Why It is Hard to Find AI in SMEs: A Survey from the Practice and How to Promote It

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Abstract: AI seems to be an important aspect of Industry 4.0, which was introduced about 10 years ago. The main results of interviews about AI with 411 people from 68 companies have been summarized in this paper. Most of those companies were SMEs. Main challenges for the application of AI have been identified. Concrete solutions that can support the implementation and application of AI are presented. The need to adequately support AI in SMEs is underlined and specified.

1 INTRODUCTION

The term Industry 4.0 shall promise a new era of industrial production (Kagermann et al., 2013). Production plants should be more flexible to react faster to market demands, more user-friendly, and more predictable (Kagermann et al., 2013), e.g. through condition monitoring. A huge potential is predicted, which is in a range from 10 to 35 % for additional productivity on conversion costs (Rüßmann et al., 2015), whereas other studies identify savings even up to 70 % (Bauernhansl et al., 2016). This potential shall partly rely on Artificial Intelligence (AI) (Wahlster, 2017).

Since the term Industry 4.0 is known for about 10 years (Wahlster, 2017), we want to review the state of the utilization of the term AI in the industrial environment. Do people exactly know what AI is in the context of manufacturing? How far goes the implementation and success of AI in manufacturing? What are the concrete benefits of using AI? If the phrases of huge potential are not just good for marketing purposes, it is expectable that AI is well known in companies.

The paper is structured as follows: At first, we summarized the key findings out of the conducted interviews about AI in the production area companies, with a focus on Small- and Medium Enterprises (SMEs). Secondly, we lined out requirements and potential strategies to support the usage of AI in the companies. Afterwards, two best practice solutions are introduced. Finally, we draw a conclusion and give an outlook for potential future steps. The contribution of this paper is to uncover potential challenges with regards to AI based on conducted interviews and to offer concrete strategies to support AI.

2 CHALLENGES AND HURDLES OF AI IN PRODUCTION

This article is based on conducted interviews with 411 people from 68 companies located in Germany, Austria, and Switzerland. The purpose of the interviews was to primarily find out, *(a)* how common the use of AI in production is, *(b)* what effects employees recognize and observe by the use of AI and *(c)* how the economic effects of AI are being measured in industry. Therefore, we interviewed experienced employees in production that are decision-maker including foremen and plant managers, from different industry sectors, predominantly from machine and plant construction companies. The revenues of the respective companies are up to almost 250 million Euros per fiscal year. The minimum revenue of the respective companies was 12 million Euros, each based on the fiscal year 2019. We used an interview guideline in form of a structured questionnaire including several open questions. The latter seemed important and adequate for the present case since we wanted to avoid leading people in a certain direction by preparing closed questions and therefore get an unintentional bias by limiting the number of possible answers. The goal of the interviews was to

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get sound feedback from the practice. Therefore, the interview partners and the companies were not chosen representative, we did not follow a strict, narrow SME definition, whereas most of the companies fit into the established ones. Additionally, we did not distinguish the different industry sectors with regards to the presented results of our interviews, since there was no significant difference identified.

2.1 Basic Challenges with Regards to Intelligence and AI

To thoroughly analyze the potential impact of using AI it is – amongst others – first of all, necessary to understand what intelligence means and what it might be or might not be. To begin with, AI is an expression, that is little concrete. Even though people sometimes love unspecific and generic expressions and unsubstantial but good sounding phrases, it is usually not helpful for making a business successful. Furthermore, there is no common definition of what intelligence is – at least up to now. Not having a common definition of intelligence, how can we define artificial intelligence? Dealing with catchwords, not really being clear about the concrete meaning, might not be efficient. Let’s consider human beings and the human intelligence first: What makes a human being intelligent? If he or she is analytical in the way he or she is thinking? If he or she can solve problems sufficiently and in a timely manner? If he or she is creative? If he or she is empathic? If he or she is able to draw logical conclusions to problems? If the speed of processing information is fast? The ability to concentrate on issues and their solutions? The ability to learn new things and to unlearn unnecessary or less successful strategies? The ability to memorize things? All of it might make sense, but is it the full truth? We don’t know.

Let’s look at some of the attempts to define intelligence. The psychologist William Stern defined intelligence as the ability of an individuum to adjust his or her thinking intentionally and goal-oriented to new demands (Stern, 1912). Intelligence might be understood as the common adaptability to new tasks and conditions of life. The social psychologist Peter Hofstätter defined intelligence as the ability to determine the structure and the ability to discover and reveal redundancies (Hofstätter, 1966). The psychologist Robert Sternberg assumed, that intelligence comprises analytical, practical as well as skills related to experience. In this context, intelligence is mainly related to the interaction of individuals with their environment. The psychologist Linda Gottfredson says, “intelligence is a very general mental capability that, among other things, involves the ability to reason, plan, solve problems, think abstractly, comprehend complex ideas, learn quickly, and learn from experience. It is not merely book learning, a narrow academic skill, or test-taking smarts. Rather, it reflects a broader and deeper capability for comprehending our surroundings-’catching on’, ’making sense’ of things, or ’figuring out’ what to do.” (Gottfredson, 1994)

As you see, the existing definitions of the word “intelligence” are often widely generic themselves, but also different. As stated above, generic definitions don’t really help to be successful in the long-run. Regardless of all the different definitions of what intelligence could mean, we can state justifiably so that human intelligence is hard to squeeze in a certain definition and that it probably comprises a broad range of different aspects, such as learning experience, ability to goal-oriented problem-solving, foresighted thinking and acting, but probably also moral aspects, empathy, and creativity. As we saw before, those aspects are hard to really specify and to sufficiently concretize in a generally accepted definition. The human brain is still one of the mysteries in our world. It is complex and has been explored only very little compared to its potential and ability. Hence, we might want to be careful with using the word “intelligence”.

Let’s now move on to the expression AI. It might be helpful to understand AI not as an attempt to copy human intelligence or human behavior and try to optimize it. It might be more useful to understand AI as the simple and reasonable attempt to further improve processes with regards to effectiveness and efficiency by using “modern”, state-of-the-art technologies. In industry, we see lots of attempts to improve processes under or disguise of AI. In fact, AI seems to be nothing else than stated above: Improving processes with regards to effectiveness and efficiency by using state-of-the-art technologies, that are able to react to changes in their environment within a certain scope.

One of the results of the survey we conducted underlines the issue with the expression “artificial intelligence”. The answers are of a wide variety. Some of the interviewees see AI simply as the ability of machines to adequately react to certain events in a faster way than human beings can do – whatever *’fast’* means. Others even consider chatbots as intelligent systems. Obviously, these people had not much to do with chatbots so far, otherwise, they knew, that chatbots are everything else but intelligent. Some interviewees named machine learning (ML) as part of AI. A majority of the latter were not able to name concrete new business models behind their attempt to use ML in their respective company. Only a handful of interviewees stated, that AI has nothing to do with intelligence, but can solve some problems more efficiently and effectively than human beings can do.

2.2 Usage of AI in Manufacturing

We will now show a summary of selected results, explain them briefly, and share some implications.

The first noticeable fact based on the given answers is, that only 4% of the interviewees stated that they have personal experience with AI. Only 5% stated that they are currently using AI in manufacturing. On the other hand, 67% of the interviewees believe that AI has - respectively would have - a positive economic impact (see Fig. 1).

In this context, it seems to be of interest to figure out the reasons, why so little companies are using AI in manufacturing. 24% of the interviewees stated, that their company is too small for AI. 5% stated that there is not enough potential for improvement by using AI. Since several companies have revenues between 30 and 50 million Euro, it is surprising that many interviewees think their company is too small for using AI or has not enough potential for improvement.

One of the challenges in particular in SMEs seems to be a lack of expertise in the field of AI. On the other hand, there is more than one-fifth that saying that their company is currently evaluating the potential use of AI. At least SMEs seem to be sensitized and try to figure out if the implementation of AI in manufacturing makes sense. Overall, it seems that SMEs are slowly catching up but have still a long way to go due to a lack of resources and experience in AI.

2.3 Benefits of AI: Is It Measurable?

Most of us would hopefully agree, that it only makes sense to implement and use new technologies and methods, if the economic outcome can be objectively measured and if it helps you staying competitive. To our surprise, only 5 % of the interviewees[1] stated, that they measured the economic impact of AI in their company.

This is a critical point here seems to be the fact, that only very few companies measure the economic success of AI. But where is the sense in implementing AI, not knowing if there is a concrete positive impact and how big this impact is – in terms of savings or increased profits?

Let's look deeper into the challenges of measuring the success of AI in manufacturing by using predictive maintenance as an example. Predictive maintenance is supposed to prevent unplanned downtime of machines in manufacturing processes by using machine learning. The overall goal is to alert as to what is needed to avoid stoppages of production in the future.

Predicting the future seems to be a pretty ambitious goal. How many of you think that anyone or any algorithm or any software solution is able to predict the future? Generally, it is not possible, of course. The more degrees of freedom a system has, the worse is the predictability, because it is impossible to capture "all" data that have or might have an influence. For example, the temperature, machine vibrations, humidity, quality of raw material, utilized capacity, dust, the age of machines, and the quality of spare parts. This list would be almost endless if you tried to capture "all" data. Not using "all" data would presume, that you know in advance, what data to collect, and what data are unnecessary. Furthermore, the more data are captured, the more data are needed for a precise model. Since the system is dynamic and the behavior might change over time, in real-world systems it is impossible to get enough observations to learn a model in all stages. However, for specific systems, predictions can be made within a certain range, as in (von Birgelen et al., 2018) the condition of a single blade of a machine can be identified and a better point in time for maintenance can be predicted, compared to what humans can do. But this is not a free ride for applying predictive maintenance. A holistic evaluation has to be done for every use case.

Based on the interviews, it seems nothing else than sort of a self-fulfilling prophecy that AI has a positive economic impact. However, it is difficult to evaluate whether or not predictive maintenance reduces machine downtimes and at the same time saves cost for maintenance. Let us explain that a bit more accurate: Overall, predictive maintenance usually reschedules the point of maintaining machines, which might be shifted to an earlier point in time to prevent machines from unintentional stoppages. If you maintain a machine based on the suggestion of an algorithm earlier then you would have done it in the past by using regular maintenance schedules, how can you say that this particular machine would have really had an unexpected downtime without the use of predictive maintenance? How can you definitely say that maintenance based on predictive maintenance is better than regular maintenance programs? How can you definitely say that changing e.g. wear parts based on suggestions of predictive maintenance solutions is better than regular maintenance programs? And furthermore, how can you be sure that it is more cost-effective to rely on predictive maintenance? The an-

[1]Comprises only people working in companies, that implemented AI solutions in manufacturing.

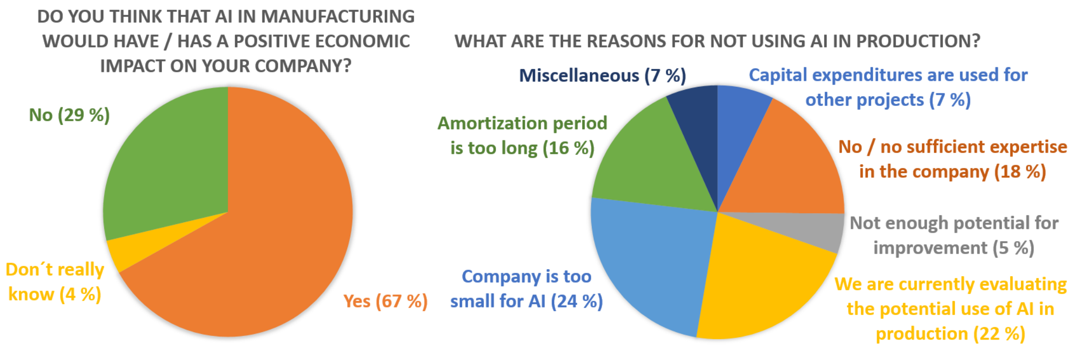

Figure 1: Results of the interviews.

swer is: In many cases, you simply can't tell. And that might be one reason that most of the companies have no calculations, or at least no proven about savings or profit increases with regards to predictive maintenance.

One conclusion might be, that it is good to have adequate support from AI, but that it is still helpful to scrutinize the result and use your own (real) intelligence, before making any decisions with regards to maintenance in manufacturing. Not fully giving up our position in the driver seat in favor of AI might be a good advice in the long-run. So use the benefits of AI, but be at least a bit cautious and alert of how far you (blindly) rely on AI in manufacturing.

3 SOLUTIONS TO SUPPORT AI IN SMEs

In this section, we introduce strategies to support and foster AI applications especially in SMEs. Therefore, we identified three main aspects: Usage of the term 'AI', easy application of AI, and concrete determination of its benefit.

3.1 Differentiated Usage of the Term AI

As outlined in section 2, there is no common and generally accepted definition of the term 'AI'. Furthermore, AI and ML are often seen synonymous. Additionally, the terms are just frequently used for marketing purposes to promote a product or a whole company as being innovative and up-to-date. All this makes it difficult to use the term 'AI' correctly and in the right context, especially for people that do not have deep knowledge about AI. Furthermore, many people are not aware of the difference between use cases ('the problems' to be solved) and the solution itself. AI is not the use case, it is just one possible solution. But with the hype of AI, it seems that the use case is not important. Important is that the solutions include AI.

However, as far as the community is not able to provide a common definition, it is not possible to always use the term in the right context. The contribution of the scientific community should be a more stable and functional definition of AI for the industry sector. Nevertheless, if the definition is available, the community has to apply it properly. This includes companies that want to promote their products as well as the research institutes that promote their work. Everybody in the community should clearly distinguish between the 'underlying problem' and 'solution'. If the tackled problem has been solved, the quality of the result is the crucial point, not if AI is part of the solution.

3.2 Easy Application of AI

Hurdles for the application of AI are, according to the interviews, the missing expertise, costs/amortization time, and the size of the company, which might be interpreted as missing infrastructure. Certain tools for AI and especially machine learning, such as R (Ghatak, 2017), the Python library TensorFlow (Abadi et al., 2016), or ML.NET (Ahmed et al., 2019), are available and basically relatively easy to use. But these tools just provide algorithms. Some important and time-consuming steps, such as data acquisition, pre-processing, and the algorithm configuration has to be implemented or adapted by the users. Even if the algorithms are available, their application requires a much deeper knowledge.

Some approaches try to automate machine learning (Auto-ML), e.g. TPot (Olson et al., 2016) or auto-sklearn (Feurer et al., 2015). Such methods can be helpful by selecting and optimizing the selected algorithms and their configuration, but there is still an initial effort to get the data and combine them with the used methods. There are first research projects that address these issues, such as ManuBrain (Burggräf, 2020) or KOARCH (Bunte, 2020). In KOARCH, a Cognitive Architecture for Artificial Intelligence in Cyber-physical Production Systems (CAAI) has been introduced (Fischbach et al., 2020). The CAAI does not only automate the selection process of algorithms, but it also selects the whole pipeline of data preprocessing, modeling, and model usage. Furthermore, if there is sufficient knowledge about the respective production plant, it is possible to automatically adapt production plant parameters and create a closed-loop application, e.g. for optimization. If the production plant provides OPC UA server, the CAAI has simply to be connected to these servers and a declarative aim has to be selected, e.g. 'energy optimization'. Due to the usage of virtualization, it is easy to set up the system and prepare its application. A graphical user interface can be integrated, which enables the usage of CAAI without programming skills. Nevertheless, the CAAI does not aim to replace AI experts. It is seen as a reasonable extension since it is likely that AI experts might find better solutions. Nevertheless, such approaches are a good starting point for SMEs, which can be used to get in touch with AI technology and evaluate the benefits without unreasonable costs.

To conclude, SMEs do not need algorithms that have a slightly better run time or outperform another algorithm on an artificial data set. From their perspective, new algorithms only make sense if there are problems identified that cannot be solved with an existing one. SMEs do often not have the basics for the application of AI, e.g. infrastructure and experts. They might need external support during the first steps that have to be enabled by solutions with relatively low effort and low preconditions regarding the expertise and infrastructure.

3.3 Determine Benefit

Based on the results of the interviews, we could identify two groups with regards to the determination of AI benefits. The first group is convinced of the benefit of AI, its simple presence is obviously enough to satisfy them, since they have a strong belief in AI technologies. The other group is per se skeptical and does not believe that AI can be beneficial for their business. Somehow or other, it is improvident not to evaluate the concrete benefits of AI. If you don't measure benefits, how can you 'sell' your solution as being successful?

As mentioned above, it is not always easy to evaluate the benefit. So, it is comprehensible that companies do not create costly studies before they integrate AI into their machines, just to have a reference value for evaluation. However, this is seen as a precondition to evaluate the benefit. As a result, it is mostly unknown which processes can be supported by AI and which are not predestined for it so far. It would create a huge benefit if evaluation data were available to convert from try-and-error to a comprehensible decision based on reliable knowledge and data.

From a scientific point of view, it is necessary to have a broad knowledge base to evaluate the potential benefit of the usage of AI upfront. This requires that especially companies, research institutes, and universities need to work closely together, gather relevant data, and publish the concrete improvements being achieved with AI, but also the hurdles and challenges they are faced. But even if companies might have such data available, they are mostly reluctant to share them with a broader community because of confidentiality and with regard to their competitors. Furthermore, the benefit might be company-specific and thus must be described in detail to gain leverage. For example, optimization of a production module in a sequential production line provides a large benefit if it is the bottleneck of the production line. The same optimization in another company can be with less or without benefit if the module is not the bottleneck. Another hurdle might be, that people are not willing to share failures with regards to implementing AI solutions. But from a scientific perspective, it is also important to know what doesn‘t work well and especially why. One contribution to solve this issue could be a clear guideline, how an evaluation should be done, and how to balance the need for confidentiality of gathered data and the need to share those data with the AI community. To gain more efficiency and effectiveness companies can cooperate e.g. with universities and set up joint research projects related to concrete business cases. Those joint projects have a good chance to be funded e.g. by governmental organizations. Furthermore, companies can also benefit from the knowledge of researchers and experts at universities. In the end, it is a win-win situation.

4 BEST PRACTICES

There are several examples of the successful AI applications in industries, that we introduce in this section. We chose anomaly detection and optimization as best practice examples. Besides these areas of application, there are many more use cases that can be solved with AI, such as decision support, extending the pay per use to *pay per stress*, which considers the wear of a machine, or use AI for the generation of test cases. All presented use cases have been implemented by members of the authors' institutions.

4.1 Use Case 1: Anomaly Detection

Anomaly detection is a good first use case to apply AI. The goal of anomaly detection is to observe the plants' behavior and detect changes and variations in that behavior. However, the results are usually shown to the operators, but no further processing steps, such as scheduling maintenance or diagnose the root cause of the anomaly are performed. This further processing requires much additional effort for e.g. data labeling and modeling. Experienced operators can be well supported by an anomaly detection algorithm, since it is sometimes not obvious to identify the assignable cause of an anomaly. By knowing the anomalous signal, operators can mostly identify the cause of the anomaly by themselves. Overall, anomaly detection can support operators to identify undesired states of the machine, detect performance drifts, and ensure the product quality.

We implemented anomaly detection functionalities to a production plant in the food industries. Since food is a sensitive product, it is important to identify malfunctions in production as early as possible to not risk contamination. For each module in the production plant, a model of the normal behavior was learned by the application. Hybrid automaton were used for it, as introduced in (Niggemann et al., 2012). The model enables the differentiation between discrete, continuous, and time failures and thus covers all relevant issues. Since the underlying process contains fast-changing signals, it was a challenge to acquire the data with an adequate sampling rate. However, we were able to monitor the production plant and identify unexpected behavior, so that the operator can be adequately supported. The used approach was perfectly matching the companies' need for additional observations of their plant to maximize operating safety. The key for the project was a well-defined use case, where the benefit of the AI technology can be verified easily, as well as a bunch of algorithms that could be easily tested to identify the most suitable one. However, the easy application of AI, as described in section 3.2, would have reduced the effort of experts significantly.

4.2 Use Case 2: Optimization

Optimization is a broad field. In this respective use case, we focus on the optimization of industrial equipment. Typically, optimization is used to improve product quality, reduce resource consumption, or increase throughput. In many cases, the optimization has a direct impact on profitability, which makes it very interesting for companies.

In our specific example, the resources of an industrial cleaning process were optimized. This process needs water, energy, and an operator. Depending on the local parameters, e.g. type of pipe, amount of dirt, and type of dirt, the operator has many parameters which he can adapt. Differences between operators have been identified, some clean with more water and high pressure only once, where others use less water and less pressure but clean multiple times. The aim of this project was to support the user to identify the best matching parameter for the current cleaning task. Since it is an individual process, the challenge was to get reliable data, such as the size of the pipe or the accumulation of dirt. Because these values are given by the operator, the data contains uncertainties. To deal with this, a Bayesian network was used to perform the optimization. Therefore, the basic structure was modeled by experts and the probabilities between the notes are learned from the collected data. Furthermore, a rule-based system was implemented to support the decision process. Overall, the system can now support the operator by identifying the best parameters for the respective cleaning process. Details of the solution can be found in (Shrestha and Niggemann, 2014) and (Shrestha and Niggemann, 2015). The key to this project was again a well-defined use case with a clearly planned benefit. The Bayesian network was created by experts. Automated methods suggested in section 3.2 would probably not reach the same good results.

5 CONCLUSION AND FUTURE WORK

The main results of the 411 interviews are that there are not many applications of AI in SMEs and the AI expertise in SMEs is still low. The benefits of AI are not often really measured, so most people just blindly trust that AI is beneficial. To support the usage of AI, the term should be defined properly in the context of automation systems, the usage of AI has to be simplified, and the benefit has to be measured, to have a solid basis for decision-making. However, AI in SMEs can not only be successful, it is also manageable as shown by the two best practices. The best practices also show that the suggested solutions can help, but they are not panacea.

Due to the method of the interviews, there are some limitations: The interviewees were mainly from SMEs and working within production. The companies were predominantly machine and plant construction companies. So, the introduced results in section 2 can be understood as a snapshot of the practice that might differ in different industry sectors.

There are additional points that should be addressed in future work. Especially the definition of AI and the measurement of its' benefit has to be done by a broader community in a joint effort. But not only the definition is important; everyone can start right now to use the term AI more carefully and question it as needed. To ease the usage of AI, it can be supported through projects such as ManuBrain or KOARCH. Even if these projects follow a general idea, they focus on specific aspects of the (semi-)automatic application of AI.

Properly used, AI is beneficial to companies and can actively support problem solving in different areas of manufacturing.

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