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A Strategic AI Procedure Model For Implementing Artificial Intelligence

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Abstract

For most industries, Artificial Intelligence (AI) holds substantial potentials. In the last decades, the extent of data created worldwide is exponentially increasing, and this trend is likely to continue. However, despite the prospects, many companies are not yet using AI at all or not generating added value. Often, an AI project does not exceed its pilot phase and is not scaled up. The problems to create value from AI applications in companies are manifold, especially since AI itself is diverse and there is no 'one size fits all' approach. One often stated obstacle, why many AI projects fail, is a missing AI strategy. This leads to isolated solutions, which do not consider synergies, scalability and seldom result in added value for the company. To create a company-specific AI strategy with a top-down approach, a generic but holistic framework is needed. This paper proposes a strategic AI procedure model that enables companies to define a specific AI strategy for successfully implementing AI solutions. In addition, we demonstrate in this paper how we apply the introduced strategic AI procedure model on an AI-based flexible monitoring and regulation system for power distribution grid operators in the context of an ongoing research project.

Keywords

Artificial Intelligence; Strategy; Framework; Procedure Model; Digital Transformation

1. Introduction

For most companies, regardless of their industry or size, the utilization of Artificial Intelligence (AI) can generate meaningful value for companies [1–3]. Studies predict that AI will be responsible for a third of the German economic growth of the manufacturing industry [3]. Moreover, AI utilization will be necessary to keep pace with global competitors to defend its market position or extend it [4,5]. Thus, the added value that companies can achieve not only consists of a financial dimension but can also include others like competitiveness, better services for customers, or more sustainability. Within the next eight years, Germany's GDP is predicted to increase by 11.3% and its companies' productivity by 4.6% [6]. Within the next five years, a third of the growth is predicted to derive from AI applications [3]. Taking this into account, AI is an useful and necessary field of action for any company as the usage of AI is predicted to be essential to stay globally competitive and thrive economically [4,5]. Furthermore, studies indicate that AI derives meaningful value by increasing companies' revenue and reducing their costs [1]. Moreover, harnessing AI has additional objectives, such as resource deployment minimization, innovation, efficiency increase, and optimization of a company's offer [4].

In principle, companies are open to AI: 46% of German companies are concerned with the issue [4]. AI is perceived as relevant for all companies regardless of their industry and size [2].

Despite the potentials, there are plenty of challenges and pitfalls that hinder the successful implementation of AI applications [4,2]. Although most companies expect new opportunities through AI, nearly half stated that significant investments did not yet add value [7,8]. There are many reasons why an investment in AI applications does not lead to the desired business gains and values. Companies often miss competencies and expertise within their ranks, and their recruitment. Trainings are also obstacles [9,1,4,2,10]. Furthermore, companies lack an AI or data infrastructure or invest in it without a clear understanding of applications and use cases, which leads to unfitting data governance data protection or data strategy [1,2].

Regarding the phrase 'garbage in – garbage out', data quality is an often-underestimated issue that leads to unsatisfying results [9,1]. Moreover, companies often develop isolated pilot solutions without linking the overall strategy if such a strategy exists and do not consider the solutions' scalability [2]. Another obstacle is the missing collaboration across functions, partly due to the missing commitment of the top management and missing acceptance of both employees and customers [1,4,10]. In addition, high investment costs at the beginning, missing best practices, and data privacy and security hinder AI projects. The subject is highly complex – there is no 'one size fits all' solution [4]. For a successful AI application implementation, companies must bring together their technological, cultural, and political domain and prepare the right infrastructure with the right data and talents [2,8].

Some obstacles are not isolated but interrelated with other ones. For example, studies indicate that the lack of an AI strategy contributes to the failure of AI projects and strategic considerations to be vital for a successful implementation of AI [5,8]. Research has shown that a missing AI strategy is one reason for the failure of AI projects and that successful companies have one [9,11,1,4,5,15,16,8]. Furthermore, despite the intensification of research on AI in a business context, aggregated knowledge on this topic is limited, and managers are left with little academic support for implementing AI applications within their companies [8]. A holistic approach for AI implementation, based on an AI strategy, tackles many of the obstacles mentioned earlier and thus enhances the chance of successful value generation [9,11,12,2,13,7,14].

Due to a missing AI strategy, the technology is seldom incorporated into the organization and does not create value. This often leads to an isolated solution that cannot be scaled up comprehensively or solutions that do not fit into the company's strategic direction and contributes little towards company goals [5].

Having an AI strategy would, among others:

1. Improve a company's situation by understanding whether the particular use case is linked to the overall objectives or their organization.
2. Estimate the use case's added value.
3. Prevent projects to remain in the pilot phase by planning their scalability from the start.
4. Define requirements for an AI infrastructure for the entire company, which may plan to implement more than one use case.
5. Consider strategic topics, e.g., legal, privacy, security topics, from the beginning.
6. Ease the management and employees' concerns by communicating the goals and showing them to achieve added value.

The research presented in this paper addresses the aforementioned issues by suggesting the application of a holistic, top-down AI strategic procedure model. In the following, we will present such a procedure model framework. It will enable companies to approach AI projects with a holistic concept, reducing the risk of an AI project failure and supporting its competitiveness and profit.

In the beginning, we will focus on the research gap concerning this subject. We will also define the term 'corporate strategy' that is used in the following. Thereupon, we present a framework for a holistic strategic AI procedure model. Afterward, we apply the suggested framework on an AI-based flexible monitoring and regulation system for power distribution grid operators. Finally, we take an outlook on developments to come.

2. Methodology

We based the development of the proposed AI strategy procedure framework on the method described afterward. First, we conducted extensive desk research to gather information on the current state of the art regarding available AI frameworks and procedure models. Following the collection, we compared the existing strategic AI frameworks and procedure models to gain important and successful factors that affect AI implementation. Using these insights, we derived a procedure considering the working aspects of existing solutions but specifically addressing identified shortcomings. To test the applicability and evaluate the framework, we applied it to a grid operator use case. Finally, to enhance the proposed procedure, we used the results and feedback to further develop the framework.

3. Research results

In the following we will present the results of our research.

3.1 Research gap for AI strategies

Studies show that companies that successfully use AI applications often have an AI strategy with a clear enterprise-level roadmap of use cases that aligns with the corporate strategy [1,16]. Although numerous publications in an industrial context state the need for a holistic AI strategy, there is little scientific research concerning this topic. This might be caused by AI technologies' diverse and non-uniform nature and the strong focus on technical research rather than business-strategic research. Thus, it is necessary to provide academic support for managers implementing AI applications in their companies to reduce the risk of project failure and unwanted results [8].

The strategy has to enable companies to make strategy-oriented AI decisions rather than opportunistic or tactical ones [15]. Moreover, it has to bring together the technological, political, and cultural domains, including data and security issues from the very beginning [17,8]. Unfortunately, research shows that such AI strategies cannot be uniform step-by-step manuals. They rather have to be a framework that allows companies to formulate individual strategies [7].

3.2 Corporate strategy & AI strategy

To be able to define an AI strategy, we first define a corporate strategy. According to Gleißner and Hungenberg, a corporate strategy consists of five components [18,19]:

1. Vision, mission, and long-term goals: A vision describes the long-term target state, which the corporation wants to achieve. Based on this, the mission substantiates three sub-aspects for the company's orientation, namely the field of activity, competence, and values of the company. Out of the mission, long-term company goals are conducted [19].
2. Core competence: The core competencies include those abilities of a company that is essential to operate successfully [18].
3. Business fields and competitive advantages: Business fields describe the field of activity in which a company operates. The market attractiveness and the competitive advantages are its properties as well as the target groups or customers. Out of the customers' needs, the company can deduct products and services [18].

4. Design of the value chain: The value chain is a business process in which value is progressively added to the product. Due to limited resources, the value chain must be designed based on core competencies and competitive advantages [18].
5. Strategic thrust: The strategic thrust consists of factors that may affect the corporation's value. There are three general directions as strategies' main variants: growth strategies, profitability-oriented strategies, and risk-oriented strategies [18].

We define the AI strategy as a subset of the corporate strategy. It comprises 'business fields and competitive advantages' and the 'design of the value chain'. This is due to the four fields of AI application. These are:

1. Internal optimization [20,21],
2. supplementing the existing business area [22],
3. new business areas [22], and
4. digital business models [20].

Except for the internal optimization, all application fields concern the corporate strategy's subfield business fields and competitive advantage. The internal optimization concerns the design of the value chain.

3.3 Applying a top-down-approach for the strategic AI procedure model framework

Several reasons speak in favor of using a top-down approach for an AI strategy. First, it enables coordination throughout the company, which prevents the isolation of AI use cases and promotes synergies [11]. In addition, the coordination of experiments, implementations, selection of AI technologies and vendors across the business prevents the duplication of effort, the usage of competing methods, and multiple vendors [23]. A top-down approach facilitates companies to include strategic goals and consequences into implementing AI projects' running or planned implementation [24–26,14]. Due to these reasons, we propose a top-down approach for the framework of the strategic AI procedure model presented later in this paper.

4. Description of the framework

The framework of the strategic AI procedure model consists of three levels along the top-down-approach as shown in figure 1:

- the corporate strategy level to set the target,
- the meta-level of archetypal AI use cases to mediate between the corporate strategy and AI infrastructure level,
- and the AI infrastructure level, including design fields.

The result is a defined roadmap with prioritized design fields for the implementation.

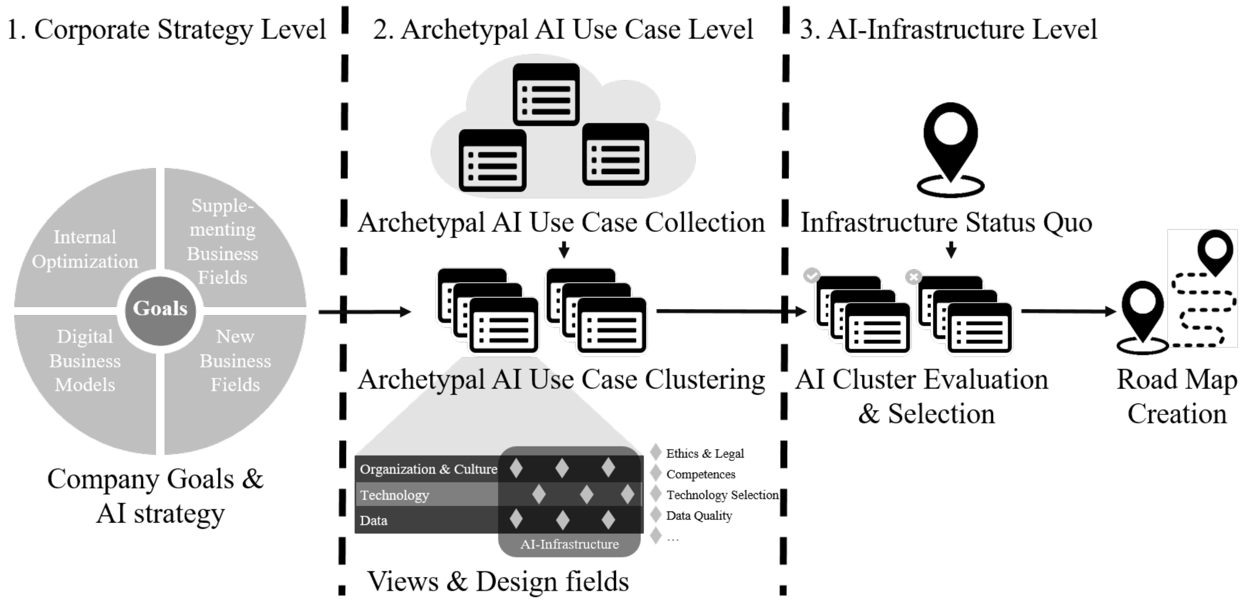

Figure 1: Framework of the strategic AI procedure model

4.1 Corporate strategy level:

Ransbotham et al. have shown that tying a strategy for AI to the company's overall strategy is essential [7]. As stated above, we define an AI strategy as a subset of a corporate strategy, as it comprises the design of the value chain and sometimes the design of the business fields. It follows and aims to realize the corporate goals.

The corporate strategy is a precondition. Based on the enterprise's mission and long-term goals, it provides a frame and extracts specific corporate goals for the AI strategy. The company should consider multiple questions: Which of its core competencies is affected, or does it have to elaborate on new ones? What is the thrust of the AI strategy (is it a growth strategy, profitability-oriented strategy, or risk-oriented strategy)? What is the AI approach, and does it affect business fields (internal optimization, supplementing existing business areas, new business areas, or digital business models)? The long-term goal of implementing AI applications must be pointed out clearly, and it has to fit into the overall corporate strategy.

4.2 Meta level: Archetypal AI Use case collection:

This level contains a collection of archetypal AI use cases. Due to technological progress and wide variety, the collection remains open for additions. This collection shall support identifying use cases under the aspects of identifying synergies with other use cases and technologies, planning scalability, preparing for selection, and supporting understanding of AI capabilities. Supporting this, each archetypal use case contains variables that are important for the selection process. In the following, we list a selection of key questions for several variables, which shall help to determine the relevant variables: *Type of AI:* What is the technology capable of? Does it assess, deduce, or react? Does it imitate human behavior or make rational decisions? *Value creation:* How does the use case create added value? How is it used? What are its limits? *Addressed problems*: Which problems is it tackling? *Input:* What is the required information or data input? *Output:* What is the required information or data output? *Requirements:* What are its requirements on data (amount, quality), domain knowledge, resources, talents, hardware (sensors, GPU, etc.), infrastructure, etc.? *Interconnections:* Are there interconnections with other technologies or use cases, e.g., synergies, dependencies, exclusions, or redundancies? *Interpretability:* Can humans interpret the technology? Do they have to? *Time:* Are there time constraints? How long is the approximate computing time? How long is the approximate training time? *Capacity:* How much server capacity is needed? *Scalability:* Does the use case has to be scaled up? How do we ensure its scalability? *Models:* What models can be used for this use case?

Based on the company goals using the archetypal AI use case collection, use cases can be pre-selected. Important factors are the use cases AI infrastructure requirements, corporate strategy fit, scalability ability, and possible synergies with other use cases or technologies. The single pre-selected AI use cases can then be clustered according to their synergies, value, etc. For instance, an autonomous vehicle use case represents such an AI use case cluster, as it contains several computer vision and decision-making models.

4.3 AI-infrastructure level:

The infrastructure is essential for the success of implementing AI applications. To examine the future AI infrastructure thoroughly, we use three views proposed in the Aachen Digital-Architecture-Management: the **organization** expanded with **culture**, **technology**, and **data** [27]. The AI infrastructure can be divided into three views. For each view, we assign several design fields. A design field contains concrete steps, tasks, and methods to create a part of the AI infrastructure. Each design field belongs to a view, although some are comprehensive and cannot be assigned to only one view. Not necessarily all design fields must be addressed by each company; that depends on the existing infrastructure and the requirements of the to be introduced AI use cases. Examples for the design fields are *Ethics & Legal*, *Cybersecurity (comprehensive)*, *organizational structure*, *roles*, *data governance*, *sourcing & ecosystems (organizational)*, *identification of new technologies*, *platforms*, *user experience (technology)*, *data procurement*, *data storage*, *data processing*, and *data quality (data)*.

On the AI infrastructure level, we propose three steps. First, a status quo analysis needs to take place. It should include infrastructure, system, and data environment analysis. Second, the company should identify relevant design fields for the pre-selected AI use case clusters, specify and compare them to the current infrastructure to estimate the needed effort. Based on this, a value and cost analysis for all clusters is to be conducted. With this information, the company can select its AI applications. Third, the selected AI use case clusters design fields must be customized and prioritized. With the prioritization of all applicable design fields of the selected AI use case cluster, the company can now create a road map for the implementation.

5. Application of the Framework of the Strategic AI Procedure Model

Although the German power grid is one of the most stable grids in the world, measured by minutes of power outages per year, the current energy (higher share of renewable energies) and mobility (battery-powered electric vehicles) transitions and the resulting volatility in the power grid are predicted to harm the grid stability. Higher volatility leads to increased usage and thus wear of the grid components. If grid operators maintained their currently time-based maintenance procedures under these conditions, either increasing power outage times due to grid component-related faults (higher wear and tear) or higher costs due to additional personnel (adjusted maintenance cycles) would be expected. Therefore, grid operators are particularly interested in condition monitoring and predictive maintenance. Developing an AI-based approach for these particular challenges is part of the ongoing research project FLEMING. [28]

While the development of AI algorithms is a fundamental part of the FLEMING project, the project also aims at enabling grid operators to generate value by deploying AI applications. To ensure a strategic approach for implementing this project's solution and for further AI opportunities, the proposed AI strategy procedure framework comes in. We will illustrate this AI Strategy Framework application in this context for a German grid operator who currently has no AI-based solutions in place.

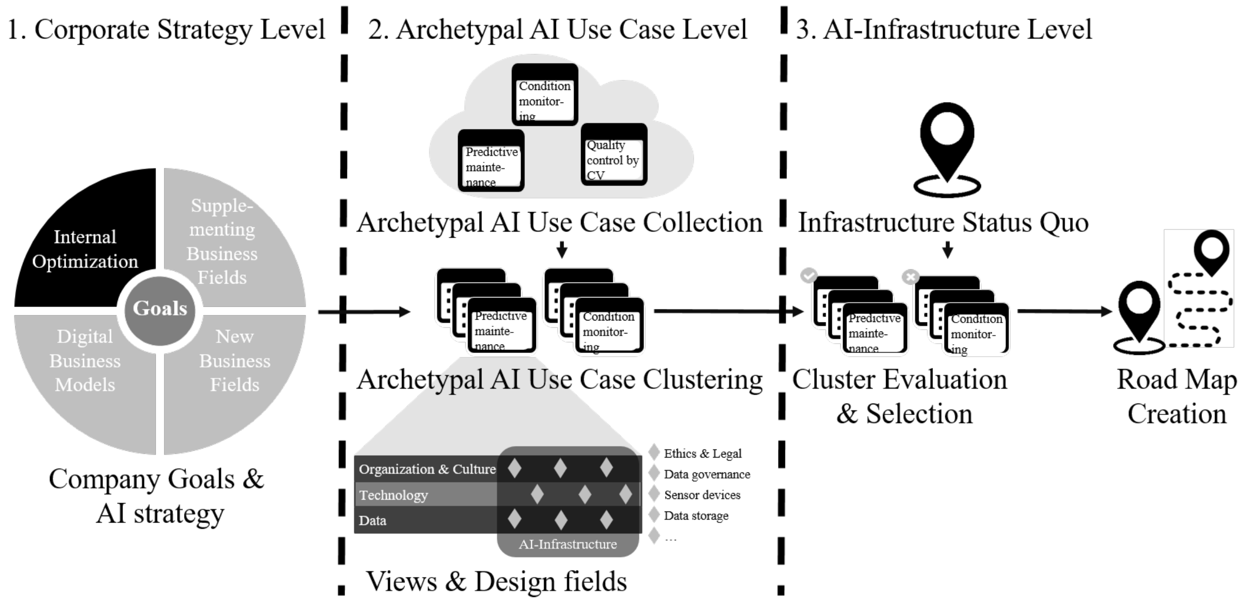

Figure 2: The Framework of the Strategic AI Procedure Model applied for a Grid Operator

As mentioned above, distribution grid operators have the strategic issue of maintaining their service quality, resulting in fewer power outages while being resource efficient. By using AI applications, they hope to strengthen their core competencies in the sense of efficient and reliable services. They focus on a profitability-oriented strategy, which does not negatively affect the corporate strategy. Thus, the AI approach is one of internal optimization. We then matched these company goals to the archetypal use case collection. For internal optimization, the collection proposes archetypal use cases as ‘predictive maintenance’, ‘condition monitoring’ or ‘quality control by computer vision’. These use cases can be considered by themselves or be clustered to a multiple-use case solution, considering their synergies, corporate strategy fit, and scalability ability. Since ‘quality control by computer vision’ does not support its goals, it is rejected.

In contrast, the first two use cases are pre-selected and, if applicable, specified (‘predictive maintenance for switchgears’). Each pre-selected archetypal use case cluster or single-use case contains comprehensive design fields and those connected to a view (organization & culture, technology, data), representing necessary elements of a holistic AI infrastructure. For the use case “predictive maintenance,” some relevant design fields could be, for example, *ethics & legal, cyber-security (comprehensive view), data governance, change management (organization & culture view), sensor-devices, platform infrastructure (technology view), data collection, storage*, and *quality (data view)*. They can be compared to the current infrastructure after conducting corresponding analyses. Moreover, the design fields can be specified and identified, which are necessary for the transformation or building of the novel AI infrastructure. For example, if the grid operator already has all the necessary sensors needed for “predictive maintenance” operating, there is no need to further stress this design field. In the following, the clusters can be evaluated regarding their value and costs, which leads to their selection.

At last, the selected cluster’s design fields are prioritized, and a roadmap for implementing it is developed. Since this approach is being developed in an ongoing research project, no validation exists at this time. However, the results from the research project will be examined and validated in more detail in subsequent publications.

6. Summary & Outlook

This paper briefly presents the opportunities and pitfalls of AI applications for the industry. We identified a missing AI strategy as a major obstacle to a successful AI implementation. To tackle this obstacle, we introduced a framework of a strategic AI procedure model and applied it to a grid operator in the context of an ongoing research project. The framework is the subject of further development. We will create a collection of archetypal use cases and elaborate on relevant factors of the AI use cases. Moreover, we will complete a list of the design fields as far as possible and specify each field. Finally, we desire further research for the selection process of AI use cases and their cost and value analysis.

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Biography

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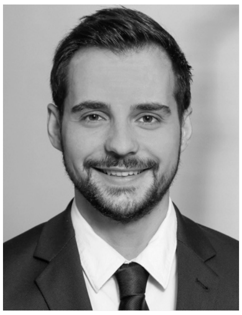

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