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Potentials of weak artificial intelligence for operational resource efficiency

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Study: Potentials of weak artificial intelligence for operational resource efficiency

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Editorial:

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Potentials of weak artificial intelligence for operational resource efficiency

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LIST OF ABBREVIATIONS

AI	Artificial Intelligence
AGV	Automated Guided Vehicles
API	Application Programming Interface
ARIMA	Autoregressive Integrated Moving Average (model)
AS	Application scenario
BERT	Bidirectional Encoder Representations from Transformers
BMU	Federal Ministry for the Environment, Nature Conservation and Nuclear Safety (German: *Bundesministerium für Umwelt, Naturschutz und nukleare Sicherheit*)
CFD	Computational Fluid Dynamics
CO_2	Carbon dioxide
CNN	Convolutional Neural Network
DDQN	Duelling Deep Q-Network
dpi	Dots per Inch (image resolution feature)
DQN	Deep Q-Network
EDPB	European Data Protection Board
FFT	Fast Fourier Transform
FPP	Forecasting Principles and Practice
GDPR	General Data Protection Regulation
GHG	Greenhouse gas
GPS	Global Positioning System
HDPE	High Density Polyethylene
KPI	Key Performance Indicator
LSTM	Long Short-Term Memory

MEMS	Micro Electro Mechanical System
ML	Machine learning
MVP	Minimum Viable Product
R&D	Research and Development
RF	Random Forest Algorithm
RNN	Recurrent Neural Network
ROI	Return on Investment
SME	Small and Medium-sized Enterprises
SVM	Support Vector Machine
VDE	Association for Electrical, Electronic & Information Technologies e. V.
VDI	Association of German Engineers (German: *Verein Deutscher Ingenieure e. V.*)
VDI ZRE	VDI Zentrum Ressourceneffizienz GmbH
WvSC	Werner on Siemens Centre

EXECUTIVE SUMMARY

In society, questions of resource efficiency and sustainable production are becoming increasingly important, which is also prompting companies to address more strongly the issue. Through the use of artificial intelligence (AI), companies have been able to realise operational efficiency gains in order to achieve competitive advantages, among other things. So far, these successes have only been transferred to a limited extent to operational resource efficiency. The potentials associated with this have been recognised in principle but have so far only been insufficiently qualified and quantified. The qualitative gap is addressed by the present study on "Potentials of Weak Artificial Intelligence for Operational Resource Efficiency" by aiming at the efficient use of material, energy, and water as well as the reduction of the resulting greenhouse gas emissions. Quantitative statements are difficult due to insufficient data. The topics of AI and resource efficiency are considered integratively and brought into the context of operational practice. The study is based on a methodical literature research, a survey of small and medium-sized enterprises (SMEs) and larger companies as well as on expert interviews. The main target group of the study is SMEs. For them, potentials for increasing resource efficiency are identified and incentives for the use of AI are created. Within this framework, an empirical survey of the current dissemination and application of AI is carried out together with links to resource efficiency. Overall, it is shown that resource efficiency currently represents the basic motivation for the operational application of AI in the rarest of cases. Nevertheless, resource efficiency is in many cases a positive side effect of the use of AI. The study provides a comprehensive overview of such application scenarios and practical examples. It is concluded that there is a need for further research on the use of AI, including the investigation of possible negative effects due to increased energy consumption for computing power or raw material consumption for the required information and communication technology. In addition, the topic of AI must be supported by research specifically for SMEs. The comprehensibility of and educational opportunities for AI must be improved.

1 INTRODUCTION

Resource efficiency and artificial intelligence are topics whose integrated consideration forms the basis for this study. At the beginning of the study, the two concepts are defined and the motivation for their consideration is elaborated. Prof. Dr. Eng. Alexander Sauer (University of Stuttgart and Fraunhofer Institute for Manufacturing Engineering and Automation IPA) provides additional insights into the topic in an expert interview – with a focus on small and medium-sized enterprises (SMEs). Furthermore, the objectives of the study are explained, the main research questions are outlined and the methodology for answering them is presented.

1.1 Motivation

Artificial intelligence (AI) can solve concrete application problems using computer programs that usually require human intelligence. Through algorithms and data, AI systems are capable of self-optimisation. Section 2.1 discusses the basic concepts related to artificial intelligence in detail. Typical AI tasks include classification, segmentation, and regression, for example. In this way, application fields such as root cause analysis or text and image understanding can be automated.

In the corporate context, the introduction of AI is often associated with the goal of increasing the efficiency of operational processes by automating routine activities. Companies gain flexibility and adaptability, giving them a competitive edge. The ability of AI to enable the evaluation of very large amounts of data makes certain problems solvable[1] in the first place.

Various recent studies[2] show that AI solutions can also be implemented in SMEs. Issues of resource efficiency and sustainable production are becoming increasingly important in society. This is prompting companies to look more closely at artificial intelligence in this context in the future and identify untapped potential. However, the potential of AI for operational resource

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1 Cf. Senior, A. W.; Evans, R.; Jumper, J.; Kirkpatrick, J.; Sifre, L.; Green, T.; Qin, C.; Žídek, A.; Nelson, A. W. R.; Bridgland, A.; Penedones, H.; Petersen, S.; Simonyan, K.; Crossan, S.; Kohli, P.; Jones, D. T.; Silver, D.; Kavukcuoglu, K. and Hassabis, D. (2020).

2 Cf. Deloitte Private (2021).

efficiency has not yet been sufficiently investigated. This gap is now to be closed with the present study.

1.1.1 Resource efficiency in operational practice

Since the 2015 Paris Climate Conference and the resulting decision to limit global warming to below 2°C (compared to the pre-industrial era), the reduction of man-made environmental impacts has increasingly moved onto the political and social agenda. As a result, the German Federal Ministry for the Environment, Nature Conservation and Nuclear Safety (BMU) adopted the national climate protection plan in 2016. This envisages a reduction in greenhouse gas emissions of at least 55% by 2030; compared with the international reference year 1990. The national climate protection plan identifies industry as a relevant field of action and derives detailed targets and measures[3]. In 2018, for example, the industrial sector contributed 22.5% to Germany's total greenhouse gas balance. Of this, 15% comes from the necessary energy supply; the remaining share is attributable to industrial processes[4].

As one of these measures, an energy audit became mandatory a few years ago for all companies that are not classified as SMEs according to the EU definition[5]. The aim of this audit, which is required by law, is to derive energy efficiency potentials on the basis of a previously conducted balancing of energy consumption data. Some companies go one step further and establish an energy management system according to DIN EN ISO 50001[6]. The aforementioned commitment and the comparatively low complexity of identifying and implementing initial energy efficiency measures led to a strong focus on energy as a resource as soon as efforts were made to reduce the company's environmental impact. However, this focus neglects key natural and operational resources. Holistic optimisation can only take place with the inclusion of all natural resources. For example, in an ecological balance sheet covering scopes 1 to 3 in accordance with the recognised standard of the Greenhouse Gas Protocol, all production, consumption and auxiliary materials contribute

3 Cf. Federal Ministry for the Environment, Nature Conservation and Nuclear Safety (2016).
4 Cf. Federal Environment Agency (2021).
5 Cf. Federal Office of Economics and Export Control (2020).
6 Cf. DIN EN ISO 50001:2018.

to the environmental impact of the company[7]. The German Resource Efficiency Program (ProgRess I), first adopted in 2012, envisaged a 100% increase in raw material productivity by 2020 compared with 1994 levels[8]. However, with an improvement of around 65%, this was clearly missed[9]. Accordingly, the targets have been updated. An annual increase in raw material productivity of 1.6% by 2030 is targeted in the German Sustainability Strategy of 2016. The German Resource Efficiency Program ProgRess III, which will be relaunched in 2020, lists specific measures for achieving these goals. Among other things, digitisation is prominently mentioned as a relevant enabler[10]. Added to this is the considerable contribution of material costs (42%) to the overall cost structure of manufacturing[11]. The enormous leverage effect of material efficiency programs becomes clear, respectively. Even small material savings often translate into a significant economic advantage. Companies in the manufacturing sector are consequently striving to save resources and, in particular, materials in order to be able to compete internationally in addition to reducing their own environmental impact. Accordingly, it should be noted that resource efficiency and economic efficiency are not contradictory, but in many cases complementary objectives.

Within the present study, operational resources are understood to be both the natural resources of material, water and energy and the greenhouse gas (GHG) emissions generated, which are also to be classified as natural resources via the uptake function in ecosystem services (sink function). Since materials and energy are required for the production of operating supplies and machinery, they also consist of the natural resources, which are considered as a subset of the operating resources in this study. People and time are explicitly excluded from the concept of operational resources in this study.

Increasing resource efficiency is a key lever for reducing environmental impacts and costs at the same time. Despite these advantages, resource efficiency in companies is often seen as a side effect and not specifically promoted. Various stakeholders – such as politicians, customers or investors –

7 Cf. Bhatia, P.; Ranganathan, J.; Gage, P.; Corbier, L.; Schmitz, S. and Oren, K. (2004).
8 Cf. Federal Ministry for the Environment, Nature Conservation and Nuclear Safety (2020).
9 Cf. Federal Environment Agency (2020b).
10 Cf. Federal Environment Agency (2020a).
11 Cf. Federal Statistical Office (2017).

are already placing increased focus on this issue and are calling for an efficient strategy to improve corporate sustainability performance, particularly in the area of climate neutrality. This goal can only be achieved by incorporating resource efficiency into operational practice. This was also emphasised by Prof. Dr.-Ing. Alexander Sauer, head of the Institute for Energy Efficiency in Production EEP at the University of Stuttgart and director of the Fraunhofer Institute for Manufacturing Engineering and Automation IPA.

Interview Prof. Dr.-Ing. Alexander Sauer

How do you perceive the willingness of SMEs to take on the task of reducing their own environmental impact?

Prof. Sauer: Whereas a few years ago only a few pioneers set their own company on an ecologically sustainable path out of intrinsic motivation, interest in this area is currently increasing significantly. This development can be observed across diverse industries and company sizes. In this context, a wide variety of drivers provide incentives to address the reduction of one's own environmental impact. While an increasing number of internal and external stakeholders expect climate strategies from companies, stricter requirements and regulations on the part of legislators can also be expected in the coming years. This makes more and more companies take action.

Even though SMEs often have limited access to capacities for the development and especially the realisation of a climate strategy, direct decision-making structures and higher flexibility are relevant enablers for the implementation of sustainable production. We are observing this through various projects and case studies that we are currently working on at Fraunhofer IPA. In this country, SMEs are said to have a strong innovative capacity. Many companies use these to position themselves strategically through a sustainable orientation.

What potential does resource efficiency offer in the industrial environment for achieving climate targets?

Prof. Sauer: We live in a society where growth is the central guiding principle of our way of economising. Already today, we are operating outside our planetary boundaries and consuming more resources than our earth can regenerate. In view of the growing world population and the continuing increase in consumer demand, resource efficiency must be significantly increased. Consequently, we need a massive decoupling of growth and resource consumption in the short to medium term. Resource requirements are closely linked to almost all ecological impacts of human activity. From extraction to processing and transport, environmental impacts are incurred that make agreed climate targets a distant prospect. A reduction in resource requirements within production thus has a direct impact on the emission intensity of processes, products and consequently our consuming society. Operational resource efficiency thus supports the achievement of both individual and overall societal climate targets.

How do you assess the contribution of AI to increasing the resource efficiency of SMEs?

Prof. Sauer: Digitisation as such has been considered a key tool for improving the sustainability performance of manufacturing companies for some time now. The analysis of large volumes of data and the associated derivation of possible optimisation measures are often only possible with the establishment of digitisation solutions.

The integration of AI methods is the logical next step on the way to exploiting resource efficiency potentials in production environments. There are also opportunities for SMEs to achieve competitive advantages and strengthen or establish unique selling points through the targeted integration of AI.

1.1.2 The AI ecosystem in Germany

Since the term “artificial intelligence” was coined at a conference at Dartmouth College in Hanover, New Hampshire (USA) in 1956, this multidisciplinary field of research has been constantly evolving. At the latest when IBM's Deep Blue was able to beat the then reigning world chess champion Garry Kasparov in a regular chess match in 1997[12], the topic of artificial intelligence also entered the perception of German society. This also brings industrial applications into the focus of research. In November 2018, the

[12] Cf. Newborn, M. (2003).

"Artificial Intelligence Strategy of the Federal Government"[13] was published. This not only launched the "AI made in Germany" seal of approval, but also laid the foundation for the establishment and expansion of an AI ecosystem that is intended to make Germany a leading AI location worldwide.

As part of this ecosystem, the KI Bundesverband e. V. (English: *AI Federal Association*) represents more than 300 innovative SMEs, startups and entrepreneurs involved in the development and application of AI. The goal is to establish and further promote an active, successful and sustainable AI ecosystem in Germany and Europe. In addition, the KI Bundesverband – also with its regional groups – contributes to strengthening Germany as an AI business location. However, many industries still have some catching up to do. That is why the KI Bundesverband has set up working groups. For example, the "Industry 4.0 & Manufacturing" working group addresses specific issues relating to AI in the manufacturing sector.[14]

One issue of particular concern to the KI Bundesverband relates to the challenges posed by global warming[15]. The perception in this context is ambivalent. Artificial intelligence is portrayed as either a saviour or a climate sinner. The "Climate" working group is therefore taking a critical look at the use of AI in the context of sustainability. On the one hand, opportunities and fields of action for politics and industry are discussed, and on the other hand, risks such as rebound effects or possible significant energy consumption of the AI infrastructure and ways to minimise them.

In addition to the KI Bundesverband, there are many regional initiatives with the goal of imparting knowledge and promoting the widespread use of artificial intelligence in companies in the respective region. In doing so, they are shaping the nationwide AI ecosystem through their work. As an example of a regional initiative, the "AI for Hamburg" initiative is presented below.

13 Cf. Federal Ministries of Education and Research, Economic Affairs and Energy, Labour and Social Affairs (2018).

14 Cf. KI Bundesverband (2020).

15 Cf. Spreiter, L.; Witte, K.; Just, V.; Damm, P.; Bohnhoff, T.; Rahtgens, C.; Asanger, F.; Maas, S.; Britsch, C. and Förstner, F. (2021).

AI for Hamburg – Network for the promotion of AI

Introduction of AI for Hamburg

Mainly through international AI expertise in a business context, AI for Hamburg[16] promotes the knowledge and broad use of artificial intelligence and especially machine learning in companies in the region.

The AI for Hamburg initiative was founded and established in 2019 by various partners. The goal is to further develop the Hamburg metropolitan region into a beacon of artificial intelligence in Europe.

Barriers of SMEs to the use of AI

The topic of AI is still fraught with a great deal of ignorance and uncertainty, particularly in the SME sector. There is a lack of trust in the technology, and AI solution providers are often unfamiliar. Other obstacles for many SMEs are the lack of data availability and the question of how to finance the measures. It is often not apparent what data can be used for AI applications or what quantity and quality of data is required.

Advantages of a regional technology platform for SMEs

AI for Hamburg uses various channels and events to communicate which solutions can be implemented with AI today. The aim is to support SMEs in particular in order to better understand the corresponding opportunities and risks, develop smart solution concepts and find partners for implementation.

Although the potential applications of AI for increasing social sustainability or climate protection have already been widely discussed[17], application fields of AI for resource efficiency in the manufacturing sector receive rather little attention in the public debate.

[16] Cf. AI.HAMBURG (2021).

[17] Cf. Kaack, L. H.; Donti, P. L.; Strubell, E. and Rolnick, D. (2020).

SMEs face major challenges in adapting new technologies because the available human, economic, time and also natural resources are limited and the scope for experimentation is small. This is especially true for the introduction of AI, since in addition to technical resources (software and hardware), a (digitised) database must also be available. In addition, new skills are required from employees[18]. This and how the introduction of AI in SMEs can succeed is shown, for example, in studies by the VDI/VDE-Gesellschaft Mess- und Automatisierungstechnik[19] and the Mittelstand 4.0-Kompetenzzentrum Dortmund[20]. In addition, practically oriented assistance offers for the selection, initiation and implementation of AI projects in SMEs now also exist. One example of this is the “KI-Sprechstunde” (AI consultation) of “Gemeinsam digital”[21], the Mittelstand 4.0 competence centre in Berlin. The AI consultation with AI trainers is the first point of contact for SMEs and provides support in finding relevant application scenarios. Guidance is provided for further collaborations with network partners and suitable technology services in the marketplace are discussed[22]. However, these assistance offerings lack the visibility to contribute to a comprehensive transformation of the middle market.

In addition to the previously mentioned offers of assistance, there are also a variety of funding opportunities for SMEs, such as the “KI-Leuchttürme” (AI lighthouses) funding program. The German Federal Ministry for the Environment, Nature Conservation and Nuclear Safety (BMU) is funding projects with the initiative “AI Lighthouses for the Environment, Climate, Nature and Resources” in which AI is developed and used to address ecological challenges and which also stand as an example of resource-saving digitisation.[23]

1.2 Targets

The aim of the study is to discuss the impact of AI in terms of operational resource efficiency related to the natural resources of water, energy, materials and greenhouse gases in the manufacturing sector. The focus here is on

[18] Cf. Lundborg, M. and Märkel, C. (2019).
[19] Cf. VDI/VDE Society for Measurement and Automation Technology (2020).
[20] Cf. Mittelstand 4.0 Competence Center Dortmund (2020).
[21] Cf. Gemeinsam digital (2021).
[22] Cf. Witte, K. and Gradl, M. (2021).
[23] Cf. Federal Ministry for the Environment, Nature Conservation and Nuclear Safety (2021).

SMEs. For these, the implementation and realisation of AI often represent a major challenge, but one that is also associated with opportunities. The study deliberately focuses on SMEs, as they often lack the time and personnel to gain an overview of the possibilities of AI and the associated methods and technologies. The necessary expertise to select and implement AI projects in their own operations is also often lacking. For this reason, the study is not only intended to show examples of AI for operational resource efficiency, but also to provide practical assistance in implementing it in one's own company. Accordingly, the study is guided by the following questions:

Research questions of the study

- What weak AI technologies and methods can manufacturing SMEs use to increase their operational resource efficiency?
- What potential in terms of operational resource efficiency does weak AI enable for manufacturing SMEs?
- Which application scenarios of weak AI are most promising to increase operational resource efficiency in SMEs?
- What success factors and barriers exist for the systematic application of weak AI to increase operational resource efficiency in SMEs?
- What implementation examples exist for successfully increasing operational resource efficiency in SMEs through the use of weak AI?
- Which fields of action arise for SMEs, science and politics?

In the context of this study, owner-managed companies with fewer than 1,000 employees are considered SMEs – there is no restriction based on sales or balance sheet total.

1.3 Methodical approach

First, some key terms of the study are defined (Chapter 2). The starting point for answering the research questions is a systematic literature review of the current state of research on AI application scenarios along the value chain of manufacturing companies that have an impact on operational resource efficiency. The results of this literature review will be used to design an expert survey in the form of an online survey. The aim is to investigate the practical relevance of the researched application scenarios and to further qualify them with regard to their success factors and barriers as well as their influence on operational resource efficiency (chapter 3). A methodology for analysing the potential of application scenarios, including a maturity and metrics model, is then presented. This can be used to make the saving of resources by weak AI measurable (Chapter 4). In chapter 5, the potential analysis is exemplified by eight selected application scenarios. The application scenarios are underpinned with successful practical examples from SMEs. Chapter 6 is dedicated to the success factors and barriers in the implementation of AI. In chapter 7 the fields of action for SMEs, politics and science are derived and elaborated. The study is concluded with a summary and conclusion in Chapter 8.

2 BASICS AND TERMINOLOGY

This chapter explains the basics and central concepts in the subject areas of artificial intelligence and resource efficiency. As a result of a literature review, typical application scenarios of AI with a documented impact on resource efficiency are shown. This potential is further quantified and qualified by an expert survey in chapter 3 and application scenarios and practical examples in chapter 5.

2.1 Weak artificial intelligence

There are numerous definitions of AI in the literature and to date there is no uniform explanation of the term. This is because AI describes a multidisciplinary field of research that brings together a variety of methods and technologies. What unites them is the ambition to develop systems that emulate and even surpass human cognition.

In general, a distinction is made between “weak” and “strong” AI (”artificial narrow intelligence” vs. “artificial general intelligence”). In this context, “strong” AI is characterised above all by the fact that it possesses cognitive abilities that are superior to or on a par with humans in almost all aspects. In contrast, “weak” AI can be superior to humans, but usually only in those areas for which it has been explicitly programmed and trained[24]. The breakthroughs of AI perceived by the general public, for example by IBM in the quiz show Jeopardy and DeepMind in chess and Go, respectively, thus also represent application scenarios of “weak” AI. While these systems are clearly superior to humans in their respective domains, they have no capabilities apart from that. Basically, it can be stated that it has not yet been possible to develop a general, “strong” AI. Accordingly, the focus of this study is on “weak” AI, so the term “AI” used for the rest of this study should be considered synonymous with it. Nonetheless, “strong” AI is a topic that continues to engage researchers and is worth observing[25].

[24] Cf. Bostrom, N. and Yudkowsky, E. (2014).
[25] Cf. Marcus, G. (2020).

Distinction of weak to strong AI

- "Weak" AI is focused on solving concrete application problems based on known methods from mathematics and computer science. The developed systems are capable of self-optimisation. To this end, aspects of human intelligence are also emulated and formally described, or systems are designed to simulate and support human thought.[26]
- The decisive criterion of "strong" AI is that corresponding AI systems have the same intellectual capabilities as humans in a broad range or can even surpass them in this[27].

From a technological or methodological perspective, the algorithms and models of "weak" AI belong to the field of machine learning (ML). This term was coined as early as 1959 by Arthur Samuel. He used it to describe a program capable of producing a particular behaviour that was not explicitly specified as part of the programming[28]. Today, in the context of ML, a distinction is usually made between supervised and unsupervised learning. Another, more special case of ML is reinforcement learning. For all three areas, there are numerous application examples that are already implemented today and for which so-called deep neural networks are mostly used. These have proven to be particularly performant and are one of the key drivers of the major advances in the application of AI over the past decade. Thus, ML algorithms or weak AI take on diverse tasks in a wide range of areas – from speech and object recognition, autonomous control of vehicles to the derivation of recommended actions in expert systems.

An overview of established AI methods can be found in Appendix A. The rapidly developing research field of artificial intelligence regularly generates new or extends existing methods. For this reason, Appendix A does not claim to be exhaustive. Rather, it is intended to give an impression of the breadth of solutions currently available.

26 Cf. Federal Ministries of Education and Research, Economic Affairs and Energy, Labour and Social Affairs (2018).

27 Cf. Federal Ministries of Education and Research, Economic Affairs and Energy, Labour and Social Affairs (2018).

28 Cf. Joshi, A. V. (2020).

2.1.1 Supervised Learning

Supervised learning methods are characterised by their ability to learn implicit and explicit relationships between input and output variables. For example, the algorithm learns whether a cat or a dog is depicted in new and unknown images based on previously marked image files. For this purpose, in supervised learning, it is mandatory that training data with corresponding marks or labels are available. The two most common applications for supervised learning are classification and regression. These are presented below and elaborated on using suitable examples.

Classification

The aforementioned expample of assigning images to the categories "dog" or "cat", represents a binary classification task. In a classification, an attempt is made to assign one of the possible and predefined result classes to the respective input data. The number of possible classes and the number of labels to be assigned are not limited to two; e. g., in addition to the existing classes "dog" and "cat", a class "bird" can also be added. In this context, one speaks of "multi-class" or "multi-label" classification. However, classifications are in principle always bound to discrete result values, i.e. a finite number of classes.

Another example of a binary classification is the classification of produced goods into the two classes "meets the quality requirements" and "does not meet the quality requirements", respectively. Based on the evaluation of production data and the application of a classification algorithm, rejects can be detected automatically.

Linear and non-linear regression

In contrast to classification, the task of regression models is to predict continuous values. Here, the learning mechanism works analogously to the classification: The algorithm learns to generate results from unknown data on the basis of training data with corresponding characteristic values and associated result values. "What are the rental costs for additional office capacity?" or "What will sales be next month?" are classic examples of questions that can be answered with a regression.

Although classification and regression may well be considered related approaches, they differ in one important respect: Shortened, classification algorithms try to predict whether a class or label can be assigned to the input data. On the other hand, the goal of regression algorithms is to make a prediction, in the sense of how big (or small) the result value will be[29].

2.1.2 Unsupervised Learning

In contrast to supervised learning, no corresponding labels are assigned to the training data in unsupervised learning. In their absence, the approaches therefore aim at basically characterising the available training data and drawing conclusions based on them, depending on the objective. Thus, the patterns inherent in the data are recognised by the algorithm without any feedback. The classical tasks for unsupervised learning are clustering as well as dimension reduction.

Clustering

In clustering, the algorithm attempts to relate the given input data based on certain metrics. Probably the most common example of this is the segmentation of users or customers. These are grouped into similar clusters based on their behavioural and purchasing patterns, so that individualised offers can be played out per group. In addition, clustering proves extremely useful for discovering natural distinguishing features in exploratory analyses and serves as a starting point for further decision-making[30]. Often, clustering results can also be used as input to supervised learning algorithms[31].

Dimension Reduction

Due to increasing digitalisation, the amount of available data is growing exponentially in many companies and institutions. However, it turns out that larger data sets do not necessarily lead to improved predictions from ML algorithms, as insignificant and redundant information can affect the accuracy of the prediction. The goal of dimensionality reduction is therefore to reduce

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[29] Cf. Provost, F. and Fawcett, T. (2013).
[30] Cf. Provost, F. and Fawcett, T. (2013).
[31] Cf. Danks, D. (2014).

the size of a given data set without a crucial loss of information by reducing the number of variables examined.

2.1.3 Reinforcement Learning

Reinforcement learning occupies a certain special role in the categorisation of ML approaches. Due to the active inclusion of feedback – in the simultaneous absence of pre-marked training data – the methods of reinforcement learning, are neither directly attributable to supervised nor unsupervised learning. The underlying idea is based on the fact that the algorithm interacts with its direct and task-specific environment. In the process, it receives feedback in the form of positive or negative signals, on the basis of which it can learn the appropriate action or strategy in each case. In doing so, the algorithm is usually directed to trade off between exploring its environment and using the knowledge it has already learned. Other specific application scenarios can also be found in robotics and autonomous driving or the autonomous control of vehicles.

2.2 Resources and resource efficiency

Resources

Resources, whether tangible or intangible, form the basis for any entrepreneurial value creation. In the following, the term resource is classified from an economic and political perspective.

This study follows the definition of natural resources of the German and European policy. In addition, the guideline VDI 4800 Part 1 “Resource Efficiency – Methodological Principles, Principles and Strategies” describes a methodological framework for determining and evaluating resource efficiency, which serves as the basis for the present study[32].

[32] Cf. VDI 4800 sheet 1:2016-02.

Resources from a business and policy perspective

- From a business perspective, **resources** comprise all economically necessary factors for production – i.e. in particular operating and auxiliary materials, as well as energy, capital, personnel, expertise and time[33].
- In German and European politics, on the other hand, the term resource is defined in terms of **natural resources** as follows:

"Resource that is part of nature. These include renewable and non-renewable primary raw materials, physical space (surface area), environmental media (water, soil, air), flowing resources (e. g. geothermal, wind, tidal and solar energy), and biodiversity [see also VDI 4800, Sheet 1[34]].

In this case it is insignificant whether the resources serve as sources for manufacturing goods or as sinks for absorbing emissions."[35]

However, since not all natural resources are highly relevant to operations or interact with them, only certain resources are included in the resource efficiency analysis in order to link the societal objective of reducing the consumption of natural resources with opportunities for operational action. The term "operational resources" is therefore used in this study to refer only to the natural resources of material, water and energy, as well as to the GHG emissions generated, which are also classified as natural resources via the uptake function in ecosystem services (sink function). The use of natural resources can often only be determined with a great deal of effort within the company itself, as consumption is rather derived from the upstream and downstream chains of the respective operational resource. One example is the production of operating supplies and machinery. They, too, require materials and energy and thus also consist of natural resources. They are therefore considered in this study as a subset of operational and natural resources. People and time are explicitly excluded from the concept of resources in this study.

33 Cf. Schebek, L.; Abele, E.; Campitelli, A.; Becker, B. and Joshi, M. (2016).

34 Cf. VDI 4800 sheet 1:2016-02.

35 Cf. Kosmol, J.; Kanthak, J.; Herrmann, F.; Golde, M.; Alsleben, C.; Penn-Bressel, G.; Schmitz, S. and Gromke, U. (2012).

Resource efficiency

Resource efficiency is a widely used term not only in business, but also in politics. In it, the entrepreneurial principle of efficient management comes together with that of sustainable development. Sustainable development seeks to preserve “natural capital” – society's natural resources. In this context, the term resource efficiency is defined by guideline VDI 4800-1:2016-02 as follows: “Ratio of a particular benefit or outcome to the resources required to achieve it”[36]. In the operational environment, such a benefit can be the manufacture of a product, the execution of a certain process or the provision of a service. Related to this benefit in the form of an object or circumstance follows the definition of so-called system boundaries (system framework), within which the resource consumptions are to be determined. This definition of system boundaries depends on the given issue, but usually covers the complete life cycle in the sense of a life cycle assessment according to DIN EN ISO 14040, in order to be able to identify possible problem shifts to upstream or downstream processes.[37]

2.3 Typical application scenarios

After the basics from the fields of artificial intelligence as well as resource efficiency have been highlighted, typical application scenarios of weak AI in the industrial environment are presented in the following. These were identified based on a literature review. Chapter 5 describes these and other application scenarios and their contribution to resource efficiency in detail.

During the literature review, the PRISMA method was used. Due to the timing of the literature search, publications up to September 2020 could be included. The PRISMA method first identifies a large population of potentially applicable literature using a targeted but broad search string in scholarly databases, such as Scopus or Google Scholar (n = 1,347). The search string includes the identified AI methods (see Appendix A) as well as the resource efficiency terms relevant to this study: energy efficiency, material efficiency, water efficiency, and greenhouse gas emissions. In addition, there is further literature from additional sources, such as references from discussions with

[36] VDI 4800 sheet 1:2016-02.
[37] Cf. VDI Zentrum Ressourceneffizienz (2017).

subject matter experts (n = 49). In the subsequent PRISMA step, duplicates are first removed – the population is reduced accordingly (n = 1,163). A preliminary selection of the identified literature follows. For this purpose, both titles and abstracts of the scientific articles are read and checked for content consistency with the desired topic area. This leaves 139 publications that will be subjected to detailed analysis. By reading the full texts, the respective relevance is checked, which allows further sources to be excluded from the following processing, for example due to a lack of focus on the manufacturing sector. The remaining 54 publications are subjected to further analysis and classified in terms of application scenarios and AI methods used. Those application scenarios which are mentioned several times in the identified literature are summarised below.

In very few cases, the implementation of an application scenario succeeds with exactly one of the machine learning methods described in Section 2.1. The solution of a concrete problem often requires the interaction of different methods from various disciplines (including statistics, signal processing, ML). For example, it is useful to clean the data in advance using classical statistical methods (e. g., outlier analysis) and then perform a dimensional reduction of the variable space (unsupervised learning) before applying a regression or classification (supervised learning). Careful selection and skillful combination of the various methods can often produce higher quality results.

Predictive Maintenance

The application "Predictive Maintenance" is made possible by recording relevant time series data over the usage period. These are intended to map and monitor the condition of the infrastructure being analysed. The goal is to find patterns to predict failures and prevent them through early maintenance actions. Yet predictive maintenance often requires no more than a comparatively simple mathematical calculation: At what point does the condition of a machine require repair or even replacement in the most efficient way?

Among other things, a variety of different methods of weak AI are applied, whereby the choice of method also affects the complexity of the implementation. For example, some computational models can work with existing data and predict the next maintenance interval without the need to install new sensors or software. For other methods, a more specific data basis is required, necessitating, for example, the installation of camera systems or other sensors. With their help, complex ML algorithms, such as neural networks, can be used to detect fault conditions in production and suggest preventive measures. The often necessary installation/implementation of this software and hardware during the ongoing operation of the production infrastructure is another hurdle that should not be neglected. A prerequisite for successful use of the respective AI methods for the application scenario "Predictive Maintenance" is in any case a solid data basis on which the models can be trained and learn.

By using "predictive maintenance", material and energy efficiency can be significantly increased by means of efficiently maintained machines, as unwanted material and energy losses due to wear of the processing tools and machines are prevented. Increasing energy efficiency in turn leads to a reduction in GHG emissions.

Production planning

Production planning can become more efficient with the help of various ML methods. Based on historical production data, algorithms can be used, e. g. to determine requirements for the future and thus configure optimally designed production lines. By analysing and classifying different manufacturing methods, e. g. with regard to efficiency, production planning can be additionally supported. For this purpose, methods of classification and trend analysis are applied in particular. Often these ML methods are combined with so-called expert systems that issue decision support and recommendations for actions based on real data and the ability to extrapolate information. In some cases, the effort required for production planning can be reduced greatly. Implementation is usually uncomplicated since the methods do not have to be installed during operation or directly on the production lines. A solid data basis is also an important basis for ensuring the functionality of the models.

Reductions in the areas of material and energy consumption and thus a corresponding reduction in GHG emissions can be achieved through improved production planning. Planning is streamlined and can be adapted to specific needs.

Fault detection and prediction/Predictive Quality

A typical application of weak AI in the area of process optimisation is defect detection in production. This can be used in particular for automated quality control of components and products. In addition, some methods allow fault prediction, which enables predictive intervention in the production process (process control) to prevent faults. Methods from almost all application areas of AI – from classification to segmentation, dimensionality reduction, and image and object recognition – are used for this application. The prerequisite for all these methods are extensive data sets, which can be obtained, for example by installing sensor technology and/or camera systems for data collection. These are necessary for training the algorithms to subsequently enable them for error detection.

Even the mere detection of defects can significantly improve resource efficiency in some cases. Early defect detection means that the deviations in the process can be corrected fast and the defective components or products can be sorted out directly. This prevents the execution of subsequent machining processes on scrap parts and accordingly minimises the waste of resources. Defect prediction has an even greater impact on increasing resource efficiency, as the occurrence of defective components or products is ideally prevented altogether. The main savings are therefore expected in the area of materials. In addition, a reduced processing effort for scrap parts is also accompanied by lower energy requirements – accordingly, an increase in energy efficiency and respectively a reduction in GHG emissions can also be observed, also due to the reduction of materials in the upstream chain.

Logistics planning

Similar to production planning, logistics planning also offers potential for simpler, more efficient and faster execution through the integration of AI methods. Using various ML algorithms, hidden patterns, regularities, and irregularities are identified using past, current and potential future data. These patterns are used to develop models that can be used to make useful predictions for the individual company. In addition, open parameters can be used to change the baseline state to explore different scenarios using AI-assisted simulation. Based on the results of the scenario analysis, the logistics system can be adapted and prepared for exceptional situations or similar. This can be applied not only to the procurement and delivery of products, but also to intralogistics within the company's own manufacturing facility. The complexity of the implementation depends primarily on the availability of the data in the process of the potential ML application; in addition, there are the requirements of the application on the computing infrastructure/IT of the company. If relevant parts of the required data sets first must be cleansed or even procured, the effort required to implement the solution increases significantly.

In logistics planning, it is possible to reduce GHG emissions as well as energy consumption by, among other things, optimising transport routes and avoiding empty runs.

Increase energy efficiency in the manufacturing process

In manufacturing processes, energy efficiency can be increased with the help of various AI methods. For this purpose, historical data from manufacturing is required in order to process it using ML algorithms and make demand forecasts or estimates for the future. In addition to increasing efficiency by optimising maintenance intervals (see section “Predictive Maintenance”), data analysis can be used to develop an expert system, for example.

This provides recommendations for action regarding the reduction of operational GHG emissions or energy consumption. Here, the required amount of data and the proper AI depend on the particular manufacturing method and the specific application scenario. Accordingly, users must identify the optimal trade-off between implementation effort and desired meaningfulness. Hence, it is difficult to make general statements regarding software and hardware costs. Nevertheless, it can be stated that common methods for increasing energy efficiency in manufacturing are often only applied as a supporting expert system and therefore in most cases do not need to be integrated into the running production. However, depending on the granularity of the desired evaluation, sensors may need to be retrofitted for improved data.

3 EXPERT SURVEY

In order to also look at the potential of weak AI in terms of resource efficiency from a practical operational perspective, an expert survey is being conducted. The goal is to test the hypotheses formulated in advance and to obtain circumstantial evidence to answer the central research questions. This part of the study focuses on the expert survey of 71 representatives from companies. This is still a relatively small study set due to the subject matter. Nevertheless, important indications and trends can be identified, which may need to be further illuminated by more extensive studies.

It is worth mentioning the high heterogeneity with regard to the respective activity focus of the surveyed companies within the manufacturing sector. First, the design and implementation of the survey will be discussed. This is followed by a characterisation of the survey participants and the presentation of the survey results. The chapter ends with a conclusion that summarises the main findings of the expert survey on the potential of AI for operational resource efficiency.

3.1 Method

A total of 25 hypotheses were formulated and classified into the following categories: Diffusion, application scenarios, maturity model, resource efficiency, business models, barriers, and general hypotheses. An overview of the categories with selected hypotheses is presented in Table 1, and the full list of hypotheses is presented in Appendix B.

In designing the questionnaire, a structured form was chosen, the structure of which can be divided into two sections. The first section contains a flexible question model that adapts to the maturity level of the respective company based on the answer to a central initial question. The second section is independent of this. All participants receive the same questions here.

Table 1: Selected hypotheses per category.

Category	Hypotheses
Application and distribution of AI	The use of AI is not reflected in the corporate strategy.
Application scenarios	Typical application scenarios are: Predictive maintenance, production planning, process optimisation manufacturing – fault detection and prediction, demand planning, increasing energy efficiency in the manufacturing process, increasing energy efficiency in building management
Motivation for the introduction of AI	Increasing resource efficiency is not the key motivation for introducing AI.
resource efficiency	The use of AI can increase resource efficiency.
Importance of external partners	Companies rely on the support of external partners for the introduction of AI.
Differences between SMEs and large enterprises	SMEs show lower penetration of AI applications compared to large enterprises.
Gen. Hypotheses	The existing technical infrastructure makes the introduction of AI difficult.

When dealing with the results of the survey, the following restrictions must be observed. Due to a flexibly designed questionnaire, it may happen that the data basis is smaller in some scenarios when evaluating subsets. In such cases, the interpretation of concrete numerical values is dispensed within the evaluation. Instead, trends are analysed based on existing data. On the other hand, many companies are still unclear about the definition of AI and its delimitation. A definition of AI was therefore provided at the beginning of the survey to give participants a consistent basis for discussion. Nevertheless, there is a possibility that participants have based their own understanding of AI and thus there are slight blurs between the individual returns.

3.2 Characterisation of the survey participants

A total of 71 people from companies in the manufacturing sector – ranging from SMEs to large enterprises – were surveyed between September and October 2020. As shown in Figure 1 a), the ratio of SMEs to large companies is balanced, with participants from SMEs accounting for 46.5% of the population. At 67.6%, a large proportion of the companies surveyed were founded before 1980; only eight companies have been established since the turn of the millennium.

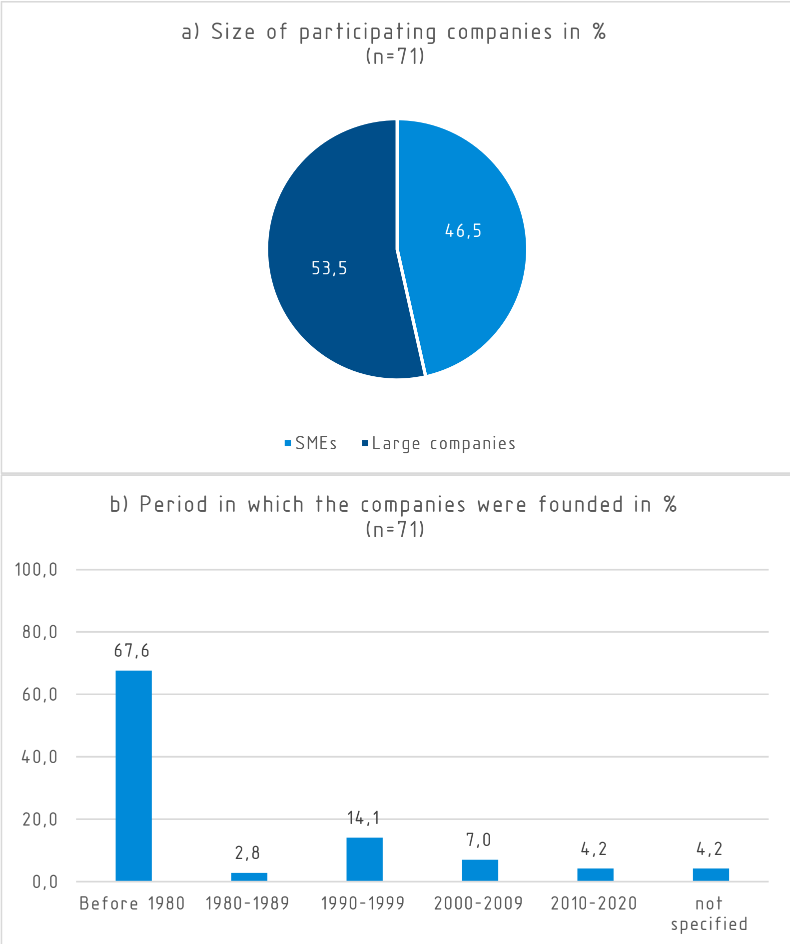

Figure 1: Characterisation of participating companies

Individuals from companies with heterogeneous activity focuses participated in the survey. Accordingly, based on the feedback, another area of manufacturing is covered. As can be seen in Figure 2 a), companies from the automotive and aerospace sectors are the most represented with a share of 19.7%, followed by mechanical engineering and the electrical industry. The companies summarised in the "Other" area are each present only once as a representation of their industry and range from pure service providers to energy suppliers.

The interviewees themselves act not only in primary but also in supporting business areas. In Figure 2 b), it can be seen that the areas of product development, production and management were mentioned most frequently, and participants from these fields of activity correspond to a total of 70% of the population. The range of functions of these individuals extends from employees with and without management responsibility, to departmental management, to executive management.

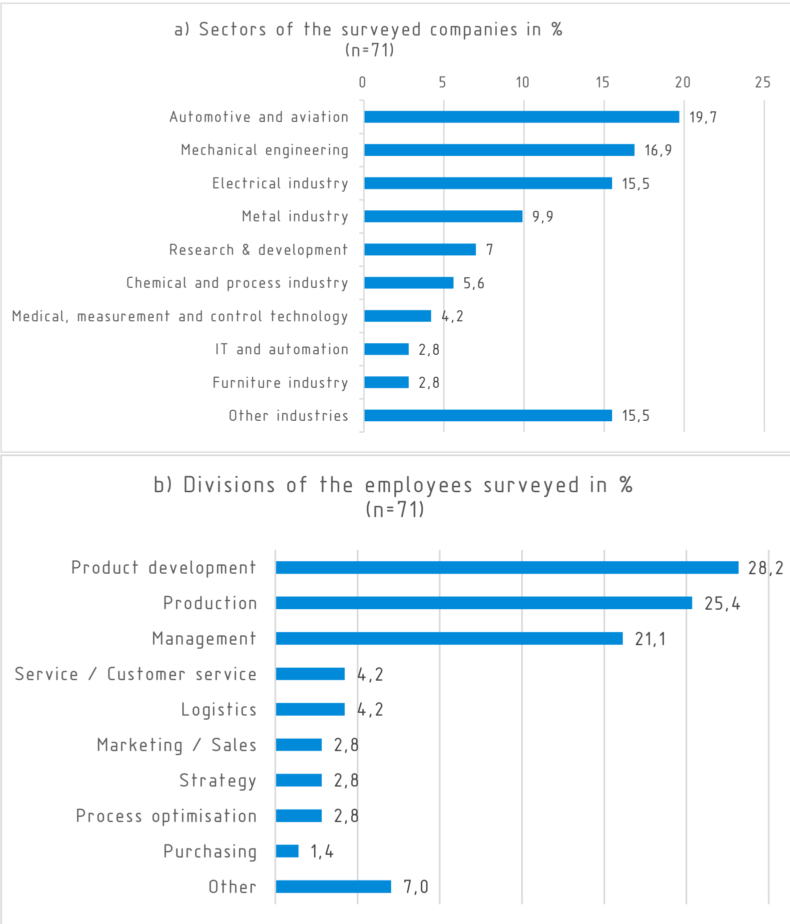

Figure 2: Company industries and divisions

3.3 Results of the expert survey

The following section presents the results of the quantitative evaluation of the expert survey. The analysis is conducted in six subsections, which are guided by the survey design hypotheses presented in Section 3.1. The goal is to work out to what extent and for which application scenarios AI is already being used in the manufacturing sector today. Subsequently, the reasons that initiated the introduction of the presented AI applications are analysed. Based on this, we identify the potential that AI has for increasing the efficiency of the resources under consideration (see Section 2.2). The fifth subsection focuses on the role of external partnerships in the development of AI. The evaluation concludes with an elaboration of differences between SMEs and large enterprises with regard to the use and penetration of AI. Success factors and obstacles to AI implementation are discussed separately in Chapter 6.

Use and importance of AI in the manufacturing sector

The proportion of companies already using AI today provides an indication of the extent to which the technology is established in the manufacturing sector. As shown in Figure 3a), 42.3% of the companies surveyed say they have already implemented at least one AI application and have built up experience within the company to use it. The majority of companies that already use AI today want to additionally identify areas of application in order to establish even more AI-supported processes in the future (28.2% of the samples). The reverse is true for those companies that have not yet deployed AI. The latter are much more reticent about the future use of AI. Overall, 33.8% of all companies say they have no experience with AI to date and do not plan to use it in the future.

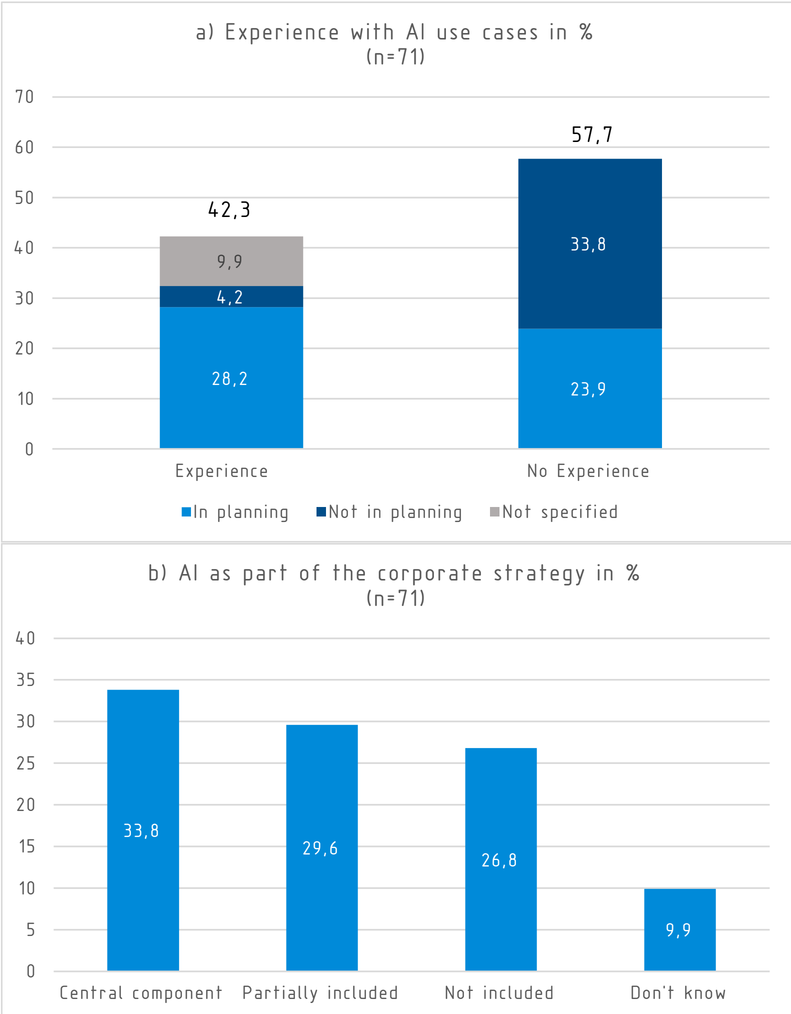

Figure 3: **Use and importance of AI.**

Figure 3b) visualises the finding that the use of AI is a major factor in the entrepreneurial activities of about one third of companies, as well as a central component of their corporate strategy. Just under 30% of companies state that the use of AI has been included at least as a sub-strategy and is thus anchored in the strategic orientation. Only 26.8% of the companies surveyed do not include AI in their corporate strategy. The results show that the use of AI in the manufacturing sector is of great importance. Around two thirds of all companies have anchored this in their strategic corporate planning.

Frequent users and applications

AI applications can be assigned to business areas and the application areas linked to them. Figure 4 a) picks up on the question of where AI is used in the enterprise. Only companies already using AI were surveyed (flexible question model – see section 3.1). Here, the selection of several answers was possible. About two out of three companies already using AI deployed it in production and about one in two in research and development (R&D). Logistics follows at some distance. With a few exceptions in purchasing and business planning, all other AI applications are primary activities. According to the definition of economist Michel E. Porter, these are those activities that make a direct value-creating contribution to the creation of a product or service[38]. The variety of application examples in which AI is used is large. In Figure 4 b), ten application areas are listed. With about 40% each, the application areas of defect detection and prediction, process optimisation in product development and production, and product optimisation dominate.

These can be categorised as production and R&D, which underscores the findings presented in Figure 4a). Process optimisation and process planning are application areas in which AI is frequently used across companies. To increase resource efficiency, AI is currently used by only 12.9% of the companies surveyed. This percentage is relatively low. Nevertheless, it is evident that in selected environments AI is perceived as a technology that can be used to sustainably increase operational resource efficiency. It should also be noted that AI applications that are introduced for other motivations – i.e. in other application scenarios – often have a positive impact on resource efficiency. In such a scenario, the increase in resource efficiency is a secondary effect, which is rarely quantified in practice.

[38] Cf. Porter, M. E. (1985).

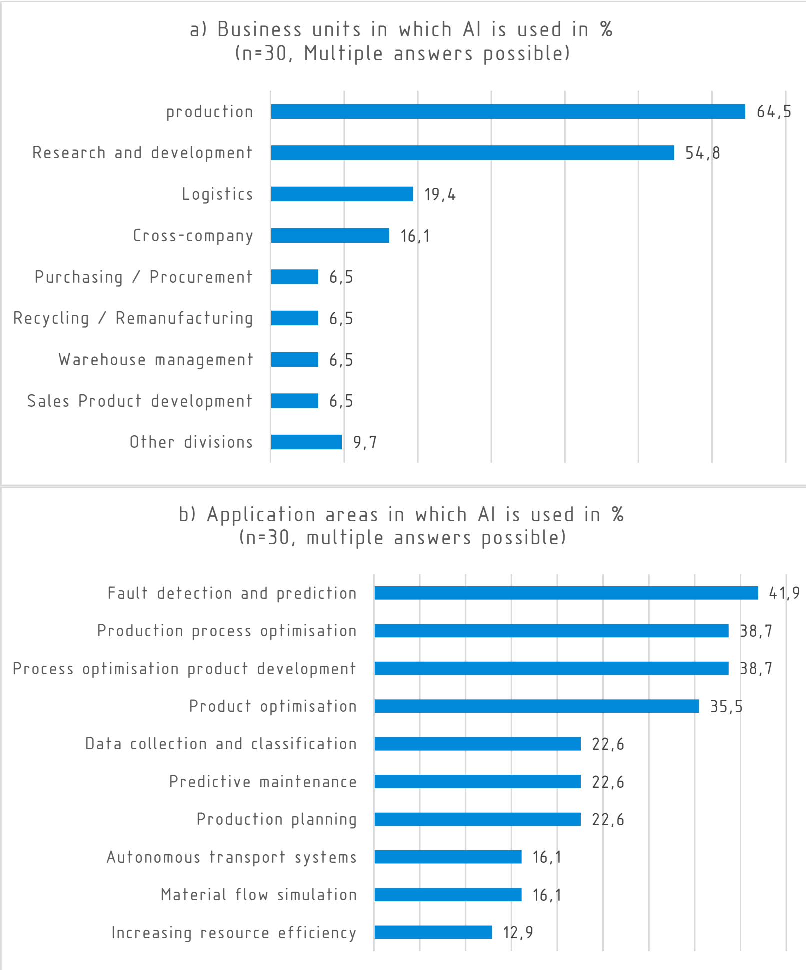

Figure 4: Enterprise and application areas where AI is used

Motivation for the use of implemented and planned AI

As shown in the previous section, more than 40% of the companies surveyed are currently using AI. Figure 5 lists reasons why companies have decided to use AI and why it is planned in the future. Here, too, multiple answers (max. 3) were possible. The percentages therefore correspond to the proportion of companies for which the respective motivation reason is decisive. As visualised in Figure 5, cost savings, quality improvements, time savings, and competitive advantages are the dominant decision criteria for companies. 25.7% of companies say they have already used AI to cut costs and 23% say they are planning to do so. Cost savings thus represent a decisive factor, closely followed by the goals of improving the quality characteristics of the product and general time savings in production. For many companies, the use of AI also offers the potential to differentiate themselves in the face of growing competitive pressure, for example through a price advantage or improved product features. It also creates the opportunity to automate repetitive tasks, allowing employees more time for more complex core activities.

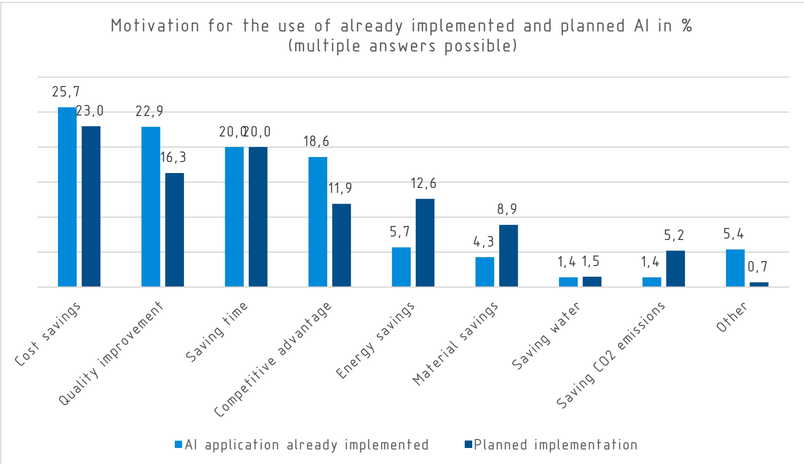

Figure 5: **Motivation for using already implemented and planned AI**

In terms of motivation for operational resource conservation of materials, energy, water and greenhouse gases, the picture turns: An increase in resource efficiency was comparatively rarely the driving motivation for solutions already implemented. The savings in energy (5.7%) and materials (4.3%) have so far only been a decision criterion for a few of the companies with regard to the use of AI. At 1.4%, water and GHG savings have an even less critical effect on decision-making. However, the increasing relevance of resource efficiency for companies is clear to see. AI applications already implemented in this area are noticeably below the indications for planned implementation for each resource, suggesting the rapidly increasing importance of AI application scenarios in relation to resources and the shift to an increased need for resource efficiency.

Potential savings of resources through the use of AI

As outlined earlier, cost savings and quality improvement are the most relevant reasons for using AI. Nevertheless, the saving of resources – not only in the pursuit of ecological goals – plays an important role in perception.

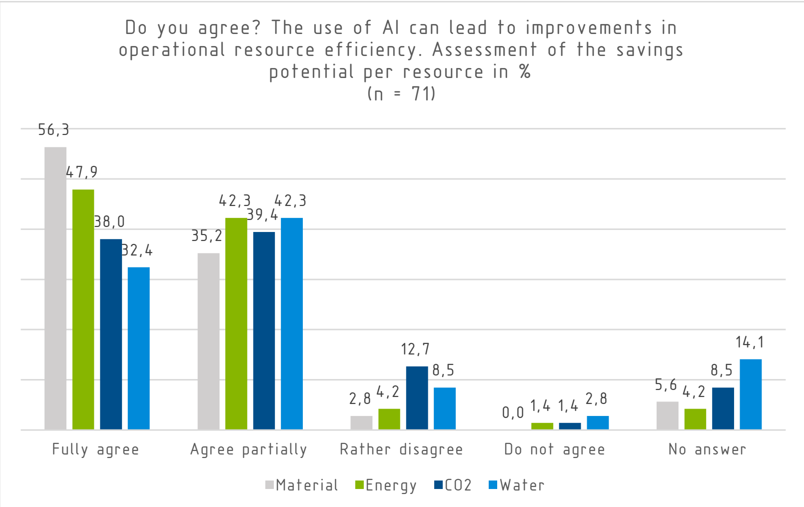

Figure 6: Estimation of resource efficiency improvement through AI.

Figure 6 visualises the result of the survey to what extent AI can help to improve operational resource efficiency. In this process, according to Section 2.2, the resources material, energy, GHG emissions, and water were subjectively evaluated according to their savings potential using an ordinal scale. Participants indicated their agreement or disagreement according to the proposition that AI can help increase efficiency. The operational resource material (56.3%) has the highest percentage of full agreement among survey participants, followed by energy (47.9%), GHG emissions (38.0%), and water (32.4%). This trend is in line with the cost structure of the companies. The manufacturing sector is characterised by a high consumption of raw materials and operating supplies. Accordingly, these represent the largest cost factor and correspond on average to over 42% of total costs[39]. The share of energy costs can also result in a significant cost factor, especially in energy-intensive industries such as the chemical industry or the steel industry. In contrast, the costs for water and GHG emissions are much less significant. It is therefore not surprising that the resource material, followed by energy, is seen as having the greatest potential for increasing efficiency through AI. Overall, the positive perception clearly outweighs the negative. When added together, the two answer options “Fully agree” and “Partly agree” achieve values above 70% for all four resources – and even more than 90% for materials and energy.

To answer the question of expected and actual resource savings, a Sankey diagram has been created (see Figure 7). Sankey diagrams are graphical representations of quantity flows, using thick arrows proportional to quantity. This Sankey diagram thus shows how the percentage expectations of resource savings of individual groups develop and which actual resource savings were realised.

In contrast to the survey in the diagram, no distinction was made between such resources as material, energy, GHG emissions and water defined in accordance with section 2.2. Instead, the sum of resource savings from each resource was visualised for ease of understanding. The volume flows presented here show the comparison between estimated expected resource savings before and estimated actual resource savings after the deployment of AI in the company. Participants rated the savings per AI application on an interval scale from 0% to more than 50%, distinguishing between the expected effect before implementation and the actual realised effect. The nodes represent expected or actual savings and are arranged by increasing size. The width of the nodes is a measure for the frequency of the corresponding classes.

[39] **Cf. Federal Statistical Office (2017).**

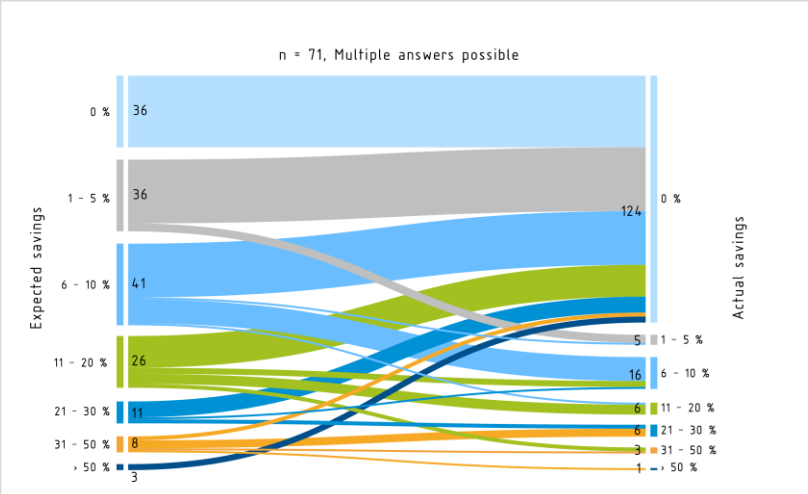

Figure 7: Comparison of expected resource savings vs. actual savings.

A comparison of the nodes on the left shows that the expected resource savings for a quarter of all AI applications are between 6% and 10%. The two nodes with expected savings of 1% to 5% and 11% to 20% follow behind with slightly lower frequencies. A savings effect of 30% or higher is linked to 6% of all AI applications. In comparison, the share of AI applications is just over 20%, with 0% attributed to their expected savings. Overall, the expected saving of resources through the use of AI shows up at an average of 9.9%.

An analysis of the feedback regarding the actual saving of resources shows a much smaller effect. On average, the actual saving is 3.6%. The average is so low because the proportion of implemented AI applications that have no impact on resource efficiency has increased by more than a factor of three (compared to the expected savings). An examination of the colour-coded flows shows that substantial portions have migrated from each node on the left to the 0% node on the right. There is a clear trend that the expected savings effects on the left tend to be adjusted downward compared to the actual savings.

It is clear that a large proportion of AI applications cannot fully deliver on their expected positive contribution to resource efficiency. Two out of three applications show no effect, even though the expectation of more efficient use of resources was attached to them.

However, the concrete figures of the savings effects must be evaluated with the knowledge that an exact measurement of the savings is complex and often not available to the companies. The numerical values presented thus mostly correspond to estimated values. Nevertheless, a tendency can be observed that the expectation towards saving operational resources is greater than the actual effect.

Importance of external partners in the development of AI

This section examines the extent to which companies that have decided to use AI involve external third parties in its development and implementation. According to Figure 8 a), it shows that 40% of the companies surveyed develop AI solutions independently. Accordingly, the remaining 60% involve external partners. The degree of cooperation differs significantly. About two thirds of companies that rely on external expertise choose collaborative development. The remaining third outsource development entirely, either buying ready-made solutions off the shelf, purchasing them as a service, or contracting a service company to develop customised solutions.

Figure 8 b) lists reasons why companies choose to work with external third parties. It should be noted that participants could provide up to three response options in the survey. The percentages can thus be interpreted as the proportion of companies for which the respective reason is decisive or co-decisive. It turns out that for about every second company, a lack of personnel resources and a lack of specialist knowledge are relevant reasons for working with outsiders. In addition, 41.7% of the companies surveyed said that the time involved in implementing AI applications is too great for in-house development. In practice, this often results in a collaborative model where companies develop AI applications in cooperation with external parties. Missing personnel resources can be compensated this way. In addition, the cooperative nature nevertheless enables the sustainable development of internal expert knowledge in order to reduce subsequent dependencies on third parties.

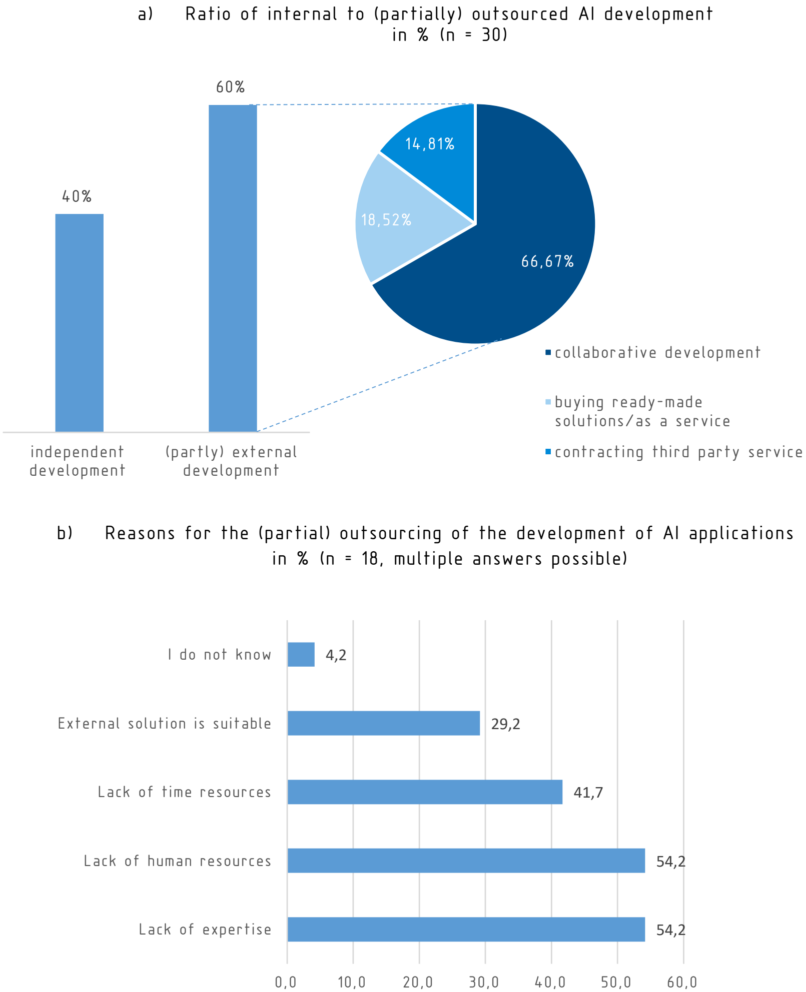

Figure 8: Acquiring external partners in AI development

The development of suitable algorithms as well as their implementation and maintenance represent a tour de force for many companies. External third parties play a crucial role in introducing new technologies and identifying suitable application examples. By providing human resources and expert knowledge at short notice, they support many companies in the realisation of AI-supported applications.

Comparison of SMEs to large companies

Large companies often show a high affinity for new technologies and are pioneers in their introduction compared to small companies[40]. The objective of this section is therefore to investigate whether, in the manufacturing sector, the diffusion of AI applications is more advanced in large companies than in SMEs. Figure 9 a) shows the percentage of companies that have already implemented at least one AI application for both SMEs and large enterprises. An almost identical ratio can be seen between the two groups, according to which around 42% of all companies in both SMEs and large companies have already gained experience with AI. In terms of planned AI applications, the SMEs share is 57.6%, ten percentage points above large companies. However, it should be noted that 15.8% of the employees surveyed from large companies were unable to provide any information in this regard. There is a possibility that there is less transparency across business sectors due to size. As a result of frequently occurring silo effects, it can be assumed that employees often lack an overview of the AI used in other areas. Figure 9 c) describes the percentage of companies that have incorporated AI into their strategy. A distinction is made as to whether AI is a fixed component of the corporate strategy or has only been included as a sub-strategy. At around 40% of large companies, AI is a central component of strategic planning, and at a further 21% AI has been implemented as a sub-strategy. At about 40% of large companies, AI makes up a central component of strategic planning, and at another 21%, AI is included as a sub-strategy. The reverse relationship is true for SMEs. At 27.3% of companies, AI is a central component and at around 40%, AI is integrated as a sub-strategy. If the two options are added together, the result is a narrow lead for SMEs in terms of the proportion of companies that take AI into account in their corporate strategy. The fact that AI can also be a driver for the development of new digital business models is evident among both SMEs and large companies.

[40] Cf. Seifert, I.; Bürger, M.; Wangler, L.; Christmann-Budian, S.; Rohde, M.; Gabriel, P. and Zinke, G. (2018).

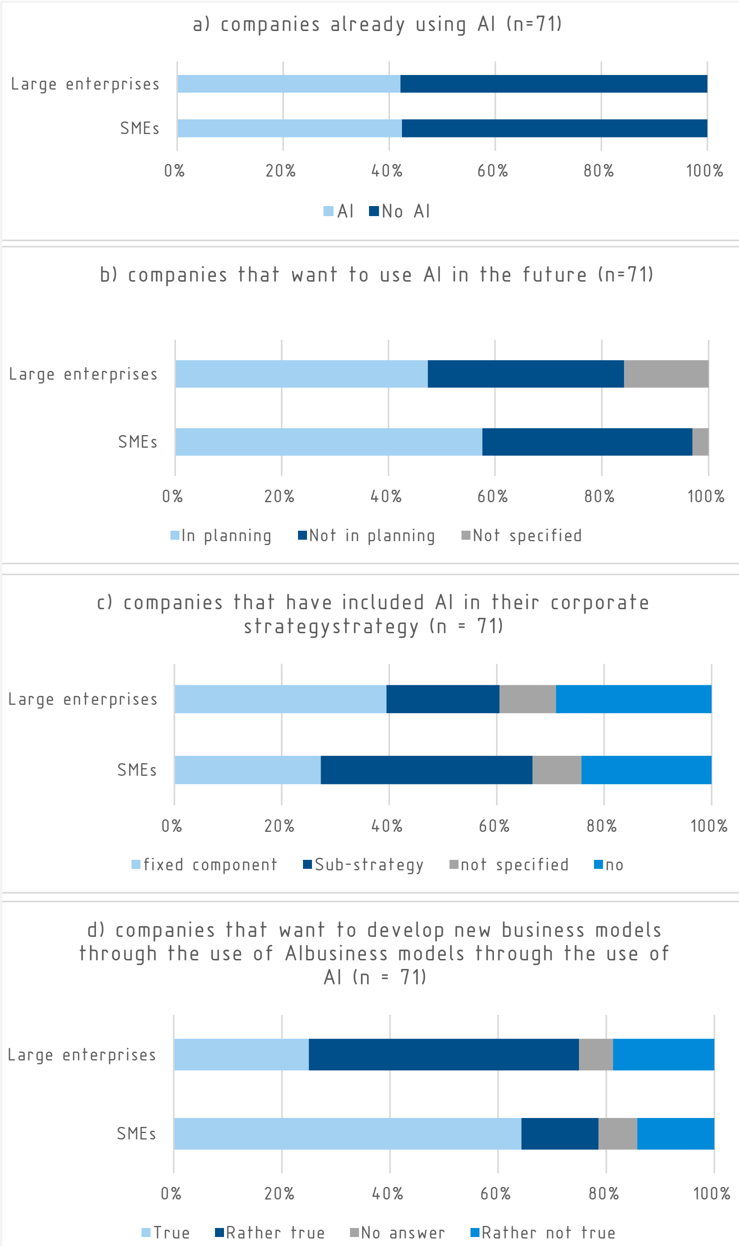

Figure 9: Comparison of SMEs and large enterprises related to the (future) use of AI

Figure 9 d) illustrates that two thirds of the SMEs surveyed explicitly plan to build new business models through the use of AI – another 14.3% are considering doing so. Large companies, on the other hand, are more cautious in their forecasts in this regard. Only a quarter of the companies surveyed plan to develop AI-supported business models, and a further 50.0% consider this conceivable. The proportion that estimates the potential for establishing new business models through AI to be low is 14.3% for SMEs and slightly higher at 18.8% for large companies.

Overall, a consistently balanced relationship emerges between SMEs and large companies with regard to the use of AI to date. Only minor differences are noted in Figure 9 a) to d). These illustrate the extent to which AI is taken into account in strategic corporate management and the expectation of being able to develop new business models with AI.

3.4 Conclusion

The expert survey makes it clear that AI has already penetrated many areas of the manufacturing sector. 42.3% of the companies surveyed are already using AI today – with a clear upward trend. It should be noted that no significant difference was found between SMEs and large companies in terms of the proportion of companies using AI. Rather, a very balanced relationship is shown by the fact that, according to the survey data, the number of AI applications implemented and planned is independent of the size of the companies. SMEs are proving to be courageous in introducing new AI applications and are gaining valuable expert knowledge in their market segment in this way.

On the way to a safe and profitable use of AI, the majority of companies (60%) rely on a collaborative approach. External partners play a significant role in identifying and implementing companies' first AI applications. In addition, as-a-service concepts enable rapid access to AI building blocks, especially for SMEs. It is expected that external AI expertise will continue to be a sought-after service in the manufacturing sector.

For many companies, AI represents an important factor in positioning themselves in the face of growing competitive pressure and exploiting potential in the long term. AI methods are used particularly frequently in production or product development – i.e. in areas that make a direct value-creating contribution to the manufacture of the product or service. The use of AI is often linked to the goal of reducing costs (25.7%), improving quality (22.9%) and making processes more time-efficient (20%). This is demonstrated by a large number of application scenarios in the area of process planning and optimisation. An increase in resource efficiency often results in a positive secondary effect. However, saving resources is the main motivation for using AI in only a few applications (12.9%). This is also due to the fact that changes in resource consumption are perceived but rarely quantified.

Companies are aware of the opportunities that arise from the use of AI. Already today, about two thirds of all companies have integrated AI into their strategic planning and have thus given it a strong prioritisation. The potential for using AI to make more efficient use of both operational and natural resources is perceived as promising. Depending on the resource, 80% to 90% of companies agree that the use of AI can lead to an increase in resource efficiency. This is particularly evident in the use of materials, as this accounts for the largest share of costs in the manufacturing sector, averaging over 42%[41]. However, many companies find it difficult to realistically assess the potential of AI, as evidenced by a wide divergence between expected and actually realised resource savings.

[41] Cf. Federal Statistical Office (2017).

4 METHODOLOGY FOR POTENTIAL ANALYSIS OF APPLICATION SCENARIOS OF AI

The use of AI offers a wide range of opportunities to increase operational resource efficiency – both from a theoretical and practical perspective. Section 4.1 describes the necessary tool to analyse AI application scenarios and evaluate them in terms of their potential to increase operational resource efficiency. In the following section 4.2, a maturity model is presented which enables SMEs to classify their own position within six selected topic areas by means of their potential.

4.1 Classification of application scenarios

Figure 10 shows four dimensions that can be used to classify and evaluate application scenarios.

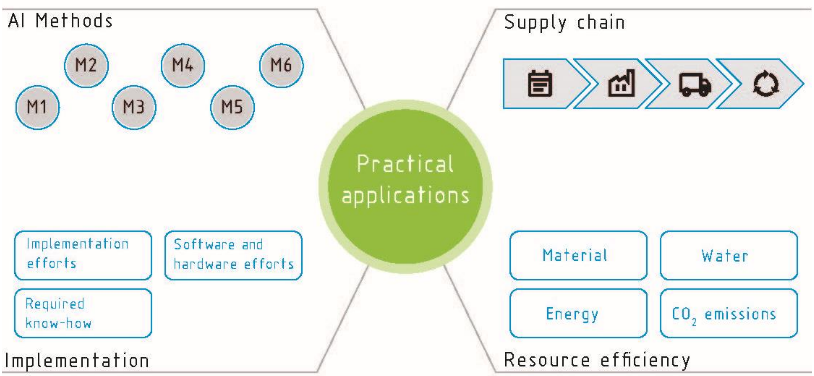

Figure 10: Dimensions for classification and evaluation of practice applications.

Building on Section 2.1, the first dimension describes AI methods on which the application scenario is based. The second dimension deals with the value chain of the companies and specifies to which company activities the application scenario is to be assigned. The effort required for implementation is then evaluated. The fourth dimension can be used to determine the impact of AI on operational resource efficiency. For this purpose, a key performance indicator model is presented that can be used to measure efficiency improvements.

4.1.1 AI methods

The weak AI methods presented in Chapter 2.1 and elaborated in Appendix A form the cornerstone of each application scenario. These are statistical methods that can be used to solve various problems. It is important to understand that there are numerous algorithms per AI methodology that can be considered for a solution in principle. In this context, the algorithms are differentiated by different requirements for the input data, the type and number of adjustable parameters for controlling the algorithms, and the associated capabilities for solving objective functions. In this way, e. g. binary classification tasks can be solved using simple decision trees up to multilayer neural networks. The output of the models is always the same, namely a classification of the feature carrier into one of the two classes. It is difficult to assess which of the algorithms will provide the most accurate results. Often, several algorithms are exploratively tested and their results are compared.

4.1.2 Inclusion along the value chain

Due to the versatile possibilities of using AI, it is worthwhile to incorporate the application scenario to be classified along the value chain of companies. In Figure 11 a model is presented following economist Michael E. Porter, which divides activities in the enterprise into primary activities and supporting activities[42]. Primary activities are defined as those that make a direct value-added contribution to the creation of a product or service.

On the other hand, supporting activities are those that are necessary for the successful execution of primary activities and are often relevant across companies. Practical examples can be assigned to one or more of these corporate activities, depending on their characteristics. Since the majority of resources, especially materials, are used in primary activities, this is a particular focus.

[42] **Cf. Porter, M. E. (1985).**

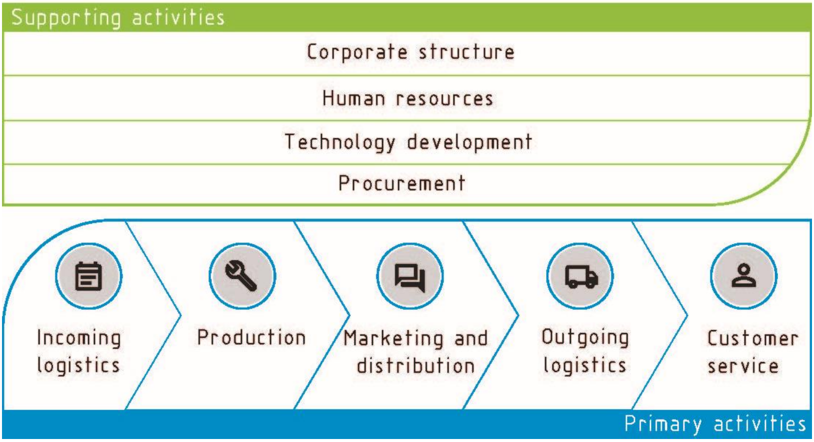

Figure 11: Delineation of primary and supporting activities of the value chain[43]

4.1.3 Implementation effort

The implementation effort describes the human, temporal, tangible, and intangible resources that must be expended to start up and maintain an application scenario. Maintenance is included in the software and hardware effort and expertise. In Table 2, the three factors of implementation effort, software and hardware effort, and required expertise are listed, which together make up the implementation effort. Likewise, the possible characteristics are defined on the basis of a three-level scale.

[43] Cf. Porter, M. E. (1985).

Table 2: Evaluation criteria for implementation with corresponding gradation of low, medium and high effort

Evaluation criteria	low	medium	high
Implementation effort	All human and temporal resources are available. All necessary data are available and accessible.	Human and temporal resources are only available to a limited extent. For example, it is first necessary to collect extensive training data.	The staffing and time requirements are critical. For example, very extensive training data is required, for which additional sensor technology must first be installed.
Software and hardware expenditure	Use of system-independent software. No integration into existing systems necessary	Minor interventions/ Changes in existing systems	Extensive investment in application-specific software and hardware, including integration, required.
Required expertise	Hardly any previous knowledge is required. The system operation is intuitive and/or gives direct recommendations for action	Expertise is needed that goes beyond the normal scope of work, such e. g. regular maintenance.	Extensive expertise is required. Only specialists can use the method.

Implementation effort

Implementation effort refers to the time and personnel required to implement the corresponding AI method. A crucial factor often includes the collection and labelling of data. This process can take a long time. Depending on the amount of data required, new types of technology – such as a combination of many computing capacities into clusters – may be necessary to process the data efficiently.

Software and hardware expenditure

The software and hardware effort refers to the additional measures associated with the implementation and operation of AI methods. Upgrading is not always necessary here, as machines are already often networked with each other in the course of digitalisation and data on throughput times or system settings, among other things, is collected. This may require, for example, the purchase of special software or the adaptation of existing software or hardware in the form of special sensors.

Required expertise

The required expertise refers to the necessary methodological and technological knowledge level of the personnel responsible for implementing and operating the solution. A high level of effort arises primarily from the range of technologies brought to bear and the diversity of AI methods required. Preparatory tasks such as elaborate data preparation may also require additional expertise. Ultimately, operating an AI solution may necessitate an expanded requirements profile, as classic IT skills such as DevOps[44] are indispensable in addition to knowledge of statistics and data science.

4.1.4 Key figure model for measuring resource efficiency

According to VDI 4800 Sheet 1, resource efficiency is defined as the “ratio of a specific benefit or result to the resource input required to achieve it”[45]. In this study, only the natural resources of raw materials, energy, and water, as well as ecosystem services, are considered based on GHG emissions (see Section 2.2). This results in the criteria for measuring resource efficiency: Increasing energy, material and water efficiency and reducing GHG emissions.

In order to quantify the value contributions of the measures, a selection of key figures is provided below. The target definition is made with a view to increasing value contributions from the perspective of improving resource efficiency. For sustainable and long-term improvement, the individual measures must be in line with the underlying corporate strategy.

The selection of the key figures listed in Table 3 is based on the principles of key figure formation stated in VDI 4801 for the approach to increasing resource efficiency[46]. It is recommended to apply the selected key figures on different operational reference levels, provided that the key figures can be determined for the different levels. The recommended reference levels are therefore to be considered site-, production-, process-, plant- or product-related. The more detailed the reference level, the more difficult it appears to

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[44] DevOps is a combination of development and IT operations and describes an approach to software development during ongoing IT operations.

[45] VDI 4800 sheet 1:2016-02.

[46] Cf. VDI 4801:2018-03.

precisely delineate the measurability of a system boundary in the actual practical operation of companies. If, for example, a separate water meter is not installed for each plant within the production, a plant- or process-related determination of the key figure "water consumption" can consequently not be carried out.

The key figures listed here are intended to provide an initial guide to practical application. For specific application scenarios, additional metrics may be needed to capture the impact of artificial intelligence on resource consumption.

Table 3: Key figure system for measuring resource efficiency

Resource	Key figure	Unit	Description
Materials	Material consumption	kg, litres, m^3	Differentiation of material types of all material input factors, including auxiliary and operating supplies.
	Offcuts	kg, litres, m^3	
	Scrap	kg, litres, m^3	
	Recyclability	kg, litres, m^3	
	(Specific) Material costs	€	
Energy	Energy consumption	kWh, J, (I)	Energy sources in the form of heating oil, natural gas, electricity, district heating, diesel, gasoline and other.
	(Specific) energy costs	€	
Water	Water consumption	m^3	
	Recyclability	m^3	
	Water costs	€	
GHG emissions	Scope 1	kg CO_2e	Consumption volume and emission intensity of energy sources and process-related emissions
	Scope 2	kg CO_2e	Consumption volume and emission intensity of the energy mix used

4.2 Maturity model for companies

When using AI methods, requirements arise for several subject areas in the corporate context. The proposed maturity model distinguishes between the topics of AI strategy, people, processes, data, and technologies and platforms.

The delineation is done in accordance with current scientific literature and after consultation with experts in the field of data analysis[47, 48, 49].

The maturity model presented is intended to enable SMEs to classify their own position within the topic areas on the basis of their potential. The maturity levels within the topics are based on the requirements for the use of AI methods. Therefore, it is not mandatory to strive for the highest level of maturity in all subject areas for the successful use of AI methods. A distinction is made between low, medium, high and very high. A detailed description of the expressions can be found in Appendix C.

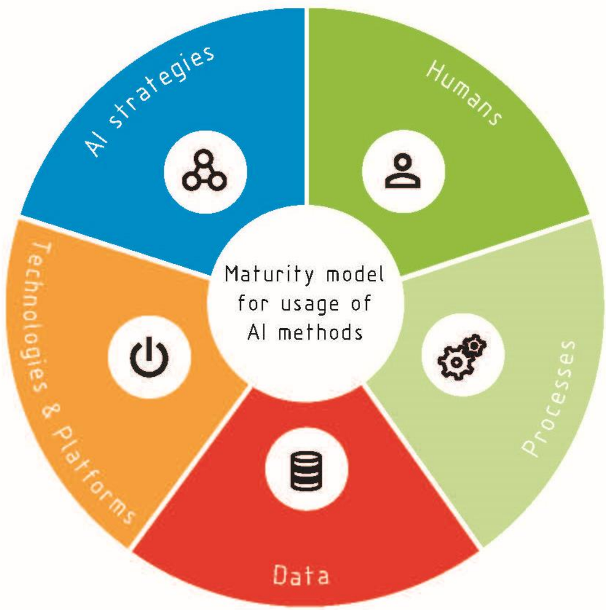

Figure 12:Dimensions of the maturity model

[47] Cf. Abdelkafi, N.; Döbel, I., Drzewiecki, J.; Meironke, A.; Niekler, A. and Ries, S. (2019).

[48] Cf. Alsheiabni, S.; Cheung, Y. and Messom, C. (2019).

[49] Cf. van Buren, E.; Chew, B. and Eggers, W. (2020).

Each of the AI methods is transformative technologies, and the alignments and ambitions are critical. For this reason, their expression is central content of the subject area **AI strategy.**

For the successful use of AI methods, the technical skills of the employees are crucial. Access to required technical skills and the recruitment of appropriate employees pose challenges for companies. It is also important to train existing employees and to build up or deepen competencies. The development and use of AI are supported and promoted in this way. The subject area **People** therefore considers the aspects of organisational design and the development of talent models in the company.

Processes shall be established, defined, and designed to enable successful AI implementation. Although AI pilots can be used to demonstrate the potential of AI methods, their full benefits cannot be captured until they are integrated into operational processes. The topic area of processes allows us to classify the extent to which processes are already supported by AI methods and embedded in operational processes.

In addition to the technical competencies of the employees, **data** represents a central basis for a long-term and successful use of AI methods. The topic of data therefore considers how and to what extent the goal-oriented and structured handling of data is anchored in the company. Also to be considered are the nature of data collection and linkage, as well as the importance of transparency of the data processed and explainability of the results obtained by AI methods.

Last, the topic area **Technology and Platforms,** looks at how AI methods are used in the enterprise. Depending on the requirements of the AI methods used, the use of local IT infrastructure up to the complete application in the cloud is possible. It is also of central importance how AI methods can be used. For example, if there is a toolbox of AI methods that can be implemented in a modular fashion, these can be used more efficiently than software solutions that have been developed or sourced individually and application scenario-specifically.

The maturity model presented here is used for self-assessment and requires insights into different areas of a company. This was not possible for any of the companies considered in the following chapter due to insufficient data, which is why the application of the maturity model cannot be practically demonstrated within the scope of this study. When applying the maturity model, the primary aim is not to determine the maturity level quantitatively in figures, but to increase the knowledge gained about the AI applications used in one's own company and their impact on operational resource efficiency through the application of methods.

5 POTENTIAL ANALYSIS OF SELECTED APPLICATION SCENARIOS

In this chapter, application scenarios of artificial intelligence are presented which show a high relevance with regard to resource efficiency both in the literature research and in the expert survey. The potential analysis presented in chapter 4 is applied to these application scenarios and supported by practical examples from German SMEs.

The starting point of this study is a comprehensive literature review (Section 2.3). By means of this, 54 publications were identified, which can be assigned to 15 potential application scenarios. The expert survey conducted refers to these potential application scenarios and qualifies them further with regard to their practical significance in companies. This results in eight application scenarios with particular relevance for operational resource efficiency.

The potential analysis of these eight selected application scenarios analyses their technological implementation, the required effort and the impact on resource efficiency qualitatively and, wherever possible, also quantitatively. A quantitative assessment of the impact of the introduction of weak artificial intelligence on resource efficiency is sometimes difficult for the application scenarios. This is due to the fact that many applications are not significantly introduced to increase resource efficiency. Rather, it is ostensibly operational factors, such as saving time and increasing efficiency in the production process, that are key to the introduction of the technology. The associated increase in resource efficiency is rarely measured directly. For this reason, the described key figure model from chapter 4.1.4 can only be applied to the application scenarios to a limited extent. However, the value of the use cases, especially for SMEs, is to show how AI helps save resources in a wide range of industries. This collection represents a valuable contribution to the fledgling field of resource-efficient AI.

Therefore, where a quantitative assessment was not possible, a qualitative assessment of the impact on resource efficiency is made according to Table 4. It should be noted that the qualitative assessment of GHG emission savings is often based on energy and material consumption. However, these are only directly linked to GHG emissions under the assumption of the use of conventional energy sources (such as coal and gas), but not when renewable energy sources are used. Information on the actual energy mix of the companies in the application scenarios is not available but could have an influence on the assessments made. The qualitative assessment of the impact on GHG emissions is based on conventional energy sources.

Table 4: Qualitative evaluation criteria for increasing resource efficiency

low	medium	high
The increase in resource efficiency is a purely secondary effect in the application scenario. The magnitude of the savings is not significant relative to the overall process of the application scenario.	Increasing resource efficiency is a sub-goal of the application scenario. The extent of the savings is relevant in relation to the overall process.	Increasing resource efficiency is an explicit goal of the application scenario. The extent of the savings is significant in relation to the overall process.

General statements on the potential of an application scenario to increase resource efficiency in a context outside the examples cannot be derived from this study. There is still a need for research in this area, which must holistically investigate the potentials that can actually be realised.

To illustrate the relevance of the selected application scenarios for SMEs, at least one practical example describes their implementation in each case. Here, the respective challenges and qualitative aspects of the solution are emphasised and the reference to resource efficiency is established. Table 5 shows an overview of the selected application scenarios and the corresponding practical examples. The content description of the practical examples as well as the included data were provided by the companies themselves with kind permission for the present study. These are voices directly from the field.

Table 5: Overview of application scenarios and practical examples

ID	Application scenarios	Practical examples
AS 1	Predictive maintenance	LUIS Technology GmbH, LUVIS AI GmbH and Stadtreinigung Hamburg AöR – Significant increase in maintenance quality using auto-encoders
AS 2	Optimisation of the process chain	Gestalt Robotics GmbH – Optimisation of line clearance through a digital twin
AS 3	Optical error detection	Werner-von-Siemens Centre for Industry and Science – test field for the promotion and testing of AI application
AS 4	Error prediction	atlan-tec Systems GmbH – Predictive Quality in the production of HDPE pipe systems
AS 5	Planning of the process chain	Julius Zorn GmbH – Optimisation of warehousing and production planning using forecast algorithms
AS 6	Product optimisation	IANUS Simulation GmbH – AI-supported optimisation of extrusion tools
AS 7	Autonomous transport systems	Blechwarenfabrik Limburg GmbH – Process-optimised transports thanks to a intelligent automated guided vehicles
AS 8	Sustainability Analytics	juS.TECH AG – Logistics and Route Optimisation

5.1 AS 1: Predictive maintenance

The potential analysis for the application scenario of predictive maintenance is carried out in section 5.1.1 using the example of milling machines. The practical example of the cooperation of LUIS Technology GmbH, LUVIS AI GmbH and Stadtreinigung Hamburg AöR in section 5.1.2 shows the implementation of the application scenario for a turbine on a sweeper vehicle.

5.1.1 Predictive maintenance of milling machines by analysing acoustic frequency spectra

The following application scenario describes the use of AI in the production line for predictive maintenance of milling machines and can be incorporated along the value chain in production[50]. For the potential analysis of the application scenario, the technological implementation (Table 6), the effort estimation (Table 7), and the potential estimation in terms of resource efficiency (Table 8) are each summarised in tables. In this application scenario, predictive maintenance of milling machines used to machine steel components is investigated. During this process, the cutting head of the milling machines continuously wears out, reducing cutting accuracy and increasing scrap. In addition, the unexpected breakdown and repair of machines can mean the

[50] Cf. Li, H.; Wang, Y.; Zhao, P.; Zhang, X. and Zhou, P. (2015).

shutdown of production lines, which can lead to significant costs in operations.

Table 6: Technological implementation of AS 1

Factor	Description
Hardware	Sensors for detecting acoustic frequency spectra and vibration oscillations as well as a dynamometer for recording the milling force
Data	Time series analysis of acoustic frequency spectra of the milling machine and measurement of the applied milling force
AI method	**Logistic regression:** This is a non-linear statistical method that is used, among other things, for reliability analysis and lifetime prediction of machines. The acoustic measurement data, which provide information about the degree of wear of the machine, act as input variables. The output of the model can be interpreted as the probability of a particular state. In the specific case, for example, it is the probability that the cutter head of the milling machine needs to be replaced due to wear.
Essential work steps	Essential work steps in chronological order: • Data collection is performed on four separate milling machines in different operating settings, each with new and used cutting heads. • The data from three machines serve as training data, the data from the fourth as test data. The acoustic signal is decomposed into several frequency bands using a wavelet transform. • Comparison of the correlation coefficients of the two characteristics milling force and acoustic signals with the respective frequency bands. • Training of two models: Model 1 based on milling force data and frequency spectra and Model 2 based on frequency spectra only. • Evaluate algorithms based on their ability to determine remaining useful life. • In the experiment conducted, both models were able to accurately predict the time at which the cutting head should be replaced (after 40.5 min), with Model 1 being slightly more accurate at 39.3 min than Model 2 at 39.0 min. • Measuring the milling force in real time often requires considerable effort, which is why model 2 is recommended for practical use.

By using AI, the condition of the milling machine's components is monitored and the remaining useful life is determined. Acoustic frequency spectra, which result from the rotation of the cutter and are transmitted in real time, serve as the basis for the data. Using a logistic regression analysis, the frequency spectra are analysed and compared with target state parameters. The continuous wear of the cutter can thus be observed and the remaining useful life determined. If the deviations exceed a previously defined critical value, machine maintenance can be initiated at an early stage and at selected times.

Table 7: Effort estimation for AS 1

Evaluation criterion	Effort	Description
Implementation effort	low	The main reason for this is the direct data acquisition at the machines used through the use of few sensors and the comparatively small number of input variables.
Software and Hardware expenditure	medium	The additional sensors required and the connection of the sensor data to the model are major expense drivers.
Required expertise	medium	In addition to the development of the logistic regression model, a technical understanding is needed to collect and especially interpret collected data from the milling machine.

For the company, the advantage is that planning reliability increases with regard to the milling machines used. Wear can be anticipated and the replacement of cutting heads can be planned to ensure that the quality and volume of production remain high in the long term. In addition, significant costs can be saved by reducing unplanned downtime. The impact on resource efficiency is shown in the following table.

Table 8: Qualitative potential assessment of AS 1 to increase resource efficiency following the metrics model

Resource	Influence	Key figures & description
Materials	medium	**Material consumption in kg:** Reductions in steel scrap due to early detection of inaccuracies and avoidance of unexpected machine failures and the reduction of the associated startup processes can be expected to result in medium material savings.
Electric energy	low	**Energy consumption in kWh:** Due to the reduced scrap rates and the avoidance of startup processes in the event of machine failure, energy savings can be expected to a small extent.
Water	no influence	no influence
GHG emissions	medium	**Emission of kg CO_2e:** Reduction in CO_2e emissions resulting from the material savings in steel and the reduction in electrical energy used. Further secondary effects on GHG emissions can be derived from savings in the supply chain. Overall, savings in the medium range can thus be achieved.
Other effects		• Cost savings by reducing production downtime • Reduction of maintenance costs • Increase the reliability of the machines

5.1.2 Practical example AS 1: LUIS Technology GmbH, LUVIS AI GmbH & Stadtreinigung Hamburg AöR

Significant increase in maintenance quality using autoencoder

Presentation of LUIS Technology GmbH, LUVIS AI GmbH & Stadtreinigung Hamburg AöR

Since its foundation in 1999, LUIS[51] has been developing into a leading manufacturer for camera monitor and driver assistance systems in Europe. LUIS is best known for its self-developed turn-assistant. In order to become more involved in the field of intelligent systems, LUIS participates in LUVIS AI GmbH, founded in 2020[52]. LUVIS AI is used to develop products – especially in the areas of “Embedded Vision” and “Predictive Maintenance”.

The third partner involved in this practical example is Stadtreinigung Hamburg AöR[53]. Stadtreinigung Hamburg sees itself as an innovative company and is always on the lookout for new ideas to realise its goals. The best example of this is the cooperative project presented below, in which the turbine of a sweeper is monitored via an acceleration sensor installed on the housing.

Challenges of the customer

Due to the daily use of the truck-mounted sweepers in two-shift operation, the turbines are heavily contaminated and damaged by foreign bodies and the weather. For this reason, the goal was to introduce a monitoring system that continuously records the turbine condition and generates early warning signals. These in turn should be presented visually as well as acoustically. In this way, imbalances are to be detected at an early stage so that they can be corrected quickly and cost-effectively, depending on their cause. This can be done, for example, by early cleaning, which is carried out, among other things, by an internal flushing device. This should reduce the load on the turbine bearing to a minimum.

[51] Cf. LUIS Technology GmbH (2021).

[52] Cf. LUVIS AI GmbH (2021).

[53] Cf. Stadtreinigung Hamburg (2021).

Solution through the use of AI

The concept involved transferring an existing auto-encoder[54]-based technique that had already proven successful in evaluating acoustic transmission or ball bearing signals. The data is pre-processed locally and transmitted to a server via a 4G connection. There the fast Fourier transform (FFT) and the envelope FFT are calculated as well as some parameters from the time domain. Once the auto-encoder detects deviations from the expected signal, an AI-based classification is performed based on known disturbances. In a third step, customer-specific, easily learned signatures can be assigned to further defects without the need for a completely new training of the classification or the auto-encoders.

In terms of hardware, a 32-bit microcontroller is used, which enables excellent digitisation and signal preprocessing by means of an integrated low-noise and broadband AD converter in conjunction with MEMS (microelectromechanical system) accelerometers. On the software side, open solutions are used in the area of databases and machine-to-machine techniques. The primary goal is to take into account current IT security standards. Optimised software algorithms ensure high performance on moderate hardware.

Success factors and barriers

By its very nature, the explicit classification of faults requires the presence of known fault conditions during operational use. This implies a project time downstream of the core development in order to clearly assign the errors detected by the system to individual technical defects. In this case, the hardware and software development was completed within the specified time frame without any problems. The suitability of the sensitive and very cost-efficient MEMS-based accelerometers used can be confirmed so far.

[54] An autoencoder is a neural network with the task of compressing input information and correctly recreating the reduced information in the output. Thereby the dimensions

Results with special reference to operational resource efficiency

In the future, the monitoring of mechanical components that are subject to a certain amount of wear or possible misuse will be driven even more by the operational costs that occur. The use of AI-based monitoring solutions prevents the unforeseen failure of components and enables their use over a significantly longer operating time compared to an interval-based maintenance strategy. LUIS thus sees a high degree of optimisability in the time-consuming and cost-intensive maintenance processes. By means of AI and the application of continuous monitoring processes, the maintenance quality is significantly increased. Preventive maintenance due to unnecessary component replacement with the associated machine downtime is reduced to a minimum. AI techniques are particularly qualified for use on systems whose complete frequency behaviour is unknown to the user. Recognising maintenance problems therefore no longer has to be an expert assessment.

5.2 AS 2: Optimisation of the process chain

The potential analysis for the application scenario to optimise the process chain is presented in section 5.2.1 using the example of energy savings in the manufacturing process in wafer production. The practical example of Gestalt Robotics GmbH in section 5.2.2 shows the implementation of the application scenario for the optimisation of line clearance[55] by a digital twin at a medium-sized manufacturing pharmaceutical company.

5.2.1 Energy saving in the manufacturing process in wafer production

Efficient energy use is particularly important in energy-intensive industries such as the semiconductor industry. AS 2 describes the application of AI in manufacturing, which is the most energy-intensive unit in semiconductor factories after building management[56]. Specifically, the energy input per

[55] Process of job cleanup of all products and scrap parts that are no longer used for the next production.

[56] Cf. Yu, C.-M.; Kuo, C.-J. and Chung, C.-T. (2016).

production step of a wafer is measured. Table 9 shows the technological implementation of this application scenario in detail.

Table 9: Technological implementation of AS 2

Factor	Description
Hardware	Not further explained, no additional sensors/hardware installed
Data	Data is collected across the 48 manufacturing steps of a semiconductor factory. A manufacturing step is defined in such a way that it can consist of several machines performing the same operation. Identification of 19 data points (also called features) along the production line that relate either to position measures (e. g., average machining time) or to dispersion measures (e. g. variance of machining time).
AI method	To examine the effect of process steps on energy expenditure, the 19 identified characteristics serve as independent variables in a regression analysis. The respective influence of the characteristics on the dependent variable, the energy consumption per work step, is examined. Four different models are used for the regression, with a focus on neural networks (cf. Appendix A), which are particularly suitable for non-linear dependencies.
Essential work steps	Essential work steps in chronological order: Collection of data from the manufacturing process over a period of 120 production days to study energy consumption Selection of four algorithms, each trained with five different parameter sets Optimisation of each model to reduce energy consumption per work step Evaluation of the models against the objective function of the mean absolute percentage error Selection of the model with the lowest average mean absolute percentage error

In the manufacturing process, wafers are the substrates on which electronic components are implemented. The wafer manufacturing process is considered very complex, with a blank going through up to 500 production steps for completion. This results in a high level of complexity, especially in process planning. However, the number of steps also offers the potential to collect manufacturing-related data in large quantities suitable for the development of appropriate machine learning applications. The following application scenario describes how AI can be used to optimise the manufacturing process so that less energy is required to produce a wafer. An estimate of the effort required for this is recorded in Table 10.

Table 10: Effort estimation for AS 2

Evaluation criterion	Effort	Description
Implementation effort	medium	The data used was collected from 48 production tools (in this case to be understood as a group of machines performing the same operation in a semiconductor manufacturing fab) of an 8-inch wafer foundry. The time span of data collection covers 120 production days.
Software and Hardware expenditure	low	The software applications NeuroSolution 5 and STATISTICA 7 have been used for training the models. Due to the graphical user interface, further programming knowledge is not necessary.
Required expertise	high	The AI algorithms used are, among others, complex neural networks whose selection, optimisation and interpretation of the results require a deeper understanding.

As a result of the model, a regression coefficient is obtained in each case for one of the 19 characteristics studied. The coefficient indicates the percentage positive or negative effect on energy consumption if the corresponding characteristic is changed by 10%. The regression coefficients are to be understood as potential adjusting screws with varying potential for energy savings in manufacturing depending on their specific value.

In addition to energy savings, the measures often have other effects that can potentially lead to a conflict of goals. Therefore, a holistic view of the respective measures is necessary in order to take into account possible other effects, such as on material consumption, production volume or personnel expenses. In the scenario studied, there is an energy-saving potential of up to 17.2% when the potentials of the 19 features are added together. A detailed description of the savings potential based on the key figure model is shown in the following table.

Table 11: Qualitative potential assessment of AS 2 to increase resource efficiency based on the KPI model

Resource	Influence	Key figures & description
Materials	no influence	
Electric energy	high	**Energy consumption in kWh:** The energy required for wafer production accounts for 41% of the company's total energy consumption. By optimising process steps in the production line, power consumption can be reduced by 17.2%. This 17.2% must be considered remarkably high, as it is assumed that production is already operating close to optimum.
Water	no influence	
GHG emissions	high	**Emission of kg CO_2e:** In this AS, all manufacturing steps of a producing company are considered holistically. The reduction in electrical energy used thus implemented is accompanied by savings in GHG emissions to the same extent.
Other effects		When optimising the process chain, conflicts of objectives are possible between the respective savings potentials and third factors such as time and quality.

5.2.2 Practical example AS 2: Gestalt Robotics GmbH

Optimisation of line clearance through a digital twin.

Presentation of Gestalt Robotics GmbH

Gestalt Robotics GmbH[57] is a leading service provider and technology supplier at the interface between classic industrial automation and AI. In addition to intelligent applications of classic industrial robotics and mobile systems, one focus of the company is on AI-supported image processing. The customer addressed in this practical example is a medium-sized manufacturing pharmaceutical company. In addition, an integration partner is involved who specialises in the design and integration of new production lines in the pharmaceutical industry.

Challenges of the customer

The customer's challenges in this practical example lie in the area of so-called “Line clearance”. As part of this, production must be checked for impurities and residues during product or process changeovers and restored to a defined initial state. Depending on the size of the lines, this

[57] Cf. Gestalt Robotics GmbH (2021).

process can take hours and has not been done in a targeted and purely manual way in the past. The process affects not only the machines involved, but the entire environment.In the past, this meant a high economic cost due to the time burden on personnel and line downtimes. In addition, impurities remained partially undetected, which was reflected in the quality of cleaning. This gave rise to the motivation to partially automate the line clearance process, i.e. to carry out cleaning in a more targeted manner. In addition, the goal was to reduce the line clearance process time from an average of over two hours to less than 30 minutes.

Solution through the use of AI

By creating digital twins of production environments, specific object classes or anomalies in the environment can be reliably and robustly detected and also spatially assigned. In this way, semantic environment maps can be automatically created and visualised in real time, which can also be read by humans. In the concrete practical example, this means that remains are detected automatically and the human is instructed and coordinated to remove them in a targeted manner using a map displayed on a tablet.

The concrete solution in the practical example makes use of existing cameras in individual machines on the line and is supplemented by additional stationary cameras as well as a camera on a mobile robot to cover large surrounding areas. In addition, the digital twin is connected to the line control system. In the specific case, the AI calculation takes place directly on individual smart cameras, but can also be performed flexibly and scalably via cloud or edge.

Success factors and barriers

Challenges in the implementation of image analysis and associated digital twins are primarily data protection regulation (GDPR) compliance and the adaptation of the technology to the specific application scenario as well as the associated business or operator model. To ensure that the latter does not become a cost trap, especially for SMEs, the practical example started with a two-week proof-of-concept project that proved the feasibility and in the course of which concrete key performance indicators (KPIs) were determined to determine the return on investment (ROI). Only in the next step, based on the concrete prospect of success, was the implementation carried out in close cooperation between the three partners. In addition, SMEs have the option of choosing flexible payment models, such as pay per use, which help to make cost planning more precise and keep it in view. Established technology modules enable flexible use for individual solutions based on the modular principle, which makes the use of a digital twin attractive for SMEs. Furthermore, machines and plant controls as well as ERP systems can be flexibly integrated via open interfaces such as OPC UA.

Results with special reference to operational resource efficiency

In the practical example, the use of the digital twin reduced downtimes by 75%, which significantly lowered energy consumption, which is not offset by added value. The increase in the quality of the line clearance and the associated reduction in impurities in the line also reduced the number of rejects in production.

In another customer project, a digital twin was created for an outdoor logistics environment that provides assistance to drivers of delivery vehicles via app and navigates them to free parking positions in a targeted manner. With the help of optimised destination guidance, energy savings could be realised as a result of reduced congestion times and a reduction in unnecessary journeys.

5.3 AS 3: Optical error detection

Application scenario 3 describes optical defect detection using the example of real-time analysis of image material during fibre injection moulding production (Section 5.3.1). An excursion to the Werner-von-Siemens Centre for Industry and Science in section 5.3.2 provides an example of how AI applications can also be tested outside the company itself.

5.3.1 Real-time analysis of image material for defect detection in fibre injection moulding production

Due to their diverse material properties, fibre composites are considered an important resource in the manufacture of high-performance components. In addition to the material properties, a major advantage is the direct production of three-dimensional moulds. Fibre injection moulding is one of numerous manufacturing processes used to produce fibre composites. This process takes place in several steps. First, the fibres are blown through an inlet opening into a closed mould. While the fibres attach to the upper and lower mould, the air can escape through small openings in the mould parts.

Once sufficient fibres have been injected into the mould, the blank is compacted by pressing the moulds together so that it has the contours of the upper and lower mould. Subsequently, a hot air stream ensures that the binder melts and the chemical reaction to form the composite takes place[58]. Currently, it is not yet possible to monitor fibre injection in real time without having to stop the process. Unlike other mould filling processes, it is not possible to measure a change in pressure and/or temperature.

The following application scenario describes the analysis of image material for the early detection of faults during the injection process[59]. Table 12 shows a detailed overview of the technological implementation of this application scenario.

58 Cf. Förster, E. (30 May 2003).

59 Cf. Moll, P.; Schäfer, A.; Coutandin, S. and Fleischer, J. (2019).

Table 12: Technological implementation of AS 3

Factor	Description
Hardware	Industrial camera with the following specifications: Frame rate of 20 frames per second, resolution of 200dpi, field of view of 400×400mm. In addition, LED strips are used for homogeneous illumination of the background.
Data	Several sequences of injection moulding applications are recorded to generate training and test data. A total of 484 images are selected and marked manually.
AI method	An essential step in the application scenario is the automatic detection of fibres. For this purpose, thresholds are defined that are suitable for segmenting elements on digital images. Specifically, areas where fibres have already been applied are to be demarcated from vacant areas. This allows the progress of the spraying process and the layer thickness of the fibres to be displayed in real time. The following three segmentation methods are tested and compared: **Otsu Thresholding:** Otsu Thresholding is a special method of segmentation in image processing and analysis. The segmentation is based on an analysis of gray levels and the subsequent calculation of difference values on the pixel level. **k-Means-Algorithmus:** k-Means is a commonly used method to group objects into a predefined number of clusters. The assignment is based on the distance of the objects to their nearest cluster in the multidimensional space. **Convolutional Neural Network (CNN):** CNNs are based on a deep learning architecture and are able to process input in the form of a matrix. Therefore, the CNN method is particularly suitable for image analysis. During model development, a U-Net architecture was used, which is particularly suitable for segmentation tasks.
Essential work steps	Essential work steps in chronological order: • Installing the camera and aligning the lighting from the opposite side • Generate training and test data by capturing and manually labelling 484 images from the injection moulding process • Pre-processing of image captures to adjust image size and reduce colour deviations • Test of three different methods (Otsu Thresholding, k-Means and CNN) for fibre front detection • Evaluation of the three AI models based on the number of correctly predicted pixels of 100 test images, which were manually labelled. • The Otsu Thresholding method and the k-Means algorithm show very low error rates of 1.40% and 1.6%, respectively. In contrast, the error rate of the CNN is higher by a factor of two and is 3.01%. • Acquisition of the segmentation line with OpenCV for visualisation of the fibre front • Transfer of the fibre front to a monitor in the production area for inspection by specialists

The effort for the implementation of AS 3 is in the medium range. Comparatively little effort is required to generate training and test data. A differentiated view of the effort can be found in the following table.

Table 13: Effort estimation for AS 3

Evaluation criterion	Effort	Description
Implementation effort	medium	Integration of the camera requires possible redesign or new construction of the lower mould.
Software and Hardware expenditure	medium	Development of AI methods in Python programming language based on open source packages. Using the freely available findContours algorithm of the OpenCV library, the segmentation line is drawn on the images. An industrial camera including LED lights is required for image capture.
Required expertise	medium	The open source software is well documented, knowledge of Python and C++ is required.

By evaluating the image material, the fibre front can be visualised and monitored during the injection process. This results in the advantage that inequalities in fibre distribution can be detected at an early stage and corrected during the process. In addition, image captures at the end of the injection process can be used for automatic quality control by comparing them with reference images. The resulting effects on material consumption and the quality control process are shown in the following table.

Table 14: Qualitative potential assessment of AS 3 to increase resource efficiency following the metrics model

Resource	Influence	Key figures & description
Materials	low	**Material consumption in kg:** By detecting uneven distributions and repairing them during the injection moulding process, it is possible to reduce the number of rejects from incorrectly produced moulded parts. This leads directly to lower material consumption of fibre composites in production. Depending on the scrap rate and its percentage change, real-time analysis can be expected to produce savings on a small scale.
Electric energy	low	**Energy consumption in kWh:** The reduction in scrap is associated with shorter machine run times. This allows the estimated energy consumption to be reduced to a small extent.
Water	no influence	
GHG emissions	low	**Emission of kg CO_2e:** Reduction in CO_2 emissions resulting from material savings in fibre composites and reduction in electrical energy used. Further secondary effects on GHG emissions can be derived from savings in the supply chain. Overall, savings can thus be achieved in the low range.
Other effects		• Increase in the quality of the moulded parts produced • Reduction of costs in quality assurance through a higher degree of automation

5.3.2 Digression: Werner-von-Siemens Centre for Industry and Science

Test field for the promotion and testing of AI applications

Presentation Werner-von-Siemens Centre for Industry and Science

The Werner-von-Siemens Centre for Industry & Science e.V. (WvSC) is part of Berlin's future location Siemensstadt 2.0 and focuses on dynamic, collaborative research at the point of value creation. An open ecosystem with new ways of working is the foundation of the association. The planned co-working and co-creation area, including manufacturing and laboratory space for prototyping, will enable joint research between scientific institutions, universities, industry, SMEs and startups. Short distances make encounters and quick testing of ideas possible. Thus, innovative research & development (R&D) and accelerated product and technology development take place without transfer costs.[60]

The association is supported by federal and state funds within the framework of the joint task “Improvement of the regional economic structure”. The current projects are co-financed by the European Regional Development Fund.

Focus of the research projects and goals of the WvSC

The WvSC is a non-profit association which, according to its statutes, focuses on the future topics of production technology change, mobility change and energy change. The cross-sectional technologies “additive manufacturing”, “new materials” and “digitisation” are currently being used in their various facets. The addition of further technology fields such as “Connectivity/5G” is planned.

Since summer 2020, the first research projects have been running under the umbrella of the WvSC in the application fields of “Electric Drive Technology”, “High-Temperature Applications” and “Maintenance, Repair & Overhaul”.

[60] Cf. Werner-von-Siemens Centre for Industry and Science e.V. (2021).

In additive manufacturing, artificial intelligence will be applied for automated design support. AI is also expected to provide better quality in repair processes by transforming the otherwise static repair chain into a dynamic and in-process chain. In the process, inspections are to be individually, digitally and automatically managed by the digital decision-maker.

The objectives of the WvSC are to promote science, education and research and to renew the industry. The association promotes the pre-competitive exchange of knowledge between these areas in order to open up new fields of technology and future topics and to accelerate innovations. The findings are processed in such a way that the general public can be informed about them. The primary goal is to strengthen Berlin as a business location.

Advantages of a regional technology hub and how SMEs can benefit from it

With the help of the WvSC, SMEs are given easier access to research projects. Applying for research funding requires a lot of experience with research programs – this experience is often not available in SMEs. The WvSC actively networks its members on a topic-specific basis. It brings together the ideas of SMEs with the knowledge holders for the execution of research projects in the scientific institutions.

Practical examples

WvSC research projects are currently developing solutions with AI. Among other things, data pipelines are being designed for networking electrical systems and reading out operating parameters in a cloud architecture. A database will be made available so that AI algorithms can be trained.At many points in the value chain, however, the prerequisite of sufficient data must first be created with which an artificial intelligence can be trained. The member company 5thIndustry GmbH has implemented a project with Siemens AG in this regard: Data that is generated in the production process (e. g. g. serial numbers) is no longer recorded on paper but in an app. It is only through the consistent digitisation of process steps and product data that the use of (weak) AI often becomes possible.

5.4 AS 4: Error prediction (Predictive Quality)

Application scenario 4 describes fault prediction (predictive quality) using the example of forming sheet metal blanks into body parts (Section 5.4.1). The practical example of atlan-tec Systems GmbH shows in section 5.4.2 the implementation in the production of HDPE pipe systems.

5.4.1 Failure prediction during the forming of sheet metal blanks into car body parts

A widely used process for the production of body parts for the automotive industry is deep drawing. In this process, a flat sheet blank is clamped in a die and formed with the aid of a punch. Since the quality requirements for body parts are very high, even minor surface damage can lead to high reworking costs or scrap. During deep drawing, such damage can also have a negative effect on the condition of the die and punch. In such a scenario, there is often no alternative to replacing the relevant components, which leads to additional costs in maintenance and means the production line comes to a standstill.

Forming the sheet blanks is the second of a total of six work steps before quality control. Defective intermediate products resulting from deep drawing therefore take up additional resources in the production chain before they are sorted out. The quality inspection of the body parts is partially automated in modern facilities, but a final inspection by a specialist is required.

The following application scenario describes the use of neural networks for the prediction of surface damage still during deep drawing[61]. This makes it possible to adjust system settings in real time to prevent the damage from occurring in the first place. The factors necessary for technological implementation are listed in Table 15.

To predict faulty body parts, two ML models are set up separately and connected in series. The first is a classification model that predicts whether a sheet will experience damage during deep-drawing. As a result, probability values are output, on the basis of which the sheets can be classified. When optimising the classification model, a confusion matrix is used to determine

[61] **Cf. Meyes, R.; Donauer, J.; Schmeing, A. and Meisen, T. (2019).**

the proportion of correctly and incorrectly predicted defective and nondefective plates. For the production of car body parts, a high hit rate of defective sheets is important to prevent damage to the punch or die. For this, it is accepted that a certain number of plates will be incorrectly predicted as faulty. However, the associated costs are lower than if a sheet that is defective is not recognised as such.

Table 15: Technological implementation of AS 4

Factor	Description
Hardware	To perform stress analysis, strain gauges are attached to record the elongation of the sheet via the change in electrical resistance in the strain gauge. The strain gauges are attached to the holder for the plates. In addition, several laser sensors are attached for distance measurement.
Data	To train the algorithm, time series data from more than 4,000 deep-drawing runs are collected from production. The electrical stress during forming of the sheet and the laser distance measurement to the sheet are used as input data.
AI method	**Recurrent Neural Networks (RNN):** In contrast to the forward information processing in classical neural networks, RNNs exhibit feedback mechanisms. These allow information exchange with neurons of the same and previous layers. This results in the ability to consider information in its temporal context, which is why RNNs are particularly suited for processing time series data.
Essential work steps	Essential work steps in chronological order: • Data collection of more than 4,000 runs of the deep-drawing process • Preparation of data such as deleting time series data in which the stamp does not move • Manual marking of defective and non-defective sheets • Random division of data into training and test data in the ratio 80 : 20 • Since significantly fewer error than non-error data series are available, an oversampling method is used. In this process, the underrepresented group of data series is multiplied to obtain a balanced ratio of the two classification groups. • The classification model is evaluated using a confusion matrix. The values obtained are 0.9427 for the true-positive rate and 0.9000 for the true-negative rate. • The mean square error is used as the objective function of the regression model and is 0.039.

When a body panel is predicted to be defective, this raises the question of at what point in the deep-drawing process the damage will occur. The second ML model, a regression model, builds on this and predicts the time to damage in milliseconds. The effort presented here is estimated in Table 16.

Table 16: Effort estimation for AS 4

Evaluation criterion	Effort	Description
Implementation effort	high	The time required to collect the training and testing data took eleven months. In addition, time was needed for model development and implementation.
Software and hardware effort	medium	No indication of the software used, conceivable development of RNNs by open source software. Each deep-drawing line requires several lasers as well as strain gauges to generate the necessary data.
Required expertise	high	RNN development requires programming skills and a deep understanding of machine learning, especially for model architecture creation and feature engineering tasks.

Resources can only be saved efficiently in predictive quality application areas if the system settings of the machines are changed so that the damage does not occur in the first place. This, in particular, is where the challenge lies, as the accuracy of the prediction decreases as the length of the time period to be predicted increases. For the deep-drawing process of metal sheets, a necessary time span of 1,000 milliseconds was identified, which is necessary to adjust machine settings still during the process. The following table shows the potential savings in resources that result from the use of predictive quality.

Table 17: Qualitative potential assessment of AS 4 to increase resource efficiency following the metrics model

Resource	Influence	Key figures & description
Materials	low	**Material scrap in kg:** By predicting defective metal sheet elements and correcting them immediately, the scrap rate can be reduced by 94%, from 3.6% to 0.2%. The resulting reduction in the number of defective intermediates takes up fewer additional resources in the production chain, suggesting a small-scale impact.
Electric energy	low	**Energy consumption in kWh:** By reducing the amount of scrap, it is possible to reduce the use of machinery and thus energy consumption. In combination with reduced production line downtimes, energy savings can therefore be expected on a small scale.
Water	no influence	
GHG emissions	low	**Emission of kg CO_2e:** Reduction in CO_2 emissions resulting from material savings on sheet metal elements and reduction in electrical energy used. Further secondary effects on GHG emissions can be derived from savings in the supply chain. Overall, savings can thus be achieved in the low range.
Other effects	–	none

5.4.2 Practical example AS 4: atlan-tec Systems GmbH

Predictive Quality in the production of HDPE pipe systems

Presentation of atlan-tec Systems GmbH

atlan-tec Systems GmbH specialises in the technological field of digitalisation and Big Data. In doing so, it benefits from more than 28 years of competence and technical expertise in the environment of major international industrial projects.[62]

At the same time, the growing need for digitisation is increasingly seen in the SME sector, which atlan-tec is supporting on the path to digital transformation. The services offered are primarily composed as follows:

- Merging laboratory data, quality data, machine or process data from different sources or databases,
- Processing and analysing this data,
- Generate data models, soft sensors, predictors, digital twins, and optimisation algorithms,
- Develop autonomous self-optimising processes and their economic optimisation.

Challenges in production

The following practical example refers to a concrete application scenario in pipe production. The production process is shown in Figure 13.

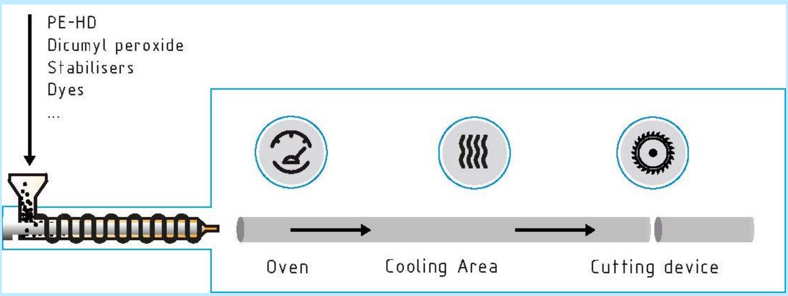

Figure 13: Initial production process of plastic pipes

[62] Cf. atlan-tec Systems GmbH (2021).

In order to be able to determine the cross-linking density of the material, a sample must be taken. Since laboratory analysis takes an average of 24 to 48 hours, it can be performed only once a day. This means that pipes produced during this period cannot be delivered to customers until a positive laboratory result is available. In case of faulty cross-linking density, the pipes will not be delivered. This can mean production of up to 4,000m of scrap. On average, this pipe production process results in a 10% to 20% scrap rate due to excessive delay between production and quality control and lack of real-time analysis.

Solution through the use of AI

Accurate prediction of laboratory analysis can allow immediate intervention in the manufacturing process and avoid the production of further scrap. This first requires the training of a neural network: Collected production data (dosages, temperatures, pressure values, torques, etc.) and laboratory data (crosslinking density of the material) form the data basis for this. These are fed into a database and used as a training set for the neural network. The costs in this specific scenario amount to approximately €35,000. Subsequently, the trained neural network is included in the production process as a predictor of connectivity density. The resulting production process is shown in Figure 14. Costs of around €25,000 will be incurred for implementation and other expenses.

Results with special reference to operational resource efficiency

By implementing the trained neural network into the production process, the meshing density can be predicted every minute with an accuracy of 98.5% according to the current status. The time delay between production and quality control is thus minimised and personnel can intervene immediately in the production process in the event of deviations in the cross-linking density without producing further rejects. The end result, particularly relevant in terms of resource efficiency, is a significant reduction in the reject rate. After less than six months, the project has also paid for itself financially.

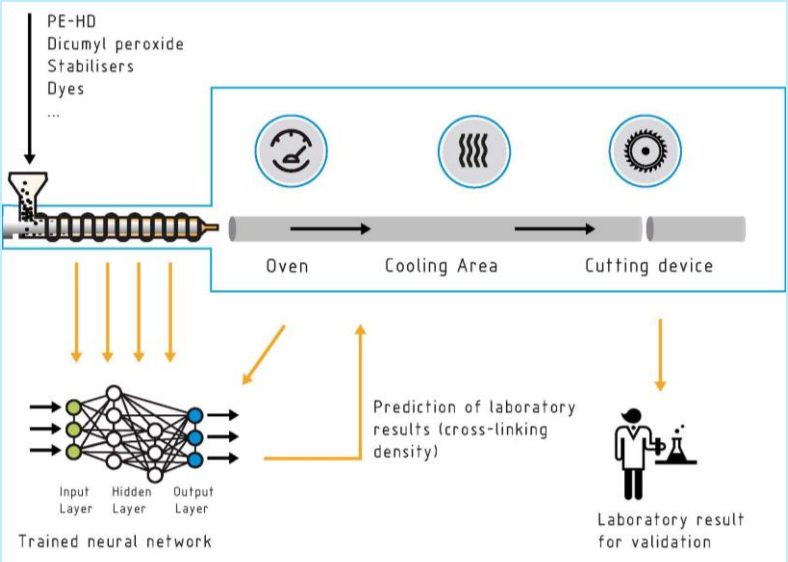

Figure 14: Production process of plastic pipes involving trained neural network

5.5 AS 5: Planning of the process chain

Application scenario 5 describes the planning of process chains using the example of simulation and modelling of operating states in micro-manufacturing (section 5.5.1). The practical example of Julius Zorn GmbH in section 5.5.2 shows the implementation of the application scenario in warehousing and production planning.

5.5.1 Simulation and modelling of operating conditions in micro manufacturing

Micro manufacturing is becoming increasingly important, especially in medical technology, but also in the automotive industry. This is due to the increasing need for miniaturisation of systems while maintaining or increasing functionality. However, process planning in micro manufacturing is associated with a high degree of complexity and even minor changes to manufacturing parameters can result in significant additional costs and quality losses. The miniaturisation of parts, components and production machines often leads to changes in physical and technical properties and often to quality losses. The following application scenario describes the use of a generalised linear regression model to optimise the manufacturing process using the example of a micro rotary swaging process.[63]

Table 18 shows in detail the technological implementation required for this application scenario. The goal is to simulate process chains using various input parameters and optimise them against predefined target variables. The micro rotary swaging process can be divided into four sections. First, the wire to be processed is heated and made malleable. A laser is then used to further heat and compress the end of the wire to create a thickening. The final step involves cold forming the thickened end to its final shape[64].

Table 18: Technological implementation of AS 4

Factor	Description
Hardware	No additional hardware needed.
Data	Data is collected on the four process parameters: feed rate, oscillation frequency, die closing pressure and diameter of the finished wire. In addition, data is collected on logistical parameters such as process duration as a function of processed distance, material consumption, material scrap, and processing and downtimes.
AI method	Linear regression: Linear regression is a standard method for predicting numerical target variables. This involves examining the relationship between a dependent variable from one or more target variables. A linear correlation between the dependent and independent variables is assumed. Alternatively, Support Vector Machines (SVM) and neural networks can be used. These are particularly suitable for showing complex relationships such as non-linear dependencies.
Essential work steps	Essential work steps in chronological order: • Conduction of 55 experimental runs of the micro rotary swaging process to collect training and test data • Training of a linear regression model with the process parameters feed rate, oscillation frequency and die closing pressure as independent variables. The diameter of the finished wire serves as the dependent variable • Simulation of different scenarios with corresponding process parameters • Creation of material flow simulations for the simulated scenarios • Evaluation of the scenarios based on logistical factors such as process duration, scrap rate, material consumption or processing and downtimes

In micro process planning, it is important to understand the interdependencies between process parameters and the resulting influences on quality, costs and time resources. By looking at individual parameters, the causal effect on the finished micro-component can be quantified as long as all other

[63] Cf. Freitag, M.; Kück, M.; Alla, A. A. and Lütjen, M. (2015).
[64] Cf. Rippel, D.; Lütjen, M. and Scholz-Reiter, B. (2014).

system settings remain unchanged. Statistical regression methods are particularly suitable for investigating the dependencies of two variables, and they were also used for optimising micro production. With the help of a regression model, scenarios with different process parameters can be simulated at will. This is particularly valuable when the process is complex and depends on a large number of parameters. A simulation of process designs is thus preferable to an iterative testing of all possible combinations for economic reasons.

Table 19: Effort estimation for AS 4

Evaluation criterion	Effort	Description
Implementation effort	low	The implementation effort is low, as no integration into an existing IT infrastructure is required.
Software and Hardware expenditure	low	Modelling a regression model is comparatively simple and can be done with common open source software. Additional hardware is not necessary, as the data can be collected directly from the manufacturing process.
Required expertise	medium	Programming skills are not essential for linear regression analysis. However, the creation of the cause-effect relationships and material flow simulations, as well as the evaluation of the simulated scenarios, requires in-depth process knowledge.

Based on the simulation of different process parameters, material flows can be created for the corresponding scenarios. After appropriate verification of technical feasibility, the scenarios can be evaluated and selected in terms of resource efficiency. The effort required for this is estimated and described in more detail in Table 19. This results in potential savings compared to the materials, tools and energy used (see Table 20).

Table 20: Qualitative potential assessment of AS 4 to increase resource efficiency following the metrics model

Resource	Influence	Key figures & description
Materials	medium	**Material consumption in kg:** By optimising the production parameters, the rejection rate of micro components could be reduced. This directly reduced material consumption per micro component produced. Realised by the material flow simulation and evaluation of the scenarios on the basis of logistical factors, a savings potential in the medium range is thus assumed.
Electric energy	low	**Energy consumption in kWh:** By reducing downtime, energy consumption can be reduced. As a result, energy savings can be expected to a smaller extent.
Water	no influence	
GHG emissions	low	**Emission of kg CO_2e:** Reduction in CO_2 emissions resulting from material savings on micro components and reduction in electrical energy used. Further secondary effects on GHG emissions can be derived from savings in the supply chain. Overall, savings can thus be achieved in the low range.
Other effects		• Savings in processing times and downtimes • Reduction of setup times possible

5.5.2 Practical example AS 5: Julius Zorn GmbH

Optimisation of warehousing and production planning by means of forecast algorithms

Presentation of Julius Zorn GmbH

Julius Zorn GmbH (Juzo) develops and manufactures state-of-the-art compression therapy and orthopaedic products. The production takes place with the most modern technology and in compliance with high quality criteria. The individual requirements and wishes of customers are implemented with the help of the latest technologies, such as computer-controlled knitting machines and digitally controlled sewing and colouring machines. [65]

Challenges in warehousing and production planning

The challenge in the project lies in the creation of usable forecast figures that have a practical application for operational resource planning and thus contribute significantly to the reduction of capital commitment or cost

[65] Cf. Julius Zorn GmbH (2021).

savings. A potential analysis has shown that there is a very large savings potential in warehousing and production planning, as these areas were previously planned without time series analysis. By means of a professional time series analysis paired with a forecast algorithm, a planning of the operational use of resources (man, machine, material) in the area of warehousing and a production planning, the differences between target and actual figures existing in the past are to be minimised and thus the informative value of future planning optimised.

Solution through the use of AI

Through an algorithm-based time series analysis of past sales figures, a monthly rolling forecast can be generated with high accuracy. Open source solutions are used to solve the challenge. The programming language R and the established library FPP2/FPP3 (Forecasting: Principles and Practice), which includes professional time series analyses and forecast models are used.

Success factors and barriers

The biggest challenge is to acquire the necessary knowledge in data science and time series analysis. This hurdle can be overcome by further training. Experience has shown that with about four hours of training per week, very good usable results can be achieved after only three months. In addition, the topic is also being worked on in the company on the basis of a bachelor thesis in cooperation with the Augsburg University of Applied Sciences (Professor Feucht, Dean of the Faculty of Economics). The aim is to build up the necessary competence with the company's own employees right from the start.

If Data Science knowledge is available within the own team, the option for further possible application areas within the company is created. Consistent employee training has provided basic skills in the following technologies, among others:

- Big Data applications,
- professional statistical analyses,
- interactive visualisations and data analyses,
- Process automation through the application of application-specific code,
- Algorithm development and deployment,
- machine learning and
- AI applications (neural networks, deep learning).

Table 21: steps and tools to optimise inventory management and production planning

Challenge	Tools and Libraries	Improvements achieved	Achieved Savings
• Create a monthly rolling forecast to improve sales and production planning	• Time series decomposition and analysis • Holt-Winters (ETS) and ARIMA algorithms • Programming language R and library FPP2/FPP3	• Showing the influences of seasonality and trends • Improve forecast accuracy by using proven algorithms to analyse time series and create forecasts	• Reduction of excess inventories for finished goods • Reduction in inventories of work in progress and raw materials • Savings in ongoing warehousing costs
• Implementation of a tool for the analysis of price quotations	• Regression analysis • Base R and library “moderndive”	• Tool for better price forecasting • Detection of anomalies in quotations for raw materials and purchased parts • Price negotiations can now be conducted based on figures, data and facts	• 3%–5% reduction in direct material costs • Detection of anomalies in price quotations, some of which led to renegotiations with significant savings
• Visualisation of KPIs and presentation of target achievement status with interactive dashboards	• Interactive data visualisation (“ggplot2”, “flexdashboard” and “shiny”)	• Company-wide communication of KPIs and their target achievement status • Identify deviations and take countermeasures quickly	• Reduction of electricity costs • Increase in machine utilisation • Reduction of quality costs and reduction of scrap

Results with special reference to operational Resource efficiency

By using the data from the Holt-Winters forecast, material and production planning is very precise. When planning the necessary operational resources, it is possible to react quickly to trends and seasonal changes, as these can be made visible in the forecast models and thus taken into account in planning. The use of the R programming language and the FPP3 package, as well as the use of an algorithm, enable the automated creation of the forecast, which is complemented by several graphical analysis options of the time series and forecast models. These additionally help with resource planning.
The following results were obtained:

- Production can be planned very precisely twelve months in advance.
- Inventories decrease by 12%.
- Finished goods inventory can be very precisely controlled to the correct range. This reduces the tied-up capital by 10%.

Stock-outs are at a historically low level.

5.6 AS 6: Product optimisation

In this application scenario, a methodology for data-driven product planning and retrofit planning is first presented in Section 5.6.1 and its positive effects on resource efficiency are discussed. The practical example of IANUS Simulation GmbH in section 5.6.2 shows the implementation of the application scenario for the optimisation of extrusion tools.

5.6.1 Methodology for data-driven product generation and retrofit planning

Industry 4.0 and digitisation have transformed manufacturing in many ways, offering companies the opportunity to systematically improve products in future generations and retrofits by learning from product usage and behavioural data. Since the use of this data is by no means trivial, the application scenario for data-driven product generation and retrofit planning is presented below[66]. The methodology covers all steps from the data-based identification of optimisation potential to the implementation of improvements in future product generations and retrofits. For the potential analysis of this methodology, the technological implementation (Table 22), the effort estimation (Table 23), and the potential estimation in terms of resource efficiency (Table 24) have each been summarised in tables.

The benefits of a data-driven approach to strategic product planning are numerous and fall into three categories: firstly, in deep customer insights through the ability to identify latent customer needs and address them in future product generations or upgrades, and secondly, in sound product insights through a deeper understanding of the product and its strengths and weaknesses. The third category is the derivation of conclusions through careful analysis of the collected data. This enables better decisions in the product planning and development process.

In order to derive product improvements, the principle of concretisation or abstraction of the contradiction-oriented creativity method is applied. The first step is to abstract the hypothesis under consideration. It then examines which aspect of the product should be improved and whether that improvement would represent an undesirable change in the value proposition.

The area where the selected aspects and data points overlap defines abstract solution principles. These are applied to the influencing factor of the hypothesis and lead to a concrete solution. The identified product improvements are then examined for their impact on product development and retrofit planning. This step is used to check whether the improvement should be implemented as a retrofit or only in a new product generation. The decision depends on two criteria: the complexity of the change in implementing the desired product improvement and the likelihood of cannibalisation effects.

[66] Cf. Meyer, M.; Frank, M.; Massmann, M.; Wendt, N. and Dumitrescu, R. (2020).

Table 22: Technological implementation of AS 6

Factor	Description
Hardware	Not specified.
Data	Complex technical systems have hundreds of possible data points. Since it requires a tremendous amount of effort to analyse all relationships that may occur between data, a focus is placed on specific aspects and data points as early as possible. It is helpful here to derive hypotheses about product use and customer behaviour in order to find starting points for data analysis. This can be done using a five-step process: • Setting up a partial model → general understanding of the product • Creating value propositions → catalogue of fields of action • Clustering and prioritisation → fields of action to be investigated • Determination of the influencing factors → influencing factors on the fields of action • Determination of hypotheses
AI method	When the necessary data are available, the hypotheses can be tested. This requires selecting an appropriate method from the following six categories: • Visualisation: e. g. plots and projections • Correlation: e. g. Covariance and Chi-Square Test • Regression: e. g. linear regression, non-linear regression and multilayer perception • Prediction: e. g. autoregressive models and recurrent neural networks • Classification: e. g. support vector machine, nearest neighbour classification and decision trees • Clustering: e. g. sequential and partial clustering
Essential work steps	The approach of the methodology for data-driven product generation and retrofit planning can be realised by a three-phase process model: 1. Hypothesis identification and prioritisation a. Determination of hypotheses b. Prioritisation of the hypotheses → prioritised hypotheses 2. Data analysis: a. Identification of the required data for validation b. Data-driven validation of the hypotheses → validated hypotheses 3. Derivation of product improvements: a. Derivation and evaluation of product improvements b. Determination of the impact on product generation and retrofit planning. → Recommendation for action

The complexity determines whether the change is limited to individual components or encompasses large parts of the product structure. For the latter, the probability increases if there is a lack of product differentiation. Consequently, a new product generation must stand out from a retrofit by offering an additional benefit in order to avoid cannibalisation effects.

Table 23: Effort estimation for AS 6

Evaluation criterion	Effort	Description
Implementation effort	high	An infrastructure is needed to collect the data from the various business units and integrate and analyse it with any external data.
Software and Hardware expenditure	low	Open source frameworks can be used for the methodology described here.
Required expertise	high	On the one hand, technical understanding is required in production to collect and, in particular, interpret the data collected. On the other hand, the AI algorithms used are, among other things, complex neural networks, whose selection, optimisation and result interpretation in data analysis require a deeper understanding and, in some cases, programming skills.

The recommendations for action result from the evaluation of the product improvements with respect to the two criteria mentioned above. If the complexity of the change and the likelihood of cannibalisation effects is low, a retrofit is recommended. If one or both of the criteria are rated as high, the product improvement should be implemented exclusively in a new product generation.

The approach described here was applied in five different case studies. According to the experience and feedback of the participants, this methodology provides a very efficient way to derive product improvements based on the data analysis results. A major reason for this is the systematic identification of hypotheses regarding the product.

These lead directly to the data to be analysed as well as to starting points for the search for product improvements. In addition, the model-based approach in particular proves to be suitable for building up an in-depth product understanding and searching for factors for success criteria. High-quality models stood out in all case studies as having a significant impact on the quality of the results and were used at many stages of the process.

Table 24: Qualitative potential assessment of AS 6 to increase resource efficiency following the metrics model

Resource	Influence	Key figures & description
Materials	medium	**Material consumption in kg**: Product or tool optimisation is accompanied by potential savings in terms of the material used, which eliminates the need for rework, for example. This leads directly to lower material consumption in production. Depending on the scrap rate and its percentage change, savings can be expected in the medium range.
Electric energy	high	**Energy consumption in kWh:** Here, too, a positive side effect can be recorded through product/tool optimisation. In the following practical example, iterations in annual machine startup processes are reduced by more than half. As a result, enormous savings in energy consumption can be realised, indicating a potential for savings on a large scale.
Water	no influence	
GHG emissions	low	**Emission of kg CO_2e:** Reduction of CO_2 emissions resulting from material savings and reduction of electrical energy used. Further secondary effects on GHG emissions can be derived from savings in the supply chain. Overall, savings can thus be achieved in the low range.
Other effects		In one of the case studies mentioned by the authors, the application of the presented methodology is demonstrated using the example of a modular enclosure system. A driver analysis shows that the cover screw connection is the main reason for time-consuming handling during servicing. The final part of the data analysis compares the lid bolting with other handling options and identifies a better solution. Here, the parameter to be improved is the loss of time during maintenance, which is only one of many other possible effects of data-driven product development.

5.6.2 Practical example AS 6: IANUS Simulation GmbH and M+S Silicon GmbH & Co. KG

AI-supported optimisation of extrusion tools

Presentation of IANUS Simulation GmbH and M+S Silicon GmbH & Co. KG

IANUS Simulation GmbH was founded in 2006 as a spin-off company of TU Dortmund University and is today a software and service partner for 3D CF simulation of flow processes. These numerical flow simulations (CFD simulations) are used, for example, in plastics, pharmaceutical and food technology and provide a detailed insight into the processes and procedures of different machines in which flows are present.

With the help of so-called digital twins, which IANUS and its more than 30 employees offer to customers from a wide range of industries, processes can be designed and optimised in a resource and energy-efficient manner.[67]

The customer presented in this practical example is M+S Silicon GmbH & Co. KG[68]. This is the origin of the M+S Group in Dortmund and was founded in 2001. M+S specialises in the production of extrudates, corner vulcanisations and HTV mouldings, which can be manufactured in any desired colour and based on individual samples, data sets or drawings. Approx. 250 employees process silicone rubber in a wide range of variants. The material optimally adapts to the most diverse requirements in terms of shape and design.

Challenges of the customer

M+S Silicon processes various profiles, hoses, foams and sheets made of silicone rubber for more than ten different industries under the highest quality standards. In addition to the injection moulding process, these are mainly produced via the extrusion process and require a high level of technical knowledge in order to manage the processing process in a stable manner.

As the market demands the production of higher quality and technically more sophisticated products, iterative adaptation of the shaping extrusion dies with the help of "trial & error" is common and often even mandatory. Only in this way can the final end products be produced under economic criteria.

The task of an extrusion tool is to shape the plastic melt, which is homogeneously drawn from the extruder, into a profile form specified by the customer. For this, the corresponding mould design – i.e. the planning and development of the subsequent mould shape – is a significant factor. The design of extrusion dies is very complex as well as time-consuming and is based on empirical values.

[67] Cf. IANUS Simulation GmbH (2021).
[68] Cf. M+S Silicon GmbH & Co. KG (2021).

However, due to the complexity of the respective tools, there is a high potential for error. Errors in the die design are corrected in the run-in or sampling phase by “Trial&Error” tests. This process is particularly time-consuming and costly.

Solution through the use of AI

Mathematical modelling forms the basis for the theoretical consideration of flow processes in the design of tools. State-of-the-art numerical methods can be used to simulate the flows in extrusion tools. This makes it possible to generate certain parameters in the process processing, which offer insights into the process. Inhomogeneous flow velocities at the extruder outlet can result, for example, in different wall thicknesses of the product or in the “bending out” of the extruder of the workpiece to be produced. Excessive residence times of the flow in the mould often indicate dead zones and can result in specks on the product. In addition, too much pressure consumption means poor energy efficiency because the extruder has to produce more power.

Building on these already known numerical approaches for the simulation of flow processes, IANUS has developed a system with which such flow simulations can also be carried out quickly and easily specifically by the user, StrömungsRaum©. The simulation runs on high-performance computing clusters to guarantee the highest possible computing power and fast delivery of results. Furthermore, the system can be individually adapted to special customer wishes, requirements as well as the respective processes – so also to the individual workflow of the company M+S. With this software app, the company M+S is able to define and order a flow simulation within minutes at any time via an internet-capable end device.

The system is also capable of using weak AI to develop independent solution proposals or suggest tool contours. These suggestions are determined by algorithms and validated by prior data collection together with the customer. An example of this is evolutionary algorithms, which work in two stages: In a first step, simulations are performed for a certain generation (selection) of parameters and their influence on the target variable to be optimised is determined. Automation is essential here, as a great many simulations have to be performed for the different parameter configurations. In a second step, an algorithm is used to select those parameter configurations from the simulation results that lead to an improvement in the target variable. At each selection step, the selection algorithm is slightly adapted ("mutated"), so that an evolution towards better and better configurations takes place. The system runs through various configurations until the desired target criteria are achieved. Evolutionary algorithms are goal-oriented, but at the same time always very complex and simulation-intensive.

Based on the simulation results, the designer receives recommendations on how to optimise the tool. The person designing the tool is thus able to quickly make simple changes in the geometry of the digital tool twin on his own. Working with StrömungsRaum© makes it possible to break down previous technology barriers, since neither proprietary hardware nor special knowledge of the software is required. This modern way of numerical tool design supports the classical design, which until now was done exclusively by the person who designed the tool. The calculations are always dependent on the respective material behaviour, which is why M+S has acquired a high-pressure capillary rheometer specifically to carry out material characterisations independently. This allows the material and the own recipe to be measured and determined directly on site.

Success factors and barriers

The special material properties as well as the customised production process represent a major challenge that always has to be solved at the beginning of the project. With the help of the customer and corresponding process data, which are collected, structured and processed, basic code principles can be adapted and target-oriented results generated. This enables the AI to find iterative approaches to solutions. Another challenge is to gain the willingness of employees and motivate them to deal with a technology that is new and unfamiliar to them in addition to their day-to-day business, as well as to productively incorporate it into their daily workflow.

Results with special reference to operational resource efficiency

The following section outlines the savings that can be achieved in the startup and makeready process through digitisation and AI. Based on approx. 100 new tools per year at M+S, approx. eight rework loops per new tool are common. This results in a total of approx. 800 annual startup processes, which cause a corresponding amount of scrap. Together with a material price of currently approx. €4.30/kg and an extruder filling of approx. 30kg material per startup test, this results in losses of approx. €103,000 as well as 16,200kWh energy requirement per year (assuming normal energy consumption for an average extruder in use). On average, the number of startup processes is reduced from eight to three iterations with the help of StrömungsRaum©, which in turn results in a total saving of approx. €66,200/year.

5.7 AS 7: Autonomous transport systems

Application scenario 7 describes the use of autonomous transport systems using the example of automation in the production line by automated guided vehicles (AGVs) in a food company (Section 5.7.1). The practical example of Blechwarenfabrik Limburg GmbH in Section 5.7.2 shows how resource savings and efficiency gains in intralogistics can be achieved by implementing these systems. For both applications, an integral total solution of AGVs with AI support was chosen. The intermediate step of AGVs without AI support was skipped in the transition from a manual to an AI-supported solution. The pure AI potential is therefore difficult to separate from the overall solution.

5.7.1 Automation of production lines through automated guided vehicles

Companies must constantly improve their processes to make production more flexible, reduce waiting times and increase productivity through smaller time intervals. To achieve these goals, efficient and automated transport and material handling systems are needed. With the rapid progress of robot technologies, so-called automated guided vehicles (AGVs) have become established in various areas, e. g. in the picking and delivery of stored goods or the internal transport of materials. In the following practical application, an economic evaluation of the use of AGVs in a food company is presented[69].

AGVs are mobile devices typically used in industrial applications as automated aids for transporting materials from pickup points to drop-off points (i. e. material handling tasks). They are used especially in facilities such as distribution centres, manufacturing plants, terminals and warehouses. AGVs are connected to a central navigation system that sends instructions to the vehicles, receives their position information via various onboard sensors and guides them along predefined paths as they complete the appropriate transportation tasks. This project was carried out in a food company based in northern Italy, which produces frozen ready-to-eat foods, supplies wholesale and reaches 55 countries worldwide. In the aforementioned company, the AGV transports ingredients for food preparation from the kitchens to the production lines. Table 25 illustrates the technological implementation required for this in the company.

Table 25: Technological implementation of AS 7.

Factor	Description
Hardware	Depending on the level of automation, a certain number of AGVs must be purchased by the company. In this case, eight AGVs are acquired when the process is fully automated.
Data	The most important source of data for creating the analysis is the number of trips/transports required or their respective material requirements. Based on these data, the following additional elements were calculated: • Quantity of raw materials involved for the entire year [kg/year]. • Number of trays [trays/year] Number of employees required in the current scenario. This was derived based on daily scheduled production during a work shift.
AI method	AI is used in the prioritisation of orders and the determination of optimal routes in order to be able to supply the production lines with material at all times and not to overload buffer locations.
Essential work steps	At the beginning, an overview and an analysis of the actual situation are necessary in order to be able to carry out a detailed transport analysis. Boundary conditions and basic assumptions are then defined. These include e. g. space limitations, vehicle characteristics, or the required tasks of the person operating the vehicle. Then all the relevant data mentioned above can be collected. Based on this, an investment evaluation is carried out taking into account a scenario analysis. The last step is the implementation of the FTS.

Until now, the ingredients have been brought to the various lines by hand on individual standard trays on a trolley. One of the main disadvantages is

[69] Cf. Tebaldi, L.; Di Maria, G.; Volpi, A.; Montanari, R. and Bottani, E. (2021).

that only one tray can be transported at a time. This inefficient system requires at least one person present. High labour costs are incurred because certain productions require two or three people at the same time. The automation of this process aims to solve this problem.

The facility under study consists of three different production lines, all of which are considered in the analysis performed. To carry out the present study, the initial condition of the plant to be evaluated should be recorded and a detailed analysis of the transport of ingredients from the kitchens to the production lines should be carried out. Direct observations are made in the production area to determine the paths taken by ingredients from preparation in the kitchens to arrival on the production lines.

Table 26: Effort estimation for AS 7

Evaluation criterion	Effort	Description
Implementation effort	high	The effort required for the introduction of AGVs is estimated to be high. In addition to preliminary economic analyses to assess profitability and efficiency, new systems must be integrated and coordinated with production processes. In addition, employees must be familiarised with the new production process.
Software and Hardware expenditure	not applicable	No information is given about the software used. However, this is very likely to be provided by the AGV manufacturer. In addition to the procurement of the AGVs, magnetic strips and lasers still have to be installed in this practical application, as the AGVs orient themselves according to them and operate the production lines.
Required expertise	medium	The introduction of the new system is the biggest hurdle. However, since suitable software for operating the AGVs is usually provided by the manufacturer in this case, only the people who embed the new system in the new production process, taking into account the optimum routes and required work steps, need to be trained with regard to the operation of the AGVs.

During the observations, the time it took each employee to transport, weigh, unload, the raw materials and to pick up the empty trays and return them to the kitchens was measured and recorded. Based on the given space and routes for transporting the ingredients, the length of all possible routes was first calculated. Dividing the path length by the average speed of each person employed allows an estimate of the time required to cover all possible paths between kitchens and production lines. Further estimation of effort in terms of implementation, software and hardware and expertise required is shown in Table 26.

The results of this evaluation show that the human needed less time than the AGV to cover the total distance, i.e. back and forth. However, while personnel can only transport one tray, the use of an AGV allows up to six trays to be transported. In total, one employee can transport about 165 kg of ingredients per hour and a shuttle can reach 600kg. This illustrates the significant savings opportunities that the use of an AGV brings in terms of resources, time and personnel (see Table 27). A total of eight AGVs are required for the complete automation of the production lines. Of particular interest is the payback period, which is about one year and eight months. The initial investment is justified by annual savings of approximately €279,000. The investment evaluation shows that full automation with a net present value of approx. €290,000 is the most lucrative solution.

Table 27: Qualitative potential assessment of AS 7 to increase resource efficiency following the metrics model

Evaluation criterion	Effort	Description
Materials	medium	**Material consumption in kg:** The introduction of AGVs can save ingredients by avoiding human-caused damage during transport and disruption of the cold chain. The reductions in scrap quantities allow savings to be expected in the medium range.
Electric energy	low	**Energy consumption in kWh:** Cold chains and cold storage facilities can be designed to be more energy efficient, which also leads to a reduction in energy consumption. Since only indirect energy savings are achieved here, the potential for additional energy savings is to be considered low.
Water	no influence	
GHG emissions	medium	**Emission of kg CO_2e:** Reduction of CO_2 emissions resulting from material savings in the form of ingredients, the reduction in the number of transports when routes are optimised and the reduction in electrical energy used. Further secondary effects on GHG emissions can be derived from savings in the supply chain. Overall, savings in the medium range can thus be achieved.
Other effects	high	Significant time and personnel savings. When the production lines are fully automated, 600kg/h of raw material are transported (instead of 165kg/h by one employee).

5.7.2 Practical example AS 7: Blechwarenfabrik Limburg GmbH

Process-optimised transports through an intelligent automated guided vehicles

Presentation of the Blechwarenfabrik Limburg GmbH

Blechwarenfabrik Limburg GmbH is a manufacturer of steel packaging for so-called chemical-technical filling goods such as paints, varnishes and glazes. The company has further sites in Denmark, Poland and Russia and, with almost 150 years of experience, is one of the oldest steel packaging manufacturers in Germany.[70]

Challenges of growing production and material transport

The old company building of the tinware factory was located in the middle of Limburg's city centre and was over 120 years old. Production had grown over the years and the production process was correspondingly inefficient. The production ran over four floors. Material was transported with the help of forklifts and differences in height were mastered via elevators. Accordingly, a high and error-prone logistical effort was required to be able to manage the material transport.

Solution through the use of AI

To solve these challenges, the company decided to build a new site. In the process, the flow of materials was optimised as one of the central topics. No more forklifts or manual warehouses are used throughout the production process. The production lines are automatically loaded with raw materials by automated guided vehicles (AGV). At the end of each finishing line are palletising robots that palletise finished goods according to customer orders.

The finished goods are then picked up by the automated guided vehicles and transported to the outgoing goods department, where they are either

[70] Cf. Blechwarenfabrik Limburg GmbH (2021).

shipped directly after a stretch hood process[71] or stored in the fully automated high-bay warehouse.

In the high-bay warehouse, stored finished goods are distributed fully automatically in the four aisles by stacker cranes in a so-called chaotic process. This means that the goods do not have a clearly assigned location in the high-bay warehouse, but are distributed randomly in the aisles when viewed from the outside.

Only lattice boxes are always stored in the lower rows, because they have a high weight. Apart from that, the AI-assisted distribution is oriented towards available space and minimisation of travel distances, which are optimised by means of prioritisation in the applied algorithm and transmitted to the automated guided vehicles.

Success factors and barriers

Prioritisation was a challenge, as the manufacturing facility consists of 15 different producing lines, almost all of which can manufacture multiple products and produce at different speeds. This creates an ever-changing basis that the AGVs must observe.

The chaotic warehousing protects the company from delivery problems. Moreover, due to the random distribution of goods and different products in the high-bay warehouse, the company is usually able to deliver goods even if a rack aisle fails.

Results with special reference to operational resource efficiency

The result of switching to fully automated transport and storage as opposed to the manual option is an orderly efficient process. Less damage occurs during transport. In combination with all the other optimised processes at the new site, this helps to save around 100t of tinplate per year, among other things. Furthermore, the risk of accidents due to human error is reduced to a minimum.

[71] In a hood stretching process, loose palletised cans or canisters are covered with a film in this application scenario and thus fixed for transport.

5.8 AS 8: Sustainability Analytics

The selected application example on Sustainability Analytics in Section 5.8.1 refers to a CO_2 optimisation made possible by machine learning and cloud technologies. The simulation and optimisation solution has been successfully implemented in practice on an entire fleet of vehicles. It helped the company in question to record and predict CO_2-relevant KPIs. This also makes it possible to manage the company in line with CO_2-related legal requirements. This application scenario is underpinned by two practical examples. The former presents in section 5.8.2 the reduction of resource usage implemented by juS.TECH AG through intelligent vehicle coordination and the latter presents in section 5.8.3 the intelligent and demand-driven utilisation of the compressed air system in production implemented by GEDIA Automotive Group, which is highly relevant for almost all manufacturing companies.

5.8.1 CO_2-relevant optimisation using machine learning and cloud technology

The quest for sustainable value chains has long been on the management agenda in the automotive industry. Drivers, as shown in Figure 15, are primarily external factors such as regulations, societal pressures, competition and shifts in market demand for zero-emission products. However, internal factors such as corporate culture and strategy also reinforce the urgency of aligning value chains more sustainably[72].

This development often results not only in an improvement of the company's environmental impact, but also in a significant economic advantage. These competitive advantages can be achieved by offering niche products, cutting costs and, above all, anticipating risks along the value chain to enable sustainable management of the company.

[72] Cf. Chin-Chun, H.; Tan, K. C.; Zailani, H. M. S. and Vaidyanathan, J. (2013).

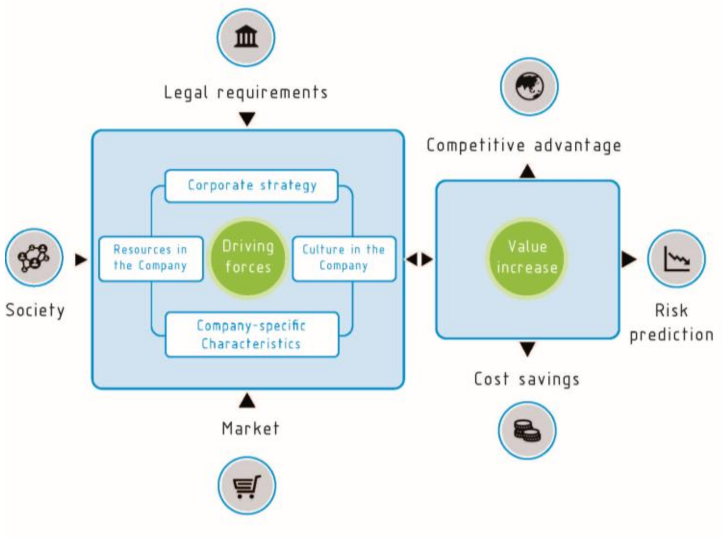

Figure 15: Internal and external factors influencing sustainable value chains and their potentials

In the automotive sector in particular, sustainability is currently being driven by a reduction in CO_2 emissions. The European Union imposes penalties should CO_2 emissions from vehicles registered in the European region exceed a critical threshold. Interestingly, emissions do not play a role in the production of the vehicles. Instead, average consumption of the individual vehicle in the use phase is used as the basis for calculating the fleet average. A new challenge here is the consideration of emissions in established decision-making processes, which requires the collection of data from many business areas. Market demands, production capacities and strategic goals of companies (see Figure 16) must allow for CO_2-optimised fleet control using AI[73].

[73] Cf. Deloitte Consulting GmbH (2021).

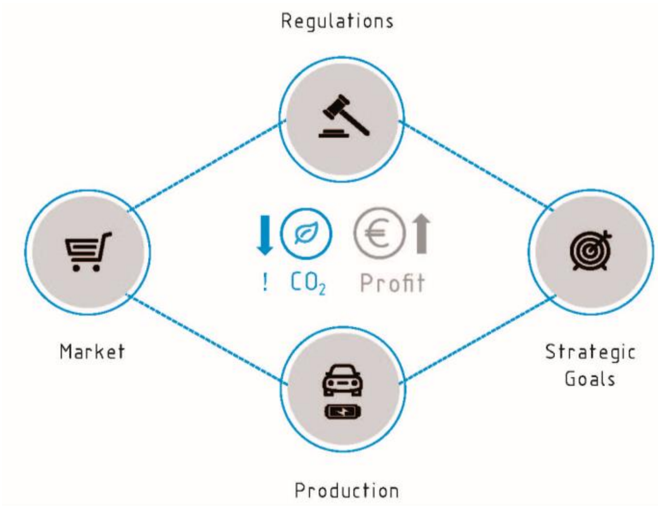

Figure 16: Facets of a CO_2 fleet optimisation scenario

In order for targeted fleet management to be possible at all, future developments must be precisely predicted. This is usually done using historical data that can be extrapolated into the future using ML algorithms. However, in the case of penalties, external data is necessary, since information about the time and place of a vehicle registration is primarily the responsibility of the authorities in the respective European countries. The design and choice of an appropriate ML model are therefore essential for the precision of the predictions. One possible solution approach is (cf. Figure 17) to use classification and/or regression algorithms to best estimate the time offset between a supply chain reference date and the actual registration date.

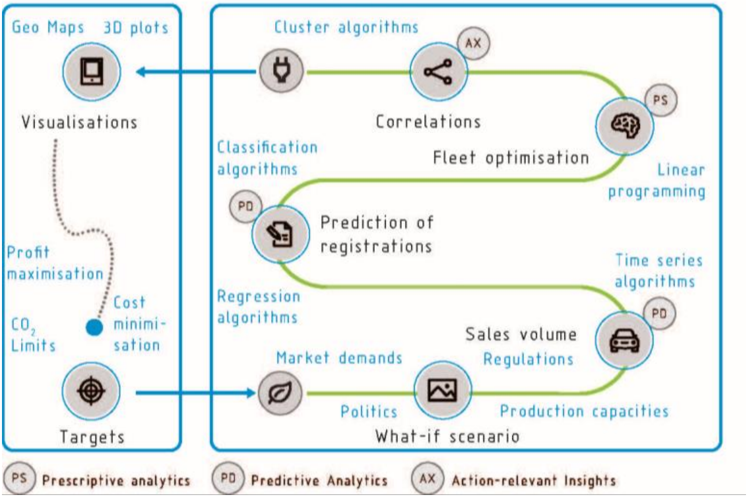

Figure 17: Application of AI along a Sustainability Analytics Solution

With the help of these forecasts and the integration of the information obtained with company-specific KPIs and production capacities, a fleet can ultimately be managed in a CO_2-optimised manner. The factors required for technological implementation are described in Table 28.

The complexity consists primarily in the data integration from different planning processes. In doing so, the data must be harmonised from an aggregation on which CO_2 taxation is possible at all. Aspects of vehicles relevant to CO_2 taxation may not be planned in sales or production. This makes CO_2-optimised control, as an integrated solution from the different processes, a data harmonisation challenge even before the actual use of AI. Table 29 shows a further assessment of the three evaluation criteria “Implementation effort”, “Software and hardware effort” and “Required expertise”.

More critical, however, is the availability and quality of external data. Data on vehicle registrations is collected in the regulatory processes of each country. Country-specific restrictions apply, which mean that the data is not available in the same quality across countries. This is particularly critical when forecasting future events. The random forest model must be trained with actual vehicle registrations to be able to make reliable predictions at all. The quality of external data is therefore sometimes most critical to the successful use of AI.

Table 28: Technological implementation of AS 8

Factor	Description
Hardware	An infrastructure is needed to collect data from the various business units, integrate external data and evaluate it. On-premise, cloud or hybrid solutions can be used.
Data	Internal data is collected from existing planning processes in sales and production and then integrated with financial data. Information on registered vehicles is obtained from external data sources. The CO_2 values for each vehicle are either stored as master data or can be approximated and integrated into the processing procedures with the aid of technically defined application interfaces (APIs).
AI method	The quality of potential insights from such an analytics solution can be significantly increased by using ML models in the determination of target figures as well as in the prediction of future vehicle registrations. Since the quality of the findings decreases over time, a seamless transfer into recommendations for action must be realised. Cluster algorithms can provide support here: **Random Forest Algorithm**: A Random Forest (RF) can be used in both regression and classification methods. RF can be used to predict the timing of a vehicle registration. This is done by estimating the number of days that lie between an existing reference date and the actual registration date. The prediction of the events is defined and solved as a quantitative target. **Auto ARIMA Algorithm**: The planned sales figures in sales can initially be extrapolated into the future with the help of a time series analysis. This allows market trends or seasonal effects to be automatically evaluated and assumed as suggested values at the start of a simulation. One possible time series analysis is the so-called "AutoRegressive Integrated Moving Average" (ARIMA). This time series analysis method is very dynamic, as the choice and parameterisation of the model are determined by preliminary testing procedures from the data itself. **K-Mean Algorithm**: Especially in complex problems, it is important to understand the correlations between the usually conflicting target variables and to translate them into appropriate recommendations for action. One common method is to cluster data depending on these different targets. In the case of Sustainability Analytics, this means grouping vehicles into clusters in terms of their CO_2 emissions and profitability. Here, the target variables must first be normalised before correlations can be formed. The K-Mean algorithm can be used to create the clusters automatically, since the algorithm is able to determine them for a given number of "K". This helps, for example, to identify vehicles that have the highest CO_2 emissions and at the same time low profitability and can therefore be reduced in their sales figures.
Essential work steps	• Collection of relevant data • Data processing • Model evaluation for the prediction of registration data • Implementation of the selected model • Continuous monitoring and adjustment of the model

Table 29: Effort estimation for AS 8

Evaluation criterion	Effort	Description
Implementation effort	high	For the creation of a “Minimum Viable Product” (MVP), an implementation effort of three to four months can already be expected.
Software and hardware effort	medium	The evaluation of the models can be done flexibly via cloud analytics solutions such as the Azure ML Service. Depending on the IT strategy, the actual implementation of the model is either done via cloud analytics solutions themselves or within the on-premise solution such as the Predictive Analytics Library in SAP HANA.
Required expertise	high	Due to the cross-process solution, an equally comprehensive understanding of the business processes as well as the data generated therein is necessary. Especially in large corporations, this knowledge is usually not available. Moreover, especially in the creation of the ML model, statistical knowledge must be combined with the expert knowledge so that, in addition to obtaining new knowledge, it can also be interpreted and explained.

Successfully steering fleets towards a CO_2-reduced portfolio depends significantly on the accuracy of forecasts of future events such as expected vehicle registrations. Retrospectively, this accuracy can be more than doubled using AI. The basis for measuring accuracy in this case is the Mean Average Error with respect to the actual registration date versus the assumed or predicted registration date. If the targets are met as planned, this will enable CO_2 emissions from manufactured vehicles to be reduced by more than a third over the next few years (see Table 30).

Table 30: Implications for AS 8 resource efficiency using the metrics model

Resource	Influence	Key figures & description
Materials	no influence	
Electric energy	no influence	
Water	no influence	
CO_2 emissions	high	According to the latest studies, car manufacturers will have to reduce the CO_2 emissions of their vehicles registered in the European region by around 38% in order to meet the targets. Since the penalties are significantly high, it can be assumed that companies can use sustainability analytics solutions to achieve these CO_2 reductions in line with corporate goals. Overall, potential savings are therefore realistic to a high degree.
Other effects	–	none

5.8.2 Practical example AS 8: juS.TECH AG

Reduction of the use of resources through intelligent vehicle coordination

Presentation of juS.TECH AG

juS.TECH AG from Uelzen is a business consultancy and develops applications in the field of artificial intelligence with a focus on sustainable digitalisation. As a focus, use cases in small and medium-sized enterprises are identified that achieve great benefits with little resources. The company is affiliated with the juS.TECH Institute, which conducts transfer research in the field of digitisation in order to sustainably shape the transformation to a new digital age from the very beginning.[74]

Challenges of the customer

The following real-world example looks at a logistics application that focuses on reducing resource use (in the form of fuel) by intelligently coordinating vehicles en route to a logistics hub. In the present example, the vehicles can only approach certain ramps due to structural reasons or excessively long distances. Therefore, traffic jams may occur in front of individual ramps. This is very time consuming and costly.

The special challenge is that many complex processes have to be weighed under many different aspects at a very high speed. People quickly reach cognitive limits here due to the complexity. Accordingly, truck planning must be agile, as environmental factors such as congestion, breakdowns and freight inspections cause permanent disruptions to planned operations. A rigid process or long planning in advance is therefore not expedient.

Solutions through the use of AI

To solve this problem, juS.TECH has developed a model that recognises complex relationships in the data and allows users to view specific time periods. This model is based on the methods of deep learning and is constantly trained by time series data augmentation. In order to include

[74] Cf. juS.TECH AG (2021).

image data in the solution, computer vision approaches are used, including generative adversarial networks. In the first step, all possible data sources were investigated for model generation. Data available in this case study are:

- the display of the truck fleet in real time,
- camera monitoring of the plant premises (security),
- the indoor GPS for tracking cargo and logistics vehicles,
- the planning overview of the loading ramps and
- the overview of the container supply vehicles.

Using the data already available, an initial proof of concept can be created. In the process, the available data is brought together centrally on a Green Cloud server[75].

Other data used to improve accuracy are digital freight documents. Here it is sufficient to scan them only when the truck enters. In the first step, the actual routes, manoeuvring areas and loading processes are made digitally visible with the help of camera monitoring. By handing in the loading documents when entering the site, a forecast is made of how long the truck will block a ramp. Resource savings are based on reducing disturbances that occur in the process. The biggest disruption to truck delays is highway congestion. The crucial data point in the process is the actual release of the ramp for the next truck. This means that the departing truck has already left the manoeuvring area and no other vehicle will occupy the manoeuvring area.

This value can then be used to control the following approaching truck. If there are any delays in the actual process, which can be identified by comparison with the present planning, the following vehicles are recommended to use a specially calculated average speed. This not only reduces consumption during the journey, but also eliminates waiting times

[75] **Concept that targets the environmental benefits of consuming IT services over the internet.**

in front of the logistics hub. Particularly in the case of refrigerated cargo, idle times lead to a significant increase in resource consumption.

Success factors and barriers

The implementation difficulty of an AI-supported solution approach often lies in the high development costs for a single medium-sized company. At the same time, knowledge about possible use cases has not yet reached the broad mass of companies. Another factor relates to the lack of process infrastructure in conventional operations and the careless handling of data. As a result, digital processes often fail to deliver value because traditional processes are already flawed. In this specific project, the topic of change management plays a decisive role. The professional groups of professional drivers and dispatchers are restricted in their own freedom of decision by AI-supported recommendations. It can be easy to get the impression that the quality of work, responsibility and experience of individuals are becoming less important.

Results with special reference to operational resource efficiency

With the help of this solution, resource savings of up to 20% can be achieved on days with a particularly high number of incidents.

Since fuel is an expensive operating material, not only is a positive contribution made to the GHG balance, but costs are also reduced. Other resource savings that occur incidentally include reduced paper consumption, decreased empty runs of staging vehicles in the container area, reduced shunting damage to vehicles and decreased energy consumption of logistics vehicles located in the hall. By using green cloud solutions, the GHG footprint is constant even as the amount of data increases.

juS.TECH works together with strong partners in Germany. This makes it possible to host the entire digital infrastructure in a greenhouse gas-neutral manner while benefiting from European data protection guidelines. As clouds become increasingly important, the topic of green cloud in particular is a result of efforts around operational resource efficiency – environmentally, economically and socially.

5.8.3 Practical example AS 8: GEDIA Automotive Group

Intelligent and demand-oriented utilisation of the compressed air system in production

Presentation of the GEDIA Automotive Group

The GEDIA Automotive Group has been in existence for over 100 years and has been producing body pressings and welded assemblies for the automotive industry throughout the world since 1955. Today, the company employs more than 4,300 people at eight production sites and has interests in joint venture and research companies. To ensure continuous optimisation of production operations, measuring systems for data acquisition are implemented at all relevant nodes in the company. The following practical example highlights the data-driven optimisation of the compressed air system at the main production site in Attendorn.[76]

Challenges of the customer

Compressed air is an important energy source, used in about 70% of all industrial sectors. At the same time, compressed air is expensive and energy-intensive to generate and thus a relevant cost factor in production. One obstacle in optimising the compressed air system for GEDIA is the decentralised main location in Attendorn with six plants. This has resulted in four different types of compressor stations. The mandatory stand-by or idle compressor costs to avoid a defect waste energy and are economically inefficient. Furthermore, GEDIA has found that too high manufacturer specifications for the reserve compressed air regarding the production machines lead to unnecessary excess capacities of the compressed air system.

Solution through the use of AI

After a superior control of the compressor manufacturer (Kaeser Kompressoren SE) was launched, GEDIA took this as a starting point to optimise the complete system. Based on this, measuring points are set to accurately determine consumption and pressure values to ensure stable air pressure for the machines. All volume flows are measured, which in

[76] Cf. GEDIA Automotive Group (2021).

turn allow detailed statements to be made about whether a compressor is being operated efficiently over a measurement period. One result of this is the conversion of a compressor station, the removal of two large compressors and the installation of a small compressor to replace the work of the large compressors, for example, over the weekend when there is less operation.

In addition, the manufacturer's specifications of the compressed air required for the respective machines could be re-evaluated. Here GEDIA has made a reduction of the pressure on the network to a point where it is still possible to produce safely. In figures, this means that by dispensing with theoretical reserve specifications, the network is operated at 6.5bar instead of 7.5bar. This seemingly small difference can save a large amount of energy. This is made possible by the intelligent control of the compressed air supply by means of an adaptive 3D advanced algorithm[77] based on the consumption and pressure measurements at the implemented measuring points. Switching and control losses, pressure flexibility, operation at the frequency converter and losses during no-load operation are also included in the optimisation procedure. The achievable possible optimum is then simulated and the respective compressors are controlled, whereby the demand pressure is decisive.

Success factors and barriers

By far one of the biggest success factors is the successful establishment of a comprehensive data measurement system within the company. Sensors are implemented at all relevant nodes and measure, among other things, energy flows and losses as well as idle times. Only this data measurement and use enable the optimisation of the compressed air system throughout the company. Positive experiences from successfully implemented projects in the past facilitate the release of budgets for future projects.

Nevertheless, internal financing remains an obstacle to corresponding application scenarios. It can happen that after implementation of a new system – for example a new compressed air system – the cause of failure

[77] Cf. KAESER KOMPRESSOREN SE (2019).

in the event of machine failures is always seen precisely in this new system. A general acceptance for corresponding innovations must be created in the entire workforce in order to be able to use and improve new systems optimally.

Results with special reference to operational resource efficiency

Resource savings is the primary reason why GEDIA decided to implement a new compressed air system. The resulting actual savings are targeted at the resource compressed air and the energy source electricity. A benchmark electricity price was used to obtain comparable data across sites and across the Group. Before implementation, the internal cost per 1,000m^3 of compressed air was €17. Currently, they are only €11 with electricity savings of over 35%.

6 OBSTACLES AND SUCCESS FACTORS FOR THE APPLICATION OF AI

In the following, the identified obstacles and success factors are presented, which are derived from the results of the literature research as well as from the analysis of the application scenarios and practical examples. The obstacles are also based on the expert survey in chapter 3.

6.1 Obstacles

Possible obstacles were queried by two different groups of participants in the survey conducted (see chapter 3). On the one hand, these were companies that do not (yet) use AI (group 1). This includes both companies that plan to introduce AI and those that do not intend to do so in the future. Secondly, companies that have already introduced AI were surveyed (group 2). Eleven potential obstacles were specified, as well as the additional answer option "Other", in order to be able to map individual obstacles. From the available answer options, participants were asked to select three answers with the greatest relevance for their own company. Figure 18 presents the results of the survey. The x-axis shows the proportion of companies that perceive the challenge listed as one of the three most relevant obstacles.

Although the percentages per barrier differ to some extent between the two groups analysed, some commonalities are apparent. In both groups, for example, the "lack of a data basis", the "lack of know-how" and a "high implementation effort" are each seen as one of the biggest obstacles by more than 30% of the companies. Also rated as relevant by both groups were the "lack of technical infrastructure", the "difficulty in identifying appropriate technologies" and the "lack of management support". The "unclear definition of AI" is also an obstacle, especially for companies that do not (yet) use AI.

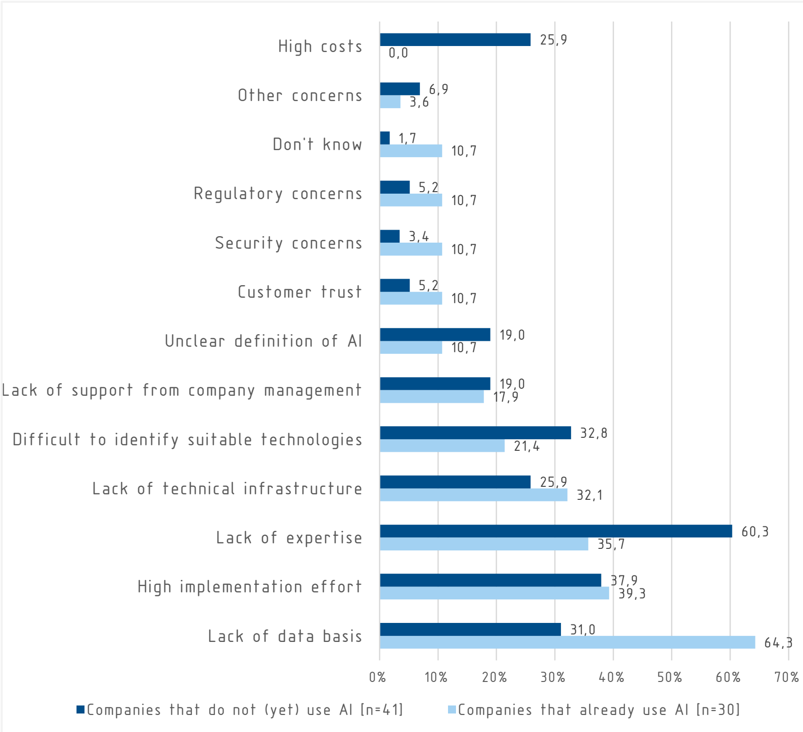

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Figure 18: Obstacles to the use of AI

However, significant differences between the two groups can also be observed. While most companies without AI experience cite lack of expertise as one of the top three barriers, companies with AI experience see lack of data as the biggest obstacle. However, as shown in Section 3.3, a large number of the companies that have implemented AI solutions obtain the necessary expertise from external service providers. The lack of a data basis is only perceived as an obstacle upon closer examination of the topic of AI. It is also notable that not a single company with AI experience cites high costs as an obstacle, while within Group 1, over 25% of the companies surveyed consider these to be a relevant obstacle. One possible explanation is that companies without experience in AI tend to overestimate the costs to implement it.

The possible loss of customer trust, any security concerns and concerns about regulatory compliance due to the introduction of AI play a rather subordinate role for both groups. Other obstacles named by the companies surveyed relate, on the one hand, to excessive expectations on the part of management with regard to the scalability of AI applications. This primarily concerns the rollout of pilot applications in widespread use. On the other hand, AI applications must be able to be embedded in all process steps in order to fully exploit the associated benefits. Figure 19 summarises all findings from the survey analysis, expert interviews and literature review Divided into the six predefined categories (technological, environmental, regulatory, social, corporate strategy and economic), a total of 20 potential obstacles to the introduction of AI in the operational environment were identified. Obstacles that are mentioned both in the survey and in the results of the detailed literature review are marked in bold accordingly and are thus considered to have a higher priority than those that were identified solely through research.

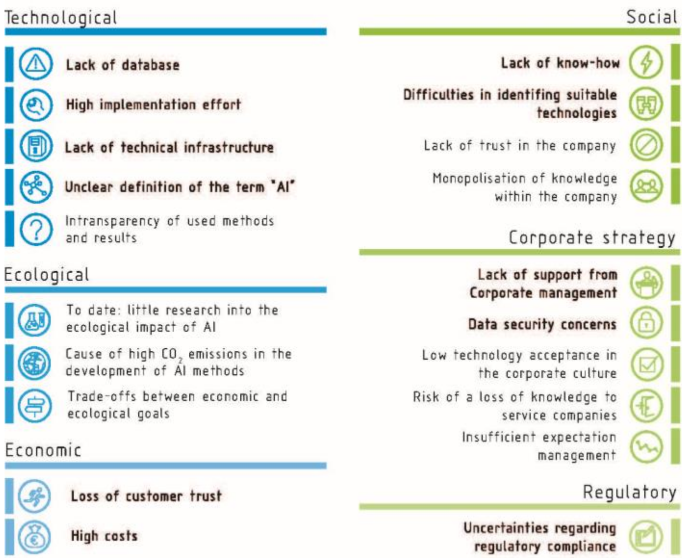

Figure 19: Identified obstacles for the introduction of AI

Table 31 represents the technological, environmental, economic and social barriers to AI deployment.

Table 31: Description of technological, environmental, economic and social obstacles to the introduction of AI

Obstacle	Description
	Technological
Lack of data basis	Insufficient data availability or poor data quality is a common problem in the industrial environment. Some companies have the relevant data sets but cannot access them at any time and in the desired form. There is also the difficulty of maintaining a comprehensive overview of the volume of data produced in-house. Incomplete and unlabelled data can complicate the use of artificial intelligence. Depending on the extent of the data issues, the implementation of AI solutions may even be prevented altogether. Data quality can be affected by various types of errors. These include e. g. duplications, misspellings and misinformation. A lack of annotation of the data also prevents the training of a system in supervised algorithms.[78,79,80,81]
High implementation effort	In particular, complex problems that cannot be approximated with existing solutions are in part characterised by a high implementation effort. The introduction of AI in such cases can be a long-term endeavour. This circumstance is reinforced by enterprise-wide rather than strictly defined use cases. Potentially necessary supplementary changes of a corporate organisational nature may lead to further significant delays.[82,83]
Lack of technical infrastructure	Poor technical infrastructure is perceived as a relevant obstacle. This applies, for example, to slow internet connections or poor network expansion and a lack of connections between production machines and a central or even decentralised platform. In particular, lack of or poor network coverage that does not allow reliable data exchange prevents AI applications that rely on real-time data access.[84,85]
Unclear definition of the term "AI"	Especially in small and medium-sized enterprises, there is often a widespread ignorance or misconception of AI. Accordingly, some AI solutions are in part perceived as uninteresting for their own business activities. Some companies perceive AI in the context of digitisation as an additional challenge rather than a helpful new technology. The perceived threat to existing business models through the use of AI promotes its perception as a risk rather than an opportunity. As a result, there is currently insufficient or difficult-to-understand communication of the possibilities of AI in the industrial environment.[86]
Intransparency of the methods and results used	For people outside the field as well as for experts, the way AI works is sometimes incomprehensible. Depending on the AI method and algorithm used, the solution path to the conclusion is often not documented. An inference on possible errors or a manual check of the output result is usually not possible with these so-called black box algorithms. This lack of transparency discourages users from implementing it, as AI is associated with a loss of control or transparency.[87]

[78] Cf. Weichenthal, S.; Hatzopoulou, M. and Brauer, M. (2019).
[79] Cf. Schoonhoven, J. J.; Roelands, M. and Brenna, F. (2019).
[80] Cf. Wangermann, T. (2020).
[81] Cf. Lundborg, M. and Märkel, C. (2019).
[82] Cf. Schoonhoven, J. J.; Roelands, M. and Brenna, F. (2019).
[83] Cf. Brynjolfsson, E.; Rock, D. and Syverson, C. (2017).
[84] Cf. Wangermann, T. (2020).
[85] Cf. Lundborg, M. and Märkel, C. (2019).
[86] Cf. Wangermann, T. (2020).
[87] Cf. Schoonhoven, J. J.; Roelands, M. and Brenna, F. (2019).

	Ecologically
Little research to date on the ecological impact of AI	The current state of research regarding the potential impact of AI solutions on a company's environmental performance is still manageable. So far, comparatively few scientific publications deal with the topic. This acts as a barrier for companies that see a reduction in environmental impact as a driver for AI introduction.[88]
Causing high GHG emissions in the development of AI methods	Training an AI model can emit up to 300,000kg of CO_2 equivalent, according to studies[89]. This is roughly equivalent to the emissions of five passenger cars over their entire product life cycle. This can be attributed to large energy consumption in data centres and server farms. For companies that attach great importance to environmental protection, this can be a major obstacle to investing further in AI – especially if the simultaneous ecological optimisation in their own business activities cannot be clearly quantified or predicted (cf. “Little research to date on the ecological impact of AI”).[90,91]
Trade-offs between economic and environmental goals	In some cases, the economic aspect conflicts with the ecological goal. In some cases, ecologically sound measures are priced higher than those with a purely economic focus. In such cases, it must be weighed up which factor is the more relevant for the company. Accordingly, the implemented AI must also be trained for such decision problems.[92]
	Economically
Loss of customer trust	Uncertainty and lack of knowledge about AI among the general public and potential customers are seen as a barrier, as some companies consider a loss of customer trust to be possible if AI is introduced into their own business processes. Accordingly, artificial intelligence would have a direct and negative impact on economic activity. The statement is based on a survey of companies. Thus, a causal relationship between implemented AI and customer trust has not been scientifically proven.[93]
High costs	A perceived high implementation effort often translates into high costs. Here, the link to previously mentioned barriers exists. Thus, both the lack of technical infrastructure and poor or missing data lead to a significant increase in implementation costs. In contrast, many solutions use open source technologies. This means that small projects can often be implemented cost-effectively. In many cases, therefore, AI implementations are less a matter of finance and more a matter of confidence in the usefulness and cost-effectiveness of the solutions.[94]
	Social
Lacking know-how	Lack of expertise is one of the biggest barriers companies face when implementing AI. Often the required knowledge is not available in the company. Additionally, the required information is usually not directly available to companies, as many applications are still part of research or not easily transferable to their use case. Lack of understanding around how introduced AI systems work results in uncertainty around the new technology. The resulting concerns of decision-makers in the manufacturing sector often prevent an active engagement with the technology and, accordingly, the implementation of AI solutions. Training and information offers can contribute here to sensitisation and reduce corresponding biases.[95,96,97,98]

6.2 Success factors

In addition to obstacles, success factors that support or simplify the implementation of AI solutions were also identified during the literature review. These can be divided into the four categories of social, technological, corporate strategy and regulatory factors (see Figure 20). In addition, enablers were queried during the interviews regarding the specific practice examples described in Chapter 5. Corresponding overlaps with the results of the literature search are marked in bold in Figure 20.

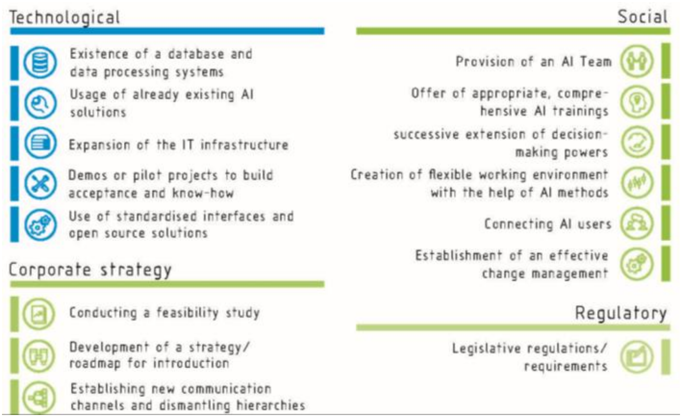

Figure 20: Identified success factors for the introduction of AI

In addition, two further success factors were mentioned that could not be identified from published literature (feasibility study, change management). The following Table 32 describes in summary all success factors and serves as a first introduction to a goal-oriented knowledge transfer for interested companies.

88 Cf. Chen, H. (2019).
89 Cf. Mathur, D.; Ahmad, Z. and Chamuah, A. (2020).
90 Cf. Vinuesa, R.; Azizpour, H.; Leite, I.; Balaam, M.; Dignum, V.; Domisch, S.; Felländer, A.; Langhans, S. D.; Tegmark, M. and Fuso Nerini, F. (2020).
91 Cf. Jones, N. (2018).
92 Cf. Mathur, D.; Ahmad, Z. and Chamuah, A. (2020).
93 Cf. Wangermann, T. (2020).
94 Cf. Lundborg, M. and Märkel, C. (2019).
95 Cf. Chen, H. (2019).
96 Cf. Schoonhoven, J. J.; Roelands, M. and Brenna, F. (2019).
97 Cf. Wangermann, T. (2020).
98 Cf. Lundborg, M. and Märkel, C. (2019).

Table 32: Description of technological, strategic, social and regulatory success factors for AI deployment

Success factors	Description
	Technological
Existence of a database and data processing systems	Companies with prior knowledge of Big Data, or those that have been collecting much of their in-house data for some time, have great advantages over companies that do not have access to an existing database. So a first step for companies towards AI is often to implement methods for collecting and mining data and to develop an improvement in internal processes for sharing that data. Furthermore, it must be checked in which form the data are available and whether they can be processed.[99,100,101]
Use of already existing AI solutions	Especially for easy-to-implement use cases that have already been sufficiently researched, a cost-effective and suitable technology can often be found very quickly to solve the problem. In addition, it is often possible to integrate existing interfaces or AI applications from other companies, such as chat bots, into your own company. This creates acceptance and supports the establishment of initial interfaces with the topic. In addition, the implementation effort is significantly reduced. Likewise, existing AI solutions partly enable implementations according to the modular principle. Accordingly, a targeted and cost-effective deployment is offered (cf. Section 5.2.2). The use of established solutions also often enables flexible payment systems to be used. Thus, service models (e. g. pay-per-use) can be used to specify the cost planning of projects to be implemented (see Section 5.2.2). However, this approach also poses a risk, as expertise may be shifted to the implementing service provider. The successful introduction of such an AI measure, regardless of the technology used, depends significantly on compatibility with the existing system.[102,103,104]
Expansion of the IT infrastructure	A high-performance IT infrastructure is crucial for companies. This applies to broadband expansion as well as mobile networks and (virtualised) computing infrastructures. SMEs are not only located in metropolitan areas, but also in rural areas. In any case, they depend on a good network connection. This applies both to the location of the company and to the places where services are provided.[105]
Demonstrations or pilot projects to build acceptance and know-how	Often, companies that have had positive experiences with the implementation of initial simple demonstration projects have also been able to achieve great success in the further introduction of complex solutions or in their expansion. In such a step-by-step approach, the complexity of the projects often increases from project to project, with simple demonstration applications (so-called quick-win applications) forming the beginning and leading to complex AI solutions. This decelerated introduction of AI also has a positive effect on employee acceptance.[106,107]
Use of standardised interfaces and open source solutions	When identifying a suitable AI solution, the choice of a standardised interface as well as an extensible architecture lends itself to certain applications and framework conditions. This enables the simplified integration of, for example, machine and plant controls as well as ERP systems (see section 5.5.2) and a scaling as well as further development of already implemented AI. Open source solutions also benefit from swarm intelligence, as they can be adapted and optimised by free developers around the world (cf. also Section 5.5.2). This can provide a significant competitive advantage over other more rigid solutions.[108,109,110]

Corporate strategy	
Conducting a feasibility study	Before introducing an AI solution, conducting a proof of concept helps to determine or roughly estimate costs and efforts. This should simplify the allocation of necessary resources. Cost traps are thus avoided and the sustainable and consistent implementation of the solution is made possible. During the preliminary study, meaningful key performance indicators (KPI) must be identified in order to be able to make well-founded statements regarding the expected payback period based on their respective characteristics (cf. chapter 5.2.2).
Development of a strategy/ roadmap for introduction	A key success factor in the introduction of AI solutions is the development or existence of a clear and long-term strategy for the implementation, use and further development of the technology. For this, a clearly delineated problem must exist in order to identify suitable AI measures. In addition, potentials and limits of the measure to be implemented, but also of AI in general, must be identified in the specific use case. Depending on the volume of data, it can take days and even weeks to train an algorithm. Therefore, a detailed roadmap should then be developed that provides for the right AI architecture, a platform for deployment, a strategy for data integration and appropriately trained data scientists. All key parties such as investors, authorities, customers, departments should be identified. Care must be taken not to require an ever-increasing amount of data as demand for AI solutions grows.[111, 112]
Establishment of new communication channels and reduction of hierarchies	Potentially, the reduction of hierarchies and the simplification of communication channels can be supportive in the introduction of AI. Thus, the reduction of communication distances – E. g. between the person at the machine, the programmer and the person operating the AI – lead to better distribution of existing knowledge within the company. The emergence of knowledge monopolies is inhibited and active communication promotes the integration of new technology into everyday work.[113]

[99] Cf. Uren, V. (2020).
[100] Cf. Schoonhoven, J. J.; Roelands, M. and Brenna, F. (2019).
[101] Cf. Lundborg, M. and Märkel, C. (2019).
[102] Cf. Uren, V. (2020).
[103] Cf. Wangermann, T. (2020).
[104] Cf. Chen, H. (2019).
[105] Cf. Wangermann, T. (2020).
[106] Cf. Uren, V. (2020).
[107] Cf. Schoonhoven, J. J.; Roelands, M. and Brenna, F. (2019).
[108] Cf. Streibich, K.-H. and Zeller, M. (2019).
[109] Cf. Chen, H. (2019).
[110] Cf. Mathur, D.; Ahmad, Z. and Chamuah, A. (2020).
[111] Cf. Eidam, B. (2020).
[112] Cf. Schoonhoven, J. J.; Roelands, M. and Brenna, F. (2019).
[113] Cf. Rakova, B.; Yang, J.; Cramer, H. and Chowdhury, R. (2021).

Social	
Provision of an AI team	Knowledge and experience can be built up via a specially provided AI team, which favours the successful implementation of the AI project. Team members serve as a central point of contact for questions and issues related to AI. At the same time, the group ideally takes an active role in communicating with the workforce to raise awareness of new technologies as well as experiences during implementation. The success of the introduction of an AI measure is often strongly related to the people involved in the introduction.[114,115] In addition, the development of knowledge enables the sustainable processing of AI projects as well as the identification of further use cases within the company (cf. chapter 5.5.2).
Offering appropriate, comprehensive AI trainings	Comprehensive training of the workforce on AI lowers the inhibition threshold of application. Furthermore, any feelings of anxiety regarding rationalisation or increasing complexity in the workplace can be discussed and ideally eliminated. Conversely, implementation projects are often severely hampered unless adequate acceptance is created about the potential of artificial intelligence within the company.[116,117] Such training and education can be carried out quickly, effectively and at a low threshold as an online offer (cf. chapter 5.5.2).
Gradual expansion of decision-making powers	Especially when introducing an AI for the first time, an audit-free self-sufficiency of AI is often considered critical. Accordingly, acceptance within the workforce is significantly increased when AI is initially monitored regularly as a decision support and introduced quality metrics. The option of being able to veto is seen as a tried and tested means, especially during the implementation/transition phase, even though this can be counterproductive in appropriate cases.[118]
Creating a flexible working environment with the help of applied AI methods	The flexible participation and involvement of employees are seen as an effective enabler in the successful introduction of AI measures. Thus, during implementation, they are given the opportunity to define their own role in the process. This increases acceptance and identification with the new technology and supports its integration into the respective daily work routine.[119]
Networking of AI users	A critical success factor can be the use of the platform or AI measure/technology by different participants within the industry. Thus, synergy effects can be achieved and the community benefits from the accumulation of knowledge. An exchange of experiences at eye level makes it possible that not every company has to go through the same obstacles and possible negative experiences.[120] Institutions such as the Werner-von-Siemens Centre for Industry and Science, for example, offer an effective platform for topic-specific and targeted networking. The pre-competitive exchange of knowledge between SMEs thus made possible promotes the development of new fields of technology and future topics (cf. section 5.3.2).
Accompanying the implementation through effective change management	There is often a perception that professional groups will have their own decision-making freedom undermined by AI-assisted recommendations as a result of the introduction of AI. The result can be a lack of confidence in the new technology. The impression can be given that the responsibility and experience of the individual are becoming less important. This is where effective and structured change management must come in to initiate and accompany the transformation process. Affected persons must be sensitised and informed. Prospects must be highlighted and communicated at an early stage (cf. section 5.8.2).
Regulatory	
Regulation/legislative requirements	Often, topics regarding Big Data and AI are already regulated by the legislator – this circumstance can be both an obstacle and a success factor for the company.[121]

7 FIELDS OF ACTION FOR SMES, POLITICS AND SCIENCE

The main purpose of this study is to investigate the impact of AI on operational resource efficiency in the manufacturing sector. The focus here is primarily on SMEs. For them, the implementation and realisation of AI often pose a major challenge at first. SMEs, politics and science are advancing both the resource-efficient use of AI and resource efficiency through AI with a lot of commitment – commitment should, however, be further increased. The recommendations for action are derived from the results of the systematic literature research, the expert interviews based on this research and the findings of the practical examples. Figure 21 provides an overview of the identified fields of action.

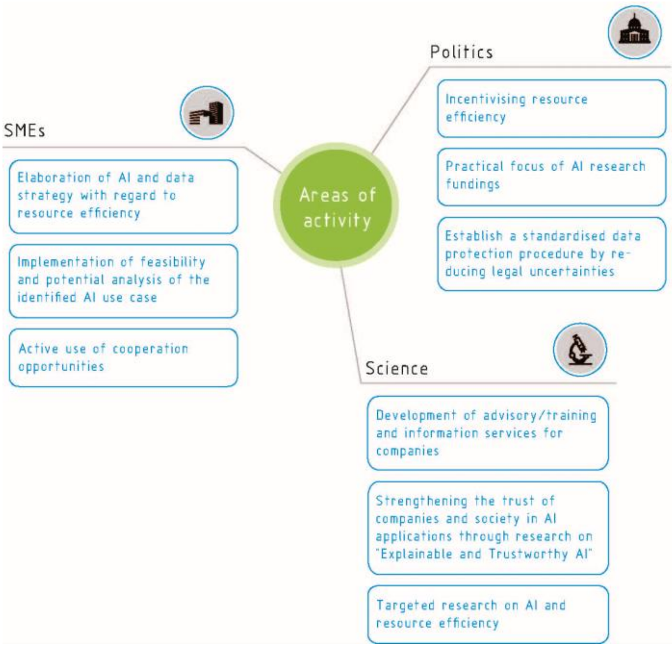

Figure 21: Overview of identified fields of action

7.1 Fields of action for SMEs

The fields of action for SMEs are based on the proven process for successful implementation of AI projects: Strategy, feasibility, implementation and scaling.

7.1.1 Data and AI strategy

SMEs in particular are in a position to react quickly to technological developments and market potential and to implement research results in a targeted manner in new products, processes or services. Digitalisation is increasingly changing the traditional value chain and new business models are emerging. The importance of data as a resource is continuously increasing. The essential driver and decisive core component here is the application of AI. This offers SMEs the opportunities to align innovation processes in such a way that new insights and intelligent value creation can be generated from the available data.

Recommendation for action

Elaboration of the data and AI strategy, also with regard to resource efficiency

The survey clearly shows that in more than half of the companies surveyed (56.4%), AI is not yet or only partially part of the corporate strategy. However, in order to be able to leverage the described potential of AI also with regard to operational resource efficiency, it is recommended that these companies in particular rethink and adapt their corporate strategy. Without a clear strategic direction for the company to act in a data-driven manner, the implementation of AI initiatives will be significantly more difficult.

Digital transformation measures help to save operational resources. Both the expert survey (section 3.3) and the potential analysis of the application scenarios (section 5) show that increasing resource efficiency has so far often only been a positive side effect of digitisation measures. Quantifying these successes has often not been a focus for SMEs. Furthermore, untapped potential lies dormant in the companies, for example for identifying leakages, deviations from standard values, reducing faulty production or monitoring scrap, which goes hand in hand with saving natural resources. SMEs in Germany are urged to look into the use and embedding of AI in corporate processes so as not to suffer a significant competitive disadvantage.

A compelling first step in this direction is the elaboration of a data and AI strategy that incorporates aspects of resource efficiency as well as aspects of economics. Increasing resource efficiency is becoming increasingly important. Energy and material consumption in companies can often be easily recorded with suitable measures. However, without establishing a data and AI strategy, documentation of savings in the form of data monitoring often takes a back seat or is not undertaken at all. In most cases, the resource savings are only perceived as a positive side effect in the companies. However, the information potentially gained and evaluated in this way offers SMEs promising opportunities for identifying and realising further resource efficiency potential, which should definitely be exploited.

The study "Artificial Intelligence" offers clues on how to establish AI in corporate strategy and existing business models: Potential and Sustainable Change in the Economy in Germany[122]. This contains guidance applicable to SMEs on the elaboration of an AI strategy in eight steps.

7.1.2 Feasibility and potential analyses

The AI application scenarios presented in this study (Chapter 5) can be used across industries in many manufacturing SMEs to increase resource efficiency. Which scenarios are selected by SMEs and to what extent they are implemented must be individually adapted to the boundary conditions of the business. After determining the in-house opportunities for applying AI, it is essential to evaluate the resource efficiency and business benefits.

At this point, reference is made to the methodology for potential analysis of application scenarios in chapter 0, which serves as a guide and recommended action for SMEs. In doing so, section 4.1 presents the necessary tool to analyse AI application scenarios and evaluate them in terms of their impact on operational resource efficiency. Building on this, section 4.2 presents a maturity model that enables SMEs to classify their own position within six dimensions.

[122] Cf. eco – Verband der Internetwirtschaft e. V and Arthur D. Little (2020).

Recommendation for action

Conducting feasibility and potential analyses for identified AI application scenarios

SMEs should regularly review potential AI application scenarios in terms of feasibility and potential within their individual framework conditions, as developments in the field of AI in particular are advancing rapidly. For this purpose, predefined evaluation criteria can be used, which cover, among other things, fairness, causality, transparency and security.

7.1.3 Implementation and scaling

A lack of time and personnel as well as a lack of expertise to introduce digitisation measures in their own operations often stand in the way of SMEs getting an overview of the possibilities of digitisation in industry. The results of the expert survey confirmed this finding. However, the survey results also show that other obstacles such as high implementation costs or the identification of suitable technologies often still prevent SMEs from using AI.

Recommendation for action

Implementation and scaling through active use of cooperation opportunities

Nevertheless, in order to be able to implement and scale identified AI application scenarios, SMEs should actively use cooperation opportunities. Especially if the experience is not yet available in the own company, it is recommended to consider cooperation partners: AI ecosystem networks, startups, universities or service providers. When involving external experts, care should be taken to ensure an appropriate transfer of knowledge into the company. Cross-company networking, for example in associations, can also be beneficial for the implementation of AI initiatives.

In its national AI strategy, the German government focuses on measures that enable SMEs, among others, to use, develop and incorporate AI applications into their business processes[123]. The federal government's data strategy also follows this approach[124]. In particular, SMEs are to be supported in leveraging the potential of data-based value creation. SMEs should use this opportunity as a starting point for implementing and scaling their individual AI application scenarios in order to actively participate in initiatives such as "Mittelstand Digital" of the German Federal Ministry for Economic Affairs and Energy and funding programs such as “KMU-innovativ” of the German Federal Ministry of Education and Research.

Active use of initiatives and funding programs offers SMEs the opportunity to identify opportunities and challenges of the new technology, to implement them in concrete applications and, last but not least, to obtain simplified approval of funding. Since SMEs in particular are particularly flexible and fast when it comes to opening up new markets, networking with suitable cooperation partners will enable them to compete successfully on the market with new products and processes. In particular with regard to the development of suitable algorithms as well as their implementation, many SMEs are still dependent on external support (see chapter 3.3). Accordingly, these hurdles can be reduced through the appropriate and active use of cooperation opportunities and the resulting short-term provision of human resources and expert knowledge.

7.2 Fields of action for policy

Policymakers can continue to positively influence the advancement of artificial intelligence in many areas. This relates above all to the promotion of resource-efficient action, the practical orientation of AI research funding and the creation of more AI-friendly data protection practices.

7.2.1 Incentives and motivation for resource efficiency

Worldwide and also in Germany, raw material consumption has increased since 1990 and there is no sign of a trend reversal so far. However, raw material extraction inevitably involves environmental impacts such as water pollution or biodiversity loss. In order not to exceed planetary boundaries

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[123] Cf. Federal Ministries of Education and Research, Economic Affairs and Energy, Labour and Social Affairs (2018).

[124] Cf. Press and Information Office of the Federal Government (2021).

even further and to preserve our livelihoods, this trend must be reversed and resource efficiency increased: Resources must therefore be used more effectively and efficiently.

Recommendation for action

Incentives and motivation for resource efficiency

Until now, many companies have been unable to measure and report their resource consumption and, in particular, the savings achieved through AI applications. However, an assessment of resource consumption before and after the introduction of AI applications is the basis for identifying potential for improvement. Incentives and framework conditions must therefore be created to quantify and promote resource efficiency in companies. This can be achieved through politics with the help of appropriate funding and networking programs. In addition, the metrics model developed and used in this study (see Section 4.1.4) can help companies quantify their resource efficiency.

Over the past few years, various consulting services have been established with regard to resource efficiency, also in connection with digitisation. Nevertheless, resource efficiency in the use of artificial intelligence in companies tends to be perceived as a side effect and the quantification of the improvements achieved is only possible in the rarest of cases. This becomes clear in chapter 5 by the practical examples presented. This makes it difficult to disseminate best practice examples, as the added value achieved is not visible to other companies. Therefore, it is recommended to additionally focus on funding and networking programs in order to include resource efficiency in the implementation of artificial intelligence from the very beginning. Conversely, the use of AI solutions can be explicitly promoted in resource efficiency programs

Here, funding and networking programs can have a complementary effect by creating additional incentives. Networking programs in particular can lead to the discussion of similar problems through direct exchange between companies and thus initiate initial projects in the area of resource efficiency. Here, the companies benefit from each other's experience.

In addition, the key figure model developed in this study and used in the potential analysis of selected application scenarios in chapter 5 can provide companies with an orientation for possible improvements with regard to resource efficiency. This is intended to facilitate entry into the quantification of resource efficiency and, in the future, to enable the dissemination of best practice examples for increasing resource efficiency, particularly in the use of AI solutions.

7.2.2 AI Research Funding

The survey results from chapter 3 clearly show that companies need support from politics and science in the introduction of AI in order to reduce barriers, including in the areas of "high implementation effort", "lack of know-how" and "identification of suitable technologies". There is a need with regard to a practical orientation of AI research funding on the part of policymakers, on the one hand, in order to implement the objectives of the federal government's data and AI strategy described in section 7.1.3 and, on the other hand, to be able to offer SMEs targeted and individual assistance in implementing the respective AI application scenario.

Recommendation for action

Practical orientation of AI research funding

Suitable instruments for this are facilities that provide opportunities for setting up test fields for SMEs to test resource-efficient AI and new business models in practice. These are needed nationwide with sufficient capacity in all regions and must be promoted. Furthermore, SMEs must be granted simplified access to AI technologies, computing capacities and cloud platforms through open standards. This enables the resource efficiency potential of AI to be harnessed for additional economic growth and productivity gains.

The study "Resource Efficiency through Industry 4.0 – Potentials for SMEs in the Manufacturing Sector" (2017) recommends that specific issues be integrated by the federal ministries for the realisation of the potentials of the digital transformation to increase resource efficiency[125]. It also suggests developing or elaborating future research funding priority topics for developing technologies and generating new knowledge. The practical orientation of AI research funding builds precisely on this and proposes, on the one hand, the funding of institutions such as the Werner-von-Siemens Centre for Industry & Science e.V. (WvSC) presented in section 5.3.2, in which SMEs have the opportunity to try out and test their identified AI application scenario. Second, to complement this recommendation for action, simplified access to AI technologies, computing capacity and cloud platforms should be granted through open standards. Only then will an efficient focal point with needed resources for practical AI research on the part of enablers and SMEs be provided by policymakers.

Very high potential for this is offered by the European cloud and data infrastructure GAIA-X[126], which, according to the German Federal Ministry for Economic Affairs and Energy, is supposed to link various elements via open interfaces and standards in order to link data and create an innovation platform. At the same time, the project is open to new partners, such as SMEs or startups. It could, through the use of secure, open technologies (open source, open hardware), a common repository of software components and standards based on common EU values, greatly reduce the barriers to implementing AI use cases in SMEs in the future. Building on the “Agri-Gaia”[127] project launched by the German Research Center for Artificial Intelligence on January 21, 2021, the goal was to promote an open, decentralised infrastructure for the development and exchange of AI algorithms between manufacturing companies for further AI research. Thus, industry-specific adapted AI building blocks can be provided as easily usable modules. In addition, this newly created ecosystem offers the opportunity to bring users together with developers of AI algorithms.

7.2.3 Data protection, data use and data access

Although security and regulatory concerns play a rather subordinate role in the survey results (see chapter 6.1), they remain undisputedly relevant. The

[125] Cf. VDI Zentrum Ressourceneffizienz (2017).
[126] Cf. Federal Ministry for Economic Affairs and Energy (2021b).
[127] Cf. Federal Ministry for Economic Affairs and Energy (2021a).

complexity of the German system has been significantly increased by the establishment of the Primary Data Protection Regulation and the European Data Protection Supervision Authority (EDSA). Furthermore, data protection practices, which have been uniform to date, make it difficult to conduct collaborative research across sites in different countries. The inconsistency and legal uncertainty are potential threats to the growth and development of the German economy.

Recommendation for action

Establishment of uniform data protection practice by reducing legal uncertainties

Accordingly, there is a need for action on the part of policymakers with regard to the development of data ethics standards and an AI-friendly data strategy. This is intended to create a transparent basis for SMEs from the triad of data protection, data use and data access. This requires federal-state working groups with the goal of establishing uniform research-friendly data protection practices nationwide in order to eliminate legal uncertainties through consistent and uniform principles, among other things.

Not everything that is technically possible in the use of data is also ethically justifiable and desirable for politics. The federal government's data strategy[128] states that data will only be willingly shared and used by the actors in a data ecosystem if the data infrastructure is trustworthy and the security of the data is guaranteed. Data protection and IT security must therefore be factored into products and processes from the very beginning. Furthermore, divergent data protection regulations at the state level are pointed out. The challenge for Germany here is to create a uniform approach among all state data protection authorities to develop guidelines. Up to now, the data protection authorities in the individual German states have generally been free in their interpretation of the law. However, the successful development and application of AI use cases in SMEs require reliable and transparent legal frameworks at EU level. As stated in the "VDI Status Report – Machine

[128] Cf. Press and Information Office of the Federal Government (2021).

Learning"[129], the availability of industrial data and the freedom to use it will form an essential basis for the sovereignty of an economic area in the near future – and clear regulations are needed all the more for this. This concerns issues related to ownership or use rights of data used, the limits of individual rights to data and the rights to the results of AI learning processes[130].

The federal government's AI strategy calls for an examination of existing legal frameworks with a view to new AI technologies[131]. In this context, algorithm- and AI-based decisions, services and products are to be checked for loopholes and, if necessary, adapted to make them verifiable with regard to possible inadmissible discrimination and disadvantages. The aim is, among other things, to create a legally secure regulatory framework for AI stakeholders in companies, startups, science and research, the general public and public administration[132].

7.3 Recommendations for action for science

Science as a driver and promoter of innovation can provide targeted support for the integration of AI solutions in companies. In particular, a transfer from science to practice is needed to reduce prevailing barriers to entry. This can be achieved through consulting, training and information services in the context of application-oriented research. In addition, business and societal trust in AI applications can be strengthened through research on "Explainable and Trustworthy AI". Research programs focusing on resource efficiency potentials when integrating AI solutions pave the way according to the orientation of the present study.

7.3.1 Consulting, training and information services for companies

According to the results of the survey conducted, the lack of knowledge about AI as well as its potential is a relevant barrier to its adoption. In addition to general questions regarding terminology and definitions, there is a particular

[129] Cf. VDI/VDE Society for Measurement and Automation Technology (2019).

[130] Cf. VDI/VDE Society for Measurement and Automation Technology (2020).

[131] Cf. Federal Ministries of Education and Research, Economic Affairs and Energy, Labour and Social Affairs (2018).

[132] Cf. Federal Ministries of Education and Research, Economic Affairs and Energy, Labour and Social Affairs (2020).

lack of clarity regarding suitable technologies. In addition, various concerns exist regarding the integration of innovative technologies into established processes (see chapter 6.1). This involves various stakeholders throughout the company.

Recommendation for action

Establishment of consulting, training and information services for companies

As independent bodies, scientific institutions can provide unbiased and objective information about the resource efficiency potential of AI in the operational environment. By explaining the rather vague and broad term AI on the basis of concrete application scenarios and methods, the concrete benefits for companies can be demonstrated, especially in the area of resource efficiency. Low-threshold information services must be designed for this purpose. If there is a response from the industry, more in-depth training should be developed and offered on this basis. The purpose is the targeted dissemination of resource-saving AI, particularly in SMEs, by raising employee awareness.

The basic information offer should serve as a low-threshold door opener into the AI topic in the operational environment. In addition to terminology and basic definitions, various methods of AI and possible application scenarios are discussed.

The training offer to be developed fulfils the purpose of objectively informing affected parties about the opportunities and risks of introducing AI methods. In addition to economic, ecological and social aspects, technological aspects are also focused on. Ideally, participants leave the offer with an overview of unfounded and justified concerns as well as potentials in their company. Also, the basics from the basic information offer should be taken up and knowledge in the field of AI methods and their advantages and disadvantages should be deepened. Correspondingly, participants should be enabled to make their own initial assessment of the extent to which AI can be of interest to their own company following the training.

Information and training offerings should have a clear focus on the targeted use of AI. So far, the integration of corresponding systems has only made sense in some applications. Often, specific industries or production processes are also better suited than others. In addition to this general information based on experience, companies must communicate the need for individual testing. Effort and benefit should be closely examined and specific evaluations should reveal the extent to which targeted rather than broad-based application is preferable. Such analyses are conceivable as consulting services by scientific institutions. For this purpose, criteria and evaluation models would have to be developed and validated. Companies are thus provided with decision support regarding the integration of AI methods in their own production environment. If required, support during implementation by qualified bodies is possible.

7.3.2 Business and societal trust in AI applications

In order for companies to actually gain competitive advantages with the help of AI, the systems used must be reliable and trustworthy. Both customers and the companies themselves must trust the systems they use. In the survey, customer trust and security concerns are only minor obstacles for companies (see section 3.3), although the traceability of AI in this context is nevertheless a basic prerequisite for its broad deployment capability.

Recommendation for action

Strengthening business and societal trust in AI applications through research on "Explainable and Trustworthy AI".

Research on "Explainable and Trustworthy AI" can increase the needed trust in AI and make the results an AI delivers understandable and explainable. Research areas in this area are mainly autonomy and control, transparency, reliability, security and privacy of AI.

AI has disruptive potential – so it is not yet possible to predict what knowledge gains and future applications will be possible with AI. Moreover, business models and entire industries can be profoundly changed by this technology. This is precisely why research in the area of "Explainable and Trustworthy AI" is particularly important. The topic area deals with developing comprehensible as well as legally compliant, ethical and robust AI. The aim is to show the way in which the AI used arrives at its results and to ensure safety when using AI. Particular attention should be paid to complex AI application scenarios that involve, e. g. the use of neural networks, which makes it considerably more difficult to explain the results. Research in the area of "Explainable and Trustworthy AI" can also identify and minimise or even eliminate risks in safety, accountability, liability and ethics that may arise in the development or during the use of AI at an early stage. This is the prerequisite for ensuring the long-term competitiveness of companies.

On the one hand, research should develop "Explainable and Trustworthy AI" itself to make AI widely applicable to companies. On the other hand, as an independent body, it can assist in developing testing procedures for AI, thus testing AI for the above criteria and enabling certification in the future. These developed test methods can thus also form the basis for standards and norms. These two steps can significantly increase trust in AI and ensure broad and reliable applicability for companies.

7.3.3 Research on AI and resource efficiency

Through the literature review described in Chapter 6.1, on the one hand, uncertainty regarding the ecological impact of AI was identified as a relevant barrier. In addition, it is assumed that significant negative environmental impacts will be generated during the development of AI methods. On the other hand, AI solutions can support the efficient use of natural resources. With regard to possible trade-offs between ecological and economic goals, there is a lack of standardised and comprehensible assessment approaches and benchmarks.

This study considers impacts of AI methods on resource efficiency in the processing environment. Relevant potentials will be identified and best practices discussed. Nevertheless, it becomes evident that the current research landscape does not explicitly focus on resource efficiency potentials to be realised through AI. However, due to an increased awareness of the benefits of future-proof and sustainable production, this aspect takes on a central role for the potential application. Scientific discourse should therefore build on existing findings and generate in-depth knowledge in this area. Added value in the context of resource efficiency should be specifically worked out. Further application scenarios must be examined and existing ones expanded to include the benefits in terms of resource savings.

Recommendation for action

Targeted research on AI and resource efficiency

Targeted research efforts on AI and resource efficiency are intended to create transparency with regard to the ecological and economic effects of a corresponding implementation. These analyses must take a holistic approach and consider all phases of the life cycle of AI solutions in an integrated manner. Users are thus provided with a low-threshold information offering regarding the benefits of AI methods in the production environment. Optimisation measures can be researched based on this basic condition.

In particular, holistic analyses are of great importance here. In order to achieve sustainability in the long term, not only the potentially positive effects of the integration of AI methods should be examined, but all life phases of the necessary software and hardware should be included in corresponding considerations. The resource efficiency potential of both the AI solutions and the hardware and electronics required for this must be considered. The respective efforts and benefits for resource efficiency must be offset over the entire life cycle. The result is an overview of net environmental impacts and resource consumption. This enables targeted decisions regarding the integration of AI solutions with a view to achieving the desired sustainable production across system boundaries. The presentation of this initial state also serves to identify relevant levers and to focus research efforts on holistic optimisation. If specific processes increase the demand on nature and resources to a particular extent, possible improvements should be researched in these areas in particular. Accordingly, the role of research, in addition to basic balancing, also lies in systematic optimisation through reduction of environmental impacts in relevant areas/life phases of the components required for AI.

8 SUMMARY AND CONCLUSION

Resource efficiency is a central topic today and in the future, which Germany as a business location in particular must address with innovative approaches in view of increasingly scarce raw materials. This study shows that weak artificial intelligence has great potential to contribute to resource-efficient actions. However, the study also makes clear that obstacles must first be removed and existing success factors strengthened in order to fully tap these potentials. On the one hand, the potential lies in the prerequisites and capabilities of companies to use weak artificial intelligence across the board in operational practice. On the other hand, science must accompany and support the transformation process towards a greater integration of AI in the operational environment. This is particularly true for small and medium sized enterprises. For this reason, this study focuses particularly on these.

Furthermore, it identifies available weak artificial intelligence technologies and methods. A comprehensive literature review links this to the manufacturing value chain to identify typical application scenarios. These are reviewed in terms of their influence on operational resource efficiency. Here we see that many applications of weak artificial intelligence are not yet implemented with a view to increasing resource efficiency. Saving natural resources is often a positive secondary effect of implementing artificial intelligence, but not its primary motivation.

An expert survey with 71 participants tests these and other hypotheses for their accuracy in the operational environment. Regarding the motivation of the use of weak artificial intelligence, a differentiated and promising picture emerges: Although the objectives of AI applications already implemented were mostly focused on saving costs (25.7%) and time (20%) as well as improving quality (22.9%) and creating competitive advantages (18.6%), resource savings will become more of a focus when introducing AI applications in the future (Energy: increase from 5.7% to 12.6%, Materials: increase from 4.3% to 8.9% and CO_2 emissions: Increase from 1.4% to 5.2%).

At the same time, a challenge of many AI applications reveals itself. The survey conducted shows that expectations of resource savings potential are higher than the savings actually realised, but this can also be attributed to the fact that many resource consumptions are often not measured at all and are therefore only estimates.

Another key result of the survey is that 60% of the companies surveyed refer to external support in the implementation of AI applications. Lack of know-how (54.2%) and lack of personnel (54.2%) and time (41.7%) are cited as the main reasons against in-house development.

To demonstrate the feasibility of the potential analysis and to drive the dissemination of best practices, eight application scenarios of weak artificial intelligence are selected: Predictive maintenance, process chain optimisation, optical failure detection, failure prediction, process chain planning, product optimisation, autonomous transport systems and sustainability analytics (chapter 5). Positive effects on operational resource efficiency are attributed to them both in relevant literature (cf. section 2.3) and during the expert survey (section 3). For each application scenario, at least one practical example is used to show how and with what results the implementation can succeed. The application scenarios and practical examples are examined and presented using primarily qualitative resource efficiency considerations.

In order to demonstrate the feasibility of the potential analysis and to promote the dissemination of best practices, eight application scenarios of weak artificial intelligence are selected (chapter 5), which were attributed positive effects on operational resource efficiency both in relevant literature (cf. section 2.3) and during the expert survey (chapter 3). For each application scenario, at least one practical example is used to show how and with what results the implementation can succeed.

From these studies and results, key corporate strategic, technological, economic, ecological, social and regulatory success factors as well as barriers are derived. In terms of barriers, it was possible to identify differences between companies that already use artificial intelligence and those that do not yet.

Companies that have already gained experience with artificial intelligence see the lack of a data basis, the high implementation effort and a lack of expertise as the biggest obstacles to further implementations. For companies that have not yet gained any experience with artificial intelligence, significant differences in the weighting of the respective obstacles can be seen in some cases. Lack of expertise, high implementation effort and the identification of suitable technologies are the highest barriers to entry here.

In addition to obstacles, the present study also identified success factors that favour the implementation of artificial intelligence application scenarios. Even small investments in employee training (e. g., free training on video platforms or online courses) can simplify and support the implementation and operation of the AI solution. Networking with the AI ecosystems described in section 1.1.2 is another relevant success factor. It does not take much effort for interested companies to participate in and benefit from the services offered. Other success factors often require far more extensive upfront time and financial investment. Thus, the design of an AI strategy, the creation of the necessary acceptance within the company and the expansion of the IT infrastructure can tie up significantly more forces and resources.

The findings of the study result in recommendations for action for SMEs, politics and science. Accordingly, SMEs must quickly create the conditions for the introduction of artificial intelligence and should start with a targeted data and AI strategy. In addition, conducting feasibility studies for potential AI applications can mitigate risk during implementation. Here, use can and should be made of test fields provided for this purpose (e. g. g. Werner-von-Siemens Centre for Industry and Science). When implementing and scaling, SMEs should take advantage of collaboration opportunities and offerings from the AI ecosystem. Policymakers can create further incentives for resource-efficient action and reduce barriers to entry with a practical orientation of AI research funding. In addition, legal uncertainties in data protection practice should be further reduced. The scientific community can further strengthen the acceptance of and trust in artificial intelligence by establishing and expanding consulting and training services and by conducting research in the area of “Trustworthy and Explainable AI”. In addition, the lack of linking of the subject areas of artificial intelligence and resource efficiency to date means that targeted research services are required.

German medium-sized companies are observing the current developments in the field of artificial intelligence with excitement. According to a recent study by Deloitte Private, in addition to familiar expectations such as the automation and acceleration of processes and the realisation of potential savings, new business models are now also perceived as an opportunity to implement artificial intelligence[133]. To ensure that these and other expectations can also be realised with regard to increasing operational resource efficiency, consistent action is required from all stakeholders. This study provides guidance and examples for those who are ready to embark on this path.

[133] Cf. Deloitte Private (2021).

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APPENDIX A: OVERVIEW OF AI METHODS COMMONLY USED IN PRACTICE

Table 33: Compilation of artificial intelligence tasks established in practice with a selection of AI methods

Category		Field of activity	Method
Machine learning		Trend analysis	Linear regression
			Non-linear regression
		Classification	Support Vector Machines
			Logistic regression
			Decision Trees
			Naive Bayes Classification
		Segmentation	Support Vector Clustering
			K-means Clustering
			Hirarchical Clustering
		Dimension Reduction	Principal Component Analysis
		Anomaly detection	Isolation Forest
			Local Outlier Factor
	Deep Learning	Image & object detection	Convolutional Neural Networks (CNN)
		Text recognition	Convolutional Neural Networks (CNN)
		Voice recognition	Pattern Recognition
			Recurrent Neural Networks (RNN)
			Long short-term Memory (LSTM)
			Bidirectional Encoder Representations from Transformers (BERT)
			Transformer
		Natural language understanding (NLC)	Recurrent Neural Networks (RNN)
			Long short-term Memory (LSTM)
			Bidirectional Encoder Representations from Transformers (BERT)
			Transformer
		Natural language generation (NLG)	Markov chain
			Recurrent Neural Networks (RNN)
			Long short-term Memory (LSTM)
			Transformer

Category			Field of activity	Method
		Reinforcement Learning	Learning in discrete environments	Temporal Difference Control (Sarsa, Q-Learning)
			Learning in continuous environments	Deep Q-Network (DQN)
				Dueling Deep Q Network (DDQN)

APPENDIX B: HYPOTHESES OF THE EXPERT SURVEY

Table 34: Overview of the recorded hypotheses

Category	Hypotheses on the use of weak AI in SMEs
Diffusion of AI in the company	AI methods are not yet very common in SMEs.
	AI methods are more common in innovative/IT-savvy industries/companies.
	AI is already used quite widely in administration/management, but so far little in manufacturing and production.
Application scenarios	Typical application scenarios are: Predictive maintenance, production planning, process optimisation manufacturing – fault detection and prediction, demand planning, increasing energy efficiency in the manufacturing process, increasing energy efficiency in building management.
Maturity model	The use of AI is not reflected in the corporate strategy of SMEs.
	Manufacturing SMEs fundamentally lack expertise to implement AI in a meaningful way.
Resource efficiency	The use of AI can increase resource efficiency in SMEs.
	Increasing resource efficiency is no reason for introducing AI.
	Quantification of resource efficiency is hardly present in companies.
	Application of AI so far mainly serves to increase profitability, no focus on resources/environment.
	The use of artificial intelligence enables SMEs to improve resource efficiency.
	A large proportion of SMEs are not aware that the use of AI can lead to improved resource efficiency.
Business models	SMEs see opportunities in the application of AI to develop new business models in the short to medium term.
	SMEs see opportunities in the application of AI to further develop and optimise existing business models.
Obstacles	SMEs do not have the required data base for the use of AI methods.
	SMEs need support in the introduction of AI methods.
	From the perspective of SMEs, the implementation effort of AI methods is too high.
	SMEs do not have sufficient professional competencies.
	For SMEs, the (economic) benefits are not clearly visible.
Gen. Hypotheses	The existing technical infrastructure makes the introduction of AI difficult.
	A large proportion of SMEs are currently considering the introduction of artificial intelligence.
	From the SME perspective, the definition of AI is unclear.
	From the SMEs' point of view, the integration of improved technologies into existing production lines is not possible/difficult.
	SMEs do not have sufficient willingness to innovate.
	For SMEs, identifying suitable technologies is difficult.

APPENDIX C: DIMENSIONS OF THE MATURITY MODEL

Table 35: Manifestations of the maturity model: AI strategy

Low	Medium	High	Very high
AI strategy			
• No strategic goals for the use of AI methods • No information regarding the targeted use of AI methods and the measures required • No information regarding the necessary strategic adjustments to the organisational structure	• Data and its analysis are assessed as business-relevant and critical to success • Rough or superficial consideration of the use of AI in the context of strategic goals • Sift and examine strategic significance of available AI methods including potential, impact on org. structure and strategic goals and measures • test use of AI methods in the context of individual pilot applications	• a dedicated AI strategy is part of the corporate strategy • Data and its analysis are assessed as business-relevant and critical to success • the use of AI methods takes place with alignment to selected strategic goals • Formation of decision-making and expert panels for the assessment and enterprise-wide deployment of AI methods • Isolated use of AI methods and data analysis • test application of AI methods in the context of a few use cases	• A dedicated AI strategy is directly derived from and embedded in the corporate strategy • Definition of clear responsibilities for the strategic implementation of the required measures • Definition of clear goals and specific use cases across all company levels and divisions • clear decision for or against the use of AI methods in different company departments

Table 36: Manifestations of the maturity model: People

Low	Medium	High	Very high
People			
• Company structures do not take into account corporate and business units focused on the use of AI or new ones to be developed • subordinate role of skills for the application of AI methods in the recruitment process • Skills for the application of AI methods of the employees are not or only limited available • occasional internal training opportunities for AI skills	• individual employees/departments deal with the use of AI methods as far as possible detached from the rest of the use • Consideration of selected capabilities for the use or development of AI methods as part of the recruitment process • Employees are partly aware of the benefits of data and its analysis with the help of AI methods • Further training offers for AI skills for selected employees • Adjustments to the organisational structure are planned, but are not geared to the effective use of AI, or only to a very limited extent	• Corporate structures are adapted to the possible use of AI • Consideration of role-specific AI skills (e. g. Data Scientist, Data Engineer) and definition of basic requirements • the majority of employees are largely aware of the benefits of data and its analysis with the help of AI methods • selected training opportunities for AI skills are available to the majority of employees	• Corporate structures are defined based on the use of AI and are inextricably intertwined with human workflows • Requirements for effective and targeted use of AI are a central component of the adjustments to corporate structures • Aligning the recruiting process with application and use case specific capabilities • extensively used AI skills training opportunities are available to all employees for voluntary and mandatory use

Table 37: Manifestations of the maturity model: Processes

Low	Medium	High	Very high
Processes			
• No processes supported by AI methods	• Processes are partially supported by AI methods • no key figures are collected for the assessment of profitability, process stability and process quality	• Processes are supported by AI methods • Key figures for the assessment of profitability, process stability and process quality are collected	• AI methods push the further development of processes

Table 38: Manifestations of the maturity model: Data

Low	Medium	High	Very high
	Data		
• no dedicated strategy for handling all data existing in the company • no explicit/implicit responsibilities for handling data • only demand-related and isolated data collection • no automated and systematic data collection and analysis • No linking of data sources • Consideration of basic legal and regulatory data protection requirements • low importance of transparency and explainability of used data and AI methods	• superficial, strategic anchoring of the handling of all data existing in the company • Responsibility for handling data is assigned as a sub-task to a member of the Board of Management (CDO)/the Executive Board. • Data acquisition and analysis are partly automatic and systematic • Linking of isolated data sources • Transparency and explainability of data and AI methods are given limited consideration in the operational check or development process versus a positive value proposition	• broad strategic anchoring of the handling of all data existing in the company • Responsibility for handling data is one of several main tasks and assigned to a member of the Board of Management/Executive Board • linking data sources as needed • Data is partly available in real time • Transparency and explainability of data and AI methods are taken into account as a basic requirement in the context of the deployment test or development process	• deep strategic anchoring of the handling of all data existing in the company • Responsibility for handling this data is the sole primary responsibility of a member of the board of directors/management (CDO) • Consideration of all data protection requirements and internal regulations above and beyond this • High demands on transparency and explainability of the procedure and the formation of results in the context of the use of AI methods • Transparency and explainability of data and AI methods are considered critical to success

Table 39: Manifestations of the maturity model: Technologies and platforms

Low	Medium	High	Very high
		Technologies & Platforms	
• no or only sporadic use of AI methods • fragmented IT landscape	• AI methods used are individually developed or bought in • no possibility to apply used methods or purchased modules to other use cases • AI methods used or bought-in modules are not integrated into any overarching architecture	• the AI methods used are based on modular concepts, which can be combined in a similar way to a construction kit • AI methods used operate as stand-alone and already partially networked • Addressing performance constraints through the use of cloud infrastructure	• almost all methods used are based on prepared method tools, thus little need for adaptation in preparation for operational use • Use of AI methods of the highest degree of innovation, stability or industrialisation • Use-case-related deployment of cloud, hybrid, on-premise or edge computing • Performance, availability and security of IT systems are critical to success • Use of internal developments with positive economic and operational value contribution, which represent decisive competitive advantage

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