounts of data were available in the beginning, i.e., data on more than 1.000 projects, only few correlations between the target variable and assumed input variables occurred. The expected business improvement was thus adjusted to a lower level. With the current data quality and availability, an ML based solution may not lead to an improved prediction. However, the organization implements enhanced data standards so the data outlook is positive. The project partner thus aimed for the PoC wherefore we prepared datasets to test different analytical solutions. For a random forest regressor for example, 380 projects were used to train and test the AI model.

5.4.4 Analytics view for the prediction of annual construction costs

In this section, we present the analytics view for the same use case, see Figure 5.11. We tested different supervised machine learning regression models to predict projects’ annual construction cost values. We mainly evaluated the performance of a random forest regressor and a multiple linear regressor. However, as the data exploration already revealed, they could not yet beat the current human-based estimations

and therefore not yet provide the minimum expected performance. In the upcoming years, data related issues are however expected to be reduced, thus the solutions can be improved step by step. We also tested simpler models that follow a different analytical strategy not considered within AI. The preferred model learns the typical quarterly distributions of construction costs from past construction projects for different project types at first. It is provided with several input variables including human-based estimations and rules. It then estimates the expected distribution of upcoming construction costs. This model proved to be superior for the moment. It achieved similar performance as the current estimations purely based on humans. If unrealistic estimations are readjusted, it can beat the current solution. However, this still requires notable human inputs, so this is an interim solution which integrates a data-driven analysis into the existing workflow. On this basis, the share of data-driven predictions should be enhanced and equipped with advanced ML techniques in the future. We provided our project partner with two software prototypes: One that is integrated via Tableau and the other one is integrated into an Excel spreadsheet via VBA coding. Each software is currently in use, so our prototypes show two paths for a practical integration into the existing data workflow and working procedures.

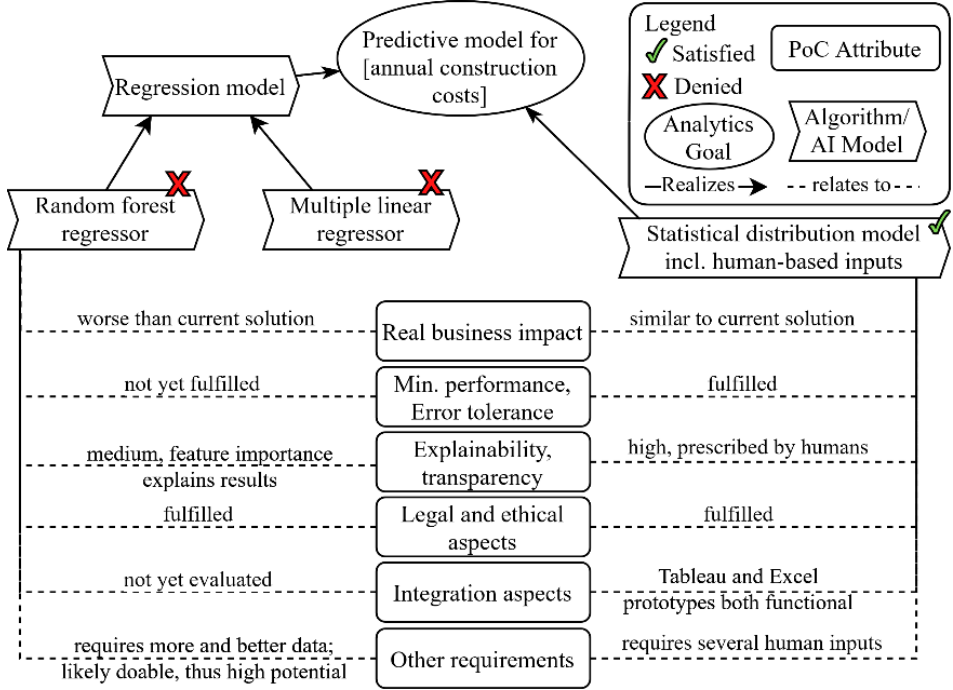


Figure 5.11. Summary of the analytics view for the prediction of annual construction costs

5.5 Usefulness and practical application tips

5.5.1 Usefulness of the conceptual model

The business view differs the top-down and user-centered strategies. In the practical setting, the business users grasped the top-down strategy in a very short time and were able to formulate the required entities. The user-centered strategy was more complicated to grasp and thus required more time. The two strategies also led to different results. The top-down strategy is more rigorous and stricter by capturing and analyzing only business goals and associated processes. The process analysis leads to ideas for AI use cases affecting the internal business aspects, i.e., mainly the current business operations. As such AI use cases lead to the typical AI success story, the strategy fulfills its purpose. The top-down strategy is also very useful to assess the strategic alignment and the process fit of each use case idea as it models the relations between relevant goals and processes.

The user-centered strategy in contrast captured detailed everyday issues that the business users face. The context map is useful to gain a broader business understanding that includes influencing factors not only associated with the internal business operations, but employees' whole working environment. In

combination with relevant tasks, challenges and additional information, the user journeys provide rich information to derive various AI use case ideas. These were derived, e.g., from the mere challenges that business users face every day like an overload of projects they must supervise and thus the requirement for data-driven, automated assistance. However, the broader spectrum of ideas and their disentanglement from current processes meant that these use case ideas are less aligned with existing business and consequently with available data.

The data view provides guidance to perform data understanding and data preparation tasks. However, the data processing details are elaborate to grasp with the meta models. In Figure 5.10, the data processing steps are still a great simplification. For example, the datasets for project master data and construction costs are managed by the customer and inherent a different logic for the ProjectID. These had to be adjusted at first. The same accounts for projects that required addendums. Each addendum receives an additional ProjectID, but their construction costs had to be added to the parent project. The target variable, i.e., annual construction costs per project, also had to be calculated for all projects at first as the data tables only included the aggregated total construction costs spent. Hence, while Figure 5.10 only says ‘merge’ for the construction costs and then ‘join’ for the two datasets, the reality covers about a dozen steps. Such details are better suited for an accompanying document like a data map including a data collection and preparation report. The data view should instead present the relevant datasets that were used and summarize the most important data processing steps. This helps to communicate both these aspects and the associated insights to the business users. For the analytics view, a similar observation is true. It is highly iterative with the data preparation tasks and emerges step by step, so that not every single step should be modeled. It is useful to map and compare the performance of different AI algorithms regarding the different PoC criteria. Thus, the data view and the analytics view serve as an effective tool to communicate the project progress, the main procedure steps and to capture the relevant results in more detail ex-post.

5.5.2 Efficient use of the conceptual model

The design of the models requests a lot of effort from all stakeholders. As practical settings have strict budget, time, or staff restrictions, using the framework in an efficient manner is of great importance.

One consideration asks whether all elements should directly be modeled and in which level of detail. The business view is where the initial ideas for AI use cases are generated together with the business users. It is the base for all upcoming steps and will decide whether promising use cases are found or not. Thus, a thorough identification and evaluation is key. The meta models should be applied with detail to allow for a broad spectrum of relevant information and subsequent use case ideas. For the top-down strategy, the collection of existing processes in the strategy map should be emphasized. When analyzing the processes, an emphasis on required and generated data is recommended. For the user-centered strategy, the user journeys should emphasize the user tasks and associated information. The data and analytics views in contrast are required to assess which use case ideas are feasible but not to generate new business cases. As such, the models should be used as efficiently as possible, i.e., as a guideline which overarching activities to perform and to capture the relevant results ex-post.

An important efficiency consideration is to follow the most impactful and feasible use case ideas only. To do so, we introduced evaluation steps and criteria for each view. These proved very valuable as the number of AI use case ideas has been large in the beginning. The project groups identified 47 ideas for AI use cases. Eventually, we ended up designing two complete PoCs, although one served three groups. Lots of ideas faced the issue of not being equipped with sufficient data, so especially the process fit, data availability and data exploration insights must be considered when evaluating the AI use cases.

Another related aspect deals with termination conditions. There is no guidance when to stop collecting business question goals during the business view. We used time restrictions to set a limit when designing the business view. We followed the assumption that the most relevant business question goals will likely be formulated early on which was indeed the case. For the data view, we analyzed the use cases according to their business prioritization. Lots of use cases ideas also required similar data understanding, preparation and analytical tasks. Identifying interdependencies between different use cases early on is strongly recommended and can be done using the business views.

5.6 Conclusion

This paper asks how to support the identification and evaluation of AI use cases with modeling techniques. To do so, we extend a framework for the requirements of AI and a real-world case study. The procedure starts with a business view aiming for business question goals and associated AI enabled insights. Two strategies are proposed that lead to a variety of AI use case ideas. The business view is a universal approach to identify such ideas and is built upon well-established business concepts. We added distinct evaluation criteria that allow to estimate the expected business impact to follow the most promising use cases first. The second phase, data view, results in a qualified statement on the use case's feasibility as well as the required datasets for the AI solution. To do so, data understanding tasks were added to the framework. In addition, data exploration insights help to assess the expected business impact in greater detail. However, the real-world complexities when choosing, collecting, and processing required data for a new use case pose wicked challenges. It is questionable whether one should model each required processing step in detail or model the main steps only but keep the details for a separate data preparation report. The third phase, analytics view, is highly iterative with the data preparation steps of the data view. It provides guidance to build and evaluate an AI model that is fed with currently available data. Only this way, the true business impact can be stated. For such a proof of concept, we added additional AI specific criteria that must be outlined, e.g., explainability, transparency and legal aspects. These must be specified with the end users and other relevant stakeholders. The analytics view is again useful to provide procedural guidance and present the main results.

It is of great importance to apply the meta models in an efficient manner. We discuss several aspects to achieve that, e.g., evaluation criteria, ending conditions and when to use the models in detail. Regarding the latter, the meta models should be viewed as a means to an end to achieve the practical goals. They can very well support a project aiming for AI use cases by providing the entities which should be identified and modeled. It also prescribes the potential design of the results, thus serving as an auxiliary tool to communicate the results and the progress. Still, intermediate results may need to be adjusted several times to meet the ever-changing discoveries and constraints when designing new AI solutions from scratch. Hence, the real-world situation demands a trade-off between a rigorous application of the meta models and the actual practical benefits.

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6 How Non-Tech Medium Enterprises Identify Promising AI Use Cases

Matthias Brunnbauer, Gunther Piller, Franz Rothlauf

Abstract

When AI expertise and financial resources are scarce, identifying AI use cases is difficult. These barriers are in particular true for non-tech medium-sized enterprises. This paper proposes an approach to start an AI initiative, which was tested in a real-world case study. You best start by analyzing your existing business processes using a top-down approach. Consult external AI experts to derive purposeful AI use cases and evaluate them for their impact against their feasibility. Process fit, data availability and quality are the key feasibility criteria.

To be submitted.

6.1 AI adoption to improve business

6.1.1 AI success and failure stories

Artificial Intelligence was selected as the top game-changer technology by CIOs in 2019 as it offers various chances to improve business (Howard & Rowsell-Jones, 2019). AI can increase process automation, enhance employee and customer engagement and deliver new cognitive insights. A beverage bottler may use AI to optimize promotions on retailers, while a food delivery service may apply AI to optimize delivery routes (Guan et al., 2022). AI is a versatile field that can support many different businesses as it subsumes a variety of technologies (Benbya, Davenport & Pachidi, 2020): These include robotic process automation, robots, expert systems, natural language processing, computer vision as well as deep learning and machine learning techniques. ML is a relevant subfield of AI (Enholm et al., 2022), especially supervised and unsupervised ML. The latter is used to detect patterns from unlabeled data, i.e., the target variable is not known. Supervised ML solves classification and regression problems and is trained with labeled data, i.e., outputs (targets) are known.

Despite the huge potentials granted, realizing business value from AI remains difficult. Organizations often report small business impacts only (Brock & Wangenheim, 2019) while others face severe failures. A survey of more than 2,500 executives reveals that 40% of organizations that have made significant investments in AI have not yet realized any business benefits (Ransbotham et al., 2019). Examining the practical use of AI in 152 organizations finds that organizations often start with too ambitious AI projects (Davenport & Ronanki, 2018). Instead of starting with “moon shots,” organizations should start with the low-hanging fruits first, i.e., the improvement of existing business processes. Typical AI success stories indeed most often deal with increased automation of relevant processes (Collins et al., 2021). Reasons are that the underlying processes, the current solution and the addressed stakeholders are known, but also data is often collected over several years.

6.1.2 AI readiness factors and AI adoption in non-tech medium-sized enterprises

Also within small and medium-sized enterprises (SME), the main opportunities lay in the automation and acceleration of existing processes (Ulrich, Frank & Kratt, 2021). However, SMEs fail at successful AI adoption more often than large enterprises as they face additional inhibitors. They most often have only little AI expertise, face financial limitations and therefore face difficulties to identify suitable use cases (Bauer, van Dinther & Kiefer, 2020). This is especially true for non-tech industries, e.g., healthcare, public services and financial services lag behind regarding AI maturity (Guan et al., 2022). But how to start AI adoption in a non-tech SME without required resources such as profound AI knowledge? One relevant aspect is to build teams with business domain experts, AI specialists and data scientists. The latter can be external consultants who help to define the AI business potentials, define required data and design the AI solution. In general, there are several AI readiness factors as shown in Table 6.1 (Pumplun, Tauchert & Heidt, 2019; Jöhnk, Weißert & Wyrcki, 2021). Being agile with an innovative company culture is also relevant and may be better the smaller the organization. Thus, positive and negative factors for SMEs exist (Hamm & Klesel, 2021).

Top management support is also a readiness factor and can be ensured by a close link of the AI project leaders to the C-suite. For that, middle managers are important as they build the bridge between top management’s strategy and employees’ daily operations (Groskovs & Ulhøi, 2018). This is especially true for SMEs due to the short distance between C-suite and employees. For projects such as introducing AI, middle managers often supervise or even guide the project. Their deep knowledge about products, processes, staff and technical requirements is crucial. Thus, their voice and engagement mediate the success of AI innovations (Rohlfers, Hassi & Jebsen, 2022).

Category	AI readiness factors
Strategy alignment	<ul style="list-style-type: none"> • Identify AI business potentials • Ensure top management support • Ensure AI process fit • Ensure AI readiness among customers and employees • Foster data-driven decision making
Resources	<ul style="list-style-type: none"> • Build team with AI specialists, business analysts, data scientists • Ensure financial backup and provide required IT infrastructure
AI knowledge	<ul style="list-style-type: none"> • Ensure basic AI understanding • Upskill employees with AI skills • Ensure AI ethics
Culture	<ul style="list-style-type: none"> • Ensure innovate company culture and change management • Integrate required divisions
Data	<ul style="list-style-type: none"> • Provide high quality data • Provide sufficient infrastructure

Table 6.1. AI readiness factors

6.1.3 From promising AI use case ideas to proof of concepts

Strategic alignment is a relevant AI readiness category. One factor demands the identification of AI business potentials, i.e., meaningful AI use cases that fit the business strategy. Thereby, organizations should start with a small portfolio of AI flagship projects and view AI as a way to solve clearly defined business problems. Organizations should aim for projects with quick wins and strengthen employees' AI skills as well as AI acceptance. If the initial projects prove to be successful, the AI portfolio can be scaled up (Lee et al., 2019).

You can break down AI adoption projects from use case identification until deployment as shown in Figure 6.1. Identify purposeful AI use cases first. Evaluate them for their expected business impact and the feasibility (especially from a data view). For promising use cases, design a proof of concept (PoC). It includes AI-specific requirements and an AI model that shows the current true performance. If the PoC is successful, start piloting and eventually implementing the use case. Then, continuously maintain and improve your AI solution. With increasing AI readiness and expertise, revisit previous phases or use cases that were postponed at the beginning.

The paper at hand presents an approach how to identify and evaluate AI use cases until the PoC stage. We thus cover phases 1-3 from Figure 6.1. Our approach was used in a real-world case study and is grounded on practice-based knowledge. Based on our findings, we derive several practical recommendations, e.g., which approach to follow, what to prepare on your own and how to communicate your AI adoption project.

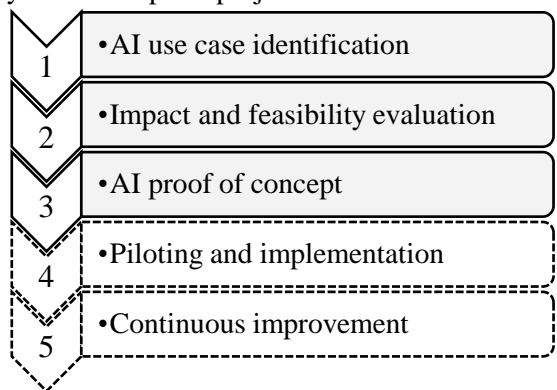


Figure 6.1. AI project phases

6.2 The process model to identify and evaluate AI use cases

As successful AI solutions often improve existing processes and solutions, analyzing those is a useful starting point to identify AI use cases (Sturm, Fecho & Buxmann, 2021). AI can also emulate human performance (Andrews, 2018; Bawack, Fosso Wamba & Carillo, 2021), thus analyzing users' or business users' tasks, challenges and modes of operation is also a valid starting point. One process model combines both possibilities (Brunnbauer, Piller & Rothlauf, 2021): It extends the practice-based model CRISP-DM (Martinez-Plumed et al., 2019) by specifying the business and data understanding phases to identify AI use cases and to evaluate their impact and feasibility. We add the steps to design the PoC to evaluate the true business impact and assess additional requirements. The overall process model is shown in Figure 6.2 and briefly explained next. The phases are specified with detailed actionable activities, techniques, outputs and required roles. These are summarized in Appendix A.

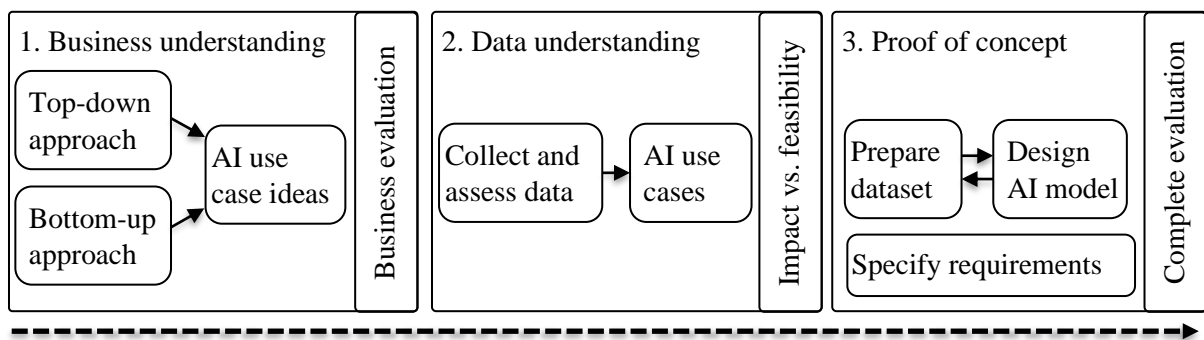


Figure 6.2. Process model to identify and evaluate AI use cases

6.2.1 Business understanding

This phase aims to identify business-driven AI use case ideas. To do so, apply a top-down and/or a bottom-up approach.

Top-down approach

The top-down approach aims to find existing solutions where AI may enable an improvement. It requires the involvement of business division leaders, e.g., middle managers, who are familiar with the overall business goals and processes but also the day-to-day operations. AI experts are required to derive AI use case ideas. The approach lets you analyze your existing business hierarchically, i.e., business goals and their aligned processes, tasks, decisions and process outputs such as products (Nalchigar & Yu, 2018). This includes five key activities. You first create or analyze your strategy map that includes strategic and operative business goals together with the relevant key performance indicators (KPI) (Kaplan & Norton, 2000). Next, map relevant business processes related to the business goals and prioritize them. Then, select key business processes to model and analyze them in detail. Then try to identify data-driven process steps, tasks, decisions, or process results. Together with an AI expert, work out which instances can be improved or supported by AI. This leads to ideas for AI use cases that are equipped with relevant context information and eventually prioritized.

Bottom-up approach

The bottom-up approach aims to match AI's technological potentials with the in-depth business knowledge of your employees. It requires selected employees with deep business domain knowledge and long-time job experience. You can, but do not have to involve middle managers. Consult an AI expert who is familiar with user-centered ideation or an additional expert for the latter. The approach comprises five activities within a user-centered approach (Micheli et al., 2019; Liedtka, 2015). The approach begins with an explanation of basic AI techniques to the practitioners before they explain their key business-related problems and needs. Then ask for and collect relevant contextual information that is related to the problems and needs. Summarize all information in a context map. Then structure

relevant data within user journeys before starting an ideation phase. Counseled by the AI experts, ideas to improve certain aspects within the user journeys are designed. The resulting AI use case ideas are summarized with all relevant context information and eventually prioritized.

Evaluation and use case selection

The initial business evaluation allows you to prioritize all AI use case ideas for their expected business impact. Assess the expected improvement, the alignment with business and the newness. The evaluation criteria are explained in more detail in Appendix B. You may dismiss AI use case ideas already now if the business value is not clear or the idea is not well defined. Also ask which use case ideas are highly similar and cluster them if applicable.

6.2.2 Data understanding and impact-feasibility-evaluation

The business understanding phase is followed by a data understanding phase. If applicable, combine data collection and exploration for selected use case ideas.

Data understanding phase

The data understanding phase should be guided by an AI expert together with the data scientist. Start by asking which data is required to equip the target variable of a use case idea. Identify the data sources and owners as well as the type of required data. Do the same for all assumed relevant input features and structure your findings. Then evaluate which of the required data is available and collect it. The collected data must be described first. Then it is evaluated for its quality, i.e., completeness, validity, interpretability, and accessibility (Pipino, Lee & Wang, 2002; Wang & Strong, 1996). Afterwards, the data scientist performs a data exploration to evaluate the fit of the data for the aspired analytical goal, e.g., by analyzing connections between assumed input data and the target variable if applicable.

Evaluation of impact versus feasibility

These steps allow you to assess the feasibility of your ideas especially from a data perspective. Four criteria can be used: Data availability, data quality and exploration insights, but also the project definition as a whole and the process fit can be analyzed. The data exploration insights also allow you to assess the expected business improvement in more detail. Thanks to the enhanced impact evaluation complemented with the feasibility of each use case idea, these can be mapped in an impact-feasibility-matrix (Brethenoux & Karamouzis, 2019). Follow AI use cases that are both impactful and feasible.

6.2.3 Proof of concept with full evaluation

The PoC should demonstrate the true potential of an AI-based solution from various perspectives (Davenport & Seseri, 2020): Above all, it must outline the true performance of the AI model with the currently available data. To be comparable, a minimum required performance respectively an error tolerance should be defined. We recommend to define a KPI that is tackled, e.g., cost or time parameters. As AI solutions are usually upgraded over time as more and better data is available, the PoC should address this fact. Even if the current performance is not (yet) sufficient, it may be the case in the future. Besides that, other factors should be considered (Engel, Elshan & Ebel, 2021): AI systems require a certain level of explainability and transparency (Minh, Wang & Nguyen, 2022). This may be demanded by the end users but also by law. AI specific legal restrictions have to be taken into account, e.g., the European Union (EU) is currently developing the EU AI Act which will become a mandatory legal frame for AI applications used in the EU (EU, 2023). In addition, it must be ensured that the training data but also the AI system as a whole do not violate ethical standards. This is especially true if the people, e.g., AI systems within hiring processes, or sensitive topics are concerned, e.g., large language model's replies regarding minority related topics. AI also demands relationship requirements, i.e., workflow integration (Bughin et al., 2017). The integration into the current IT architecture and existing workflows must be flawless especially for those performed by humans.

After all requirements are specified and the true performance is evaluated, decide whether to pilot and implement the use case or not.

6.3 Identifying AI use cases in the public construction management sector

We performed a case study following the process from the previous section. We served as the external AI consultant team: One project leader with two data scientists advised by one AI expert. The project aimed to identify and evaluate data AI use cases for different business user groups. PoCs should be designed for selected use cases.

6.3.1 The case study setting

The project partner was a public institution specialized in construction and real estate management projects. Its main objective is to execute construction projects on time and within budget, with the agreed quality. It consists of a headquarters and eight independent subsidiaries. The headquarters employ around 200 employees. It contains the Controlling and Development department which commissioned our project. Their tasks include monitoring and reporting for all stakeholders. In addition, they initiate development projects, e.g., they currently introduce an enterprise-wide data warehouse to enable more in-depth data analyses in the future. The organization has not used tailored AI applications nor identified AI use cases before. They also have not evaluated their AI maturity before and no AI strategy is in place. Thus, the organization is a novice concerning AI maturity and deployment (Schuster, Waidelich & Volz, 2021).

In total, the entire organization manages several hundred construction projects each year. Their monetary value adds up to around 400 million euros annually. The two main customer segments are the military sector (A) and the local state government (B) with civilian projects. Both demand strict budgeting and scheduling, wherefore the headquarters must deliver precise schedule and cost estimates. Both customer segments are directly aligned to business units within the headquarters. The latter coordinate incoming project inquiries. They first clarify key requirements, i.e., the main characteristics of the construction project. Depending on the project's location, each project is assigned to one of the eight subsidiaries. They perform the detailed design and construction planning and employ between 100-250 practitioners. At each subsidiary, 3 to 8 project managers coordinate about 10 to 30 projects each. For large construction projects, an additional project lead is instated who is working for one of the four engineering domains: Structural, civil, supply or electrical engineering.



Figure 6.3. Construction project life cycle

Figure 6.3 outlines the life cycle of a construction project. It consists of nine main phases. In the past two decades, phases after the main design phase were increasingly outsourced to external partners due to staff shortages. This leads to several issues. Employees require increased time to manage external service providers, e.g., tendering services, managing the award process and controlling the work results. Nowadays, a key business activity is to coordinate internal and external engineering staff resources. Likewise, this leads to a gradual loss of in-house expertise in the respective engineering domains. Another issue is the large number of projects that each project manager has to supervise. Time-consuming but important tasks such as risk management cannot be carried out sufficiently at all times.

We collaborated with nine groups as summarized in Table 6.2, which also includes the numerical overview of the results. For business understanding, each group either performed the top-down or the bottom-up approach. The latter was used with three groups, top-down with six. All groups conducted the data understanding phase afterwards. The groups consisted of practitioners and/or division heads (middle managers) from distinct business divisions. They all participated voluntarily at the project and were acquired by the project sponsor. For each group, we ran one half-day workshop for business understanding and another half-day workshop for the data understanding phase. Both workshops were followed by shorter follow-up meetings to specify, discuss and evaluate the results. For selected AI use cases chosen by the project sponsor, we developed the PoCs.

6.3.2 Overall case study results

In total, the groups identified 47 use case ideas. For some of them we specified AI use cases. PoCs were designed for four groups. Table 6.2 lists the business objectives of exemplary AI use case ideas. Figure 6.4 shows the impact-feasibility-matrix for each use case idea and per group.

The 20 use case ideas that resulted from the top-down approach mainly focus on predictive tasks. They would often serve customers' demands, e.g., enhance cost predictions, or improve resource allocation. Most of them were well defined and well aligned with existing business goals and processes. Data for the target variable was mostly available due to the previously collected process data. Most ideas solely aimed to improve an existing solution, so the degree of novelty was mainly low. Thereby, the vast majority of the top-down use case ideas were expected to result in an incremental improvement, e.g., for a single part within a process. After the impact and feasibility evaluation, 14 of the 20 ideas were specified as AI use cases.

With the bottom-up approach, 27 use case ideas were formulated. They covered a broader business view and mainly aimed to identify or specify cause-effect relationships and patterns that affect project success. These, if implemented, could support the determination of suited team setups or lead to new cognitive insights and better decision making. As they were not directly derived from business goals or existing processes, their business alignment and the process fit were comparably low. They were also less well defined. On the other hand, most ideas have not been addressed before. They would at times require entirely new process structures, e.g., to collect and prepare data. This makes them unsuitable for short-term pilot projects, but on average they promised greater improvements than the top-down ideas. The data understanding phase however led to the dismissal of most ideas due to a lack of available data or data quality issues. Only two ideas were specified as AI use cases in more detail. For example, we dismissed the AI use case idea shown in Table 6.2 to predict the likelihood of low-quality work, or even the cancellation or bankruptcy of external contractors. These risks are not well managed by now, thus detecting cause-effect relationships and subsequent risk assessments are strongly desired. The group inquired the idea of an AI-based cognitive assistant to provide these tasks. This would allow to initiate required countermeasures earlier on. However, there is barely any data available that would support the assumed influencing factors. Frequent changes of contact persons are not recorded nor their performances. The work results of the firms are not tracked nor is any data on their economic situation known. Without such and related criteria, the aspired cognitive insights are barely achievable.

Similar issues were found for some ideas coming from the top-down approach, e.g., for the prediction of the likelihood and volume of additional expenditures in Table 6.2. Additional expenditures are often recognized at a very late project stage as there is no automated process to detect corresponding issues. However, there is no central data pool that lists such additional expenditures. Data could at most be indirectly derived from databases that contain approved costs. This data is not linked to any information why a project caused additional expenditures, nor it got a time stamp when the need was realized and requested. Thus, it is rather unlikely to infer reliable insights.

Groups, approach		Division	AI use case idea's goal with high business priority
1.	Top-down	Headquarters division customer A	Predict annual construction costs of current and upcoming projects for next six years
2.		Headquarters division customer B	Predict deviations from planned to actual construction expenditures and provide early warning system
3.		Controlling Division (headquarters)	Predict share and monetary value of required external architectures and engineers per project
4.		Project managers customer A	Predict required staff-hours per project and detect deviations from planned to actual
5.		Project managers customer B	Predict likelihood and monetary value of additionally required construction expenditures
6.		Supply engineering	Predict required project specific staff-hours to manage external architects and engineers
7.	Bottom-up	Headquarters division customer A	Detect patterns related to order clarity affecting project progress and provide early warnings
8.		Headquarters division customer B	Predict likelihood of external risk such as low-quality work, cancellation or bankruptcy of external firms
9.		Project managers customer A	Detect the most efficient project constellations per project type and provide recommendations accordingly

Table 6.2. Exemplary goals of AI use case ideas from each group

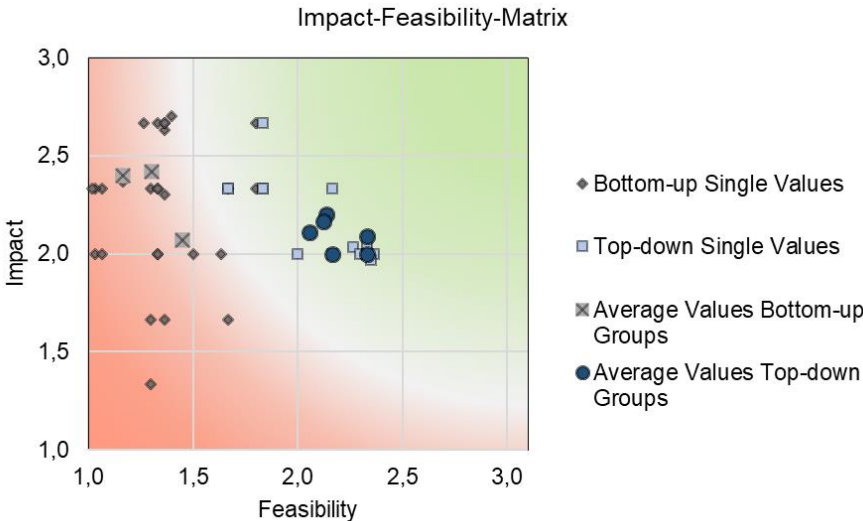


Figure 6.4. Expected business impact and feasibility of the AI use case ideas¹

¹ The feasibility criteria “data availability” and “data quality and exploration insights” are double-weighted. Some single values have been slightly increased or decreased to better detect them in the figure.

6.3.3 Development of a top-down use case: Predict annual construction costs

This section presents one use case from the top-down approach. It is a typical use case for the whole project and was suggested by three groups. It was developed until the PoC stage and is briefly summarized in Table 6.3.

During the life cycle of a project as shown in Figure 6.3, construction costs are estimated multiple times. Customers push for continuous improvements of the estimations as they need to plan internal budgets and expenses that sum up to dozens of million euros each year. In addition, the expected construction volume is an indicator for the required staff-hours of architects and engineers. Better predictions could thus aid internal staff planning. The current process to estimate projects' construction costs is sketched in Figure 6.5. The headquarters extracts all relevant information from different data sources once a year. They prepare a spreadsheet including current and upcoming projects and send it to the project managers. They then have to estimate the construction costs for up to six years for several hundred projects. This task is both time-consuming and error prone. The use case aims to (semi-)automate the predictive task. Thereby, project managers could save time and at best the estimation accuracy may be enhanced. Such predictive tasks can be supported especially by supervised ML models. As the current process is used for several years, lots of tacit knowledge about relevant influencing factors and data is in place. The goal of the use case idea is well-defined, well aligned with business and seen as valuable. The estimation accuracy can be measured, e.g., by the mean average error of the model. It can then be compared with the current human-based solution. Thus, the business evaluation calls for a promising use case idea.

The data understanding phase showed that lots of data was available in the first place. For one group, e.g., we could initially gather data records for 1,495 projects. Nevertheless, the data quality assessment and data exploration revealed serious problems. Some values for construction costs were entirely missing, e.g., for the years 2007 and 2008, while others had unrealistic data for the project progress. For one group, 380 projects were of sufficient quality. Meaningful correlations between assumed input data and the target variable were present for some project characteristics only, e.g., project size. The current data situation does not allow to cover most features that were considered to be relevant. We expected a model based on this data to only partially meet the goal of the use case. It may still save time but is unlikely to improve estimation accuracy. Due to the importance of the use case, the project partner still aimed for the PoC to test the integration and its true performance.

We tested different ML models, e.g., a random forest regressor, which however slightly missed the aspired performance of at least holding the estimation accuracy. It would save valuable time only if the results were not cross-checked afterwards. This is not yet doable so the ML model cannot yet replace the existing solution. It still promises good potential because the organization now knows which data records to maintain well in the upcoming months and years. Data acquisition processes can be updated and thus enable an enhanced solution in near future. We also designed a solution with a simpler model which would not be considered an AI model though. It learns the typical progress of the construction costs depending on project size and type. Human-based rules and estimations are added to ensure validity, e.g., no costs can occur previous to planned construction start. We used 243 ongoing projects to test the model. It scores as good as the current solution.

These results indicate that the PoCs cannot yet replace but complement the current procedure, e.g., by cross-checking it. The expected improvements on the short-term are incremental as large time-savings are not yet possible and prediction accuracy remains about the same. However, although the models are still simple and not based on high quality data, they perform (almost) as good as practitioners with long term job experience. On this basis, improving forecast quality while saving time for project managers seems achievable with increasing amount and quality of data. In the medium term, enhanced ML-based models can be introduced step by step.

Component	Description
Business case	<ul style="list-style-type: none"> • Analytics Goal: (Semi-)automate the prediction tasks for annual construction costs (target variable); preferably use a supervised ML regression model • Business goals: Save time for project managers; increase or at least hold estimation accuracy; enhance customer satisfaction • KPI: Deviation of true against predicted values (new vs. current solution) • Relevant Stakeholders: Project managers, headquarters, customers • Influencing factors: Project characteristics, e.g., size, project progress, share of external staff, commissioned construction volume, ...
Impact evaluation	<ul style="list-style-type: none"> • Expected improvement: Medium, mainly time savings aspired • Business alignment: High, serves key business goals; formulated by 3 groups • Newness: Low, replaces or complements existing solution
Data understanding	<ul style="list-style-type: none"> • Data from 1.495 projects initially available, 380 after cleansing • Data quality: Some missing data records, often implausible and invalid records • Data exploration reveals only a few significant correlations • Data outlook: More and better data very likely available for current features
Feasibility evaluation	<ul style="list-style-type: none"> • Data availability: High, lots of initial data • Data quality and exploration insights: Low, see above • Process fit: High, part of existing process (mainly step 3 in Figure 6.5) • Project definition: High, clear goals, well understood existing procedure
PoC criteria evaluation	<ul style="list-style-type: none"> • AI model: Supervised ML regressor, e.g., random forest, multiple linear regressor • Trained with 380 projects: not yet at aspired performance, but high potential • Alternative (non-AI) model: Statistical distribution model trained with 380 data records, tested on 243 ongoing projects; about as good as current solution • Explainability, transparency: Medium for random forest, high for non-AI model • Legal, ethical aspects: None with high relevance • Integration aspects: Both Tableau and Excel prototype tested for the non-AI solution; workflow remains similar to Figure 6.5, model complements or replaces step 3; aspired AI model can be integrated in a very similar manner
Summary	<ul style="list-style-type: none"> • Aspired AI solution not yet possible but with good potential on the medium term; non-AI semi-automated model possible as intermediate solution • Not yet a standalone solution, but to cross-check current procedure

Table 6.3. Summary of a top-down AI use case: Prediction of annual construction costs

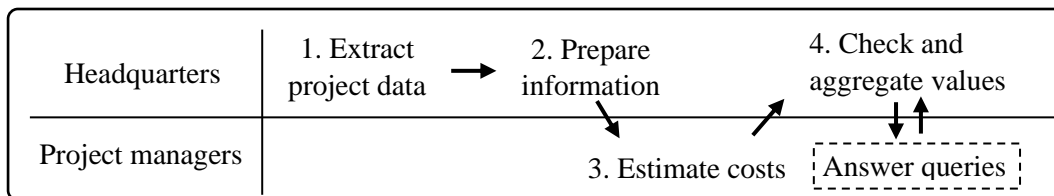


Figure 6.5. Current process to predict annual construction costs

The PoC thus gives a realistic view on the expected business impacts. To demonstrate the integration into existing IT and workflows, we created two prototypes. One was integrated into Tableau as it is already used for controlling purposes. The other was integrated into Excel via VBA as it is the tool currently used for the predictions. Regarding legal and ethical requirements, no notable restrictions were present. Considering explainability, the initial model is straightforward and thus easy to interpret. An enhanced ML-based model, e.g., using a random forest regressor, would however reduce the explainability.

6.4 Recommendations to identify AI use cases in non-tech SMEs

Our case study leads to recommendations how a non-tech medium-sized enterprise may operate to identify purposeful AI use cases.

6.4.1 Action 1: Get familiar with AI and team up with external AI experts

Before you start your AI journey, you need to get familiar with AI. For your upcoming project, set up a cooperation between external consultants and selected internal employees.

Recommendation 1.1. Get familiar with AI and expect no moon shots

Despite external support you must get familiar with AI's basics. If the knowledge gap is too big, communication and mutual understanding is endangered. Your internal project lead should thus know AI's most basic characteristics before starting the project (for a brief practice-based AI introduction, see Davenport & Ronanki, 2018; For extensive information on AI, see Russell & Norvig, 2020; For extensive information on statistical learning, see James et al., 2013). With one group we encountered the situation that a practitioner expected an ML-based system to be implemented in a few weeks only and be usable from the spot. At this stage, however, the use case was not precisely defined and the data understanding phase had not yet taken place. Even though the group stated that lots of data is available, which was true, using this data for an AI algorithm is a different challenge. Eventually, only a small portion of the data was of sufficient quality and the use case did not make it to the PoC stage. In such cases it is vital to communicate that better data and features are required in future to enable AI's possibilities. Non-tech organizations indeed tend to have unrealistic expectations about AI and its demands (Sandkuhl, 2019). Thus, ensure to communicate AI's potentials as well as the project goals in a realistic manner. This includes no groundbreaking impacts in the beginning, but rather several promising use case ideas and lots of new knowledge on available data, its quality and suitability for AI solutions. On the short-term, expect incremental impacts at most. This also requires explaining that the project is part of the overarching digital transformation process, as AI is not a standalone technology. The goal is to foster a long-term transition to AI-supported products, decisions and processes.

Recommendation 1.2. Engage external AI experts and required employees

To identify AI use cases, team up internal business domain experts with AI experts and data scientists. For a low cost and scalable project, we recommend engaging external consultants who are at best familiar with your business domain. Consider also contacting research institutions. Before you consult external AI experts, decide which internal resources you want to engage. First, include business division leaders or middle managers respectively. They form the link to top management, know about key business goals and should join the top-down approach. They also know which employees are suited to join, i.e., who administer processes, products or decisions but also advocate change projects. Better start with fewer groups and define a fixed period of time to ensure predictability of cost and time. We started with a one-year cooperation which was prolonged for another one and a quarter year after promising results came up. Set up the cooperation with the goal to define and evaluate AI use cases. You can incorporate PoCs for selected AI use cases as an additional project goal. If you found purposeful AI use cases, consider engaging other AI experts or vendors that have worked on similar use cases before.

Ensure to identify other key stakeholders knowing about available data early on. Data quality and the suitability of available data for the use cases at hand were the main limitations for our case study. Make sure to include data owners, data architects and data engineers whenever required. They may have to introduce new data collection as well as preparation standards and procedures to enable your aspired AI use cases. In our case study, we formulated which data was of decent quality and recommended to introduce new standards accordingly. Also ensure data staff's commitment. In our case, one employee alone managed the largest data pool we used, which at times caused delays. Identify further bottlenecks and clearly communicate your requirements. Include your internal IT staff for the PoC. They are required for the sound incorporation of the AI model into existing workflows.

6.4.2 Action 2: Select your approach and let your project and AI ideas evolve

Start the project by selecting the preferred approach. Then let your AI ideas evolve and do not hesitate to start with non-AI solutions.

Recommendation 2.1. Apply top-down for feasible, bottom-up for innovative ideas

To identify purposeful AI use case ideas with better feasibility, apply the top-down approach. It ensures high business alignment and that the underlying business problems are well known and data has likely been collected before. The ideas may not address entirely new problem domains, thus expect top-down ideas to mainly promise incremental improvements for existing business. Due to its narrow business view, you may miss more innovative ideas. If you aim for them, also apply the bottom-up approach.

If you apply both approaches, perform the bottom-up approach first. Involve selected employees and broadly explore their business environment and business-related challenges. Derive AI-enabled solutions with the help of your consultants. To evaluate them but also to find additional ideas, perform the top-down approach. The strategy map is well suited to critically assess business alignment and process fit of each idea. In our case study, the use case ideas with high business alignment and process fit were not only more feasible, but also preferred by the top management.

To save both time and money, prepare information beforehand that is certainly required: For the top-down approach, preselect the most relevant business goals and processes on your own. Equip them with KPIs and sketch the information that is used and generated throughout your processes. Present a summary to your consultants and start to discuss touching points for AI enabled improvements. For the bottom-up approach, we propose a more open procedure, where no information is prepared in advance. Thus, top-down would be more time and cost efficient. As it also led to more feasible results, the business units that joined our project last all used the top-down approach only.

Recommendation 2.2. Let your AI ideas evolve: Consider also non-AI solutions

Many use case ideas might be similar or overlap in certain aspects. Identify such similarities and combine use cases whenever applicable. Consequently, the same data sources are often relevant to many use cases. This allows you to cluster several use case ideas which, e.g., shrinks the effort for the data understanding tasks.

Also be prepared to let your use case ideas evolve. Some may be shelved, others may be adjusted due to new insights, e.g., after collecting and analyzing required data. If not enough high quality data is available, consider to start with a simpler solution at first. Our exemplary AI use case to predict the annual construction costs showed that an AI use case may first be tackled with an intermediate non-AI solution. Indeed, AI often replaces existing data-driven solutions by delivering a superior algorithm (Chui et al., 2018). However, if a current business solution is not yet digitalized nor automated, directly introducing AI could be one step too early. If sufficient data is not (yet) available as well, do not be afraid to start with a non-AI solution whilst already formulating the AI related requirements. Begin to adapt data collection and processing steps that are required for the aspired AI enabled solution. This way, you already set up important infrastructure. During the next months or maybe years, superior AI algorithms can replace the previous solution.

6.4.3 Action 3: Choose suitable AI flagship projects and frame AI as a co-worker

You might identify several ideas for AI use cases but only few will be feasible. Choose the right ones and foster user engagement by communicating AI as a valuable co-worker.

Recommendation 3.1. Select and focus on the right projects

As it is not difficult to define several ideas for AI use cases in the beginning, you could easily end up with dozens at the end. The real challenge is to sense which ideas are feasible, but also preferred by both end users and top management. Hence, discard unfeasible ideas as early as possible. Choose the first AI

pilot projects wisely: At best, look out for existing data-driven and/or semi-automated solutions that can be enhanced using AI techniques. To do so, after business understanding, first prioritize AI use cases that are closely aligned to existing business processes whilst promising a decent improvement. Second, during the data understanding phase, prioritize the use cases for their available data. Especially data for the target variable and the most important assumed input data should be available. The third step is to assess the use cases for the insights from the data exploration. Prioritize the ideas according to data quality insights and whether promising correlations between target and input data can be found. To do the latter, we would often create a small dataset with high quality data in order to perform an initial data exploration. If we found promising insights, it is worth collecting and preparing more data. This is especially relevant if lots of data is available but has never been used or prepared for a data-driven software solution. The adequacy of the available data for the underlying business goal and potential AI algorithm is key. After these main evaluation steps, choose the most promising use case(s) for the PoC stage.

Recommendation 3.2. Communicate AI as a valuable co-worker

To ensure end user acceptance, clearly explain AI's role. Most AI use cases aim to support or automate existing processes which was also true in our case study. Thereby, we emphasized that the use cases aim to support, but never to replace the end users. In fact, this was common ground for almost all use case ideas. As some construction projects and situations are quite special and rare, the practitioners would not expect an AI-based system to replace them entirely. They instead hoped for automated support regarding their day-to-day tasks and for the "typical" construction project. We emphasized AI's potential to become their co-worker which they highly corresponded with. Consequently, all groups showed great engagement in creating "their" co-workers.

We also recommend you communicate AI as a valuable co-worker who can very well support you. Otherwise, you risk an AI solution to be rejected. For example, if a well performing AI-based system assists physicians' documentation tasks, they will likely accept it. But if the system entirely replaces their anamnesis and medication tasks, they reject it as they fear being replaced but also liability for wrong decisions made by the AI system. Nevertheless, it is true that AI has replaced jobs by now. You may consider this aspect for your AI use cases as an ethical requirement. Evaluate if an aspired solution leads to AI being the co-worker or the job killer. If it's the latter, consider whether such a use case should really be piloted first.

6.5 Concluding comments

AI promises tremendous business potentials but is especially complicated to adopt within non-tech SMEs. If you neither have the sufficient in-house expertise nor large financial resources, how should you start AI adoption? We recommend certain actions to identify and evaluate AI use cases that were tested in a real-world case study. You should at first get familiar with the very basics of AI as a technology. To analyze the potentials AI offers to your business sector, hire external partners for initial support, i.e., at least an AI expert and a data scientist. In parallel, select internal business units and employees that are willing to participate at a research and development project. Include the division heads respectively middle managers. Communicate the project goal being the development of purposeful AI use cases aiming to support existing and future business challenges. Select the approach that is suited for you: Top-down for more feasible, and/or bottom-up for more innovative ideas. Be prepared to dismiss lots of initial ideas and make sure to follow the most promising ideas.

However, do not expect moon shots and disruptive changes all over. The reality may not even be a single implemented AI solution after a year. Expect data related issues to restrict the short-term potentials. Thus, keep in mind that AI adoption is a part of the long-term digital transformation process. Your knowledge about AI and its opportunities to support your business will continuously increase even if initial AI use cases do not deliver immediate impact. As soon as the first AI use cases are successful, gradually scale up your portfolio with more complex AI projects.

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6.6 Appendix

Appendix A

Procedural recommendations

In order to design and evaluate AI use cases until the proof of concept stage, you can follow the procedures presented in this Appendix. The proposed roles represent the minimum that is required. You may integrate additional experts that you consider necessary for certain activities. The top-down, user-centered and data understanding approaches are adopted from Brunnbauer, Piller & Rothlauf (2021, 2022).

Top-down approach

The top-down approach requires the involvement of business division leaders, e.g., middle managers, who are familiar with the overall business goals and processes. They select business domain experts, usually from their staff, who administer important processes, tasks, decisions, products and who at best support change projects. AI experts are required to derive AI use case ideas. The top-down approach includes five key activities that guide a business unit step by step. For a low-cost approach, you can prepare activities 1-3 in detail on your own and only include consultants from activity 4 on.

Activities	Output	Instructions	Roles
(1) Understand business unit's goals	• Strategy map	<ul style="list-style-type: none"> • Explain project goals and potential benefits to business unit • Identify and discuss business unit's strategic and operative goals, KPIs and related challenges • Structure, link and prioritize goals 	<ul style="list-style-type: none"> • Project lead • Middle manager • Domain experts
(2) Identify relevant processes	• Processes within strategy map	<ul style="list-style-type: none"> • Identify relevant business processes for goals with high priority • Map processes to the strategy map and add KPIs to them • Prioritize processes from business perspective 	<ul style="list-style-type: none"> • Middle manager • Domain experts
(3) Specify tasks and decision points	• Detailed process models	<ul style="list-style-type: none"> • Analyze and model the prioritized processes • Record information and data needed and generated throughout the processes • Specify data-driven decision points, process steps tasks and outputs 	<ul style="list-style-type: none"> • Middle manager • Domain experts • (AI experts)
(4) Derive AI use case ideas	• Initial AI use case ideas	<ul style="list-style-type: none"> • Identify tasks or decisions to be improved by AI solutions • Derive initial AI use case ideas including target variables • Collect and map relevant influencing factors 	<ul style="list-style-type: none"> • AI experts • Middle Manager • Domain experts
(5) Prioritize AI use case ideas	• Prioritized AI use case ideas	<ul style="list-style-type: none"> • Specify use case ideas: Goal and objective, target, influences • Summarize, structure and compare use case ideas • Prioritize them for expected business impact 	<ul style="list-style-type: none"> • Middle manager • Domain and AI experts • Project lead

Table 6.4. Top-down approach to identify AI use case ideas

Bottom-up approach

The bottom-up approach requires selected employees with deep business domain knowledge and long-time job experience. You can, but do not have to involve middle managers. Consult an AI expert who is familiar with user-centered ideation, e.g., design thinking (DT) or an additional expert for this purpose. Different to the top-down approach, the consultant(s) should join from the very start. They already explain the most basic AI techniques to your business domain experts in the first step and are deeply involved in the user-centered approach. The bottom-up approach comprises five key activities.

Activities	Output	Instructions	Roles
(1) Emphasize and define	<ul style="list-style-type: none"> •Needs overview •Design challenge 	<ul style="list-style-type: none"> •Explain project goals and potential benefits to business unit •Explain basic AI techniques and potentials to business users •Ask for business users' key needs and challenges and capture them •Derive and discuss the design challenge 	<ul style="list-style-type: none"> •Project lead •AI (and DT) expert •Domain experts
(2) Observe needs and influences	<ul style="list-style-type: none"> •Specified user needs •Context map 	<ul style="list-style-type: none"> •Interview practitioners about needs, tasks and related challenges •Identify relevant internal and external influencing factors •Structure user needs and influencing factors in a context map 	<ul style="list-style-type: none"> •AI (and DT) expert •Domain experts
(3) Define personas and user journeys	<ul style="list-style-type: none"> •Personas •User journeys 	<ul style="list-style-type: none"> •Select and describe personas by specifying user needs and tasks (and/or) •Describe typical user journeys including tasks, user needs and relevant influences 	<ul style="list-style-type: none"> •Domain experts •AI (and DT) expert
(4) Generate AI use case ideas	<ul style="list-style-type: none"> •Initial AI use case ideas 	<ul style="list-style-type: none"> •Define brainstorming questions addressing user needs and tasks •Generate AI-enabled solution ideas •Define target variables and add relevant influencing factors •Cluster ideas to derive initial use case ideas 	<ul style="list-style-type: none"> •AI (and DT) expert •Domain experts
(5) Prioritize AI use case ideas	<ul style="list-style-type: none"> •Prioritized AI use case ideas 	<ul style="list-style-type: none"> •Specify use case ideas: Analytics goal and business objective, target variable, influences •Summarize, structure and compare use case ideas •Prioritize them for expected business impact 	<ul style="list-style-type: none"> •Middle managers •Domain and AI/DT expert •Project lead

Table 6.5. User-centered bottom-up approach to identify AI use case ideas

Data understanding phase and evaluation

After identifying business driven AI use cases, these must be further specified with the most important requirement: data. Consider to cluster ideas that are very similar as they may require similar data sources and data exploration steps. Preferably start with the use case ideas with the highest business prioritization. Then follow the instructions. You have to identify relevant data owners and potentially involved data engineers. Include them as they are key stakeholders for the project. The data understanding phase leads to an assessment towards available data as well as its quality and suitability for the use case ideas.

To assess whether to proceed a use case and design the PoC, focus on the expected business impact and the feasibility. All criteria are explained in Appendix B in more detail.

Activities	Output	Instructions	Roles
(1) Collect required data	<ul style="list-style-type: none"> •Data maps •Collected data 	<ul style="list-style-type: none"> •Derive and define required data •Identify data owners and data sources •Map, structure and collect required data •Define proxies for missing data if possible 	<ul style="list-style-type: none"> •Data owners + scientists •AI expert
(2) Assess data quality	<ul style="list-style-type: none"> •Data quality assessment 	<ul style="list-style-type: none"> •Describe data on meta-level and for statistical properties •Define requirements on collected data •Assess and verify data quality •Prioritize ideas from data quality perspective 	<ul style="list-style-type: none"> •Data scientists •AI expert
(3) Explore available data	<ul style="list-style-type: none"> •Data exploration insights •Feasibility from data perspective 	<ul style="list-style-type: none"> •Perform data exploration on target and influencing variables •Observe correlations and connections and perform initial tests for suitable AI techniques with selected data •Determine feasibility and prioritize ideas 	<ul style="list-style-type: none"> •Data scientists •AI expert
(4) Formulate and evaluate AI use cases	<ul style="list-style-type: none"> •AI use case portfolio •Impact-feasibility-ratings 	<ul style="list-style-type: none"> •Summarize and specify AI use cases •Specify feasibility and impact evaluation •Assign use cases to impact-feasibility matrix •Present the results and select impactful and feasible AI use case(s) for the PoC 	<ul style="list-style-type: none"> •AI expert •Domain experts •Project lead

Table 6.6. Data understanding phase to specify AI use cases and assess feasibility

Proof of concept with full evaluation

The proof of concept should demonstrate the potential of an AI-based solution from various perspectives. It allows to assess the true performance and major constrains of the use case. These criteria are also explained in Appendix B. The main activities are summarized in Table 6.7.

Activities	Output	Instructions	Roles
(1) Specify requirements	<ul style="list-style-type: none"> •Requirements for the PoC 	<ul style="list-style-type: none"> •Specify requirements: Required performance, error tolerance, transparency, explainability, legal and ethical aspects, IT and data integration, workflow integration •Identify and integrate required stakeholders 	<ul style="list-style-type: none"> •AI expert •Domain and IT experts •End user
(2) Specify AI solution ideas	<ul style="list-style-type: none"> •Potential AI solutions and algorithms 	<ul style="list-style-type: none"> •Derive potential AI-based solutions •Define the required algorithms and their accordance with aforesaid requirements 	<ul style="list-style-type: none"> •AI expert •Data scientists
(3) Compile dataset and test AI model	<ul style="list-style-type: none"> •Use case specific datasets •AI model results (Analytics view) 	<ul style="list-style-type: none"> •Define amount and quality of required data •Collect, assemble and prepare the data •Iteratively design and evaluate the AI model •Summarize the findings in an Analytics view 	<ul style="list-style-type: none"> •Data owners + scientists •AI expert
(4) Evaluate and present proof of concept	<ul style="list-style-type: none"> •PoC with complete evaluation 	<ul style="list-style-type: none"> •Evaluate business impact with current data •Evaluate the fit with other requirements •Present the results and decide whether the use case should be piloted 	<ul style="list-style-type: none"> •AI expert •Domain experts •Project lead

Table 6.7. AI proof of concept for a full evaluation

Appendix B

Evaluation criteria

The approach differs three evaluation steps. First, a business impact evaluation that is mainly informed by the results from the business understanding phase is conducted. Second, the feasibility evaluation follows which is mainly informed by the data understanding phase and in part by business understanding. Third, the proof of concept criteria are defined and assessed that allow for an extensive assessment of the use case.

For each criterion of the business impact and feasibility evaluation, a Likert-scale can be applied. For example, we applied a 3-point Likert-scale with qualitative ratings of “High,” “Medium” and “Low”. You may change the weights for each criterion according to your preferences, e.g., regarding data aspects. In Figure 6.4, we doubled the weight for the “data availability” and “data quality and exploration insights”.

Expected business impact and feasibility (business and data understanding)

The evaluation criteria to assess the expected business impact and the feasibility are summarized in Table 6.8. It includes a brief description and the roles that should preferably conduct the evaluation.

	Criterion	Description	Evaluated by
Business impact	Alignment with business	Alignment of use case idea’s goal to organization’s strategy and goals	AI project lead, top management
	Expected improvement	Expected value addition if the use case idea can be realized	AI project lead, domain experts
	Newness	Novelty of the use case idea in comparison to existing solutions	AI project lead, domain experts
Feasibility	Process fit	Alignment of the use case idea with existing business processes	AI project lead, AI expert
	Project goal definition	Clarity about use case idea’s objective, input parameters and relevant context information	AI project lead, AI expert
	Data availability	Availability of data for target variables, input parameters and context information	AI project lead, data scientists
	Data quality and exploration insights	Adequacy of available data for the aspired AI enabled solution	AI project lead, AI expert, data scientists

Table 6.8. Evaluation criteria to assess the expected business impact and the feasibility

For the expected business impact, the “alignment with business” of each use case idea is evaluated first. It is defined as “the congruence of the artifact with the organization and its strategy” (Prat, Comyn-Wattiau & Akoka 2015). The business goals defined in the strategy map are used to assess whether a use case idea is aligned with existing business. If there is a direct and positive link to a clearly defined business goal, a high rating is assigned. If there is an indirect but positive effect, a medium rating is assigned. If no positive effect is assumed, a low rating is assigned. Additionally, the “expected improvement” of a use case idea is evaluated. The business domain experts discuss the expected improvement with the project lead. If a use case idea does not add value, a low rating is assigned. If business is expected to be slightly improved, e.g., enhancing a current solution, a process, a decision, or part of an offering, a medium rating is assigned. It represents an assumed incremental improvement. If a large improvement is expected, e.g., a completely new solution is aspired, an entire process or process segment, a high rating is given. It represents a major, potentially disruptive improvement. The final

criterion to evaluate the business impact is “newness”. It evaluates whether the objective of a use case is already covered by a current solution. If no such solution exists, a high score is assigned. If a use case aims to improve or replace an existing solution, a low rating is assigned. A medium rating is assigned if a similar solution for a similar purpose has at least been discussed or tested.

Next, four criteria to assess the feasibility of a use case idea are used. Since incomplete or inaccurate project definition is a key risk factor for project failure (Sweis, 2015), the first criterion, “project goal definition”, assesses an important part of the project scope. Each identified use case idea is evaluated on the clarity of the use case idea’s objective, as well as key target and input parameters and contextual information. To receive a high rating, all criteria must be well defined. A low rating is assigned if the goal cannot be defined precisely. If the goal can be well defined but other relevant factors cannot, a medium rating is assigned. The compatibility with existing business processes, i.e., the “process fit” of the targeted AI use case, is evaluated. If a use case idea is related to existing processes or can even be integrated into them, a high rating is assigned. A medium rating is assigned if it is partially related to existing processes. A low rating is assigned if no existing process can be linked to it. The last two evaluation criteria deal with data. First, “data availability” assesses if most of the required data is available, especially for the target variables. If this is the case and also for the assumed influencing factors, a high rating is assigned. If data is missing for some relevant contextual information or influencing factors, a medium rating is assigned. If the target variables cannot be well supplied with data, a low rating is assigned. The criterion “data quality and exploration insights” analyzes the available data and asks whether it is suitable for the aspired AI solution. Data quality comprises the main criteria completeness, validity, interpretability and accessibility. The data exploration should determine basic statistical properties of available data and connections between the target variable and assumed input data. This may require a detailed the analysis of small, selected datasets. If both data quality and exploration insights are promising, a high rating can be assigned. If one reveals notable issues, a medium rating is assigned. If both reveal notable issues, a low rating is assigned.

Proof of concept evaluation criteria

The PoC criteria define more detailed requirements towards the AI use case and are summarized in Table 6.9.

PoC criterion	Description	Specified by
AI model	Describes the required data preparation steps and the AI and/or ML algorithms	AI project lead, AI expert, data scientist
Real business impact	Real improvement with current data for each AI model and dataset	AI model, AI project lead
Minimum performance and/or error tolerance	Defines the minimum performance the end users expect from the solution	End users, domain experts, AI project lead
Explainability and transparency	Defines how well the model’s results can be explained and whether the model is transparent (inputs, outputs, training process, biases)	AI project lead, AI expert
Legal and ethical aspects	Defines legal and ethical boundaries that must be considered	AI project lead, AI expert
IT and data integration	Defines which data and IT aspects must be altered for the AI model to work	Data scientists, IT, AI project lead
Workflow integration	Defines how the AI model will be fit into (existing) working processes	End users, domain experts, IT, AI project lead

Table 6.9. Proof of concept criteria for a full evaluation

This comprises an AI model that is fed with currently available data to assess the true business impact. Its performance must be compared with the minimum required performance (Davenport & Seseri, 2020) respectively the error tolerance. These must be specified by the business domain experts or the end users. However, the AI experts should be included to set realistic targets. The PoC must also consider further AI specific aspects (Engel, Elshan & Ebel, 2021): Explainability and transparency (Haresamudram, Larsson & Heintz, 2023) requirements must be specified to confront AI's black box character. Legal and ethical aspects must also be considered, especially if the AI use case concerns the people or sensitive topics (Felzmann et al., 2019). In addition, AI solutions are usually embedded within existing workflows (Salwei & Carayon, 2022), wherefore the process fit can be assessed beforehand. For the PoC, requirements for IT and data integration should be formulated. From an employee or customer perspective, the integration into their existing working processes should be defined.

7 Summary and conclusion

7.1 Results

The results of the dissertation are summarized according to the five research papers in Chapter 2-6 and their contribution to the overarching goal of the dissertation which asked:

How should a small or medium-sized organization with no experience in AI approach the identification and evaluation of AI use cases?

RQ 1: *Which procedure model is useful to guide the identification and evaluation of AI use cases?*

Because AI is a data-driven technology, methodologies from related technologies can be adapted. The paper presented in Chapter 2 extends the CRISP-DM phases business understanding and data understanding that define the underlying use case. The paper identified two main strategies for the business understanding phase to identify AI use case ideas:

- Systematic top-down approach
- Explorative user-centered approach (bottom-up)

The systematic top-down approach analyzes an organization or a business unit from its strategic goals down to operative business goals and combines them with the relevant business processes. Key business goals and business processes are analyzed in more detail. The aim is to identify decision points, tasks, process steps or process outcomes that could potentially be enhanced by AI enabled solutions. The second strategy is a user-centered explorative approach with a bottom-up character. It involves specific business users, i.e., employees who manage relevant products, tasks or decisions, who explain their key business-related challenges. The relevant influencing factors are identified and summarized in a context map before a user journey structures all relevant aspects, e.g., user tasks, influencing factors, challenges, touchpoints and needs. An ideation phase is then used to identify AI enabled solutions that support or enhance specific aspects within the user journey.

Once the AI use case ideas have been identified, they are evaluated before the data understanding phase begins. In this phase, the required data is specified and the data that is (not) available is collected and noted. Next, the data quality is assessed and a data exploration is performed. Both aspects are relevant for the evaluation of the AI use case. The paper proposes a detailed procedure model that includes the two strategies for business understanding and the data understanding phase. It covers detailed activities, instructions, potential tools, the required roles and the outputs that are created.

In summary, the paper proposed the overarching framework and subsequently the procedure model for the business and data understanding phases which needs to be further evaluated. Two strategies for business understanding were distinguished, top-down and explorative user-centered (bottom-up), and equipped with detailed instructions, techniques, tools and roles.

RQ 2: *What is the effectiveness of the top-down and explorative user-centered approaches to identify and evaluate AI use cases?*

The paper presented in Chapter 3 builds on the procedure model of the first paper. In the case study, four groups completed the top-down approach and three groups completed the user-centered bottom-up approach, followed by the data understanding phase. For a thorough evaluation, the paper proposes an evaluation framework to assess the effectiveness of the procedure model to identify AI use cases. This comprises the alignment with business and richness of influencing factors to assess the results from business understanding, data availability and the feasibility from data perspective to assess the results from data understanding. In addition, for each individual AI use case, the alignment with AI and newness can be evaluated.

The explorative user-centered approach found a lot more ideas for AI use cases but resulted in only two AI use cases. By broadly identifying relevant business user challenges and associated influencing factors, a tremendous number of ideas for AI use cases could be derived. However, most of them were not aligned with existing processes and data. As such, the feasibility from a data perspective was very low so it was not advantageous to specify the AI use cases for these ideas. Nevertheless, these AI use cases would have had a high alignment with AI and a high newness, as they require entirely new solution ideas using modern AI technologies.

The top-down approach instead found fewer AI use case ideas, but they were better defined and aligned with business. Because they were derived from existing business goals and processes, the ideas were not entirely new and aimed to improve existing business process instances. They tended to come with a lot of data so their feasibility was rated higher on average. They also had comparably small but realistic scopes. On the other hand, some would not necessarily require modern AI techniques but may be adequately addressed by traditional data analytics techniques.

In summary, the paper proposed a thorough evaluation framework and identified key differences between the results of the top-down and user-centered bottom-up approaches, i.e., the resulting number, types and characteristics of AI use case ideas and the actual AI use cases they lead to. The top-down approach led to more feasible use cases, while the explorative bottom-up approach allowed to analyze broader business contexts and thus led to more ideas with larger scopes.

RQ 3: Which short-term and long-term business improvements are to be expected from the identification of AI use cases?

The paper presented in Chapter 4 looks at the practical implications for an organization when introducing AI, in particular the level of business improvements to be expected and the short-term versus long-term feasibility. To do so, the paper used an evaluation framework to score the added value (evaluated by the alignment with business, the expected improvement and the newness) against the feasibility (evaluated by the data availability, the process fit and the project goal definition) for each AI use case idea that was identified when applying the top-down or the user-centered bottom-up approach.

The top-down approach has identified AI use cases that seem more feasible in the short-term but do not offer disruptive business improvements. They typically aim to enhance or optimize an existing decision or task. The advantage is the presence of required data and a thorough understanding of the current solution. The bottom-up approach instead allows for the identification of more disruptive AI use case ideas with a greater expected improvement if they were to be implemented. However, they require significant upfront effort: Past data would often need to be collected in great amount, converted from non-digitized to digitized formats and labeled with immense human efforts. To do this more effectively in the future, new data collection and processing standards would be required.

An organization new to AI may want to avoid such immense side efforts at first. Instead, the paper recommends focusing on the more feasible AI projects with a narrower scope. The case study clearly showed that such use cases are preferable which is also well in line with previous literature. However, even if promising AI use cases are found, the short-term benefits are likely to be incremental. This is due to the small scope of the top-down use case ideas but also to the limitations due to the small amount of high-quality data. Nevertheless, the top-down approach promises greater chances to gain early improvements with small-scaled AI solutions. However, if an organization also wants to identify the AI use cases that have more disruptive potential, the bottom-up approach can also be taken.

In summary, the paper differentiated the practical implications of using the top-down or user-centered bottom-up approach and explains when to use which approach. For an organization new to AI, significant short-term impacts are not to be expected. The top-down approach however promises incremental impacts on the short to medium term by improving upon existing business processes. It is preferable for an organization new to AI, although the user-centered bottom-up approach can well be used to analyze the broader business environment and identify various AI use case ideas first.

RQ 4: *Which modeling techniques are useful to support the identification of AI use cases and how to apply them efficiently in a practical setting?*

The paper presented in Chapter 5 deals with the identification and evaluation of AI use cases from a modeling perspective. It includes the results and insights from the entire case study including the PoC phase. The paper proposes two useful modeling techniques for both the top-down approach and the user-centered bottom-up approach. In addition, a meta model for the business understanding phase is presented that includes the main entities that must be created. The same is done for the data understanding phase and the analytics (PoC) phase, where one modeling technique is presented for each. For all models, real illustrations from the case study are presented to help the reader visualize how to put them into practice.

To support the top-down approach, well-known business concepts can be applied. The strategy map helps to model business goals and relate them to relevant processes. The latter can be analyzed in detail using techniques such as BPMN models which help to specify tasks, decisions and process outcomes that are data-driven and could potentially be addressed by AI techniques. To support the user-centered strategy, context maps are used to capture relevant influencing factors that address the whole working environment of the business users. These factors are incorporated into one or more user journeys that summarize the business users' key tasks, related needs, touchpoints, challenges and the influencing factors. This is the basis for deriving potential AI enabled solution ideas that affect aspects within the user journeys. The data understanding phase can be supported by a data map that summarizes the available data with brief descriptions and models the main data processing steps required to design the use case specific dataset. The analytics phase can be supported by a model that summarizes potential AI techniques and maps their main results with respect to the PoC criteria.

Especially the models supporting the business understanding phase proved to be very useful. For this phase, effectiveness is key as new potentially AI enabled ideas need to be generated. The models supported the definition of ideas for AI use cases very well, resulting in a wide range of ideas. In particular, the strategy map is well suited to determine the strategic fit of each AI use case and to define relevant key performance indicators. Together with the process models, it helps to define AI use cases with a small but well-defined scope. The data understanding and analytics phases can be partially supported by modeling techniques. Efficiency is key as these phases do not generate new ideas but rather assess whether and how the AI use case ideas could be realized. The models are mainly useful for communicating the required process steps and desired results, but also for capturing the key results.

In summary, the paper specified the modeling techniques that support each phase of the procedure model and provides practitioners with real-world examples. The models supporting the business understanding phase are very helpful to support the identification of AI use case ideas, especially the ones for the top-down approach as they are well-known business concepts. The models supporting the data and analytics phases mainly help to communicate the procedure steps and to store and present the main results.

RQ 5: *How should a non-tech medium-sized enterprise with no AI-related experience start the AI adoption process?*

The paper presented in Chapter 6 is based on the full results of the real-world case study and thus nine business user groups. It is aimed at practitioners and IS managers in organizations that are new to AI. In particular, the paper emphasizes the constraints often faced by small and medium-sized non-tech organizations, such as financial and staff restrictions, that hinder the adoption of AI. The paper first explains relevant AI readiness factors and how an AI project is conducted. It then presents selected findings from the real-world case study that illustrate the real-world complexities of introducing AI into such an organizational setting. The paper explains common difficulties that limit immediate business impact of AI projects. Most notably, the small amount of available and especially high-quality data as well as false expectations and assumptions about AI are relevant factors. These reasons are highlighted by following an AI use case from the business case identification up to the proof of concept phase.

The paper concludes with six recommendations to practice. It urges the project sponsor's person in charge to get familiar with the basics of AI first and to set realistic expectations when beginning to introduce AI. The first months or potentially even years may not result in implemented AI systems, but rather in many promising ideas and several new insights into data-related issues. These issues must be acknowledged to communicate the project goals in a realistic way. The paper recommends engaging with external AI experts. Establishing a cooperation for a fixed period of time is preferable to ensure predictability of time and costs. If purposeful AI use cases emerge, new projects or cooperations could be launched accordingly. From the internal perspective of an organization, engaging middle managers is required for the top-down approach. They know about the strategic business goals, the day-to-day operations and the employees who are suited to join the top-down or user-centered bottom-up approach. If an organization also wants to take the latter, selected employees who advocate change projects should be included. The paper then explains to apply the top-down approach for more feasible, and the user-centered bottom-up approach for more innovative ideas. The paper recommends focusing on the ultimate business improvements, rather than the technology used to achieve it. As such, some use cases may be solved with data-driven technologies that are not considered AI. In addition, if a current solution is neither automated nor digitized, it may be a step too early to directly introduce AI. In such cases, it may be beneficial to first implement simpler solutions while building the infrastructure for the desired AI solution. The paper then explains which evaluation criteria are most critical for finding suitable AI use cases, namely process fit, available data, and the insights from data quality assessment and data exploration. Finally, the paper explains how to best communicate the project to the employees, focusing on AI's potential to provide great support in automating mundane routines but potentially also supporting knowledge-intensive processes. In this way, AI can become an intelligent co-worker saving employees valuable time so that they can focus on their most important tasks.

In summary, the paper proposed several practical recommendations for a non-tech SME that wants to identify AI use cases but faces limitations in AI knowledge, staff and financial resources. The paper extended the previously presented procedure model with the proof of concept phase and the evaluation criteria. The complete procedure model is presented in detail in the Appendix to Chapter 6.

7.2 Discussion

The results of this dissertation provide insights into different approaches aimed at introducing AI use cases to a non-tech SME and point out the associated complexities and limitations. Differentiating two strategies for business understanding can be beneficial. On the one hand, the typical AI success story proved to be an improvement of existing processes. The case study revealed several reasons why this is the case, i.e., proximity to existing processes ensures data availability, but also an understanding of the current solution that helps to specify the desired AI-enabled solution. In addition, it is quite possible to define the scope of an AI use case that targets specific improvements within existing processes or operations. On the other hand, AI can lead to disruptive changes by enabling use cases that offer entirely new strategies to tackle business problems. These may require more innovative solutions that do not replace or improve upon current practices. However, such use cases may raise additional issues as they often require entirely new structures regarding data, human and IT workflows. For an organization, both types of AI use cases seem interesting: Some that offer incremental, but quick improvements within existing business, others that promise more disruptive improvements but only on the medium to long term. To identify different types of AI use cases and evaluating them against such criteria, this dissertation assessed two distinct approaches to identify AI use cases from different perspectives.

The top-down approach led to AI use case ideas that were mainly aimed at improving existing process instances, e.g., enhancing the prediction of required staff hours for certain project phases. There was little variation among the top-down use case ideas which undermines the limited but focused scope of the top-down approach. Different user groups sometimes identified roughly the same use case ideas. This is likely due to the hierarchical structure of the top-down approach which first requires the formulation of relevant business goals and then asks for existing business processes. This ensures a

concise approach but may overlook other relevant business aspects. As such, the top-down approach covers only a portion of an organization's overall business environment, mainly the internal perspective. For an organization where internal operations are key, this limitation would be less significant. For example, for business sectors such as logistics, manufacturing and heavy industries, efficient operations are key. They regularly analyze their existing operations in detail and try to identify even marginal improvements enabled by new technologies. The top-down approach proposed in this dissertation would allow them to find small scaled but realistic ideas to gradually include AI in their operations. In the case study, the focal organization had the key goal to improve its internal operations to become more efficient in handling its core business. This meant that speeding up or (semi-)automating routine tasks would be highly desirable. This allowed to identify several promising AI use cases for the construction and real estate management organization with the top-down approach.

On the other hand, if the core business requires knowledge intense work that rarely follows repetitive patterns, one may not profit from the top-down approach in the same way. In the case study, project managers were faced with both routine and highly knowledge intensive tasks. These ranged from simple tasks such as resource planning for a barracks renovation up to complicated tasks such as coordinating dozens of external architects and engineers, surveyors, and construction companies building a new nuclear research facility. The top-down approach mainly addressed the simple tasks such as forecasting required staff hours but not the more complex business problems. This raises the question of whether the user-centered bottom-up approach would be more helpful for those types of problems and thus for organizations in knowledge intense domains. Since the user-centered approach asks for the key challenges and relevant influencing factors faced by the employees, it results in significantly different ideas for AI use cases than the top-down approach. For the project managers, e.g., the user-centered approach yielded several ideas with a larger scope but also complexity: They found the idea of predicting and classifying underperformance of contracted architects and engineers or construction companies. This would allow countermeasures to be taken earlier in case a contractor was to breach the contractually agreed targets. However, "underperformance" is currently not uniformly defined and has not yet been quantified. It was also not tracked before and is thus not equipped with (labeled) data. In addition, a lot of training data would be needed to identify meaningful patterns and cause-effect relationships for such an AI use case. Consequently, although this AI use case idea promises valuable cognitive support for the project managers it does not seem feasible in the short term. It had to be put on hold for the time being. As such, the bottom-up approach allowed to find AI use case ideas for more knowledge intense tasks, but they were not very feasible.

Therefore, it is important to differentiate between AI's ability to support and (semi-)automate routine tasks and standardized processes, but also to provide tremendous cognitive support for complex tasks. The latter may promise more disruptive improvements and long-term effects but is only feasible in the longer term. When starting an AI initiative, research clearly calls for small and realistic use cases first, so it is best to focus on routine and standardized tasks in the beginning. Organizations often point to the shortage of skilled workforce, so relieving their skilled workers of routine tasks seems very promising. The top-down approach will provide great support in identifying appropriate AI use cases. If an organization however mainly deals with knowledge intense tasks in their core business that are not repetitive, it should still tackle the explorative bottom-up approach. Regarding the impact-feasibility evaluation, the resulting AI use cases should clearly emphasize the feasibility. As a consequence, the bottom-up approach is useful if it is applied under the necessary conditions. It will generate the most ideas including entirely new ideas to address business problems for which there is no current or standardized solution. In addition, the bottom-up approach allows for a much deeper understanding of the entire working environment. It serves to specify the disruptive AI use case ideas and thus provides valuable goals from a strategic perspective. If sufficient resources are available, an organization can start the AI adoption journey with the bottom-up approach to identify a broad set of potential AI use cases and gain tremendous information about the relevant business drivers. The top-down approach then helps

to refine further ideas and to evaluate the process and data fit of each idea. However, if resources are limited, only the top-down approach should be taken.

This thought is in line with an efficiency consideration when starting an AI initiative, as the cost-benefit ratio is also relevant when defining AI use cases. Thereby, the top-down strategy allows for a small-scale approach as an organization can prepare many aspects on its own before engaging external AI experts. Modeling the strategic and operative business goals together with relevant processes and operations is well possible. In the best case, this information is already available and only needs to be updated and specified. Generic information about required and generated data can also be collected in advance. In the case study, all these aspects were easy to grasp and design for the middle managers and practitioners. Then, with the help of external AI consultants, the initial AI use case ideas can be specified in one or few workshops. In addition, the models to support the top-down approach are well-known business concepts such as strategy maps and process modelling techniques, e.g., using BPMN. These are applied in the new context to support the identification of potential AI enabled solutions to improve the existing business. Hence, one reason the top-down approach is easy to grasp and perform is that it uses very common business concepts.

This consideration is also relevant to the user-centered bottom-up approach. User-centered innovation techniques are less well known than traditional concepts such as modeling strategy maps and business processes. They focus on people rather than abstract entities such as business goals and process entities. For this reason, the user-centered bottom-up approach needs to be explained to employees in more detail and there needs to be more room for customization. In the case study, practitioners were familiar with strategy maps and simple process modeling techniques, but not with context maps, user journeys and user-centered workshop techniques. As a result, creating the user-centered bottom-up outputs such as context maps and user journeys required more effort than designing the top-down outputs. In addition, the role of the external AI experts in the bottom-up approach is to understand the challenges and problems of employees in detail. Therefore, they should be involved from the very beginning. The bottom-up approach thus takes more time than the top-down approach and involves the external workforce for a much longer period of time. As a result, the bottom-up approach is more expensive and time-consuming. However, as it leads to the more disruptive and promising ideas from a pure business impact perspective, the cost-benefit ratio may not be worse than for the top-down approach after business understanding. However, the data understanding phase of the bottom-up approach is also more laborious and complex, as it likely requires entirely new data sources and structures to be specified. Since its use case ideas are less feasible, the bottom-up approach eventually results in a lower cost-benefit ratio. This reinforces the recommendation to prefer the top-down approach in the beginning.

In addition to the methods and models that help non-tech SMEs identify AI use cases, AI adoption requires more but choosing the most appropriate approach. Chapter 6 addresses the broader view of AI adoption for a non-tech SME by considering the relevant AI readiness factors and formulating more general recommendations to practice. The case study proved the importance of realistic expectations towards AI adoption. Whether an organization is ready or not to start its AI adoption journey would be difficult to answer and may be the wrong question to ask in the first place. Formulating appropriate AI use cases is quite possible for an organization that is still an AI novice. However, when it comes to implementing the desired AI system, the necessary changes in IT, data and human workflows must first be sealed. This will eventually lead to an increased AI readiness so that upcoming AI use cases can be handled more effectively. In this regard, identifying AI use cases and subsequently increasing AI readiness is a reinforcing process in itself. Organizations shouldn't back up from starting their AI journey if they lack the required skills. Instead, they may opt for a cost-efficient and small scaled approach that uses external workforce for fixed periods of time. This should set a self-reinforcing process in motion that strengthens AI readiness while leading to meaningful AI use cases.

To support this process, management should emphasize the importance of data, the fuel of any AI system: Its accessibility, quality, and quantity should be gradually increased. As new software systems

usually require changes in the workflows of employees, they need to be involved in the design and adaptation process. Management thus has to advocate changes in employees' working practices but also data and IT workflows. In the approaches presented in this dissertation, employees are actively involved in identifying AI use cases so that they can participate in their design. Especially in SMEs it is comparatively easy to involve the affected employees because the distance between the management's decisions and the employees is short. In this way, employees can participate in the design of their AI solution, which is a critical aspect for end-user acceptance. On top of that, they must be actively involved in the changes required within the data and IT landscape.

Compared to the previous literature, the results of the dissertation are well in line. The type of AI use case that promises the highest success was supposed to be one that improves an existing business process. The dissertation confirms that such use cases are the most feasible and thus promise the greatest chance for realistic improvements in the near future. On the other hand, the research also found that if an organization starts out with overly ambitious ideas, it is likely to fail. The dissertation found several such use cases that promise huge improvements but are simply not feasible in the short term and probably not even in the medium term. In contrast to existing research, this dissertation provides organizations detailed guidance with two approaches to identify AI use cases that fall more into one or the other category. The results of the dissertation also confirm the relevance of the AI readiness factors elaborated by previous research. Some of these are addressed in the evaluation criteria whenever possible, e.g., the consideration of strategic alignment, relevant data aspects, and IT and workflow integration.

7.3 Conclusions

Small and medium-sized enterprises especially from the non-tech sectors are already struggling to identify meaningful AI use cases. This is due to a lack of skilled AI staff, limited financial resources and little data-driven decision making, which are typical barriers to AI adoption. But there are many other factors that an organization needs to consider. For example, an organization should avoid typical barriers such as starting with too ambitious AI use cases or pursuing use cases with unclear business objectives. Therefore, an organization that is new to AI and faces such barriers and issues may very much benefit from structured guidance and practical recommendations to tackle AI adoption. This dissertation aimed to develop methods and models to support such SMEs that are not yet experienced with AI. The central research question asked:

How should a small or medium-sized organization with no experience in AI approach the identification and evaluation of AI use cases?

Based on a case study approach with an organization that provides nine business user groups, it can be concluded that a top-down approach is the best way to start identifying AI use cases for such a SME. Since AI promises great potential to improve existing business processes and operations, this is the best starting point for finding AI use cases with a realistic feasibility and clear business impact. By analyzing strategic and operational business goals and related business processes, an organization can ensure that its AI use cases are well aligned with the business strategy and existing workflows. In this way, not only are the current solutions and associated challenges well understood, but it is also possible to adapt to current workflows and define key performance indicators that the targeted AI solutions aim to improve. These factors explain why the typical AI success story is the improvement of existing processes, and why any organization new to AI should follow this path. The latter is a finding and recommendation from the previous literature that was specified in this dissertation as the case study revealed several reasons for this observation. These findings could help other organizations to start their AI adoption journey better informed.

The case study also showed that it is possible to identify more disruptive AI use case ideas. A user-centered bottom-up approach does this by matching the full range of AI's capabilities with business-related challenges and needs of the employees. However, these AI use cases are usually not feasible in

the short term because they often require new process structures, e.g., for data collection, or require enormous human effort to collect, assess, and label the necessary data. As a result, these projects are more likely to fail, especially if they are among the very first AI projects an organization undertakes. Thus, it can be concluded that the user-centered bottom-up approach should not be undertaken as the sole approach by an organization new to AI. But it is well suited to complement the top-down approach to identify the more disruptive ideas.

The results of the entire case study illustrate the difficulties of introducing AI in a real-world environment. Even opting for small-scale AI solutions that address an existing predictive task of a well-defined business problem was not always feasible in the short term. It is not uncommon for organizations to underestimate the complexity ahead but overestimate their readiness. This is especially true for data-related issues, e.g., the poor quality of currently available data. Therefore, even if an AI use case promises business improvements, the feasibility assessment should remain the more important aspect when deciding which AI use cases to pursue. This is also consistent with previous literature that recommends avoiding overly ambitious projects at the outset. Once again, the dissertation provides more detail on how to identify these use cases and how to separate them from the more feasible use cases. It can be concluded that while it is not difficult to identify and define several ideas for AI use cases, the real challenge is to identify and select the most feasible ones first. The dissertation provides guidance on how to do this by providing two distinct approaches to identify AI use cases with detailed instructions as well as a thorough evaluation scheme.

Based on these conclusions, the central contribution of this dissertation is directed to practice. It is aimed at organizations that do not yet have experience with AI, do not yet know how to identify promising AI use cases, and face financial and staff limitations. These limitations are especially true for non-tech SMEs. The key contribution to them is the detailed procedure model that guides them in identifying and evaluating AI use cases. It includes actionable activities with detailed instructions, desired outcomes, and useful tools and techniques. In addition, modeling techniques that help to find promising ideas for AI use cases are proposed and presented with real-world results. The dissertation provides further practical recommendations to give a holistic view of the necessary actions that an organization should apply. The theoretical contribution of this dissertation deals with an enhanced IS artifact, i.e., a new procedure model developed by combining and extending existing models and practical knowledge for the requirements of identifying AI use cases. This artifact is demonstrated and evaluated in a real-world setting which extends the IS knowledge base on case studies aimed at introducing AI in a non-tech organization with one detailed case. The results also include the description of actual AI use cases that emerged from the case study.

Applying the real-world case study approach with researchers serving as consultants thus allowed for a deep dive into the practical problems and complexities from start to finish. While this approach did not allow for statistical generalization of the results, the results from each group can be compared well. The six groups that used the top-down approach ended up with similar results, which differed significantly from the results of the three groups that used the user-centered bottom-up approach. The latter showed a greater variance in the assessment of business impact and feasibility. This can be explained by the more open, user-centered strategy, which allows for a greater influence of the involved employees. The top-down approach, on the other hand, allows only a narrow scope. Here, fixed business entities such as business goals and processes play a key role compared to the perception of employees' challenges in their entire working environment in the user-centered approach.

However, the research team's role as consultants required trade-offs, such as balancing a rigorous research approach with the need to deliver real benefits to the organization. As the top-down approach proved superior, it was favored by the project sponsor, resulting in the six groups compared to the three groups implementing the user-centered approach. For a small or medium-sized organization with limited financial and human capacity, this fact is very relevant. For this reason, the dissertation always calls for the implementation of the top-down approach and considers the user-centered approach as

complementary. The emergent nature of the case study, with groups joining step by step, and the extension with the proof of concept phase in the later stages, also proved valuable. It allowed for a more detailed evaluation of the results, especially in terms of the feasibility from a data perspective.

The dissertation emphasizes that the availability of a lot of data alone does not guarantee a successful AI project, let alone a meaningful AI use case. What matters is the quality of the data and its suitability for the analytical task. This requires detailed analysis by data scientists, who are a scarce resource. Therefore, hiring external staff can be the solution to fill the AI knowledge gap. In addition to the consulting project with a fixed duration and a fixed consulting team as described in this dissertation, other formats could be tested. For example, an organization could perform the phases separately, e.g., start with business understanding only with the help of an AI expert to identify a few AI business cases. Then, they could issue new orders to evaluate the feasibility of the most meaningful business cases and act accordingly to design the proof of concepts afterwards. Research could investigate the effectiveness of these and other strategies for using external workforce when identifying AI use cases.

Further research could also assess the prevalence of unrealistic expectations about AI and how to measure them, both with respect to individual AI projects and AI adoption in general. This would help to address certain weaknesses early on to ensure a proper start to AI adoption. In addition, the relative importance of AI readiness factors could be analyzed in more detail. This would help to better communicate the requirements for AI adoption. It would also help to identify the most relevant deficits at an early stage. Possible pre-projects could be initiated to improve certain AI readiness factors while or even before tackling the AI business case identification.

One limitation of this dissertation is that the nested case study approach was conducted within one single organization. Thus, future research could test and evaluate the procedure model in other organizations. Another possibility is to specify the procedure model, e.g., for its use in specific business areas or for specific types of organizations, such as law firms or public services. On the other hand, the single case study consulting approach is very useful because of the depth of insights. Although consulting firms would likely act similarly in practice, they rarely present and discuss their real-world project outcomes and procedure models in such depth and present them in the scientific community. This dissertation instead provides recommendations how to set up such a collaboration with external partners, what to prepare in advance and what actions to take. This can help non-tech SMEs that have previously resisted initiatives or collaborations to adopt AI due to staff or financial constraints. They can adapt to the framework presented in this dissertation that is grounded but has also been tested in practice.

As AI is expected to play an increasingly important role in the future, its adoption will become critical for several organizations. The findings of this dissertation are relevant in the broader context of an organization's digital transformation process, of which AI technologies are a part. Thus, the actionable activities proposed in this dissertation, such as engaging external AI experts or implementing certain approaches such as top-down, should be embedded within the digital transformation strategy. The final paper in Chapter 6 addressed this fact by, for example, also considering non-AI solutions. After all, AI techniques offer new ways of solving existing problems, but they also open up new business opportunities. This is also true for other technologies, so potential AI solutions must always be evaluated for their cost-benefit ratio compared to existing and other technological solutions.

Finally, conducting the real-world case study helped both practitioners and the research team to reflect the complexity of trying to specify AI solutions up to the proof of concept stage. This dissertation summarizes the main findings, explains relevant implications, and formulates calls to action that are subsumed in a procedure model, distinct modeling techniques and several recommendations to practice. In the best case, other organizations in a similar situation to the focal organization will benefit from this work in the future, but also from the experience gained by all parties involved during the project.

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