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 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.

Keywords: Business improvement, top-down, bottom-up, use case identification, artificial intelligence

1. Introduction

"Don't start with moon shots" is the subtitle of a research paper that examines the practical use of artificial intelligence (AI) 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). But first, let's start with some basics.

An important subfield of AI deals with machine learning (ML) 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 et al., 2010). Technological innovations can enable various improvements to the business model (Teece, 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 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.

The research aims to help organizations achieve business value from AI and provides a range of guidance. For example, by identifying readiness factors

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and barriers to AI adoption (Alsheibani et al., 2018, 2019; Jöhnk et al., 2021; Loukides, 2021; Pumplun et al., 2019; Someh et al., 2020). Their results agree very well. Table 1 summarizes the key readiness factors of AI adoption into five categories (Jöhnk et al., 2021).

Table 1: AI readiness factors (Jöhnk et al., 2021)

Factor	Description
Strategic alignment	• 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	• Build team with AI specialists, business analysts, data scientists • Ensure financial backup and provide required IT infrastructure
AI know-ledge	• Ensure awareness and basic understanding of AI as a technology • Upskill employees with AI skills • Ensure AI ethics
Culture	• Ensure innovate company culture and facilitate change management • Integrate required business divisions
Data	• Provide access to high quality data • Provide sufficient data infrastructure

As far as AI project failure is concerned, unrealistic expectations are risky, i.e. a wrong understanding of AI 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 et al., 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 et al., 2019; Tarafdar et al., 2019).

The research also discusses ways to create value for organizations that want to launch an AI initiative. In the short term, the researchers call for the definition of small, realistic use cases (Brethenoux & Karamouzis, 2019; Davenport & Ronanki, 2018; Weber et al., 2022) even if they only provide incremental business improvement. 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 more 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 et al., 2021). In another study, different approaches, top-down and explorative bottom-up, are proposed to identify AI use cases (Brunnbauer et al., 2021). To date, none of the approaches have been tested and evaluated for their suitability in identifying 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 recommendations for organizations starting an AI initiative to improve their business.

2. Foundations: starting with AI

Let’s come back to the moon shots and elaborate what current research proposes when starting an AI initiative. General recommendations are discussed from a short-term and long-term perspective. Then the same is done for methods to identify AI use cases.

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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 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 et al., 2020; Tarafdar et al., 2019; Weber et al., 2022).

Table 2: Short-term and long-term recommendations when starting an AI initiative

Dimension	Short-term view	Long-term view
Project Scope	• Identify and pilot few AI use cases with a small and realistic scope	• Scale up step by step with new AI use cases, more business divisions, people and data
Added value	• Find AI use cases that offer quick wins, even if incremental or only for learning	• Find AI use cases with disruptive potential and highest impact on current and future business
Type of improvement	• Improve current business solutions, e.g. existing processes, decisions, offerings	• Try to find entirely new AI-enabled solutions, e.g. new products, processes or services
Data perspective	• Build on currently available data and identify prospectively required data	• Systematically build up the required data infrastructure
General Objectives	• Integrate AI into your business strategy • Get familiar with AI as the technology • Evaluate current AI readiness and AI's current potential regarding readiness	• Exploit AI's full potentials • Recruit and engage with the required AI talent • Build up AI infrastructure and fulfill AI readiness factors

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 et al., 2019).

From a value creation perspective, organizations should initially target projects with quick wins (Someh et al., 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 et al., 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 et al., 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.

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 3.

Expert interviews are conducted in two studies to explore how organizations find AI use cases (Hofmann et al., 2020; Sturm et al., 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.

Table 3: Approaches to identify AI use cases

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 potentials with business user problems

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 et al., 2021, 2022): "Top-down" aims to identify process steps, tasks, or decisions that can be improved through AI. On the other hand, "explorative" uses a bottom-up exploration of potential AI solutions by analyzing business user problems. Both are equipped with detailed activities, techniques, tools, deliverables, 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.

3. Top-down and bottom-up approach

The top-down and bottom-up approaches both aim to identify AI use case ideas (Brunnbauer et al., 2021). The main activities are summarized in Figure 1.

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.

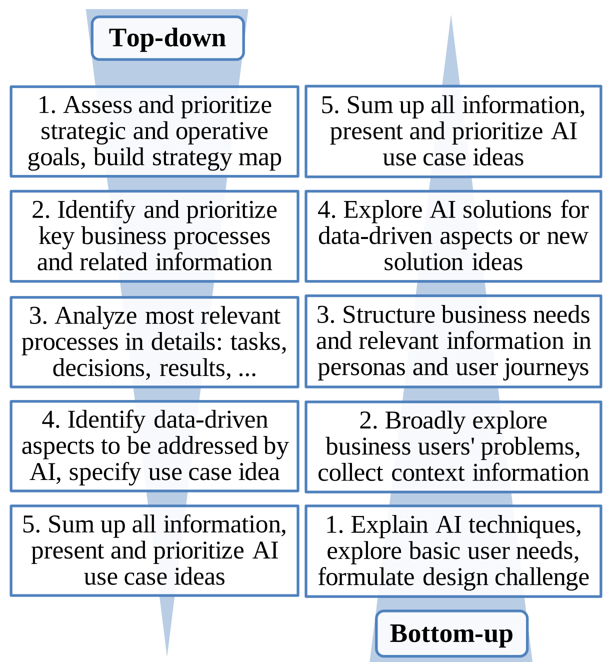

Figure 1: Top-down and bottom-up approach

3.2. 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 et al., 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.

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. 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 et al., 2015) of the approaches to identify AI use case ideas with a short- or long-term potential.

4.1. Case study setting

The project partner is a public institution specializing in construction and real estate management projects. With more than 1.000 employees and 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 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 project 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, summarized in Table 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 seven groups were supported by two external data scientists and one AI expert. The latter led the project along with an internal project leader. All groups then conducted the data understanding phase.

Table 4: Case study setting

Approach	Groups
4x top-down	1. Headquarters division A 2. Headquarters division B 3. Project management division A 4. Project management division B
3x bottom-up	5. Headquarters division A 6. Headquarters division B 7. Project management division A

4.2. Evaluation criteria

Various evaluation criteria are used to assess the results of the approaches. They are summarized in Table 5 and relate to the dimensions discussed in Table 2. For each criterion, a 3 point Likert scale with qualitative ratings of “High”, “Medium” and “Low” is used. The criteria are explained below.

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.

With regard to the value-added component, two 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 et al., 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

Table 5: Evaluation criteria

Dimension	Criterion	Description	Measurement
Project scope	Project goal definition	Clarity about use case idea’s objective, target and potential input parameters as well as relevant context information	3 point Likert-scale for all criteria: • High • Medium • Low
Added value	Alignment with business	Alignment of use case idea’s goal to organization’s strategy and goals	
	Expected improvement	Expected value addition if the use case idea can be realized	
Type of improvement	Newness	Novelty of the use case idea in comparison to existing solutions	
	Process fit	Alignment of the use case idea with existing business processes	
Data	Data availability	Availability of data for target variables, potential input parameters and context information	

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.

As far as the type of improvement is concerned, two criteria are evaluated. First, "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.

The compatibility with existing business processes, i.e., the "process fit" of the targeted AI use case (Jöhnk et al., 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.

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.

5. Results and evaluation

The case study resulted in the identification of 16 use cases 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 6. In addition, selected use case ideas from both approaches are presented.

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, the vast majority 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

Table 6: Evaluation results of each identified AI use case idea

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

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. For example, the project definition is clear in terms of the objective, but not for possible influencing factors. This leads lead 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 projections 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.

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.

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 et al., 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. 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 et al., 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 improvement.

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 knowledge of your employees**. The **use** of **human-centered and creative concepts** such as Design Thinking 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 concrete 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 et al., 2017) and an important AI readiness factor (Jöhnk et al., 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.

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 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 et al., 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 et al., 2021). Accordingly, a critical **self-assessment of current AI readiness** is recommended (Alsheibani et al., 2018; Jöhnk et al., 2021; Pumplun et al., 2019) followed by improving weak points. In addition, management should **integrate AI adoption into the digital transformation strategy** (Ransbotham et al., 2019).

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 a short-term, more incremental impact or with a long-term, 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 improvement. However, they lack both high process customization 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 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 should it scale up incrementally. 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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