Digitization of the work environment for sustainable production

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for sustainable production

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Introduction

Global pandemics, devastating wars and natural disasters with increasing frequency and impact are disrupting previously carefully balanced manufacturing networks. All industrial companies are required to examine their operations and adjust accordingly. The increasing cost of resources require enterprises to re-design their value creation processes to be more sustainable, to optimize the supplier network to become more resilient and to accelerate digitizing of operations to enhance operational effectiveness.

This year's WGAB research seminar is themed around Digitization of the work environment for sustainable production and seeks to contribute solutions to the current challenges. The scientific discourse aims to advance the sustainable and data-based organization of value creation processes.

Exemplary efforts for the sustainable production of 3D printed footwear and the circular supply chain of energy production will be discussed. With advances in sensory data collection in cyber-physical production systems (CPPS), there are new opportunities for sensing the status of manufacturing systems, which enable advanced data analytics to contribute to a sustainable production. Intelligent processes enable sustainable value creation and bi-directional knowledge exchange between humans and machines. With people at the centre of the CPPS, production systems shall be both adaptive and personalized for every worker. People need to be involved in the technological and organizational changes. Simulating the migration from a linear economy to a circular economy supports the trend of regionalized production networks. Digital assistance systems are tested to back up resilient manufacturing.

We would like to thank all authors for their efforts in preparing the contributions, which are valuable inputs to the discourse to solve the current challenges.

Luxembourg, September 2022

Peter Plapper

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Improving Sustainability of Footwear Production through 3D Printing of Shoes

Markus Trapp, Markus Kreutz, Michael Lütjen, Michael Freitag

1. Introduction

The production of apparel and footwear has a significant impact on the environment. In 2016, emissions for these two product categories accounted for about 8 % of global climate impact or 3.99 billion metric tons CO2eq. (Quantis, 2018). Trends such as "fast fashion" lead to a great demand for new clothes and shoes due to the short wearing times. Since most of the production takes place in Asia, but goods are worn worldwide, long transport routes are necessary. However, not only do transports contribute to a high environmental impact, but many emissions also occur during the material processing and production phases. In addition, the lack of recyclability is another issue. Shoes, especially sneakers, can consist of more than 60 discrete parts and many different materials (HILOS, 2022a). Often, these parts are fused almost inseparably. Therefore, it is not economically viable to separate them by type for recycling. Thus, most shoes can only be shredded and thermally utilised, leading to high demands for primary materials.

To avoid these issues and make shoe production more sustainable, additive manufacturing (3D printing) of shoes might be a promising approach. In this article, we present different approaches to using additive manufacturing technologies to produce footwear. First, we will briefly introduce additive manufacturing, highlight sustainability aspects, and show some examples of how additive manufacturing is used to make clothing and shoes. We then present a new approach to the production of customised footwear using only a Fused Filament Fabrication 3D printer. In Section 4, the environmental impacts of this manufacturing method are calculated and compared with values from other studies. In addition, we show which non-environmental factors still need to be considered in sustainability. The conclusion and the outlook on future work conclude this paper.

2. State of the Art

2.1. Additive Manufacturing

The term additive manufacturing (AM) covers all manufacturing processes whose production principle is based on the assembly or joining of volume elements, usu-

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ally in a layer-by-layer manner. For some time now, "3D printing" has gained acceptance as a collective term for various technologies (Gebhardt, 2016). Table 1 provides an overview of these categories and selected technologies and materials that can be used.

Categories	Technologies	Materials
VAT photopolymersation	Stereolithography	Photosensitive resins, ceramics
Material jetting	Drop on Demand (DOD)	Photopolymer resins, metals
Material extrusion	Fused Filament Fabrication (FFF) Fuse Deposit Model (FDM)	Thermoplastics (ABS, PLA, PC, nylon)
Binder jetting	Binder jetting	Polymer/ceramic/metal powder
Powder bed fusion	Selective laser sintering	Polymer/ceramic/metal powder
Sheet lamination	Laminated object manufacturing	Plastic/metal/ceramic foil
Direct energy deposition	Laser engineered net shaping	Metal/ceramic powder

Table 1: AM categories, corresponding technologies, and materials (ASTM International, 2012)

Regardless of the specific technology, AM processes have the following characteristics compared to conventional production processes (Gebhardt, 2016):

- 3D CAD data is directly used to generate the layer geometry
- No use of product-specific tools is necessary
- The generation of the mechanical-technological properties occurs during the construction process
- Objects can be produced in any orientation
- All technologies can use the same (STL) data set

These properties enable AM processes for quantities-independent and individualised production. Advances in materials and technologies mean that even materials such as concrete can now be similarly processed (Sanjayan & Nematollahi, 2019).

Thus, the application areas for additive manufacturing technologies span countless fields of application, from construction to fashion, agriculture, automotive, aerospace and healthcare (Jandyal, Chaturvedi, Wazir, Raina, & Ul Haq, 2022; Shahrubudin, Lee, & Ramlan, 2019).

2.2. Sustainability Aspects of AM

There are different approaches to consider sustainability aspects. The most common approach is to divide sustainability into three aspects: social, environmental, and economic, whose interaction and mutual influence can be presented differently. Three of the most common representations are shown in figure 1.

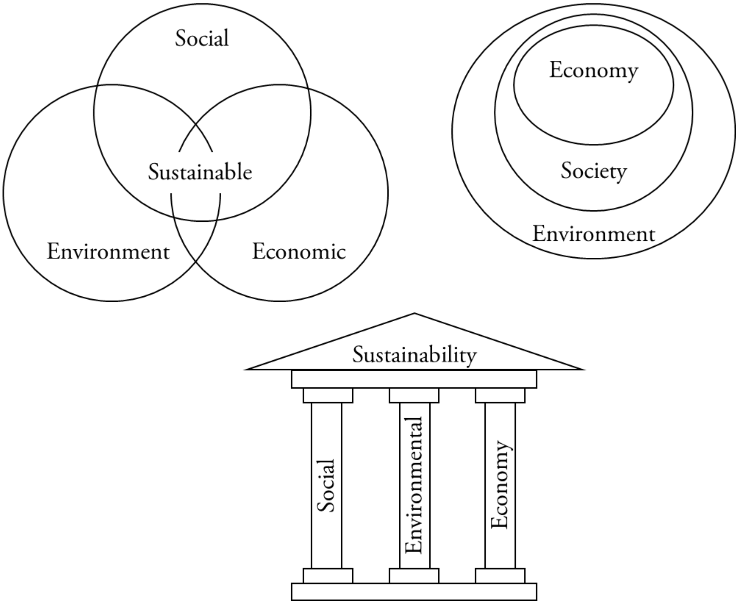

Figure 1: Different representations of the concept of sustainability (Purvis, Mao, & Robinson, 2019)

The individual aspects can be connected and weighted differently depending on the approach. One approach describes sustainability as the intersection of the three aspects. In contrast, another approach describes the individual perspectives as pillars that support the unifying roof of sustainability. A third option sees the environment as the comprehensive perspective in which society and, in turn, the economy are located. However, regardless of the specific approach, it is essential to note that sustainability is more than just considering possible environmental impacts.

The most significant impact on the environmental sustainability of AM production processes lies in the ability to execute make-to-order strategies. By producing only on demand, significant material savings can be achieved, reducing emissions (Despeisse & Ford, 2015).

Another advantage lies in the production method itself. Adding material instead of removing it means that less material needs to be pre-produced overall, thus reducing production waste. This is further enhanced since hardly any moulds, or other auxiliary materials are needed (Chen et al., 2015; Fastermann, 2014). Primary material requirements can also be reduced by using high or fully recycled materials (Büth, Juraschek, Thiede, & Herrmann, 2020). Further material savings can be achieved by optimising the geometries and design of lightweight components (Chen et al., 2015).

Most AM production processes do not require large factories or challenging logistical connections. This means that smaller, decentralised production structures can be set up, which overall lead to a reduction of transports within the supply chain and thus also to emissions savings (Chen et al., 2015; Mani, Lyons, & Gupta, 2014).

While environmental impacts of AM are well researched, knowledge about social impacts is much more limited. One aspect is that many toxic substances can be eliminated from the production process. In addition to a reduction in environmental impact, this means, above all, an immediate improvement for people since working conditions improve as the working environment becomes less harmful (Matos et al., 2019).

In addition, positive social impacts can be seen through the possibility of participation by customers. Certain AM technologies, especially FFF 3D printers and corresponding software, are already available at low prices and can change people's purchasing behaviour. People can develop from passive consumers to active prosumers through active participation in the production process by making products by themselves. By joining together to form global communities, further social cohesion and exchange are created (Chen et al., 2015). However, participation can also arise because, for example, exhibits in museums can be replicated so people with visual problems can also have an experience (Matos et al., 2019).

From an economic perspective, AM can help reduce production costs and enable more people to purchase products or spare parts and thus become part of the production process themselves, which are closely linked to social impacts (Khorram Niaki, Nonino, Palombi, & Torabi, 2019). This participation is the real benefit here and not the possibility that simply more products can be sold.

2.3. Additive Manufacturing in the Apparel and Footwear Industry

AM processes are already used in the fashion and footwear industry. For example, Spahiu, Canaj, and Shehi (2020) produced a dress using an FMD 3D printer and conducted an online survey to determine the acceptance of potential customers.

They concluded that most of the 100 respondents were aware of the 3D printing process and its benefits and would wear a 3D printed dress.

In addition to making garments from different plastics, new materials are also being developed. For example, by applying 2D braiding methods, Wu et al. (2022) have produced a 3D printing wire that can provide a wearing feeling similar to cotton by incorporating cotton powder.

3D printing of soles is often considered in the context of footwear. For example, Amorim, Nachtigall, and Alonso (2019) investigate how mechanical meta-material structure (MMS) can be used to create customisable footwear. They showed that this process has great potential but that there is still a need for development so that designers can use the materials in a more targeted way.

Zolfagharian, Lakhi, Ranjbar, and Bodaghi (2021) have developed different structures for midsoles and investigated them from the point of view of functionality regarding pressure absorption and dissipation during various sporting activities. They concluded that 3D printing is an effective technology for meeting specific requirements.

The US manufacturer HILOS produces and sells different types of shoes, e.g. sandals, clogs or mules, where the soles or individual parts are 3D printed. At the same time, the uppers or straps are made of leather and glued. The company claims that each component of the shoes is designed so that the shoes can be completely disassembled and the individual parts can be reused (HILOS, 2022b).

Well-known manufacturers have also used additive manufacturing processes to produce individual products. In cooperation between Adidas and the 3D printing specialist Carbon®, the Adidas Futurecraft 4D midsole was developed as a product for running shoes that can be manufactured using the 3D printing process. Different structures within the sole could create multiple functional zones to optimally absorb the respective loads that occur during running (Carbon, 2022). However, the processing of this sole into a shoe then follows the classic procedure by glueing the upper material to the sole.

With Flyprint, Nike has also launched a product on the market using 3D printing technology. However, in this case, the textile upper is 3D printed and then glued to a conventionally produced sole (Nike, 2018).

3. A New Approach for 3D Printing of Shoes

The previous section showed that many shoes are described as 3D printed. However, only individual components are made by using this technology.

In the following, we present an approach to producing customised shoes that are 3D printed as one single part. Therefore, at its core, the production process consists of only the following three steps:

- Individualisation of standard shoe models
- 3D printing using an FFF 3D printer
- Automated quality inspection

3.1. Individualisation of Standard Shoe Models

The approach provides of the possibility for customers and designers to meet on an online platform. Designers have the opportunity to offer their models for sale or printing. At the same time, care is taken to ensure that the shoe models are also printable. Customers can select the desired models and choose whether the shoe should have a fixed standard size or whether it should be customised to their own feet. If the latter is the case, customers can use a smartphone app to make a 3D scan of their own feet. These scans are then used to determine the measurement lines needed for the customisation. The standard shoe models are adjusted in length, width, and shape. Despite the customisation, decisive design patterns, such as logos, remain in their intended form.

3.2. 3D printing via Fused Filament Fabrication (FFF)

After selection and possible individualisation, the shoe models are prepared for printing. A slicer derives the required print commands from the CAD model and saves them in the print file, which is then transmitted to the FFF 3D printers. The 3D printers were designed and built by our project partner, the New York-based shoe manufacturer Zellerfeld Shoe Company Inc. to achieve the best possible results.

The operating principle of FFF technology is based on the extrusion of molten material. Setting the right temperature, the material melts enough to build the desired shapes. Each new layer joins the previous one to form an object. However, low temperatures prevent the individual layers from bonding properly. In contrast, high temperatures mean that the material does not cool fast enough, causing deviated contours.

In this 3D printing process, thermoplastic polyurethane (TPU) is used, which can be found in many products due to its properties. Although it is plastic, there are many products to be obtained whose recyclability and corresponding sustainability are certified by different institutions.

To have the 3D printing as efficient as possible, the shoe is 3D printed standing on the heel. This way, only a small amount of material is needed to create the required support structure. Figure 2 shows a snapshot of the 3D printing process.

Figure 2: 3D printing process (© Zellerfeld)

The shoe 3D printed with black material is held in place by the white support structure. In addition, it can be seen that the shoe consists of different structures inside. The choice of suitable configurations in different shoe areas ensures that the sole gets its cushioning effect. At the same time, the upper is elastic and firm enough to achieve the necessary stability and mobility.

Once the 3D printing is complete, only the support material needs to be removed, and the shoe is ready for sale. Although this process is still in development, a successful beta test has shown that both the customisation and the chosen manufacturing process are suitable. Figure 4 shows the ”HERON01“, the first fully 3D printed sneaker designed by Heron Preston and produced by Zellerfeld.

Figure 3: Fully 3D printed sneaker "HERON01" (© Zellerfeld)

3.3. Quality Inspection

While our project partner, Zellerfeld, designs the shoe models and performs the 3D printing, we were developing an automated quality control system intended to fulfil two tasks: quality control and knowledge building about occurring defects.

Within the scope of quality control, the 3D printed products need to be inspected concerning possible defects. Thus, the fulfilment of the quality standards has to be confirmed. In addition, possible defects are to be analysed. This includes not only the detection of defects but also their positioning. These findings will be used to adapt the printing process for critical areas, e.g. where deviations have occurred more frequently, thus reducing the probability of defects.

In mass production, many identical products generate a lot of information about possible defects. Therefore, methods of artificial intelligence (AI) such as Convolutional Neural Networks (CNN) which require many data for their training, can be easily used for automated quality control (Kuric, Kandera, Klarák, Ivanov, & Więcek, 2020). Since the process of 3D printing of individualised shoes is still under development, the number of pieces produced and thus the corresponding defects are still small. Hence, we are pursuing a different approach so that automated quality control can occur early in the development process. We use the defect-free CAD model of the shoe to be 3D printed as a reference. The printed shoes are digitised using a 3D scanner to determine the actual state. They can then be compared with the original CAD models, determining possible deviations. These deviations are grouped into corresponding clusters, evaluated according to their severity, and their position is noted. This way, it should be possible to recognise possible causes of defects and take appropriate measures for future prints despite the slightly different characteristics of the personalised shoes. These measures can be, for example, an adjustment of the printing speed for specific sections. However, this is not only about a possible printing speed reduction to improve quality but possibly also an increase for non-critical areas. In doing so, both better quality and reduced printing time can be achieved. Thus, less production waste and shorter printing times lead to a more sustainable manufacturing process.

4. Sustainability of 3D Printed Shoes

4.1. Calculation Emissions for 3D Printed Shoes

While traditionally produced sneakers can consist of up to 65 individual parts made of different materials (Cheah et al., 2013), by full 3D printing, only one element is produced, and one plastic is needed for production in the 3D printer. The calculation of the environmental impact is correspondingly straightforward. In addition to the emission during plastic production, only the energy required during 3D printing must be considered. The environmental impacts can be calculated by multiplying a specific emission factor by the amount of material or used energy, respectively. For the 3D printed shoe shown in section 3, this means:

Emission source	**Quantity**	**Specific emission factor**	**Resulting emission**
Thermoplastic Polyurethane (TPU)	0.5 kg	4.1 kg CO2eq./kg[1]	2.1 kg CO2eq.
Energy consumption	25 kWh	0.366 kg CO2eq./kWh[2]	9.15 kg CO2eq.
			11.25 kg CO2eq.

Table 2: Calculation of emissions for a 3D printed shoe

[1] Biron (2018)
[2] Umweltbundesamt (2021)

With the quantities for TPU and energy consumption measured by Zellerfeld while printing prototypes, the total value for a pair of 3D printed shoes is around 22.5 kg CO2eq.

However, it must be taken into account that the specific emission factor for TPU, in particular, is only reliable to a limited extent. Although plastic is used in many products due to its favourable properties, there is hardly any reliable information on its environmental impact (Proske, Sánchez, Clemm, & Baur, 2020). The specific emission factor for electricity corresponds to the German electricity mix (Umweltbundesamt, 2021).

It can be seen that the emission of shoe printing is significantly influenced by the emissions associated with the electricity consumed by the 3D printer. Since the manufacturing process presented here is novel, there is potential for process optimisation. Significant savings can be expected through reduced printing times and improved energy efficiency. Target values for electricity consumption of less than 15 kWh can be considered as realistic, resulting in an emission of 5.5 kg CO2eq. for one shoe. Furthermore, the use of electricity from renewable sources can also help to reduce the resulting emissions. Concerning the TPU used, it should be noted that the emission factor estimated here neither applies to bio-based material nor includes possible credits from recycling.

4.2. Classification by comparison with other data

Although some data on emissions related to footwear production can be found, a comparison is not straightforward. One limitation is that different types of shoes were considered, which can differ in complexity and weight. Since not only individual shoes are balanced, but also balances are partly averaged over the entire production, comparing the results in relative values, for example, in relation to 1 kg of shoe, is impossible. Figure 4 shows the emission values of the shoe “HERON01” compared to other results, which refer to 3D printed shoe parts and manufacturers’ data on conventionally produced shoes.

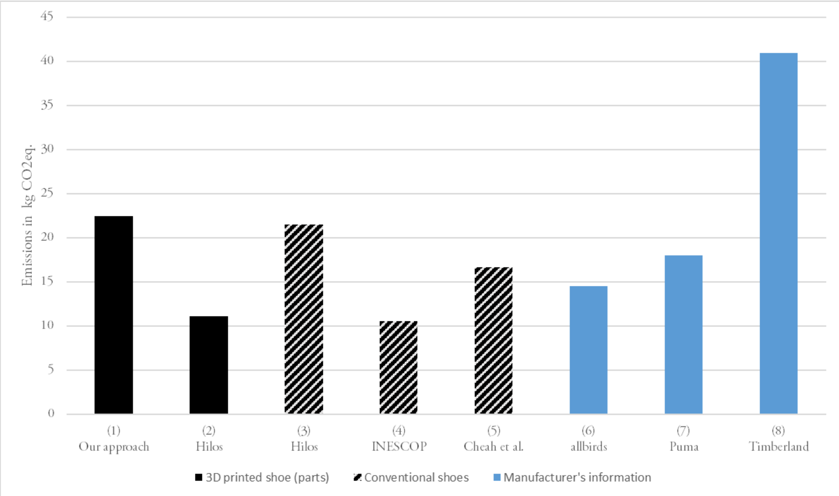

Figure 4: Comparison of different emission specifications for shoes

While our approach presents a fully 3D printed sneaker, a study by Yale's Centre for Business and the Environment investigated the environmental impact of the HILOS "slip on mule" model. This shoe consists of a 3D printed sole and a leather upper. The key findings were that CO2e emissions were reduced by around 48 % compared to traditional production. Thus, they achieved 11.1 kg CO2eq. emissions per pair as shown in Fig. 5 (pillar 2), instead of the 21.5 kg CO2eq. in the conventional manufacturing process (pillar 3) (HILOS 2022a). In addition, the researchers found that water consumption could be reduced by about 99 %. These savings resulted from the on-demand production and the new design, which allows a reduction of work steps and the number of additives such as adhesives. By taking the shoes apart by type, most materials can be reused.

A variety of data can be found for shoes without 3D printed components. For example, researchers in the *CO2Shoe* project came up with an average value of 10.6 kg CO2eq. per pair (INESCOP, 2017), while Cheah et al. (2013) state the emissions for a pair of running shoes are up to 16.7 kg CO2eq. (see Fig. 5, pillars 4 and 5).

It can be seen that manufacturers and retailers use sustainability as a marketing tool. As one example, the manufacturer *allbirds* gives a value of 14.5 kg CO2eq. for its "Wool Runner-up Mizzle" (Allbirds, 2022). In addition to presenting the emissions related to the specific shoes, CO2 neutrality is advertised through the financial support of climate protection projects. Results of other studies by manufacturers range between 18 kg CO2eq. (PUMA, 2008) and even 41 kg CO2eq. (Timberland, 2009).

Although the 3D printed shoe presented here currently still has a higher CO2 emission value, the entire production chain (including aspects like production losses or transports) must be considered to compare different production processes. Comparing emissions per pair of shoes shows that customer-independent mass production causes lower emissions due to its efficiency. However, if this overproduction leads to the mass destruction of unworn shoes, the ratios change. The Hilos study shows that significant improvements in environmental impact can be achieved by directly comparing two identical products. Concerning ecological sustainability, aspects such as water consumption are also decisive factors in addition to CO2 emissions.

4.3. Social and Economic Aspects

Even if the pure emission values do not clearly show better sustainability for shoes that are entirely or partially manufactured using 3D printing, the aspects beyond the ecological perspective must also be considered for a holistic view.

As described before, 3D printing reduces both the number of components and thus the required work steps and the types of materials. On the one hand, fewer potentially toxic substances are needed to produce the materials. On the other hand, eliminating many work steps can reduce the workload during production. Both aspects can improve social sustainability.

Using 3D printers to produce shoes can offer even more social and economic sustainability advantages. While large factories are needed for conventional shoe production, 3D printing and especially the FFF process only requires a printer, the printing data, the material and electricity. This leads directly to reduced investment costs. It is relatively easy to set up decentralised production sites allowing new groups of people to participate in the production process. The 3D printers can be easily integrated into environments that are not suitable for conventional production processes, such as retail shops in inner cities or in rural and economically not so strong regions. In this way, production in new places can help to create direct economic added value. In addition to the financial aspects, the required qualifications also open up the circle of people who can benefit from this production process. Without many work steps and no handling of hazardous substances, workers can be qualified quickly and easily. By networking the 3D printers via the internet and connecting them to central systems, aspects such as process monitoring or troubleshooting can be carried out remotely, thus taking off further pressure from the people to qualify. The reduced need for materials and decentralised production can also help to reduce the number of necessary transports. In addition to the ecological aspects, this also means that a contribution can be made to social sustainability by reducing pollution from traffic noise or the risk of accidents.

5. Summary and Conclusion

5.1. Summary

In this article, we presented different approaches to using additive manufacturing (AM) to produce clothing and shoes and highlighted their advantages from a sustainability perspective. With the "HERON01", we presented the first sneaker entirely made using 3D printing and the unique features of the production and quality inspection process. Currently, producing a pair of these sneakers generates around 22 kg CO2eq. emissions, but this value can probably be almost halved through appropriate adjustments in the production process. Other studies show that AM processes' suitability for a make-to-order strategy can significantly save emissions while increasing attractiveness through individualization. In addition to these environmental benefits, AM can also lead to improvements in social and economic areas. By eliminating toxic auxiliary materials, the working environment becomes less harmful. A reduced number of work steps can help to reduce the workload.

5.2. Future Work

Different aspects need to be advanced to improve the production process and its evaluation from a sustainability perspective. It has been shown that electricity consumption is a decisive factor in generating emissions. Thus, increasing the efficiency of the 3D printing process is of great importance. The successful implementation of automated quality control can help to both improve quality and reduce printing time. Further optimisation towards improved environmental sustainability can be achieved by using materials with higher recycled content.

More detailed calculations should be made regarding the evaluation from a sustainability perspective. Besides considering direct emissions, other aspects such as water consumption or toxicity are also of great interest. To make the results even more comparable, a presentation of relative values should be aimed.

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Enhancing digital transformation in SMEs with a multi-stakeholder approach

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1. Introduction

Digital transformation is still a tremendous challenge for companies due to the significant changes in processes, workflows, coordination, and cooperation (Legner et al. 2017). Not surprisingly, failures in digital transformation projects are reported frequently (Uchihira 2021). Typical examples are missing technology acceptance or bad integration of technologies into existing work processes (Cascio/Montealegre 2016). To better cope with these challenges, in Germany small and medium sized enterprises (SME) are supported by federal research programs. The aim is that academic knowledge about how to manage digitalization agendas can be transferred to practice. Vice versa research benefits from the observations and experiences gained through case study analysis in SMEs. In this context, it is broadly agreed but at the same time striking that a missing socio-technical systems (STS) perspective is considered as one major reason for failures in digital transformation projects (Hirsch-Kreinsen 2018).

While digitizing describes the process of encoding analogue to digital data and is thus only related to technical aspects, digitalization and digital transformation describe process improvements, process changes and business model innovation (Hess 2016; Legner et al. 2017). The interplay between technological characteristics, individual behaviour, and organizational properties (Strohm/Ulich 1998; Orlikowski 1992) matters for digital transformation. Thus, a STS perspective is state of the art in research. The perspective has always included consequences on social and economic level as well as trade-offs between different targets. Current research extends this balance between different objectives towards issues of sustainability (Lundborg et al. 2020).

Although this is widely approved (Hirsch-Kreinsen 2018), the multiple dimensions of digital change tend to be underestimated when it comes to practice. Maturity models are widespread approaches to support the dialogue and transfer from research to practise as they aim at systemizing academic knowledge for practical application. Some of them neglect the non-technological issues (Aronsson et al. 2021) while others explore a broader view on relevant dimensions (Lichtenthaler 2020, Wilkens et al. 2021a). However, the implementation journeys in practice tend to follow a narrow approach giving primarily emphasis to technological issues. The

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aim of our paper is to find explanations for this shortcoming and to derive propositions how to design a successful socio-technical implementation journey for the digital transformation in SMEs. Our assumption why current implementation is less advanced as it could be is twofold:

I. There are different interpretations of the meaning and implications of STS-theory for practical application in research.

II. The techno-centric approaches are more likely to be adapted in practice as they meet existing widespread interpretations and correspond to already developed ways of implementation and project planning in companies, especially in SMEs.

In order to underline this assumption, we first introduce conceptual baselines of STS-theory (paragraph 2). Afterwards, we take a closer look at different public-founded research projects for supporting the digital transformation in SMEs (paragraph 3) and classify the implementation projects against the theoretical background. The aim is to identify a framework for a holistic STS approach that is more likely to be adapted in practice (paragraph 4). A short summary and outlook will complete the paper.

2. Technological change and organizational transformation from a socio-technical systems perspective

The STS concept first gained prominence in the early 1950s under the impression of World War II (Trist 1981). Since then, theoretical frameworks and research methods have continuously been evolved. We first refer to the historical roots and then give attention to current co-existing interpretations in STS theory and projects. This allows to identify similarities and contradictions in nowadays scientific discourse.

2.1. Historical background of socio-technical systems

The STS perspective has its origin in the 1950s work of the Tavistock Institute in the British coal mining industry (Trist 1981). Concepts were developed against the background of the post-war reconstruction of industry during this period. A core message was that coping with the transformation challenges and reaching higher productivity as an issue of public interest in access to energy resources (the parallel to the current situation in our economy is depressing) requires more than a renewal of the technical infrastructure but needs to face characteristics of the social system and labour conditions. This was the starting point to conceptualize the complementarity between technical and social job characteristics and to include both in job description and analysis while also facing important public concern. It was initial to give more emphasis to working groups and group dynamic, to consider the benefit of autonomy and discretion. Labour was no longer conceptualized as a pure cost factor supposed to be replaced by technology but understood as potential and valuable resource to higher outcome and reliability. In the further development there was a new inquiry in research to treat the social and the technical system as an integrative unit of analysis instead of two separated spheres. Moreover, a whole research program and movement all over Western Europe emerged as a new paradigm (Fischer 1978). This was in hand with a specific set of research methodologies with longitudinal approaches and an extended operationalization of outcome factors, e.g., including indicators for individual well-being (Haring et al. 1984).

The idea of STS was transferred into design processes by socio-technical design principles, that aim at a balanced integration of technological and social aspects (Ghaffarian 2011). These principles were highly acknowledged and further developed especially within the field of information systems but also in engineering science (Ropohl 1978). This led to the academically well-known system development methodology ETHICS (Munford/Weir 1979). Despite its promising principles, STS design failed to proliferate in practice. During the challenging business environments in the 1990s, companies tend to use methods like business process re-engineering and lean management, both seeing the human being as a source of failure and taking little consideration of social factors or societal and ecological side-effects of cost-cutting strategies. Consequently, they were not considered anymore as a prerequisite for economic prosperity (Ghaffarian 2011).

It became obvious, that the STS approaches used so far, had focussed too much on a micro level and have thus excluded organisational boundary conditions and contextual factors. The dialogue was not connected to the mentioned management concepts. Grounded in this criticism, a new STS-research stream emerged also during the 1990s (Ghaffarian 2011), that was based strongly on the theory foundations of social sciences. Herein, the social system is not (just) an extension with an additional field of variables but conceptualized as inseparable from the technical system by origin (Orlikowski/Scott 2008).

2.2. Sociomaterial oriented understanding of STS in work science

Work science or ergonomics explores different approaches of STS-theory – some are more related to physical ergonomics, others to cognitive or organizational ergonomics (see Federation of European Ergonomics Societies https://www.ergonomics-fees.eu/node/7). Cognitive ergonomics emphasises the human-technology-interaction (HTI) and considers a set of variables on individual level (e.g. Abdel-Halim 1981; Thüring/Mahlke 2007; Sundar 2020). Sociomateriality is an STS understanding rooted in organizational ergonomics that goes beyond and explores a deeper understanding of the contextual embeddedness. It treats the interplay of organizational properties, technological artefacts, and human behaviour as unit of analysis when facing digital transformation (Orlikowski 1992; Iveroth 2011; Sesay et al. 2017). Technology, people, and organization are not three separable entities, but their entanglement is of key concern. According to this perspective, materiality does not exist separately from its social context and meaning (Orlikowski/Scott 2008) as the technological artefact is a social construction (Orlikowski 1992). This research direction became its further specification in the movement on sociomateriality (Leonardi 2011; Orlikowski 2007). Technical artefacts are not ascribed as objectifiable properties but are intertwined with the social practices in which they are used. Already existing specifications and interpretations lead to path dependencies and thus might cause a narrow scope for digital transformation (Panourgias et al. 2014; Wilkens et al. 2021c) or unfold different meanings to different user groups (Wilkens et al. 2021b).

The sociomaterial perspective in STS research typical leads to a research methodology that refers to real-life phenomena in qualitative case-based field work. Qualitative process analysis is very common leading to a distinctive description how the entanglement of technology, human interpretation and behaviour as well as organizational context factors look like (Orlikowski 1992; Orlikowski 2007; Orlikowski/Scott 2008; Scott/Orlikowski 2013). The explanatory power is to better understand inhibitors of digital change.

Current research elaborating on sociomaterial thinking claims to give more emphasis to the entities themselves – the IT artefact and agency – in order to capture the key characteristics of the entangled system (Weißenfels et al. 2016). This might be especially important if one considers the pervasive nature of new digital technologies such as artificial intelligence (AI) (von Krogh 2018). If technology gains decision making authority (von Krogh 2018) and becomes more and more flexible (Leonardi 2011) this is on the one hand side a strong argument for treating the concept of sociomateriality seriously. But on the other hand, it becomes obvious that there might be new characteristics of the technological entity which somehow challenge how to reflect on the interaction in the sociomaterial system (Scott/Orlikowski 2014) and to better frame new practices.

The critical debate also shows that a sociomaterial perspective often leads to an overemphasis on social aspects and an underemphasis on materiality (Cecez-Kecmanovic et al. 2014). The overall societal discourse is also neglected even though the reflection of trade-offs could adapt such criteria. Despite these critical points, the sociomateriality perspective has gained influence as it counteracts an (unintended) technology-dominated view and offers a consideration of organizational practices which are often underestimated, e.g., in studies interested in HTI.

2.3. Understanding of STS in mechanical engineering science

In mechanical engineering science, there is also a variety of STS understandings, which are related to how the discipline has changed over the past 15 years. Firstly, the need for an STS approach was articulated by Ropohl in 1978 within his influential systems theory of technology (Ropohl 1978). Herein he describes the empirical observation of the "insufficiency of socio-technical practice" that shows itself e.g., in the deterioration of psychosocial work conditions and negative ecological effects. Therefore, he proclaims, that technology cannot be understood without the context of social systems. Furthermore, he elaborates, that this higher (socio-technical) understanding can only be achieved by describing the human-technology system within a model (Liggieri/Müller 2019). Ropohl developed a system-theoretical modelling approach, which is continuously evolved towards today's industrial widespread approach of Systems Engineering (SE) (Bursac 2016). The cybernetic nature of SE is useful for integrating heterogeneous disciplines in the context of mechatronic design tasks but goes along with the abstract description of systems in such a way, that phenomena in both social as well as technical systems are modelled with equal elements, e.g., in-formation processing, control loops and mathematical functions (Liggieri 2019). This comes along with several shortcomings and reductions related to the representation of human and organizational behaviour as well as individual wellbeing and satisfaction, which are brought to light when transferring scientific knowledge from modelling in computational and laboratory settings to organizational practice. At that point of time the prescriptions are combined with taken for granted social practices of companies primarily dedicated to cost savings as an issue of lean management (see e.g. the case study from Dombrowski et al. 2017). This also leads to a reinterpretation of the prescriptions as the basic understanding of the social in modelling and the social in the implementation context differ. Furthermore, the prescriptive nature neglects the subjective perspective of how individuals construct technology for their own (see 2.2). It does not explicitly include societal norms such as ecological sustainability but the approach would be suitable to adapt related variables.

Furthermore, product innovation nowadays is much more multifaceted and associated with smart systems, data-based services as well as new kinds of business models (Spath/Dangelmaier 2016). This leads to an increasing demand to adapt the cybernetic STS understanding mentioned above.

On the one hand, technical systems become increasingly intelligent. The use of advanced information processing and AI not only enables a higher degree auf autonomy and cooperation among technical systems, but furthermore changes the way technology and humans interact. Thus, there is the need to overcome the shortcomings and reductions in the representation of human and organizational behaviour, mentioned above. For this purpose, mechanical engineering science tends to adopt methods and concepts from other disciplines. E.g., approaches such as human-centred design and human factors engineering (HFE) became more present in engineering practice lately, both originating in psychology-oriented work science (Bubb et al. 2016).

On the other hand, the use of AI also amplifies servitization by enabling the exploitation of available data (Thomas et. al 2016). Therefore, the scope of systems design is extended towards integrated services like e.g., predictive maintenance, product-service systems (PSS) and new as-a-service or platform-oriented business models (Matzner et al. 2021). Despite still having the prescriptive design-oriented and modelling driven view on the system (business model), the associated design methodologies of service design, design thinking and business model innovation intensively highlight the user and call for a deep understanding of user needs and their role in the creation of value. Especially the toolset of design thinking ensures, that the subjective view of different stakeholders is included into the design of technologies, e.g., by methods like personas, user stories or empathy mapping (Marcus 2015). Furthermore, when designing business models, engineering science must take organizational contexts into account. Therefore, methods like maturity evaluations and competence models are more likely to be used, originating in information systems science and economic-oriented work science (e.g., Rübel et al. 2018).

2.4. Comparing different understandings of STS

It becomes obvious that there are certain understandings and quite different views of STS (for an overview, see table 1). All directions refer to and elaborate on the initial research from the Tavistock Institute. Even though they do not have a specific focus on SMEs they can be applied independently from firm size. So far, these perspectives rather co-exist instead of learning from each other. The research community referring to sociomateriality benefits from field study analysis and a thoughtful reflection of phenomenon while engineering studies is much more sophisticated in modelling on a large-scale basis. This research serves as a conceptual backbone for system design and defines outcome factors on technical and social level (normative). Nevertheless, latest developments show a more holistic view, going beyond the cybernetic understanding of SE and adopting methods and concepts from other disciplines. This is a promising trend, because a comprehensive view might be important when facing the challenges of using AI in digital transformation as technological and human agency increasingly merge within organizational constraints.

STS perspective and key authors	**Typical research methods**	**Focus of analysis**	**Criticism**
Sociomateriality: The technological artefact can only be understood from the social context and is subjectively constructed (Orlikowski 1992; Orlikowski/Scott 2008; Leonardi 2011)	Field study analysis with emphasis on development processes, primarily qualitative approaches for exploring phenomena and patterns	digital transformation and design tradeoffs on system level	Neglecting the description of entities; pure process description without prescriptive design principles
Cybernetic, design driven perspective: Modelling social systems with mechanical principles respective information processing logic (Ropohl 1978)	Model based problem solving, simulation, experimentation / design of experiments or design science research	SE, HTI, HFE	Computational models of individual and group behaviour de-coupled from practice; organizational properties rather neglected
Customer design science: Focus on the customers perspective various stakeholder. Consideration of organizational and network capabilities (Marcus 2015; Boßlau 2014).	Model based problem solving (e. g. business model canvas), Design Thinking toolset (persona, empath map), empirical testing of solutions with stakeholders	Business Model Engineering	Resource based mapping of business models not considering the transformational processes and limitations of understanding organizational dynamics

Table 1: Overview of the outlined STS perspectives

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3. Analysing STS-understandings within different case studies

Implementation projects facing the digital transformation explore various translations and applications of STS-theory. Maturity models are most likely to support the transfer of academic knowledge to practice and to monitor the overall digitalization process. Differences result from the project involved disciplines and research perspectives but also from already established interpretations in companies. This is what we further illustrate by deeper analysing two research initiatives of digital transformation projects, both with emphasis on SMEs. The first case study is taken from a project on digitalization in agriculture and is primarily driven by work science. The second case study comes from a project on digitalization in mechanical engineering. By comparing these two cases in their strengths and weaknesses we refer to our basic assumptions that are different interpretations of what dimensions of STS-theory matter and that this creates shortcomings with respect to a holistic approach as an overall deficit and inhibitor of successful transformation. Learning from existing approaches and their limitations allows us to derive a proposition for a holistic framework and underline the advantages but also existing challenges while referring to the interdisciplinary digitalization project HUMAINE.

3.1. Case 1: Experimentierfeld Agro-Nordwest

The first case relates to the BMEL-funded project "Experimentierfeld Agro-Nordwest" (funding code 28DE103D18). Within this project there is an example of how researchers analyse technological change from the perspective of sociomateriality (see paragraph 2.2; Leonardi 2011; Orlikowski 2007). The examined use case are agricultural businesses, both SMEs as well as large farms (5 ha up to more than 1000 ha). The maturity model (de Bruin et al. 2005) was developed during the process of analysis and derived from the empirical data gathered from quantitative and qualitative field analysis. The model (see figure 1) monitors (1) the individual skills of the farmers (competencies and mindset of digital transformation), (2) the organizational framework and decision making (coping and dealing with internal and external demands) and (3) the technological potential in terms of the use of digital technologies. Most relevant dimensions are explored from field analysis and not based on prescriptive concepts. The sources of information are interview and questionnaire statements from farmers. Exploratory factor analysis was used to form categories within the dimensions. The analysis shows that farms are good at combining human and technical dimensions but are less good at indenting them with organizational management. The use of digital technologies such as precision farming, for example, not only requires individual skills in professional use, but also new perspectives in organizational decision making.

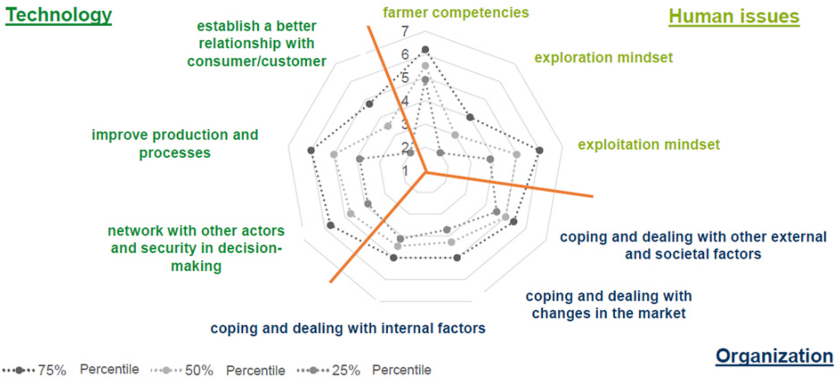

Figure 1: Digital maturity model for agriculture

The case study from the “Experimentierfeld Agro-Nordwest” project features a sociomaterial STS perspective as it explicitly integrates farmers’ subjective interpretation of the meaning of digitalization (see table 1). The demonstrated approach is helpful to explore the challenges in practice from a sociomaterial perspective and to explain shortcomings in digital transformation but it is less likely to change the dominant interpretations and path dependencies in farming firms. This also includes farmers’ interpretation of what sustainability means. Additional interview studies explored that considerably changes could only be observed when the farm is transferred to the next generation (Wilkens 2021c). The model helps to understand the entire system dynamics and why change is not a pre-designed step by step further development.

3.2. Case 2: Digital Coach

The second case originates from the Digital Coach project, which is funded by the European Union in the program "Erasmus plus – Strategic Partnerships" (funding code E10209466). The aim of the project is to understand the needs and to help with the digital transformation of manufacturing SMEs from Southeast Europe. The methodological core of the project is a maturity model, which was developed in a previous research project called ADAPTION. The model can be used to determine and define the actual and target state regarding the implementation of digital technologies in production, so called cyber-physical production systems (CPPS), using predefined classes (Morlock et al. 2017). The focus is always on a defined area, which serves as a pilot project. In total, there are 47 criteria, each has several maturity levels. The criteria are based on the dimensions of technology, organization, and individual competencies and skills as well as their intersections. To give an impression, the following figure shows the structure of the model and an exemplary criterion with the associated characteristics. It is a scientifically deduced framework of relevant categories.

Criteria	Description	TOP-Dimension	Characteristics 0	…	Characteristics 5
1. Digital connectivity of machines	Which digital interfaces or communication systems do the machines and production facilities have and in which way is communication possible?	Technical	There is no connectivity. No interfaces for digital data communication are available.	…	The machines or systems are connected to the Internet by cable (e.g., Ethernet) or wirelessly (e.g., WLAN, mobile communications) and can actively communicate with other systems via this (Internet of Things).

Figure 2: Structure of the ADAPTION maturity model

By analysing the current and target state, the digitalization potential of a company can be assessed. In particular, the strengths and weaknesses of internal company processes are examined to derive operational and strategic success factors against the normative background. The goal of the use of the model is to derive solutions for digital transformation approaches, that are most useful in the company's specific situation. In this context, it should be noted that the evaluation criteria are not to be understood as benchmarks only. The development of a company towards Industrie 4.0 is not to be understood as a revolutionary and eruptive process, but a continuous procedure that is individual for each company (Hübner et al. 2017). Thus, reaching the highest maturity level of a criterion may not be appropriate in every case. Furthermore, it can be reasonable to downgrade a specific criterion based on cost-benefit considerations regarding the function of the overall system. Regarding implementation, alternative solutions are considered. For this purpose, questions such as how to integrate the envisaged solutions into the operational processes (upstream and downstream processes) as well as if these solutions are compatible with the current job profiles, qualifications, and competencies of the employees, are used. The company's expectations, as well as the capabilities and limits of the maturity model, should be discussed in advance. Basic requirements for the application of the model are the acceptance of change processes and the willingness to train employees. The maturity model was developed by mechanical engineers with the support of social scientists, who contributed content aspects such as codetermination and interdepartmental communication in organizations. In accordance with its engineering origins, the model is characterized by abstraction, formalization, and structure. With the different criteria and the tiered logic, it is intended to map implementation projects in a standardized manner. Due to the high degree of abstraction and standardization, it is possible to use the model for different application contexts and initial situations and to make comparisons.

In correspondence with the prescriptive approach of the model the measurement explores the level of development but cannot demonstrate shortcomings that might result from the interdependence of the dimensions, missing prerequisites or various co-existing interpretations and misinterpretations within the companies. The model does not control for the respondents' meaning and interpretation of the categories.

The case study of the Digital Coach project features a design-oriented STS perspective with normative pre-designed successive stages (table 1). It supports SMEs while defining a clear guideline for concrete and small digitization steps. However, it cannot explain transformation obstacles out of this framework and why it does not prevent from failure.

3.3. Comparative case analysis

To derive indications for the subsequent synthesis, we conduct a comparative analysis of the use cases introduced before. Within this analysis, we compare the consequences of the underlying STS understanding regarding the general methodological approach, the limitations and the transfer within practice. Table 2 summarizes the characteristics of the two use cases.

	Experimentierfeld Agro-Nordwest	**Digital Coach**
Understanding of STS	Sociomaterial view	Cybernetic view
Unit of analysis	Agricultural businesses	Various manufacturing companies from south eastern Europe
Research method	Self-reported data (quantitative and qualitative)	Self-reported data (quantitative)
Contribution to the digital transformation process	Exploration of drivers and inhibitors in practice (agriculture firm). Agile instrument: development while gathering further data. Monitoring and benchmarking along parameter values of the key characteristics for the sector according to the company's firm size. Identification of interdependencies and shortcoming (from a scientific point of view).	Firm-related self-monitoring of maturity level according to parameter values of the pre-defined dimensions with underlying advices for further implementation.
Limitations in practical application	Measured dimensions do not fully meet farmers interpretation and dominant thinking in human-technologies scenarios, potential for organizational change cannot be fully exploited.	Implementation challenges outside the pre-defined monitoring cannot be identified. Interdependencies tend to be neglected.

Table 2: Comparison of STS-based use cases and maturity models

The maturity model in use in the Experimentierfeld AgroNordwest allows to gain deeper sector-specific insight where are the key challenges or shortcomings in successfully coping with digital change, especially the critical factors for technology acceptance and inhibitors of transformation. But the model is less likely to meet the taken-for-granted interpretation of farmers how to manage digital transformation.

The use of the maturity model ADAPTION applied to the project digital coach shows that practitioners tend to relate to scientifically deduced maturity levels and recommendations but reinterpret the relevance of different development fields under cost-benefit considerations leading to a technology-driven work system design. Even if the maturity model also considers organizational input factors (like e.g., abilities of codetermination within companies), these in comparison serve more as boundary conditions than as a concrete design object. This would be the same with overall societal values such as sustainability.

4. Integration of STS perspectives – exemplified with the HUMAINE project

Different STS perspectives and related maturity models explore different strengths and weaknesses, are rooted in unrequested basic assumptions of their underlying disciplines and provide different recommendations for coping with digital transformation challenges.

As there is still a need to overcome transformation obstacles and low technology acceptance – challenges that will further increase when it comes to a broader use of technologies such as AI – it is worth to elaborate on a more integrative STS approach. This is what we will outline in this paragraph.

HUMAINE is an ongoing research project and one of the German competence centres for human-centred work design in the field of AI development and usage. The competence centre is founded by the German Federal Ministry for Education and Research (BMBF) in the program "Future of Value Creation – Research on Production, Services and Work" (funding code 02L19C200). The aim of the project is to make use of the augmentation potential of AI for human-centred work design. The project consortium consists of several academic and industrial partners. On the academic side, the disciplines of work science, work psychology, social science, neuro informatics, cognitive signal processing, service design and production engineering are represented in the interdisciplinary research agenda. The industrial partners are mostly companies from the healthcare sector as well as industrial SMEs (https://humaine.info/).

The methods and tools developed in the project by the scholars from the various disciplines address issues at the interface of AI development and use. Examples include user-centred interfaces for training AI solutions, new standards for workflow descriptions (Thewes et al. 2022) with feedback-loops between AI development and its usage as well as related role development concepts. Further methods aim at improving adaptive and context-sensitive assistance systems, and a model for a human-centred process design including data privacy, trustworthiness, explainability up to personality enhancing job characteristics in AI use fields.

In order to support the digital transformation in adapting AI in work processes of SMEs from manufacturing, health and nursing the research team elaborates on two complementary approaches for enhancing maturity and technology acceptance.

I. The perspective reflecting on the human-centricity in job design (Wilkens et al. 2021a). This is the way to address the transformation challenge from a sociomaterial perspective. It gives especially attention to the users' occupational identity (Wilkens/Langholf 2021).

II. The perspective reflecting on the potential of companies (Bülow et al. 2021) and the identification and definition of maturity levels elaborating on this potential for business model development. This perspective provides access to overall economic rationalities related to AI technology. It gives especially access to the interpretation of actors involved in corporate decision making and project planning.

The approaches are complementary as they both integrate an actor perspective but from different points of view – those who have to work and interact with AI and those who take responsibility for AI decision making and integration in workflows without being individually involved.

The maturity model for human-centred job design (Wilkens et al. 2021a) allows to identify, at an early stage of development, which necessary and sufficient conditions in a concrete AI-enabled workplace are central to guarantee human-centricity in the specific job domain. This determination is made from the perspective of the AI users, focusing on the concrete work process within the actual organizational conditions. Assessments are based on a survey instrument that comprises six dimensions of human-centred design. The result of the analysis is a context-specific configuration of the maturity model that identifies the central aspects of human-centeredness in the work system under consideration. This approach is based on a sociomaterial understanding of an AI introduction as the measurement is related to the enacted reality in the organizational context. This type of diagnosis is a necessary step to approach entangled human and material agency unfolding during the implementation process of AI-enabled systems and to understand why technology is accepted or not.

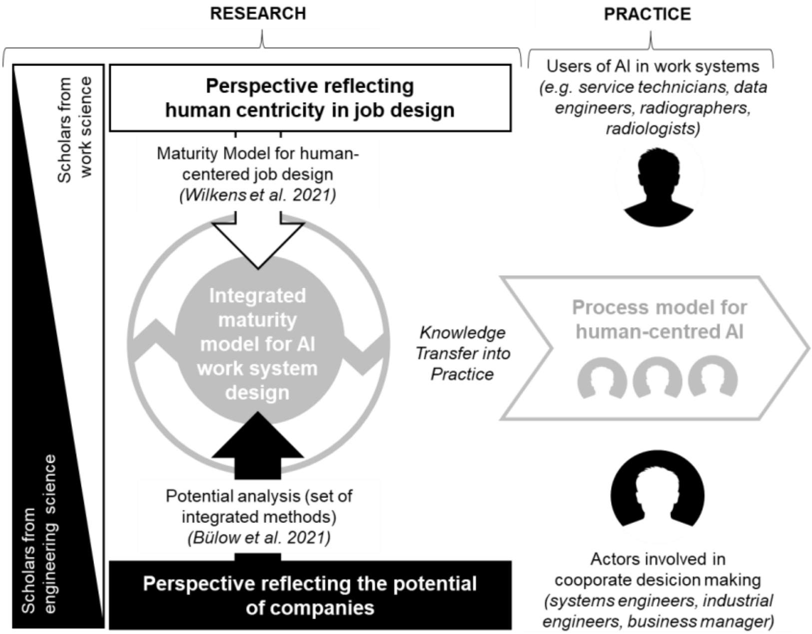

Figure 3: Integrated multi-stakeholder maturity model for AI work system design

With respect to the further development of business models the complementary perspective on STS design that draws more strongly from mechanical engineering science is important in order to reach another group of actors. In this STS approach a potential analysis provides the basis for the outline of a maturity model (Bülow et al. 2021). The development starts with a workshop series to gather enough context-specific understanding to initiate a prescriptive design process. Workshops are carried out with different partners from practice and academia, in which the potentials and challenges related to the use of AI are analysed. Interviews with these actors and their perspective on people, technology, and organization lead to the definition of requirements for the further analysis. A concept for distinguishing levels of digital work systems, which describe aspects such as legal and political constraints, business models, cross-company and work processes, work systems, specific job tasks, and psychological issues related to human-machine interaction (Adolph et al. 2020) serves as further analytical approach.

The selection and use of the different analysis methods is designed in such a way that the dimensions are interconnected across several levels. The method set consists of methods and tools originating from mechanical engineering science, e.g., design thinking methods with focus on business model engineering and lean management methods such as an adaption of value stream mapping focussing on data flows, media discontinuities, and system interfaces. It mirrors the expectation and taken-for-granted practices of project managers taking responsibility for the decision making and the integration of AI in work processes.

This data-oriented technical view on processes is complemented by the task-oriented sociotechnical workflow analysis, which focusses on changes in the human-technology interaction, task shifts, and information flows across organizational units (Bülow et al. 2021).

The two different analysis steps described above will further merge into an innovative multi-stakeholder maturity model that combines different perspectives of STS (see figure 3). This is possible because it is integrated into a process model for human-centred AI and thus combines a more analytical approach to maturity determination with a prescriptive design approach related project management thinking. The holistic STS approach gives a broader picture of how concrete AI systems are interpreted by different actors, enacted at that time of interpretation but can however be aligned for further integration into the overall corporate strategy at external and internal interfaces.

5. Summary and Outlook

Within this paper, the question of why many digitalization projects fail in practice and especially suffer low technology acceptance was approached. The striking point was that even SMEs which have scientific support and may benefit from STS perspective show difficulties in managing digital transformation. We assumed that despite a common theoretical core about socio-technical systems design, different STS perspectives are applied in practice that lead to a variety of interpretation as well as certain limitations. Subsequently, we have outlined typical research perspectives and mirrored on concrete project initiatives why it comes to shortcoming in digital transformation. Elaborating on this step of analysis we demonstrated how different perspectives might be synthesized and integrated into a holistic view with a multi-stakeholder perspective. We proposed an integrated maturity approach for digital transformation projects (for the example of AI-based work systems), bringing together former separated STS-perspectives and by doing so to reflect the digital transformation from different actor perspectives. In the following, it is to be evaluated to what extent this integrated approach now leads to a reduction of the limitations, associated with the earlier projects. Furthermore, interdisciplinary research within the proposed framework is still challenging since there is the problem of translation between the different STS-views and philosophies. So, new methods for a better communication between different disciplines could be of further interest and the project HUMAINE is an appropriate testing ground on a reflexive meta level.

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Review: Model-based Systems Engineering and Artificial Intelligence for Engineering of Sustainable Systems

What contribution can systems engineering and artificial intelligence provide for the engineering of sustainable systems as of today?

Benjamin Schneider, Oliver Riedel, Wilhelm Bauer

1. Introduction

The early phase of product development has the highest influence (approx. 80 %) on the later properties of a product, such as costs, sustainability or environmental impact. (Eigner / Stelzer, 2013; Warnecke / Eyerer, 1997). Sustainability or sustainable development is one of the key challenges that society will have to face in the coming years (United Nations, 2015). The area of sustainability with its three sub-areas, ecological, economic and social sustainability, was described already in 1998 (Bundestag, 1998). Ecological sustainability aims at "... maintaining or restoring the diverse functions of nature for the benefit of people". Economic sustainability focuses on the "... preservation and sustainable safeguarding of competitive and market functions ...". Social sustainability focuses on the "... creation of a solidarity-based society that guarantees democracy, constitutionality, freedom, social justice, prosperity and ecological responsibility." (Bundestag, 1998). In the meantime, for example, the integration of waste prevention strategies in the product design phase is already part of the recommendations for a sustainable economy. (PBnE, 2020).

The United Nations (UN) describes in its Sustainable Development Goals (SDGs) the core aspects and targets that need to be addressed in the context of sustainable development in the coming years (United Nations, 2015). It defines 17 thematic fields and 169 derived sub-goals. The thematic fields and the goals described therein are viewed critically in the scientific community. Criticism of the defined SDGs includes the dynamics and complexity of the SDGs, which require a systemic and methodical approach that has not been developed yet. (Laurent et al., 2019; Yang / Cormican, 2021).

The International Council on Systems Engineering (INCOSE) picks up on the UN SDGs in its Systems Engineering Vision 2035 as one of the key challenges that can be addressed and supported by systems engineering. (INCOSE, 2021). INCOSE takes it a step further and postulates that the goals pursued by the UN explicitly require comprehensive, system-based solutions. Furthermore, INCOSE describes in its vision an increasing integration of and support by artificial intelligence in the

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development process of future systems. Yang and Cormican (Yang & Cormican, 2021) confirm that systems engineering has great potential for modelling, structuring and transparently demonstrating the interrelationships between the SDGs. In an analysis by Khamis et al., AI solutions are attributed major contributions to the achievement of the UN SDGs. However, the analysis does not focus directly on the development of products or systems (Khamis et al., 2019).

Engineering respectively product or system development, as a key element in the creation of tomorrow's systems, is currently facing a variety of challenges. Flexibility and speed of reaction to customer requirements need to be raised. So-called Advanced Systems (AS), which are characterized by autonomy, socio-technical interaction, dynamic networking, e.g. in the sense of Systems of Systems (SoS), and an increasing relevance of the business models accompanying the product in the form of product-service systems, increase the complexity of the product. (Riedel et al., 2021). SoS describe networks of individual systems that interact independently of time or place, that were developed independently of each other, that are networked for a specific purpose and that show emergent system behavior as a result of the networking, i.e. they provide more functionalities than would be expected based on the functionalities of the individual systems (Kopetz et al., 2016; Nielsen et al., 2015; Porter / Heppelmann, 2014). In Germany, in response to the increasing demands on engineering, the cyber-physical systems propagated within the framework of Industry 4.0 (acatech, 2013), and the new properties of future products and systems described, the paradigm of Advanced Systems Engineering was established (Riedel et al., 2021), which is part of the BMBF's "Zukunft der Wertschöpfung " program within the framework of the High-Tech Strategy 2025 (BMBF, 2021). The paradigm describes complex technical systems, the Advanced Systems (AS), the Systems Engineering (SE) for the efficient handling of complex systems and the Advanced Engineering (AE) for the technical, organizational and creative support of the product creation process. (Riedel et al., 2021).

The early phase of product development, which is the focus of this article, can be characterized by means of the V-model (Figure 1) (VDI/VDE, 2021). The V-model describes a development process for mechatronic systems. On the left-hand side of the V, a system is continuously detailed and developed based on requirements. On the right-hand side of the V, system properties are compared with the requirements and the designed system is validated and verified. System development on the basis of the V-model is an iterative process that may be repeated several times. (VDI/VDE, 2021). The early phase of development is characterized by requirements elicitation and description as well as the modelling of the architecture of the product to be developed. In this phase, desired characteristics of the product are defined and initial insights into the expected implications can be derived.

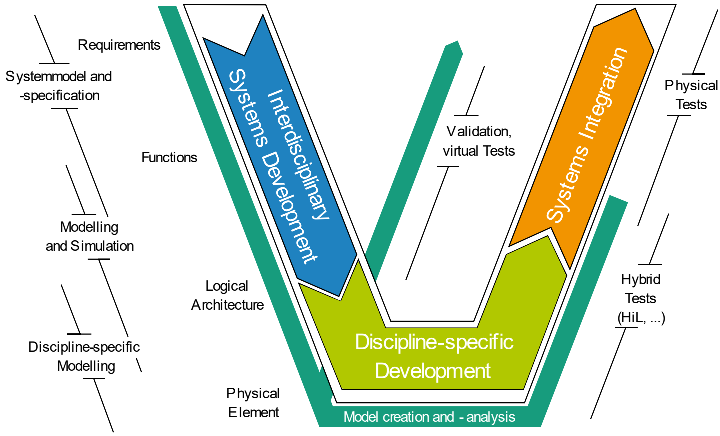

Figure 1: V-Modell according to (VDI/VDE, 2021)

2. State of the Art

The intersection of increasing requirements for the sustainable design of systems and the possibilities resulting from systems engineering and the use of artificial intelligence offers promising options for the efficient design of sustainable products and systems. In this paper, the current state of research in the intersection of the three topics is analyzed, presented and discussed on the basis of a systematic literature review (SLR). Options for action and research demands will be derived from the analysis. A brief overview of the three thematic fields is given in the following.

2.1. Systems Engineering and its Model-based Application

Systems engineering is a discipline that was mainly applied to complex, interdisciplinary projects such as the development of products for the aerospace industry (aircraft or satellites as well as military systems) in the past. With the ever-increasing complexity of systems as described above, the methods and approaches of SE are also gaining significant relevance in other sectors such as the automotive industry, mechanical and plant engineering or medical technology (Eigner et al., 2017; Riedel et al., 2021). In order to be able to develop products efficiently and exploit the possibilities of digitalization, SE today is mostly conducted in a model-based manner. Model-based systems engineering (MBSE) is defined by INCOSE as the formalized application of modelling to support system requirements, design, analysis, verification and validation. MBSE application extends from the conceptual design phase through the entire development and later life cycle phases (INCOSE, 2004). The application of MBSE is based on three pillars (1) a method, (2) a (graphical) modelling language, and (3) a software tool (Friedenthal et al., 2014).

The outcome of the MBSE application is a coherent model (understood as a model consisting of different sub-models) of the system that describes both its static structure and its expected behavior (Friedenthal et al., 2014).

Based on the design approach described in the V-model(VDI/VDE, 2021) Based on the design approach described in the V-model, the development process starts with defining the requirements and then progresses to the functional, logical and physical description of the system and its components. Once the system model is created, discipline-specific modelling begins, based on discipline-specific tools. Further verification and validation activities take place at different levels of granularity of the system until a working and verified product results.

The Systems Modelling Language (SysML) is a universal graphical modelling language that can be applied for the representation of systems (combination of hardware, software, human, ...) and supports the formal application of MBSE (Friedenthal et al., 2014).

In order to validate a system as early as possible or to be able to estimate its later properties, simulations are already carried out on the basis of the initial modelling. This usually involves a transition between the MBSE modelling tool and the simulation tool. Standards such as Open Services for Lifecycle Collaboration (OSLC) and Functional Mock-up Interfaces (FMI) can be used for the connection and transfer of information between the system model and the other simulation and modelling environments. (Bachelor et al., 2020).

Different methods for MBSE-based modelling of systems such as SPES, OPM, METUS, OOSEM are described and analyzed in detail in (Friedenthal et al., 2014; Halstenberg et al., 2019). None of the methods analyzed there so far addresses a direct integration of sustainability aspects into the development of systems.

2.2. Artificial Intelligence

Artificial intelligence (AI) has become an important topic in recent years, mainly due to the ever-increasing computing power, availability of data and storage capacities that enable real-time application of already existing algorithms. The AI approaches in focus today, inspired by neuroscience, focus on autonomous learning and self-optimization based on probability models and use cases (Goodfellow et al., 2016).

To date, there is no agreed upon definition of AI, although various definitions and tendencies are described in the literature. For this contribution, the following definition is adopted: "IT solutions and methods that autonomously perform tasks where the underlying rules of processing are not explicitly specified by humans. The execution of these tasks used to depend on human intelligence and dynamic capabilities. Now, AI takes over these tasks and learns based on the available data to better process orders, projects and workflows." (BMBF, 2018; SmartAIWork, 2020)

While there are numerous applications of AI in everyday products, the number of applications in the field of innovation management, research and development and engineering is generally still limited. In contrast to development, there are other areas within a company where AI solutions are already well established and partially implemented. Some examples of these other areas are services, marketing, production and logistics (Dukino et al., 2020). An analysis of 27 studies on the use of AI in companies shows that AI applications in engineering are only treated implicitly in most studies. Only very few studies provide elaborations or an analysis that goes beyond simple cross-references, these are (BMWi, 2019; Gil / Selman, 2019; Hatiboglu et al., 2019; Kaul et al., 2019). Therefore, this study aims to analyze which support possibilities artificial intelligence can currently offer for optimizing the sustainability of products in the early phase of product development.

2.3. Sustainability

Sustainability is a key factor for the economy. The EU taxonomy launched in 2020 aims to financially assess the activities of companies in terms of their contribution to sustainable development. The aim is to provide incentives for investments in sustainable projects and thus make contributions to the goals agreed in the Green Deal (European Commission, 2020). A central role in the context of sustainability is played by topics such as the circular economy and the reduction of greenhouse gases. Both address all three dimensions of sustainability. The SDG's (United Nations, 2015) as mentioned before also play a crucial role as objectives or requirements to be considered in the early phases of engineering.

The circular economy describes an economy that is regenerative and restorative and aims to ensure that products, components and materials retain their highest utility and value at all times. A distinction is made here between technical and biological cycles (Ellen MacArthur Foundation). The circular economy is implemented in practice through frameworks for R-strategies (Refuse, ..., Reuse, ..., Recycle, ...), among others (Potting et al., 2017). Various methods and tools for integrating circular economy strategies into product development exist. Central aspects are the design of products for long life cycles, dismantlability, reparability, maintainability and recyclability, i.e. the consideration of R-strategies (van den Berg M.R. / Bakker C.A., 2015).

LCA analysis is a key tool in assessing the effects and impacts that a product generates on the environment over its life cycle. It is a variety of combined procedures for recording and evaluating the inputs and outputs of materials or energy and the resulting environmental impacts generated by a system or product during its life cycle (DIN EN ISO 14040). Since a large number of factors, process steps and parameters have to be taken into account and modelled for the balancing of a product, LCA analyses involve a great deal of effort and are subject to certain inaccuracies. Inaccuracies result, among other things, from the data sources and the selected accounting framework or system boundaries. (Karaman Öztaş, 2018).

In the field of mechatronic product and system development, LCA analyses are currently usually based on the bill of materials (BOM) and the resulting processes (e.g. the processes inside the combustion engine of a vehicle) of a finished product and are therefore not used for an early analysis of product concepts (Del Pero et al., 2018; Ling-Chin et al., 2016).

Sustainability is a thematic area that has been addressed for quite some time. Already in the late 1990s, driven by legislation, solutions were actively developed to optimize the sustainability of products in terms of reusability and the circular economy (Bullinger et al., 1999). Various methodological approaches such as checklists, examples, design catalogues, manuals, value analyses or so-called "Design for Recycling" (DfR) tools have been developed and described (Bullinger et al., 1999). At the time, however, only slightly more than 3% of German industry used DfR software tools (Hartel, 1997). A main reason for the low prevalence of such tools is the effort involved in using the systems. The modelling of the parameters and processes necessary for a DfR analysis, which has to be carried out in addition to the creation of the other product models, often results in a discrepancy between effort and benefit. (Bullinger et al., 1999). As of 2020, DfX approaches to address a circular economy are still a niche topic that needs to gain a broader attention (Sassanelli et al., 2020). Most current approaches are based in theory. The analysis of Sassanelli et al. conclude that still today, there exists a need for new DfX methods and according tools to support decision making and balancing the different DfX methods (Sassanelli et al., 2020).

2.4. Target System for the Early Phase of Product Development

The increasing complexity of products and systems, consisting of mechanics, electronics, software and services, as well as their interconnectedness into systems of systems (in the sense of advanced systems) pose a challenge. Furthermore, the systems should address where possible all levels of sustainability and thus have as little impact as possible on their environment. MBSE and the Systems Modelling Language are considered the de facto standard for the modelling of mechatronic systems. However, factors that affect sustainability have so far only been taken into account to a limited extent in the modelling of products and Systems. (Bougain / Gerhard, 2017). Artificial intelligence promises great potential but has so far only been used in limited specific cases in product development (Riedel et al., 2021). Bressanelli et al. recommend further work on the intersection between digital technologies and the circular economy, including the combination of different digital technologies to exploit their synergistic potential (Bressanelli et al., 2022). In the following, an SLR will be used to investigate which approaches for creating and evaluating sustainable product structures already exist in science and which role artificial intelligence can play in supporting the assessment of sustainability indicators in the early phase of product development.

3. Methodology

The implementation of the SLR is motivated by Blessing and Chakrabati's observation that research in the field of "engineering design", i.e. product development, often takes place in silos. The reason for this is that researchers frequently start out with an incomplete overview of the entire research landscape, relevant for the topic they are addressing (Blessing / Chakrabarti, 2009). The use of a SLR is intended to prevent this issue. The applied method is based on the guideline described by Lame (Lame, 2019) for conducting SLR in the context of scientific work in the field of research and development or design. In accordance with the recommendations of Lame (Lame, 2019), the "Preferred Reporting Items for Systematic reviews and Meta-Analyses" (PRISMA) (Page et al., 2021), which is considered standard in the field of medical research and describes 27 items that should be taken into account when preparing a review, is adapted as far as possible to the present objective and topic area. The procedure and the resulting findings are shown quantitatively in Figure 2 and are presented and discussed in Chapters 4 and 5. Table 1 shows the search terms used for the SLR.

Systems Engineering	Systems Engineering, Systems Thinking, Systems Theory, Systems Modelling, Systems Life Cycle, System of Systems, MBSE, SysML
Sustainability	Circularity, Circular Economy, Sustainability, Sustainable Development, Life Cycle Engineering, Sustainable
Artificial Intelligence	Artificial Intelligence, Machine Learning, Neural Networks, Data Science

Table 1: Overview of the search terms used in the areas of interest

The search terms were selected to capture the work of a broad range of different communities that might be using different wordings to describe similar topics. The databases were searched in such a way that the combination of a search term from the field of sustainability and a term from the field of SE or AI was always searched for. The aim of this was to identify as wide a range of relevant literature as possible. The analysis was carried out in May 2022. After searching the databases using the search terms, removing duplicate entries, and removing articles from 2011 or older, the resulting articles were analyzed in three phases. In phase one, based on abstract and title, it was examined whether a relevance of the document to at least two of the three described areas as well as the early phase of product development of mechatronic products or systems could be identified. The resulting articles were checked for their accessibility on the basis of the access and licenses available to the authors. The remaining articles were analyzed with regard to their relevance for the early phase of product development of mechatronic products or systems relevant in this analysis. The results of the search were supplemented with articles already known in advance and identified through external references. The articles identified as relevant were grouped into categories. The results of the analysis are described below.

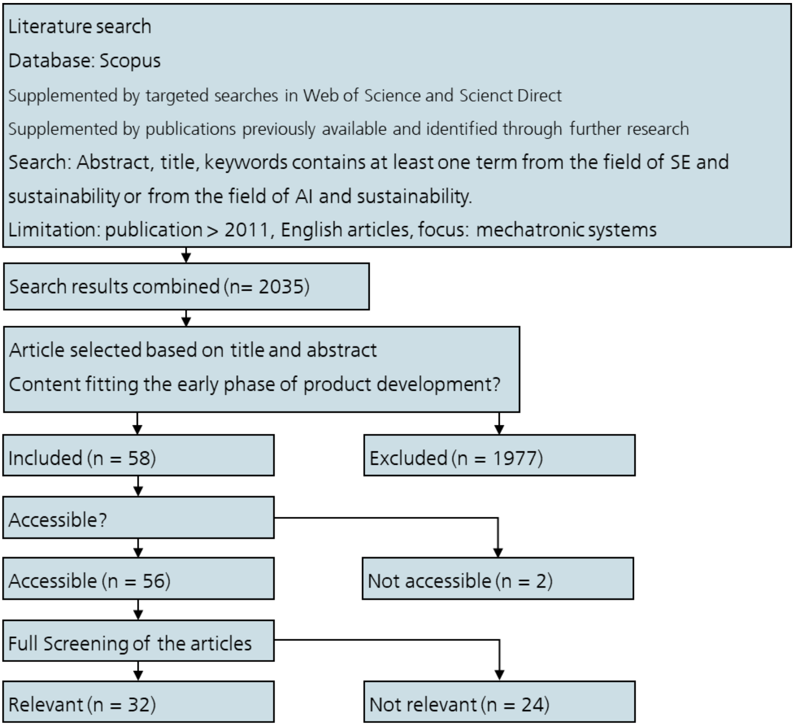

Figure 2: Procedure and quantitative results of the SLR

4. Results

After removing duplicates and applying the set criteria, 2035 articles remained for an analysis of title and abstract. Many of the identified articles were not related to the development of mechatronic systems but could be assigned among others to the fields of construction industry, urban systems, business models, learning and teaching and ecosystems. A small number (2) of the articles identified as relevant on the basis of title and abstract could not be analyzed further due to access restrictions. The publications identified and analyzed as relevant show an even trend between the years 2013 and 2021 and increase significantly for the analyzed first five months of 2022 (Figure 2). In 2022, a large number of publications could already be identified, which can be seen as an indication of the increasing attention being paid to the combination of sustainable development and the disciplines of MBSE and AI considered in this analysis, as well as the resulting increase in relevance of the topics and, in particular, the combination of the topic areas.

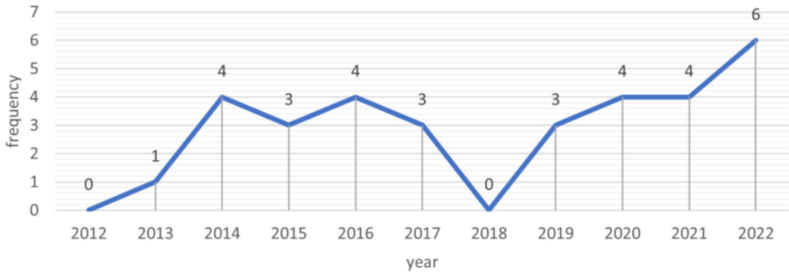

Figure 3: Frequency of the identified publications over the years

4.1. Artificial Intelligence and Sustainability

The early optimized design of products and systems can be supported by the use of artificial intelligence. Teksin et al., like many other authors, show an approach for the optimization of product properties using the example of a wind turbine. Here, experimentally determined data are used to train a model that predicts the behavior of the wind turbine based on various criteria. This model can be used to optimize similar turbines in the design phase (Teksin et al., 2022). Kadar and Kadar describe the support of regenerative design in the field of architecture based on AI (Kadar / Kadar, 2020). Doppa explains an approach for efficiently finding the optimal solution for complex system structures based on Bayesian optimization (Doppa, 2021).

Sakao et al. describe a vision of AI-based lifecycle engineering (AI-LCE). In their vision, AI approaches such as NLP (Natural Language Processing), CBR (Case-based Reasoning) and ML (Machine Learning) approaches are used to accelerate and optimize classic LCE activities. One component is the intelligent collection and use of data over the life cycle of products. The benefit lies in the reduction of time and the higher accuracy of decisions. Errors that occur in production could be caught by quick feedbacks for the same product generation through adjustments in development. (Sakao et al., 2021)

The approach of Tambouratzis et al. describes an AI-supported, sustainability-optimized material selection for plastics as early as 2014, in which general regression and artificial neural networks are applied. Furthermore, genetic algorithms enable the identification of an optimal material composition for the application at hand. The parameters considered in the optimization of sustainability are the CO2 footprint of primary production, water consumption, CO2 footprint of polymer molding and CO2 footprint of recycling. (Tambouratzis et al., 2014)

Diego-Mas et al. train an AI-based algorithm that can predict how environmentally friendly products are perceived by potential customers based only on their appearance. The algorithm is validated using tables as an example. Companies can use the results to optimize their own designs accordingly. (Diego-Mas et al., 2016)

Wisthoff et. al describe the use of a neural network or machine learning for estimating the general environmental impact of design decisions. The neural network links the LCA impact of 37 case studies on products with the respective product attributes. The interlinking enables developers to identify at an early stage which product attributes generate the highest environmental impact and to adapt their design accordingly. (Wisthoff et al., 2016)

In their review, Qin et al. identify several AI-based approaches for optimizing energy consumption in additive manufacturing. Several approaches describe indicators for optimizing the geometric design of 3D-printed components with regard to the expected power consumption during manufacturing. The authors identify a need for further research in this area (Qin et al., 2022). In their review, Ghoreishi and Happonen identify support for sustainable product development as one of three areas where AI can optimize the circular economy. AI supports the processing of large amounts of data, the development of new materials, the closure of material flows by reducing product defects and the number of prototypes needed, and the identification of alternatives to difficult-to-recycle materials (Ghoreishi / Happonen, 2020b).

In a further analysis, Ghoreishi and Happonen identify the fields of "optimization of modular designs", "fast, intelligent and precise creation of prototypes", "prediction of material toxicity", "cost reduction through testing" and "real-time data analysis" as promising application fields of AI in product development. (Ghoreishi / Happonen, 2020a)

Ertz et al. analyze the opportunities resulting from Industrie 4.0 technologies for the circular economy. Based on their analysis, they conclude that Big Data, Internet of Things (IoT) and AI technologies can contribute to extending the lifetime of products in various ways. IoT makes it possible to better adapt products to subsequent users and to optimize products in terms of maintenance and recovery. Big Data enables inferences to be made about product optimization based on user behavior and optimizing the sustainability of the product. AI can optimize product design through multi-criteria decision support systems and automated LCA analyses. (Ertz et al., 2022)

Kombaya et al. describe a procedure for the design and simulation of a Digital Twin Framework for reconfigurable production systems. The modelling is based on SysML. The framework uses the Digital Twin as well as ML for optimization in the design phase. (Kombaya Touckia et al., 2022)

In a literature review, Ghoroghi et al. investigated the current state of support for LCA analyses by machine learning approaches in the field of buildings, districts and cities, and " others". They identify four current limitations. LCA and ML are initially expensive and depend on large amounts of hand-crafted, structured training data. Computational costs and training time are other limiting factors for ML use. Many ML models (DNN, RF and SVMs) are designed as a "black box", which makes it difficult to understand the results produced. In early phases of development, the detailed information needed is often not yet available. Finally, not enough high-quality data sets collected under real conditions are available for training ML models. Currently, ML is most often used in the LCA context to generate missing data sets and optimize simulations. (Ghoroghi et al., 2022)

Choi et al. present an Engineering Machine Learning Automation Platform (EMAP) as the result of their study. This platform is cloud-based, aimed at suppliers of large and complex industrial plants and supports, among other things, the estimation of development costs and error checking for development. The focus is on risk management. The platform was validated using case studies and, according to the authors, can be applied to other use cases without the need for special machine learning experts. The tool is intended to support project managers in the area of risk management. (Choi et al., 2021)

4.2. Model-based Systems Engineering and Sustainability

Eigner et al. present an approach for assessing the use phase, the phase in the life cycle of a product with the greatest environmental impact. The life cycle phases are modelled as an extension of the V-model in the early phase of product development. The approach exploits the continuity between requirements and physical elements of the product structure created by the MBSE-based approach to establish cause-effect relationships and identify the elements of a product structure to be optimized. The system behavior to be expected during the use phase is described using use case diagrams. In connection with other diagram types and modelling, it is possible, for example, to identify the CO2 emissions generated per activity during the use phase of a product. The calculation is based on the characteristic values of an engine (usage time, emissions, consumption) for different states. In this way, direct levers for optimization can be identified. (Eigner et al., 2014)

Bougain and Gerhard describe an approach to directly consider factors relevant for a sustainability assessment in the early phase of product development within SysML models. Here, the indicators "Green House Gas Potential (GHGP)" and "Cumulative Energy Demand (CED)" are considered for four life cycle phases (extraction, production, use and end of life). The approach differs from Eigner et al. (Eigner et al., 2014) in the sense that several life cycle phases are taken into account as early as possible and a dynamic eco-design strategy is added. The approach is presented using a 3D printer. The method focuses on incorporating sustainable design requirements at the very beginning of the development process. It describes the requirements for each phase of the life cycle in a separate and weighted requirements diagram. In order to be able to make early estimates of the expected GHGP and CED, the material and weight of individual components are captured in the SysML diagram and linked to a corresponding database. Later, a link to the PDM system can be established. Here, the expected maintenance activities are also taken into account and a "maintenance factor" is introduced. In order to balance the manufacturing phase, processes and machining times are modelled. Later, a link can be established with the ERP system. The utilization phase is described with SysML behavioral models. The evaluation shows in which phase the product consumes the most, which allows conclusions to be drawn about the corresponding design strategies. Furthermore, it is evaluated which requirement is responsible for a consumption. Limitations are the lack of modelling of assembly processes, the transport phases and the necessary connection of the tool to the various databases or IT systems in the company context. (Bougain & Gerhard, 2017)

Halstenberg et al. describe an approach for the development of sustainable product-service-systems (PSS), consisting of a method, (modelling) language and software tool. The focus is on the development of the PSS as well as the integration of circular economy (CE) design principles into the development. The approach is based on the principle of MBSE, but defines its own description language, which combines approaches of PSS development and MBSE. The consideration of circular economy approaches is anchored in each main process step of the methodology. Model transformations and analyses are carried out with the aim of deriving optimal CE strategies for the selected product components. This analysis can only be carried out once the final product structure and the trace links and dependencies have been modelled. Only at this point is a holistic view of the system and thus optimization with regard to the CE strategies possible. (Halstenberg et al., 2019)

Dickopf et al. describe an MBSE-based approach for the early simulation and validation of system concepts based on SysML. By using the integrated model, twin and system-in-the-loop approaches, all life cycle phases can be accompanied and analyzed in a model-based manner. Added value results, among other things, from an early optimization of product parameters. The optimization with regard to the sustainability of the product is not directly addressed, but a detailed analysis of the different life cycle phases is supported. Likewise, an IoT-based data feedback from the actual use phase of the system is described for further analyses and optimization. The method is based on the programming or provision of interfaces for commercially available simulation and modelling tools. (Dickopf et al., 2019)

Abdoli et al. analyze the environmental impacts of SoS on the basis of the SE and the V-model. They use measures of effectiveness (MoE) from the SE context to determine the environmental impact of a SoS. The authors apply object-oriented modelling and describe a representation of a product system in a multi-SoS perspective. Further, systems dynamics are used to model relationships between policy decisions and their impacts, thus enabling the analysis of rebound effects. The method can model the structure and behavior of complex SoS and thus assess the impact of optimizations on individual systems in the overall context of the Multi-SoS in which it operates. The authors further describe that the incorporation of fuzzy logic could be beneficial to support missing data and the generally complicated modelling of multi-SoS. (Abdoli et al., 2019)

Block et al. describe an approach to lifecycle engineering based on MBSE and SysML v2. The novelty lies in the modelling of variants and different states of a product over the life cycle on the basis of the new possibilities resulting from SysML v2. Specific properties of the product can be derived from the modelled states, e.g. properties that are relevant for assessing the sustainability of a product. The different states over the life cycle are derived from different underlying business models. (Block et al., 2022)

4.3. Further Articles in the Analyzed Areas

Beyond the articles that can be directly assigned to one of the two search fields AI or SE, further articles were identified that contribute to the understanding of existing approaches and methods for assessing sustainability in the early phase of product development. These are presented in the following.

Echeveste et al. analyze desirable properties of environmentally friendly products (Echeveste et al., 2013). Kim et al. describe several approaches for the identification and consideration or analysis of sustainability indicators during product development. Here, a causal chain is defined based on the system dynamics between indicators, customer requirements and product components. This is used to analyze the product with regard to the selected indicators. (S. Y. Kim et al., 2013; S. Kim et al., 2014)

Grüneisen et al. describe a system dynamics model that can be used to optimize the management of the PSS development process. The model considers 30 cycles and can be used to support decisions. The model contains a "Repair" and a "Recycle" cycle (Grüneisen et al., 2015). On this basis, further mutually influencing cycles could be created to approximate the optimal product design. Hoffenson and Söderberg also describe a system dynamics model that can be used to assess the impact of design decisions on product quality and sustainability. (Hoffenson / Söderberg, 2015)

Kulatunga et al. present a tool that can be used to support the development of sustainable products. The tool is structured in the form of an interactive checklist and can be applied to different products (Kulatunga et al., 2015). The tool is reminiscent of DfX tools (Bullinger et al., 1999), which suggest appropriate strategies for specific requirements.

Penciuc et al. describe a method based on Product Lifecycle Management (PLM) for the consideration and analysis of all life cycle phases and the resulting effects during the early phase of product development. The method is developed and validated using the example of lightweight aluminum construction. The method describes the integration of several plug-ins into the PLM, with the aim of being able to evaluate the consequences that development decisions cause in the different life cycle phases. The plug-ins use inputs from repositories, FEM simulations and CAD data. The design decisions can be evaluated on the basis of various, previously selected indicators. In order to select the optimal strategy, several scenarios are created within the framework of the method and the resulting results are compared with each other. In this way, a scenario could be identified that optimizes both the environmental impact over the life cycle and the recycling costs. The methodology relies on standardized data exchange formats and self-programmed plug-ins. The use of MBSE approaches or modelling languages, such as SysML, is not discussed. (Penciuc et al., 2016)

Reuter defines the "Metallurgical Internet of Things". He defines metallurgy as a key enabler for the circular economy. He defines a hardware-based connection and corresponding feedback loops of all entities involved in metal production and recycling on a global level. The aim is to optimize the cycles and thus to optimize the recovery of the materials produced and used. (Reuter, 2016)

Chandrakumar et al. describe an assessment framework based on the UN SDGs and the UNEP's Design for Sustainability (DfS) indicators (United Nations Environment Programme, 2006). Based on the indicators and the analysis methodology, different designs can be evaluated against each other in terms of their social, ecological and economic sustainability. The analysis is based, among other things, on weightings of the factors adapted to the respective application and the principle of pairwise comparison. (Chandrakumar et al., 2017)

Faludi / Agogino analyze on the basis of 27 expert interviews that Systems Thinking and "The Natural Step" method are used by several experts in the field of innovation and sustainability. (Faludi / Agogino, 2018)

Mennenga et al. present a process-oriented framework for Systems of Systems Engineering (SoSE). The framework is used for planning and supports the optimization of SoS. The framework is designed based on the requirements of the development of sustainable production systems. The authors do not describe an explicit modelling approach, but mention SysML as a language that is often used for modelling similar systems. (Mennenga et al., 2019)

Drachenfels et al. describe an approach for knowledge-based lifecycle engineering (KB-LCE) using battery technologies as an example. They follow the approach of ontology-based knowledge engineering. They integrate KB-LCE into existing lifecycle engineering (LCE) methodologies. Through the common ontology, the actual processes in the LCE can be directly supported by the knowledge stored in the knowledge database. (Drachenfels et al., 2020)

Gräßler and Pottebaum develop a Generic Product Lifecycle Model from an extensive literature review. The model integrates the perspectives of product development and the sustainability-oriented approach of the circular economy. Within the framework of the associated methodology, material and information flows of multidisciplinary product-service systems are first described as the basis of the CE. Then a differentiation is made between product classes and instances. Furthermore, the stakeholder perspective of producer and consumer/user is extended to other perspectives such as recycling/ reuse and society. (Gräßler / Pottebaum, 2021)

5. Discussion

The results of the analysis show that although AI and Sustainability as well as MBSE are topics that receive a lot of attention in academia and industry at the moment, only 32 publications could be identified that actually address the utilization of MBSE or AI as a support for developing sustainable systems. It can be concluded, that so far a limited focus has been put on the support of sustainable systems design in the early design or engineering phase supported by MBSE or AI. As shown in Chapter 1 and 2, sustainability of products and systems plays a crucial role for the future of society. Therefore additional efforts seem necessary to address the multifaceted challenges design of sustainable systems poses on engineering departments. A summary on the current status and possible future research perspectives is given in the following.

Four approaches were identified which enable an estimation of the information available early in the development process and allow conclusions to be drawn about the later sustainability of the product to be developed on the basis of MBSE and SysML. Three of the four approaches allow the explicit consideration of several life cycle phases from the extraction of raw materials to the end of the life cycle. One approach is limited to modelling the use phase of the product coupled with the associated business models. Limitations of the approaches are the consistency of the models, the transition between different levels of modelling, the missing possibility to consider all life cycle phases such as transport and assembly processes as well as the necessity to include explicit data sets for the systems to be modelled in the system modelling tool. Furthermore, the recommendation systems based on DfX approaches are not directly integrated into the system modelling but must be triggered separately with data from the system model. Furthermore, only three of the approaches address the topic of modelling and balancing product variants. Individual component designs may initially appear to be disadvantageous for a variant under consideration, but similar to the SoS consideration below, when all product variants are considered, they could in turn be advantageous.

A positive note is that the authors describing MBSE-based approaches often follow the de facto language standard SysML. In the area of the description language, limitations are described for the modelling of the different life cycle phases and the continuous linking of the information and model elements. Nevertheless, the uniform language standard helps to easily comprehend the described procedures and at the same time conclusions can be drawn about optimization potentials of SysML. As was to be expected, only the most recent of the analyzed publications has so far relied on the successor to SysML, SysML v2, which is currently in the process of publication (GitHub, 2022; Object Management Group, 2019).

Systems-of-systems, which are particularly relevant for the future systemic consideration of sustainability, have received attention in the literature starting from 2019 onwards, when accounting for their combined impact on the environment. Since SoS are characterized by emergent system behavior, and thus provide more functionality in combination than would be expected based on the individual subsystems, further approaches must be developed in future to take this into account when assessing the environmental impact of SoS. Otherwise, there is a risk of optimizing subsystems locally without considering the overall context in which the systems operate.

Circular economy aspects are directly addressed by only few publications. Only Halstenberg et al. describe an approach to link corresponding indicators or evaluations directly with the modelling of the systems. The integration is based on a specially developed modelling language. The transferability and broad applicability of the approach must therefore be examined on a case-by-case basis. These findings are in sync with the findings of Sassanelli et al. which, while not focusing on systems engineering, describe the integration of CE related tools and methods in the engineering process as an underrepresented area in research and practice (Sassanelli et al., 2020).

The identified and described AI approaches promise potential for the optimization of product properties with regard to their sustainability and CE conformity. It must be noted that the identified approaches are to be regarded as proof-of-concept and only very rarely an actual integration into AI tools for direct application in the field is described. Only one article describes that the cloud-based solution developed, as usable in industrial context, without special prior knowledge in the field of ML. One challenge is to be able to apply the solutions created in the scientific field for very specific use cases to a broad range of different real world problems. For example, a solution developed for the selection of the optimal plastic will not necessarily produce equally reliable results in the selection of steel. When thinking about sustainability and circular economy, even more fundamental material or conceptual decisions must be made and supported, e.g. with regard to functional integration and hybrid materials. Suitable solutions could not be identified in the context of this analysis.

As expected in the field of research, the integration of the described approaches into the IT infrastructures implemented in companies is only addressed by a few articles. The articles that do address this pointed out the additional challenges that arise when implementing the solutions described, due to the need to realize additional interfaces to various data sources. A main challenge and future research direction is the actual transfer or direct coupling of results from research and the actual IT-infrastructures realized in industry. One approach could be to rely on standardized interfaces when developing solutions in academia.

On the basis of IoT and the concept of digital twins, it is expected that in the future it will be possible to calculate, for example, the consumption and emissions of products during the use phase on the basis of real or real-time data. Such data allows a detailed and exact evaluation of the emissions generated by the use of products and systems. One of the identified articles describes a vision for the active integration of real-time data using AI-based approaches. So far, corresponding approaches can be found in the area of Big Data analyses with regard to customer behavior, but without direct derivation of actual consumption or emissions.

6. Summary

Sustainability will be one of the main objectives for every product or system development in the future. Based on an SLR, this article presents the current status of the topics MBSE and AI with regard to the existing potentials for optimizing the sustainability of products in the early phase of development. In both areas, approaches were identified through the SLR-based approach. The limitations of these approaches were discussed in detail and future research needs are described. Beyond the identification in the two core areas, the review identified further approaches that contribute to a more comprehensive understanding of the current state of accounting for sustainability factors in the early phase of product development.

One main finding is that there is no integrated approach yet for combining the potentials of the two technologies MBSE and AI in the field of sustainability. A need for research can be identified here. Furthermore, most of the current AI-based approaches for the early phase of product development are still far from being able to be integrated into corporate processes with minimal effort, but they promise a certain potential. There is a particular need for research in this area, namely the direct and low-effort integration of AI approaches into existing processes in product development. None of the identified MBSE-based approaches covers all lifecycle phases and offers complete traceability. Furthermore, the aspect of circular economy and the choice of the right strategies have so far only been addressed in one of the identified MBSE-based approaches. A further need for research can therefore be identified in the efficient, model-based integration of circular economy factors or indicators in the early phase of product development.

Furthermore, the potentials resulting from SysML v2 for the modelling of sustainable systems must be used more extensively.

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Circular supply chain management for the wind energy industry

Conceptional ideas towards more circularity

Kathrin Julia Kramer, Matthias Schmidt

1. Introduction

Trends such as globalization and customers' requirements for individuality have led and still lead to an increase in complexity (Khan/Yu 2019). Recent events (e.g. Covid-19, Suez Canal blockage) have shown how fragile supply chains can be as assumptions for the design and management of supply chains become negated (Bocconi University et al. 2021; Khan/Yu 2019). Thus, supply chains have to be designed and managed to handle complexity and uncertainties. In addition, governments progressively announce aspired system changes towards more sustainability (e.g. European Green Deal) and are anchoring this into legislation such as the European Climate Law (Regulation (EU) 2021/1119 of the European Parliament and of the Council, 2021).

To meet the resulting requirements for supply chains, aspects that promote resilience are often highlighted (Christopher/Peck 2004). In this context, the concept of a circular economy (CE) recently gains attention as it could contribute to building a sustainable and resilient system (Bocconi University et al. 2021; Chaouni Benabdellah et al. 2021; Ellen MacArthur Foundation 2019b; Negri et al. 2021). The evolving research stream, circular supply chain management (CSCM), intends to embed the concept of a CE into the supply chain management (SCM) (Farooque et al. 2019). The tasks are assigned to design, plan and manage as well as execute material, information and financial flows within a supply chain (The Supply Chain Council 2012).

The German wind energy industry is a well-suited application for further investigations on CSCM as the country has an established wind energy industry, a long track record of installed wind turbines and aspires to further increase the share of installed turbines. Ambitious expansion targets of the government and new regulation will eventually promote the scale up of the wind energy industry (Sozialdemokratische Partei Deutschland et al. 2021). Hence, it is meaningful to learn from historical projects and shift towards a circular system prior to a possibly increased path-dependency. In addition, the wind energy industry and the concept of a CE are major contributors towards reaching the climate goals (Ellen MacArthur Foundation 2019b; European Commission 2019). However, with lifespans of roughly 20-30 years a high turnover ratio of materials in comparison to other energy

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sources exists. Switching to a circular supply chain and herewith implementing new business models could strengthen material availability and economic profitability as Germany is limited in raw material sources (Alves Dias et al. 2020; Velenturf 2021). For example, supply chain managers could reduce dependencies from scarce raw materials by using secondary materials that could be sourced following a multi-source procurement strategy (Wannenwetsch 2014). In conclusion, CSCM should consider circular strategies for the existing portfolio of turbines as well as for the newly to be installed plants.

According to Kramer/Schmidt (in press), research on CSCM for the wind energy industry is still rare. Therefore, the aim of this paper is to outline ideas to facilitate an efficient design of a circular wind energy industry in Germany. Questions from a SCM perspective are outlined that need to be answered to enable a circular supply chain. The paper is divided into seven sections. The subsequent section defines CE and CSCM, followed by section three that presents the current state of the art. The fourth section provides an overview of the current portfolio of wind turbines in Germany and roughly sketches potential future developments. In the fifth section the methodology for answering the research question 'What is required for a CSCM in the wind energy industry in Germany?' is presented that is applied in the sixth section. Thus, the organization, products and processes level for CSCM in the German wind energy industry and its belonging tasks are presented. The last section summarizes the main findings.

2. Definition of Circular Economy and Circular Supply Chain Management

For CE a multitude of definitions exist and a consensus has not yet been established (Alhawari et al. 2021; Kirchherr et al. 2017). Kirchherr et al. (2017) analysed 114 different definitions and consolidated them to a comprehensive definition that is used in this paper: "*A circular economy describes an economic system that is based on business models which replace the 'end-of-life' concept with reducing, alternatively reusing, recycling and recovering materials in production/distribution and consumption processes, thus operating at the micro level (products, companies, consumers), meso level (eco-industrial parks) and macro level (city, region, nation and beyond), with the aim to accomplish sustainable development, which implies creating environmental quality, economic prosperity and social equity, to the benefit of current and future generations*" (Kirchherr et al. 2017). Another widespread definition is given by the Ellen MacArthur Foundation. According to the foundation, the definition of CE bases on the following aspects, that are also reflected in the above definition by Kirchherr at al. (2017): First, the system changing character of the CE concept that foresees to "*decouple economic growth from the consumption of finite resources*" (Ellen MacArthur Foundation 2019). Secondly, maintaining the highest possible value in its cascading nature – use less by designing out waste and pollution, prolong the use of materials and products and regenerate natural systems. The herewith often stated strategies are also called R-principles. There are several

R-principles, with Kirchherr et al. (2017), for example, highlighting four principles: Reduce, Reuse, Recycle and Recover. And finally, to overall contribute to a sustainable development (Ellen MacArthur Foundation 2019b).
For CSCM, researchers have developed a variety of different conceptions (Alhawari et al. 2021; Corvellec et al. 2021; Kirchherr et al. 2017; Lengyel et al. 2021). In this context, Lengyel et al. (2021) argue that the CE concept is not yet fully integrated into SCM. They also state that existing literature not always considers the three dimensions of sustainable development as part of CSCM. Farooque et al. (2019) add, that next to the sustainable dimensions, a regenerative dimension should be part of CSCM. They conclude with the following definition: "*Circular supply chain management is the integration of circular thinking into the management of the supply chain and its surrounding industrial and natural ecosystems. It systematically restores technical materials and regenerates biological materials toward a zero-waste vision through system-wide innovation in business models and supply chain functions from product/service design to end-of-life and waste management, involving all stakeholder in a product/service lifecycle including parts/product manufacturers, service providers, consumers, and users*" (Farooque et al. 2019). This paper considers the holistic definition of CE by Kirchherr et al. (2017) and considers, like Farooque et al. (2019), CSCM as a multi-level and multi-objective system that embeds the circular thinking into SCM.

3. State of the Art

The research focus of this paper is at the intersection of SCM, CE and wind energy. To frame the research, a search within article title, abstract and keywords at Scopus on 21 April 2022 was conducted. The results are shown in *Figure 1* and *Figure 2*. *Figure* 1 displays the total number of publications on CE, SCM and wind energy as well as at their intersections.

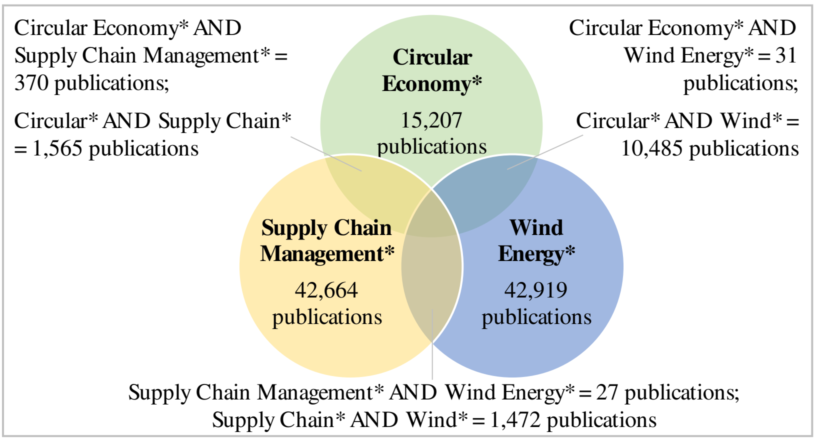

Figure 1: Scopus-listed publications about SCM, CE, wind energy and their intersections in total

The research field wind energy has, out of the three research fields, the longest track record with its first publication in 1961 and an exponential increase in publications since 2002 that led to a total of 42,919 publications. SCM counts 42,664 publications with its first publication in 1982 and an exponential growth from 2000-2010, followed by a decline until 2015 and since then, again, a rise is registered. The field CE with 15,207 publications is a relatively young research field with its first record in 2001 and an exponential growth since 2016. The intersections between the research fields show significantly less publications. For example, even as the number of CSCM publications has increased in the last years, based on the total number it is still a niche research field in relation to CE. Looking at the intersection of all three research fields and thus the research focus of this paper, the number of publications is marginal as outlined in *Figure 2*.

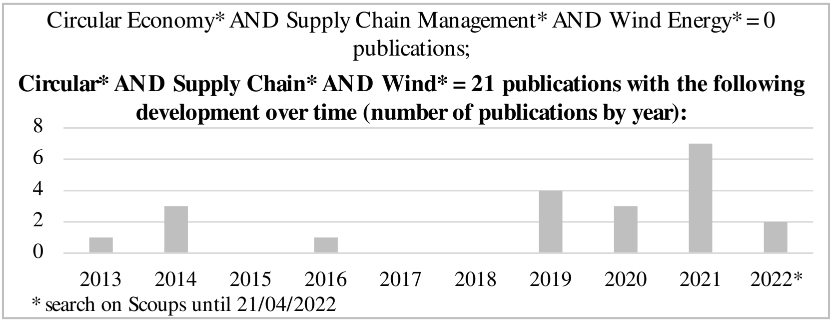

Figure 2: Scopus-listed publications on CSCM in the wind energy industry per year

The Scopus search with 21 publications in total underpins that the wind energy supply chain from the perspective of the CE has been rarely investigated. The first publication is listed in 2013, however, continuous releases are observed only since 2019. None of these publications presents an overview of the CSCM for the wind energy industry in general or in Germany. Instead, for instance, a strategic roadmap within the composites supply chain (Koumoulos et al. 2019), an exploratory study on closing the supply chain of critical materials (Lapko et al. 2019) and the second use of wind blades (Nagle et al. 2022) have been investigated.

Next to the 21 publications at the intersections of the three research fields and contrary to the non-existence of a systematic CSCM overview in the wind energy industry, CE research with a linkage to the wind energy industry exist. For example, Velenturf (2021) presents the state of the art and develops a framework for the offshore wind energy industry. This eventually could also be applied to the onshore wind energy industry. She does not reflect on CSCM or SCM and instead proposes 18 strategies from the CE perspective which are subdivided in narrowing (e.g. design to use less material), slowing (e.g. use products for as long as possible), closing (e.g. establish reverse material flow cycles) and integrating (e.g. minimize landfill sites and restore areas). Moreover, with a focus on circular business models, Mendoza et al. (2022) evaluate 14 circular business models that are implemented in the wind energy industry. The strategies are clustered into (i) dematerialization, (ii) circular production and distribution, (iii) collaborative consumption, (iv) circular sourcing, (v) long life and (vi) next life.

Next to CE research in the wind energy industry, scientific literature on general frameworks and archetypes for CSCM exist. Batista et al. (2018) develop a circular supply chain archetype based on a content-based literature review. They divide between primary, recovered and secondary material flows within a closed-loop and open-loop design. Farooque et al. (2019) highlight in their work the influence of a circular thinking within product/service design, procurement, production, logistics, consumption, end-of-life (EoL) and waste management. Further they outline supporting business models and the role of technology. González-Sánchez et al. (2020) propose a conceptual framework from a strategic management theory perspective consisting of the four dimensions (i) relational, (ii) technological, (iii) environment as well as (iv) logistics and organizational. Amongst others, they highlight that the concepts of reverse logistics, industrial symbiosis and circular business models facilitate economically and environmentally sustainable circular supply chains. They further add, that the use of smart technologies (e.g. big data analytics), collaboration within the supply chain network as well as designing new legislative, fiscal and cultural frameworks are of relevance. Montag et al. (2021) present a circular supply chain maturity framework. During the conceptualization process they frame the three dimensions organization (strategic), products (tactical) and processes (operational) with their sub dimensions. These dimensions are set to contribute to a sustainable development and should in total facilitate a holistic system thinking. The organizational level consists of management as well as information and technologies, enabling the paradigm shift. The products level with a focus on retaining the highest possible value has the three sub-dimensions, beginning-of-life (BoL), middle-of-life (MoL) and EoL. The processes dimension has the phases of an extended SCOR-model (plan, source, make, deliver, use, return, recover and enable) as sub dimensions. In this operational level, the R-principles as well as the differentiation between restorative and regenerative cycles are found.

In conclusion, none of the stated research has systematically outlined how a multi-level, multi-objective CSCM for the German wind energy industry could look like. This paper aims at making a first contribution to close this research gap. The objective is to provide an overview of key CSCM tasks from an organization, products and processes level for the German wind energy industry. Thus, a linkage of existing literature on CSCM in general and research on CE in the wind energy is provided. Questions to be answered are outlined that add to a potential research agenda for a circular German wind energy industry.

4. Wind Energy Industry in Germany

The wind energy industry consists of several supply chains offering products and services related to materials, components and wind turbines. According to a circular thinking, the wind turbines should be kept as their highest possible value prior handling single components or materials. Thus, this paper focuses as a starting point on wind turbines and provides in this section an overview of the wind turbines in Germany. In Germany a publicly available register of energy plants, the Marktdatenstammregister (MaStR), exists that forms the basis for describing the wind energy market (Bundesnetzagentur für Elektrizität, Gas, Telekommunikation, Post und Eisenbahnen 2022). Plants with commission between 01.11.1983 to 25.04.2022 are considered in this contribution.

As of 25.04.2022, 33,149 wind turbines are registered in Germany, of which 95.4% are onshore turbines and 4.6% offshore plants. The first onshore plant was commissioned in 1983 with the youngest plant being commissioned in 2022. The offshore wind energy market is not as mature with its first plant being commissioned in Germany in 2009. The last plant was commissioned in 2020, thus from 2020 to 25.04.2022 no further installation process was ended. However, planned offshore and onshore wind turbines are already registered. The geographical allocation of all registered plants shows a dominance in the North of Germany and less presence in the South. The highest share of registered plants can be found in the postal code region 2 (27.3%), followed by the region 1 (17.4%) and 3 (16.1%). The least turbines are registered in the postal code area 8 (1.3%), followed by the region 7 (2.2%) and 6 (2.6%).

For logistics, procurement and manufacturing capacity planning the number of plants is of interest. *Figure 3* shows the number of plants per year being planned, in operation, temporarily or permanently decommissioned.

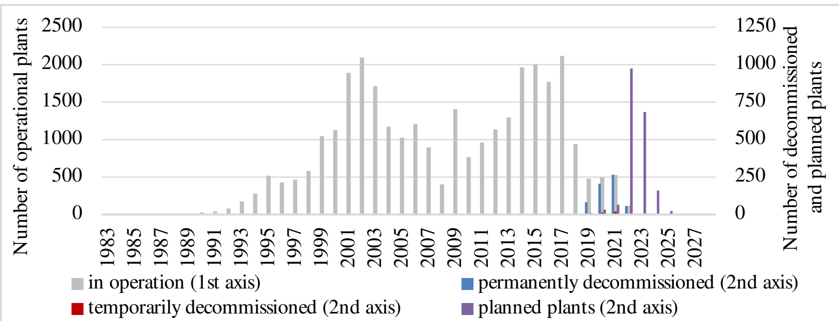

Figure 3: yearly number of planned, operational and decommissioned wind turbines

The current portfolio of registered wind turbines in Germany consists of mainly operational plants (92.1%). The average age of the operational plants is 13.6 years. However, 27.0% of all operational plants are equal or older than 20 years. The

30,545 operational wind turbines represent an installed capacity of 64,098.2 MW, leading to an average size of 2.1 MW per wind turbine. When looking at the development over time of all registered plants, technological progress has led to an increase in MW per wind turbine. For instance, in 2001 the average net installed capacity was 1.3 MW, rose to 2.1 MW in 2011 and equalled to 3.6 MW in 2021. The Compound Annual Growth Rate (CAGR) of the time window from 2001 to 2021 measures 5.1%. The higher installed capacity per plant is achieved by building higher and larger plants (Hau 2013; Lee/Zhao 2022). Especially, the increase of offshore wind energy with its typically higher capacity per plant in comparison to onshore wind energy could explain this development (Poulsen/Lema 2017).

Plants that are at present shut down or decommissioned permanently are with 0.1% and 1.9% a negligible portion. The net capacity of temporarily decommissioned plants equals to 35.6 MW and of permanently decommissioned plants to 640.3 MW. The first plant was decommissioned in 2009, however, until 2019 only sporadically eight further plants followed. In 2019, 83 plants were decommissioned, in 2020 206 plants, in 2021 266 plants and in the commenced year 2022 so far 57 plants. The average age of all decommissioned plants accounts to 20 years, varying between less than a year to up to 33 years. Originally, it was expected that most plants will be decommissioned by the end of their 20 years lasting feed-in-tariff (Zotz et al. 2019). Nevertheless, many plants that are older than 20 years and do not profit from a feed-in-tariff anymore are still in operation. The expected lifetime of a plant is dependent on several factors. Amongst others the technical conditions of the installed components, the expected energy spot price development, the operational expenditures (OPEX) and the pricing level for turbines and components on a secondary market could influence the decision of an operator to extend the lifetime or to decommission a plant. Considering an expected lifetime of a plant with roughly 20-30 years, the number of plants that reach their EoL will increase over the next years.

Currently, 5.9% of the registered plants are in a planning process, which corresponds to a net capacity of 8,952.3 MW. However, the registration in the MaStR is only in specific cases mandatory for planned plants. Thus, the 1,956 registered plants that are planned and expected to be commissioned between 2019 and 2040 are not a complete picture of the expected development. The majority (84.9%) of those plants are planned for 2022 and 2023. Why 107 plants with planned commission between 2019-2021 are not in operation yet, is not stated in the MaStR. Next to the planned turbines according to the MaStR, the German Federal Network Agency publishes historical and upcoming tendering processes. Depending on the duration of the approval and installation process, the plants can get finally commissioned. In addition, different scenarios on the long-term expansion targets of wind energy plants in Germany exist. For example, the current coalition agreement foresees to expand offshore wind energy to a capacity of at least 30 GW until 2030, 40 GW until 2035 and 70 GW until 2045 (Sozialdemokratische Partei

Deutschland et al. 2021). The agreement does not state specific targets for onshore wind. Following the targets that are mentioned in §4 in the law for the expansion of renewable energies (Erneuerbare-Energien-Gesetz – EEG 2021), an increase of 62 GW onshore capacity until 2023 with reaching 71 GW in 2030 is targeted (Gesetz für den Ausbau erneuerbarer Energien, 2021). Also taking the disassemble of old wind turbines into account, a massive expansion of the wind energy industry is envisaged.

In summary, the wind energy industry is important for securing energy supply in Germany against the background of the energy transition and current geopolitical developments. In the future, there will be an increasing demand for wind energy plants (Gesetz für den Ausbau erneuerbarer Energien, 2021; Sozialdemokratische Partei Deutschland et al. 2021). Different materials are required for the construction of these plants, and in this context global competition for raw materials is expected to increase in many areas (Bobba et al. 2020; Lee/Zhao 2022). In order to make the supply chain more resilient, the establishment of a CSCM in the wind energy industry is crucial for success. In view of the future growth of the wind energy industry, it is now the right time to develop the supply chain in a future-oriented way and not to have to rebuild it later in a more time- and cost-intensive way. Therefore, potential opportunities and requirements for becoming more circular should be investigated. This paper is intended to contribute to this by identifying open questions for the design of a CSCM for the wind energy industry. Hence, this paper deals with the research question 'What is required for a CSCM in the wind energy industry in Germany?'.

5. Methodology

Practical implications from a CSCM perspective should be highlighted in this section by following the structure of existing frameworks. A CSCM should enable a holistic system thinking with a positive effect on economic, ecological, social and regenerate objectives (Farooque et al. 2019; Lengyel et al. 2021; Mendoza et al. 2022). The proposed methodology is to be applied to the wind energy industry in Germany.

The CSCM multi-level framework by Montag et al. (2021) functions as a foundation as they embed key facets of a CE into SCM. For this work, the framework is adapted for the wind energy supply chain by reflecting the work by Velenturf (2021). *Figure 4* presents the methodology for this contribution.

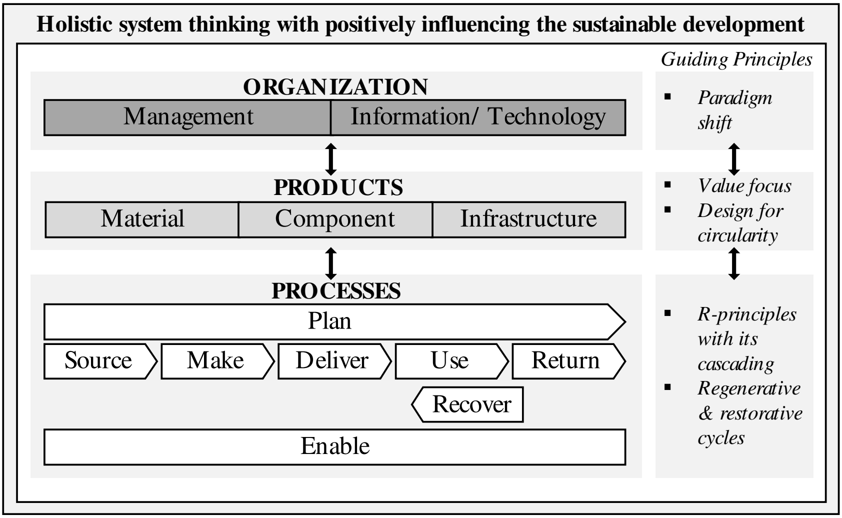

Figure 4: research methodology of this paper (based on Montag et al. 2021; Vegter et al. 2020; Velenturf 2021)

The presented research methodology consists of the three levels organization, products and processes. The organization level with its sub dimensions management and information/technology aims at enabling the paradigm shift in the wind energy industry (Montag et al. 2021). In line with Velenturf (2021), the different products to be considered are raw materials, components and infrastructure. The products are to be designed that they are capable to foster a circular thinking across all life phases, thus BoL, MoL and EoL, and therefore enable the creation, retention and extension of value. Looking at the process level, the supply chain processes must be designed and managed to comply with the R-principles and enable the distinction of regenerative and restorative cycles. The extended SCOR-model by Vegter et al. (2020) describes the different processes of the supply chains in alignment with CE thinking. Vegter et al. (2020) distinguish between the processes Plan, Source, Make, Deliver, Use, Return, Recover, and Enable. In comparison to the original SCOR-model (The Supply Chain Council 2012), the processes Use and Recover are main processes and not part of the other processes (e.g. recycling and remanufacturing being part of the process Make). However, Vegter et al. (2020) argue that extracting Use and Recover as further processes, would promote the CE thinking.

6. Circular Supply Chain Management for the Wind Energy Industry

Following section 5, the sub-sections outline the organization, products and processes level of a CSCM for the wind energy industry in Germany. The section 6 bases on literature research, discussions with experts from wind turbine manufacturers and a recycling company of wind turbines and the experience of the authors.

6.1. Organization Level

For facilitating a CSCM for the German wind energy industry the management as well as the information systems and (digital) technology need to enable a paradigm shift. From a management perspective, there are three main tasks (Montag et al. 2021; Sehnem et al. 2019; Velenturf 2021; Yadav et al. 2020):

- Describing and understanding the logistics network and the stakeholders in the wind energy industry.
- Deriving a vision of CSCM as well as defining a comprehensive target system.
- Obtaining requirements regarding the legal and competitive framework conditions.

The first step is to identify the relevant stakeholders of a circular wind energy industry in Germany. In the wind energy industry, the stakeholders are different in terms of their specialization of skills in comparison to other industries such as the automotive industry. Considering the manufacturing process of wind turbines, a wide variety of suppliers of raw materials and semi-finished products appear alongside the often globally active wind turbine manufacturers, similar to other production networks. But when it comes to installing, maintaining or deinstalling the wind turbines, special skills and technical equipment of regionally acting companies become apparent (Lee/Zhao 2022). This applies to the transport of the components as well as to the (de)installation of the turbines, e.g. offshore with special vessels. During the operation of the turbines, maintenance, repair and overhaul (MRO) services are provided by specially trained companies, for example, due to the work at high altitudes (Poulsen/Lema 2017). At the end of a turbine's life cycle, the turbine must be dismantled and components remanufactured or refurbished or materials recycled to return to the material cycles in an environmentally friendly way (Nachhaltiger Rückbau, Demontage, Recycling und Verwertung von Windenergieanlagen, 2020; Velenturf 2021). The interaction of different players (wind turbine manufacturers, suppliers of raw materials and semi-finished products, specialized installation companies and MRO service providers, dismantling, remanufacturing and recycling companies, port operators, freight forwarders, shipping companies, energy suppliers, etc.) is to be systematically described and the economic and logistical relationships and interdependencies between these companies are to be worked out in order to obtain a comprehensive picture of the wind energy industry in Germany. In addition, critical supply chain components are to be identified that may have an impact on the design of products in the future. For example, the need for sourcing secondary materials or designing the product differently to reduce dependencies on rare earths materials such as neodymium and dysprosium is discussed in literature (Bonfante et al. 2021).

To establish and operationalize the idea of a CSCM in the long term, the individual companies must develop a vision of the circular supply chain for themselves. This vision must be coordinated with the partners in the supply chain in order to avoid the formation of sub-optima. This also includes, for example, the establishment of a target system in order to measure the effects on economic, ecological, social and regenerative goals of the companies and to be able to derive improvements based on this. In conclusion, the stakeholder networks should be transformed from an association of loosely cooperating companies to a symbiotic network of companies acting in a coordinated manner with similar visions.

On this basis, meta-requirements are to be derived which the individual companies cannot directly influence and which work towards the creation of suitable framework conditions. Here, for example, the adaptation of laws and guidelines at the federal level but also at the European level should be considered, since the German wind energy industry is networked with other European countries and is part of the European electricity market. For instance, the European and German carbon emission trading, the German EEG 2021 (Gesetz für den Ausbau erneuerbarer Energien, 2021), the German law for CE (Kreislaufwirtschaftsgesetz) or more specifically the German DIN Spec 4866 on decommissioning and recycling of wind turbines triggers requirements for the German wind energy industry (Gesetz für den Ausbau erneuerbarer Energien, 2021; Die Bundesregierung 2020; Nachhaltiger Rückbau, Demontage, Recycling und Verwertung von Windenergieanlagen, 2020).

In the area of information systems and (digital) technology, a platform must be created that first increases transparency in the wind energy industry (Bundesverband WindEnergie e.V. 2019; Gebhardt et al. 2021; Mendoza et al. 2022; Velenturf 2021). This transparency relates on the one hand to the quantities of components and building units in different value creation stages (raw materials, semi-finished products, plants in operation with assumed residual lifetimes, deinstalled plants, deconstructed semi-finished products, remanufactured semi-finished products, recycled materials) and on the other hand to the available capacity of the individual stakeholders in the German wind energy industry. To develop such an information platform, the relevant data and information must be determined and a data model must be designed. Moreover, a business model and the operator for the platform should be set. Further, the way in which data is processed and transferred (including the definition of access rights) must be defined as well as incentives for stakeholders to share data. The last point in particular presents a challenge (Colicchia et al. 2019). For example, barriers to sharing sensitive data (e.g., material composition of the blades) are to be expected. Nevertheless, also initiatives like a digital product pass (Sozialdemokratische Partei Deutschland et al. 2021) could be applied to the wind turbines as well and could, for example, ease the work for remanufacturing and recycling companies. In addition, as mentioned in section 4, a register of all energy plants in Germany with master data (e.g. on location, installed capacity, operator, date of installation and decommissioning, technical data) already exists (Bundesnetzagentur für Elektrizität, Gas, Telekommunikation, Post und Eisenbahnen 2022). Next to the information to be provided by the stakeholders and the existing market register, big data analytics and the use of natural language processing (NLP) could enhance market transparency (Mendoza et al. 2022). For example Ertek et al. (2017) use NLP to identify wind turbine accidents. With increased transparency, analyses of the past developments as well as forecasts can be made, enabling data-based logistical planning and control of the network and each organization (Gebhardt et al. 2021). For instance, the risk of a bullwhip effect could be reduced if the required demand by each supply chain participant is shared throughout the supply chain (Gebhardt et al. 2021; Sahu et al. 2021). Moreover, process modelling could support the establishment of clean production, logistic and operation strategies (Mendoza et al. 2022). For example, the installation of sensors and the implementation of a predictive maintenance strategy could improve the availability of the components by reducing the downtime (Dulman/Gupta 2018). Along with the management activities it supports a shift towards a circular supply chain (Ellen MacArthur Foundation 2019b; Gebhardt et al. 2021).

6.2. Products Level

The products level focuses on creation, retention and extension of the value through the design for circularity (Montag et al. 2021). Thus, the aim is to design out waste and pollution (Ellen MacArthur Foundation 2019b). Only through an adequate product design, the R-principles can be followed on the processes level (Ellen MacArthur Foundation 2013; Montag et al. 2021). The turbine's or components' designs are typically not specifically adapted for countries such as Germany. Instead, the design reflects different wind and location conditions, e.g. a different foundation for offshore wind near the coast is needed as in deep waters or on land (Hau 2013).

Depending on the aggregation level, the view on onshore and offshore wind energy can be divided into materials, components and infrastructure. Concrete, steel, electronical components (with its rare earth materials neodymium and dysprosium), copper, aluminium, polyvinyl chloride (PVC), operating fluids, composites (glass-fibre reinforced plastic (GFRP) and carbon-fibre reinforced plastic (CFRP) are used materials (Bundesverband WindEnergie e.V. 2019; Lee/Zhao 2022). The key components are the foundation, tower, rotor blades, rotor hub, nacelle, generator, gear-box and grid connection technology (Hau 2013; Lee/Zhao 2022). And the infrastructure view reflects on the installed wind turbine with its grid and road connection (Velenturf 2021).

From a CE point of view, dematerialization of the products should be aimed for. Furthermore, no hazardous and only regenerative or restorative materials should be used. Thus, it should be aimed for a design that allows the distinction between biological/regenerative and technical cycles (Ellen MacArthur Foundation 2019b). A wind turbine enables to produce power from regenerative sources, however the construction of a wind turbine is mainly based on finite materials. As such, the Ellen MacArthur Foundation (2019b) argues that products, components and materials should be recovered and restored trough applying CE strategies, known as R-principles. Hence, wind turbine components should be designed in a way that efficient and effective maintenance, repairment, reuse, repurpose, refurbishment, remanufacturing, disassembly and regeneration is possible (Velenturf 2021). In this context, applying a modular design for components (e.g. to enable the upgradeability) and turbines (e.g. to enable the replacement of components) represents a promising approach. Modularity also qualifies for increasing the durability of the turbine and its components (Bundesverband WindEnergie e.V. 2019; Velenturf 2021). In addition, adequate quality measures for materials and production processes are to be considered. In this matter, it should also be highlighted that the continuous increase of installed capacity per turbine in Germany and associated increase of most components' size, calls for research on how to upgrade old components. With this, the attractiveness for reusing components might increase.

Further, the product design for recycling should ease a recycling in the highest possible quality. For instance, there are dependencies on rare earth materials that are used in permanent magnets for generators (Alves Dias et al. 2020). Those should ideally be replaced by alternative materials when installing new plants and be recycled out of existing plants. Another example are multi-layer composites (GFRP and CFRP) that are used for rotor blades. Composite structures complicate the realization of restorative strategies (e.g. recycling in a high quality) (Beauson et al. 2022). Thus, research is needed to find alternatives.

In relation to Germany, it should be stressed that currently only 10% of the dismantled wind turbines in Germany are put to secondary use. Further, almost 90% of the dismantled components of a wind turbine, based on the total mass, are fed into an orderly recycling process. However, often downgraded recycling takes place and mostly only the metals are being recycled for their original purpose. The demand for secondary raw materials is currently too low and characterized by reservations also due to the quality losses of the recycled material (Bundesverband WindEnergie e.V. 2019).

As the minimum effort, there is a need for aiming to avoid a design that leads to landfill or downgraded recycling (e.g. for most compound structures the case). Beyond, a product design that for example allows the integration of by-products from the industry or other industries has a positive contribution to achieve restorative cycles (Ellen MacArthur Foundation 2019b).

6.3. Processes Level

The processes level aims at implementing and executing the R-principles. As shown in *Figure 4* the processes need to be structured for different products (materials, components and the wind turbine itself). In addition, processes should differ between restorative and regenerative cycles and should aim for dematerialization. As stated above, this can only take place if the products are accordingly designed. In this relation, the choice of adequate business models is of importance. These are implemented on the process level, based on the foundation set in the organization and products level. For example, offering services instead of products requires the development of digital capabilities, a change of the pricing strategy and a transformation of the relationships with customers (Mendoza et al. 2022). For the processes level, the challenges and the questions to be answered for the different levels of investigation (material, component, wind turbine) can be identified using the extended SCOR model by Vegter et al (2020).

The Plan process foresees the product and supply chain design for the wind energy industry. In addition, the planning of the source, make, deliver, use, return and recover process is part of the Plan process. Within the Source process the procurement of raw materials, semi-finished and finished materials, components and turbines from primary as well as secondary sources takes place. The Make process comprises of the production of the components that are then delivered to the site. At the location of the wind turbine, the assembly and installation of the wind turbine occurs. In the Use process, the operation of the turbine alongside the according MRO of the installed components is in focus. As an additional approach to extend the lifetime of a turbine, components can be reused, repurposed, refurbished and remanufactured (Velenturf 2021). Those processes are part of the Recover process (Vegter et al. 2020). In some cases, this can take place at the location of the turbine and components do not have to be disassembled and returned. The Return processes describe the activities associated with the reverse flow of the wind turbines and its components. Thus, the identification of products to be returned and the decision on the decommission approach for the wind turbine as well as the disassemble strategy for the components is necessary. Further, scheduling and performing the return and finally the receipt of the returned products are part of the Return process (The Supply Chain Council 2012; Velenturf 2021). Part of the Recovery process for the materials, is the recycling, alternatively the energy recovery or the landfill to be avoided (Vegter et al. 2020; Velenturf 2021). The Enable process describes the activities related to SCM, for example performance management, data management and resource management (The Supply Chain Council 2012).

For the processes outlined, specific questions arise that need to be answered for an efficient CSCM. In this paper, questions that occur in the Plan process will be addressed in an exemplary manner. In the area of planning, the prerequisites for efficient CSCM must be created, mainly the following tasks emerge:

- Forecasting future installation and decommissioning quantities
- Design of the network depending on a previously defined target system
- Long-term planning of the capacities of the individual stakeholders of the network and also of the inventories.

First, the expected demand of wind turbines in their different life-phases is decisive. To the best of the authors' knowledge, no reliable quantity structure is available today for future installation and decommissioning quantities for wind turbines in Germany. This is an important requirement for the various stakeholders to be able to increase or reduce their capacities in a targeted manner, which sometimes entails very long lead times depending on the stakeholder (e.g. ships for installation of offshore wind turbines) (Mendoza et al. 2022; Sultan et al. 2018). The starting point for such a forecast model is the current information on plants in operation, which can be taken from the in section 4 mentioned market register, as well as the development targets of the German government with regard to the energy volumes to be generated from wind energy in the future. Based on this, influencing variables on the quantity structure to be developed need to be identified. These can be for example the following variables:

- development of MW output per turbine,
- development of land availability for the installation of wind turbines onshore and offshore,
- estimated lifetimes of wind turbines possibly depending on manufacturer, operating site, plant capacity and efficiency.

Scientific work can deal with the creation of such a dynamic model, e.g. using data-based models for forecasting and scenario analyses of the German wind energy industry. It should be considered, that a transformation to a CE will lead to a different timed allocation of demand. For instance, prolonging the lifetime of a wind turbine will lead to a later demand for decommissioning capacities.

Based on these forecasts, the circular supply chain network (production, logistics, MRO, dismantling, reprocessing, etc.) can be designed. The quantity structure resulting from the dynamic forecast model has a significant influence as well as the design of the products (e.g. which wind turbine manufacturer can actually refurbish and reuse which components). Depending on these factors, different network structures can be considered for the individual components (Sultan et al. 2018). For certain components, it may be possible to establish hubs from which the manufacturers can obtain returned components, which may already have been remanufactured to a certain extent. Furthermore, the optimal cascade of CE strategies for the German wind energy industry – in theory reduce, reuse, recycle and recover

– needs to be empirically investigated regarding the achievement of social, economic and ecological objectives (Corvellec et al. 2021; Sahu et al. 2021; Schröder et al. 2019). For example, decommissioning and transporting a German wind turbine to a country on a different continent (e.g. to India) might be less attractive than using local recycling capacities. Therefore, an optimal scenario of a circular German wind energy network looks differently when based on existing capabilities or potential future resources in Germany.

Based on the forecast model and the network design, models are required for the long-term planning of the capacities of the individual stakeholders of the network as well as the inventories at the different stages of the value chain. Hence, capacities such as human resources, fleet size or logistical, production and remanufacturing sites are to be planned. Exemplary questions to be answered in this context are:

- Which capacities will be required in the future at which point in time for the different life phases of wind turbines? What technological capabilities are required?
- Which stocks and strategies can be used for components in order to be able to balance capacity and load in the network?

For the efficient implementation of the core processes according to Vegter et al. (2020), by the various stakeholders in the wind energy industry (with its different materials, components and turbine types), there are questions related to the technical design of the processes as well as the development and implementation of problem-specific planning and control approaches for the individual core processes. Current research is already addressing some of those questions.

7. Conclusion

This paper structures the circular wind energy supply chain in Germany according to its organization, products and processes level. The aim was to contribute to the research question 'What is required for a CSCM in the wind energy industry in Germany?'. Thus, it provided an overview of tasks and related research questions. This paper represents a starting point and needs to be underpinned with further expert interviews, surveys, market data analytics and scientific research. Nevertheless, as a sustainable transformation of the economic system is urgent, the discussion on a suitable design of a circular supply chain for the German wind energy industry should start now. When developing the associated CSCM, strategies for the existing portfolio as well as for the portfolio to be developed should be reflected.

For future research, modelling demand and capacities of different stakeholders and the entire supply chain under complex dependencies is key. Thus, scenario analyses reflecting the actual and planned geographical allocation of turbines as well as stakeholder capacities (e.g. remanufacturing sites) under different CE maturity degrees should be developed. Additionally, first ideas on designing a circular wind energy network were presented in this paper. An interesting research field might also be the mapping of material flows across different supply chains. If the necessary data basis exists, artificial intelligence methods could support to analyse similarities between supply chains and to indicate synergy effects (Ellen MacArthur Foundation 2019a). This contribution focused on wind turbines located in Germany, however, for compiling the application of restorative strategies across the entire lifecycle of a wind turbine, also synergies with other countries could be meaningful.

It should also be stressed, that the theoretical concept of CE and CSCM is still evolving and further practical evaluations are needed (Corvellec et al. 2021; Sahu et al. 2021; Schröder et al. 2019). For example, it still needs to be empirical validated if CE contributes to more sustainability and resilience in the wind energy supply chains. In this context, also the different product and process design strategies need to be evaluated on their contribution towards becoming more circular. Even as the CE concept is seen as promising, implementing the idea of CE across entire supply chains or ecosystems remains a major challenge (Corvellec et al. 2021; Kirchherr et al. 2018; Lopes de Sousa Jabbour et al. 2018). In this context, for example, digital technologies and strategic cooperation could help to ease the implementation (Gebhardt et al. 2021; Kirchherr et al. 2018).

In conclusion, as the achievement of a CE foresees a system change an evolvement of different disciplines is necessary. The provided ideas form a starting point for future discussions and should encourage researchers and practitioners to join those discussions.

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Towards Designing Adaptive and Personalized Work Systems in Manufacturing

Sebastian Schlund, David Kostolani

1. Introduction

The manufacturing sector in Europe still holds significant importance. Within the European Union's (EU) non-financial business economy, manufacturing industry accounts for around 29.7 per cent of the gross value added and 23.1 per cent of the employment (Eurostat 2021). For Austria, the number of employees in industry is even expected to increase over the upcoming five years (Patsch et al. 2021). Thus, human labour still plays a significant part in manufacturing.

However, the future of EU labour will be impacted by demographic change. As the average age of workers is expected to increase, the development of age-appropriate work systems will become more important (Dombrowski et al. 2013). This evolution will push the concept of adaptive work systems. Adaptive work systems are systems that, besides taking requirements of various age groups into account, also focus on the idea of personalization – from age appropriateness to other diversity parameters such as gender, cultural background, or experience. The adaptation of work to human's characteristics, instead of humans adapting to the work environment, has been a central goal of human factors/ergonomics since its origins as a scientific discipline in the 19th century (Jastrzębowski 1857). Furthermore, this concept could also contribute to achieve the sustainable development goals (SDGs) set up by United Nations, like 'Good health and wellbeing', 'Decent work and economic growth', and 'Industry, innovation and infrastructure' (UN 2012). Recent aspirations towards human-centric manufacturing systems as one of the goals of the Industry 5.0 initiative (European Commission 2021) further push the concept of adaptivity.

Up to the present day, personalization of the work environment has not been fully exploited in real-life settings. This could potentially change with the continuous integration of advanced sensory skills into work systems. This trend has been largely driven by the development towards Cyber Physical Production Systems (CPPS) as integration and exploitation of the concept of cyber-physical systems (CPS) within manufacturing operations over the last decade (Monostori et al. 2016). Ever since the concept of CPS, the integration of sensors to allow perception drives the development towards context-aware systems. Various sensors, sensor fusion, and wireless data transmission enable the creation of digital twins as digital representations of objects and product-services (Stark/Damerau 2019). However, to this day, there is a lack of underlying standards for the development

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and deployment of context-aware systems, which is often attributed to a high diversity within domain-specific requirements (Li et al. 2015). As a result, these systems are developed in a somewhat ad-hoc manner. A transferable body of advice could benefit the scalability of applications and ease the deployment (Augusto et al. 2022). In manufacturing, a unified framework that covers the transformation from the trend of CPPS to human-centred, adaptive, and personalized work systems is still not available.

In this paper, we explore the current status of conceptual consideration of adaptation and personalization within the scope of socio-technical work system design. For the latter, we lean on the principles of socio-technical theory (Trist 1981), to consider both the social and technical dimensions and parameters within a systematic process across the entire life cycle of a work system as, among others, suggested by (Sony/Naik 2020). We collected and analysed existing approaches, both methodological and application-oriented, and aim to contribute to the following research question:

How can adaptivity and personalisation be integrated into the design of work systems in manufacturing?

The paper explores roots of the concepts of adaptive and personalized work systems and shows possible individualization dimensions for work systems in manufacturing. Based on this, exemplary concepts and implementations of individual dimensions are presented and placed in the overall context. The focus is set on implementations within the TU Wien Pilot Factory that cover adaptability concepts on workplace, process, and system level:

- Adaptive projection of work instructions and additional information
- Adaptive task sharing between humans and cobots within operation
- Natural user interfaces for assembly processes (speech, voice, hand-guiding)

Based on these results, the next necessary prerequisites and development steps are discussed and put into the context of the current great challenges within production management and human-computer interaction (Stephanidis et al. 2019).

2. Research Background

Reconfiguration has been considered as one of the main fields of interest for digitalization and enhanced data collection. This has led to an interconnection between the virtual and the physical world, also known as twinning (Jones 2020). Digital twins and CPPS allow digital processing and planning with closely interconnected physical manipulation to create self-X capabilities, thus self-aware, self-configurable, self-optimizing, and self-predictive systems or artefacts (Oliff et al., 2020). The notion of self-X implies the adaptation and alignment of behaviour, state and positions of objects towards desired system output. This allows for better recognition of the work environment and the actual state of the system. Together with actuator capabilities, it enables adaptive systems that adjust their structure and behaviour according to changing requirements (Keddis et al. 2013). The concepts of flexibility and changeability of manufacturing systems have long been some of the main objectives within the scope of manufacturing research. CPS capabilities now allow to adapt to changing demands, order volumes and their unexpected changes and even shocks from the outside environment.

Adaptation as adjustment of a system's shape and behaviour to changing conditions combines decision making, decision informatics, and human interface (Tien 2008). The degree of complexity increases in four dimensions according to the scope of the actions considered. For the first two dimensions, monitoring and feedback, adaptation is based on a set of expected (standardized, procedural, or algorithmic) actions. Cybernetic adaptation as the third dimension additionally includes dynamic actions in unknown states. Lastly, learning adaptation considers unstructured actions based on cognition, evidence, and improvisation (Tien 2008).

However, as Tien (Tien 2008) further points out, "adaption is a uniquely human characteristic", hence, adaptivity does not only cover the adaptation of technical systems but also socio-technical systems. Real-time capable perception enables adjustments of technical artefacts towards anthropometric and cognitive features and requirements of the users. This adaptation of work to human characteristics has been a central goal of human factors and ergonomics. Up to the present day, for work systems, this paradigm has been approximated to the best of our knowledge via the detour of percentile logic and orientation to the statistical normal distribution of, for example, anthropometric characteristics. The actual adaptation of work to the specific features, conditions, and requirements of individual users has so far only taken place in rudimentary form (e.g., height-adjustable workstations or adaptation of lighting parameters in accordance with circadian patterns). However, the possibilities that have opened up in recent years by the advances of CPPS, and also intrinsically safe robotics or self-learning data evaluation systems are now enabling a renewed attempt to implement the goal of adapting work to people through symbiotic human-machine work systems (Wang et al. 2019).

As work systems are socio-technical systems, participation and self-organization of work, coordination and cooperation of the organization improve performance (Gittell at al. 2009) and increase comparative advantages (Appelbaum et al. 2000). The roles, tasks and degrees of freedom of human workers are considered beyond the strictly technical understanding of humans as 'resources'. Over the last decade, the focus of work systems design in manufacturing shifted from operator-less factories and autonomous CPS (Benkamoun et al. 2014) towards the importance of human-centric work design (Ganschar et al. 2013) and worker-centric approaches like Operator 4.0 (Romero et al 2016) or Industry 5.0 (Xu et al. 2021). Recent approaches emphasize the importance of synergetic interaction of the involved agents and objects within the notion of symbiotic human-robot collaborative assembly (Wang et al. 2019) or even towards living manufacturing systems (Monostori/Váncza 2020). However, most of the work emerged in this area only handles the conceptual principles and benefits of human-centred, context-aware work systems. Standards and frameworks on which information is relevant for the agents, what data to collect, and how to infer and interpret this data to adapt the system are still absent (Malik 2007). This results in significant engineering challenges. As developers lack guidelines or at least good practices to follow during the engineering process, systems have to be developed in an ad-hoc fashion (Augusto et al. 2022). As a consequence, transferring prototypes into real-life applications presents a rocky road, while interoperability can be hindered by the absence of common practices (Alegre et al. 2016).

While adaptivity of man-machine systems is a seemingly new concept within manufacturing, in the area of human-computer interaction, transferring the technological concept of reconfiguration into man-machine systems has been a core topic for many years. Adaptivity within human-centred computing is closely connected to the emergence of artificial intelligence and motivated by the increasing availability of computers, smart phones, and internet (Ahmad et al. 2004). As these trends redefined the way technology is used, usability, i.e., the extent to which the product can be used (Yazdi/Göhner 2021), has been gaining importance. Hence, it became necessary to adjust the services to accommodate requirements with respect to the environment the technology is used in to ensure high usability. Furthermore, with the ever-widening diversity of the audience, adaptivity is considered to be the key to universal accessibility of technology (Miraz et al. 2021). Adaptive and Intelligent User Interfaces have been developed to cope with these challenges (Akiki et al. 2014). Using data collected through context sensors and artificial intelligence for advanced decision making, the goal is to meet the demands of users to achieve specific goals when using technology. As proposed by (Yazdi/Göhner 2021), the interaction between humans and machines or computers should be adapted to be *environment-specific, task-oriented*, and *user-specific*.

Environment-specificity denotes the adaptation of technology to the conditions (auditory, visual, thermal, etc.) of the environment (Yazdi/Göhner 2021). A prompt example of this concept is the use of light sensors for adaptive adjustment of brightness, common for smart phones and displays (Yigitbas et al. 2020). *Task-oriented* adaptation focuses on understanding the interaction between the human and the machine through data collection and subsequent task recognition (Yazdi/Göhner 2021). Upon gaining knowledge of the task currently performed, a machine can adapt and take over tasks from users, allowing them to focus on other activities (Álvarez-Cortés et al. 2007). Finally, *user-specificity* refers to the personalisation of systems, accommodating user's needs. As individual users differ in various dimensions such as habits, expertise, or experience, an ideal system should adapt and personalize its services to user characteristics (Norcio/Stanley 1989).

However, it is important to note that accommodating the individual characteristics of the users is achievable either through adaptability or adaptivity. While adaptive systems are marked by the system dominating the adaptation process, actively initialising actions and tailoring itself to the user in an intelligent fashion, adaptable systems are still dominated by the user. Hence, an adaptable system requires user action or user approval to confirm the personalization process (Gulla et al. 2015).

In recent years, these concepts for adaptive human-machine systems have begun to find their way into work systems. Personalization of a work system to human characteristics, preferences, and behaviour is discussed in (Cohen et al. 2018) within a framework for human-machine interaction at the workstation level. On a work organization level adaptations due to worker's fatigue and reliability (El Mouayni et al. 2019), different performance levels and human limitations (d'Avella/Tripicchio 2020) are considered. User-centric and self-configured workstations that adapt to anthropometric characteristics of individual workers are described on a framework level in (Bortolini et al. 2017), regarding specific personalization options in (Rupprecht/Schlund 2021), and by the example of an assembly system for aircraft parts in (Mayrhofer et al. 2019).

Besides conceptual and theoretical contributions, adaptivity and personalisation in terms of industrial man-machine systems have been addressed by various practical works. Personalized adaptation within multi-operator industrial processes has been shown to improve the interaction with the machine, resulting in better performance and less errors, as showcased in (Reguera-Bakhache et al. 2021). The adaptation of lighting conditions was studied in (Bauer et al. 2015), presenting an adaptable solution for personalisation of the work environment. Task-oriented systems for adaptive task sharing between workers and robots can propose optimal task allocation, increasing the cost efficiency of human-machine systems (Schmidbauer et al. 2020). Other applications of task-oriented cyber physical systems include the recognition of human activities through wearables for automated augmentation of work instructions and evaluation of work performance (Tao et al. 2018) or cameras for interaction with industrial robots (Roitberg et al. 2014).

As presented in this selection, a broad range of approaches towards adaptive and personalized work systems have been proposed in the literature. In the following section and in Table 1, we cluster these approaches and different concepts of adaptability with regard to human-centricity.

Concept	Description	Human Centricity
Adaptable Work System	The system is technically capable to be adjusted to the changes in the work environment (e.g., work process, status)	
Adaptive Work System	The system can detect changes in the work environment and adjust itself accordingly (e.g., work process, status)	
Adaptive Human-Machine Interface	The system can adjust itself to user-specific parameters which dynamically occur during the work process (e.g., activities performed by the users, errors, or stress levels)	
Personalized Human-Machine Interface	The system can dynamically adjust itself to the different user characteristics (e.g., physical parameters, level of expertise)	

Table 1: Concepts of adaptive and personalized work systems

Adaptable work systems can be adjusted to changes in the work environment. This adaptation does not have to be performed in an automated fashion but can be achieved with manual manipulations. With respect to the integrated sensory capabilities *adaptive* work systems can detect changes in the work environment and autonomously adjust themselves accordingly. Typical triggers are changes in the work environment, such as reconfigurations of assembly lines. *Adaptive human-machine interfaces* can adjust themselves to user parameters, which dynamically occur during the work process. The system therefore monitors, and analyses activities performed by the users, poses, or work positions with specific assistance needs such as overhead work, or stress levels. However, these interfaces do not differentiate between individual users. *Personalized human-machine interfaces* dynamically adapt to the individual characteristics of different users. These might be anthropometric parameters such as reach, preferred hand, level of expertise, or working habits. According to the orientation of the system's behaviour on the worker, the human-centricity of the discussed concepts improves and peaks in personalized human-machine interfaces.

The adaptation itself takes place within different time frames. Existing concepts consider quite different scopes ranging from design adjustments in reconfiguration and replanning options to hard real time adjustments. We summarized these time frames in Table 2. The response for *real time* adaptations usually covers milliseconds. These requirements usually are relevant for adaptive work systems in close interaction with the user such as active exoskeletons. If the adaptations take place within the work process, e.g., within the repositioning of material, tools and information for subsequent work tasks, *operation time* adaptations are sufficient. For update purposes, e.g., the adjustment of the work system to the anthropometric characteristics of the workers of the following shift, *re-design response times* are considered. In case adaptation is used for planning and reconfiguration purposes, adaptations take place in *design time*.

Response Time for Adaptation	Description
Real Time	Adaptation within real-time constraints to assure system output
Operation Time	Adaptation during the operation by the user
Re-Design Time	Adaptation to users' specifics within work system updates
Design Time	Adaptation to users' specifics within work system planning and design

Table 2: Response times for adaptation

3. Design Framework

The concept of work systems within the domain of manufacturing is per definition following a socio-technical perspective. Relevant normative approaches therefore follow an understanding of the respective system as selection of technological, organizational, and human-related system elements and their interrelations. The DIN guideline 6385 (DIN 2016) presents a work system model that contains the transformation of input into output by work procedures that are executed to fulfil a given task by humans and work equipment at a defined workplace under the impact of various conditions of the work environment.

As aspects of adaptation and personalization build up on information about the actual status and changes of work environment, digital representations of human parameters and behaviour as well as of the work environment are necessary. The consideration of the *work environment* includes parameters that have to be taken into account for adaptation purposes like adjustments regarding noise and exceeding temperature limits. The work environment dimension additionally represents the demarcation of the work system and the interface to adjacent ones.

In order to be capable of any adaptation, the *work equipment* contains sensors and actuators. For data analysis and data handling, it is necessary to consider cognitive functionalities (data processing, perception, cognitive control, learning) and communication infrastructure. Depending on the setting of the work system design, work equipment and *workplace* might be closely interrelated or even integrated. The use of mobile manipulators as personal companions for the material provisioning (Schlund et al. 2018) or height-adjustable workplace carriers (Nguyen et al. 2014) integrate the two dimensions.

The *human operator* brings in his or hers physical and psychological prerequisites and disposition. The operator induces context changes through the interaction with the environment like changes in the spatial information, e.g., location, orientation, and pose of the human.

In between the two principal agents - *human (operator)* and *work equipment (machine)* - information about further interrelations might be necessary. If specific adjustments are triggered by certain work tasks like special lighting in case of error-prone or quality-critic assembly tasks, start and end time as well as spatial information about the *work task* is needed. Information about *work organization* covers defined, possible, or preferred task allocation patterns for one-to-one relations between human and machine agents, as well as for individual preferences and skill sets. *Human machine interaction* includes the context of the user within the interaction with other agents and environment. Information is necessary for the adaptation of implemented modes and combinations of bidirectional feedback between humans and machines. Task orientation through the recognition of human activities (human activity recognition, HAR) allows for analytics and tracking of the *work process* and together with the human machine interaction adaptations of the work system. The conceptual framework for the work system model is visualised in Figure 1.

The presented conceptual framework aims to map the transition from today's work systems towards dynamic adjustability and contribute to a closer integration of digital enabled capabilities into work system design. Traditional work system design within the scope of manufacturing is based mainly on the principles and methods of ergonomics (DIN EN ISO 6385 2016), process organisation, and internal logistics, taking into account the interests of functional, economic, reliable, ecological, user-adapted, and safe solutions (REFA 2022). Our proposed framework extends the traditional system elements towards requirements and interrelations that are considered to be helpful to design adaptive and personalized work systems. While still building on the roots of a well-founded socio-technical system approach, it places focus on the integration of cognitive features and capabilities.

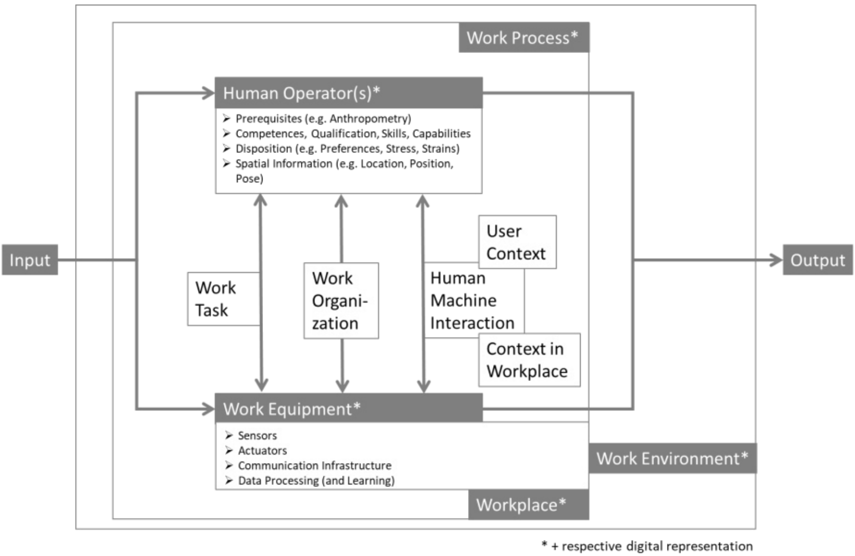

Figure 1: Work system model for personalized work systems

All dimensions of the work system (human operator, work equipment, work process, workplace, and work environment) are subject to modelling and simulation of digital representations. A digital twin of the entire work system therefore covers the dimensions and combines existing approaches like digital human models, CAD-CAM-based processes, workplace models and state trackers. For the realization of real time or operation time adjustments, fast and precise sensors, and robust datasets need to be present. Otherwise, adjustments can only take place at a very limited scope, e.g., closed feedback loops between a very specific worker pose and a predefined parameter setting of the workplace, implemented in a hard-coded fashion. For a truly adaptive work system within the understanding of Figure 1, an integrated work system twin or at least interconnected twins of the respective dimensions are necessary.

4. Examples

Despite adaptive work systems on a larger scale are still being subject of various challenges, realizations of separate adaptive or personalized functionalities already exist. Following, exemplary contributions of TU Wien are introduced that contribute to the adaptive interconnection between human operators and work equipment.

4.1. Adaptive projection of work instructions and additional information

Information provisioning for industrial site assembly, e.g., the manufacturing of larger aircraft parts, trains, or prefabricated building components, is today mainly executed via terminal displays. Projector systems enable the display of information directly on the workplace or other surfaces in direct relation to the work task, such as walls, desks or the floor. This approach prevents walking routes to static terminals, enables hands-free work, and is ergonomically favourable to head mounted devices (HMDs), especially when used over a longer period of time - like a shift. Within a setup of a carbon tape-laying process of a fan cowl, an adaptive spatial augmented system was implemented. Using a projector and a mirror-head to dynamically move the projection, the information is displayed where needed, depending on the specific task and the position of the worker. Cameras are used to detect user context and interact with the system. This is performed using the YOLO object detection algorithm (Redmon/Farhadi 2018), capturing the position of the worker and his or hers gestures to interact with the system. Figure 2 shows the concept, the demonstration setup in the TU Wien Pilotfabrik and the results of the selected evaluation metrics (Rupprecht et al. 2021). Regarding the work system model presented in Figure 1, the example is directly related to an adaptive system, considering the interaction between the operator and the equipment on a task level.

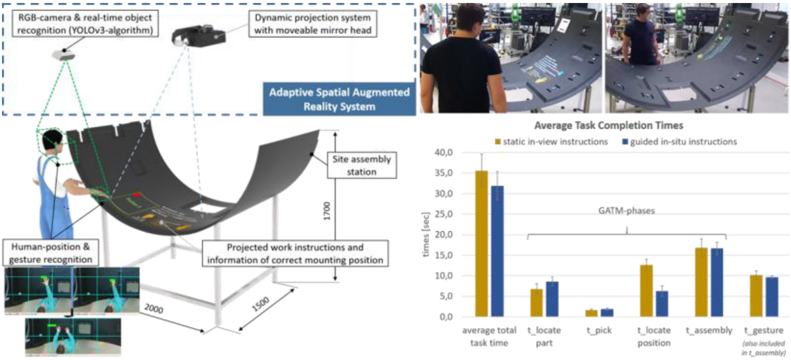

Figure 2: Adaptive projection of work instructions and additional information

4.2. Adaptive task sharing between humans and cobots within operation

The allocation of work tasks to human and machine interaction partners has been a research question since the beginning of industrial automation. Beyond leftover and compensatory approaches, complimentary task allocation is considered to be favourable from an ergonomics point of view, but up to date not often realized. The adaptive task sharing (ATS) approach (Schmidbauer et al. 2020) allows ad hoc changes in the selection of tasks that are attributed to either the human or the machine. First, the task allocation is pre-assigned by the system according to specific requirements like lot size, ergonomics, and individual (worker) preferences. Hence, the task allocation patterns are adaptive and can be personalized to a specific user. Within operation, the system allows a fast reattribution of tasks to the interaction partners. The system was implemented using a BPMN engine and Node.js Task Client. The communicating between the robot and the web interface is performed via REST API, utilising a state machine to monitor the task status. The workflow sequences have to be pre-programmed in advanced and are later retrieved during the process. Tasks that are executable by either the cobot or the human (shareables) are subject of possible reallocation before any new process operation (Schmidbauer et al. 2021). Regarding the work system model, the example is situated at the work organization level between the human and the machine and expands towards work settings with multiple human and machine agents.

Static task allocation

Human	Shareable	Cobot
Tasks not-executable by a cobot (leftover) or effort for automation is too high (compensatory)	Not foreseen	Tasks executable by a cobot at reasonable costs or tasks that are disadvantageous for humans

Adaptive task sharing

Human	Shareable	Cobot
Tasks not-executable by a cobot (leftover) or effort for automation is too high (compensatory)	Tasks executable by humans and cobots that can be shared adaptively according to decision criteria	Tasks executable by a cobot at reasonable costs or tasks that are disadvantageous for humans

Figure 3: Adaptive task sharing between humans and cobots in manufacturing

4.3. Natural user interfaces for assembly processes

In order to simplify programming of cobot applications for more flexible reconfiguration and task allocation approaches, natural as well as multimodal user interfaces tend to be more intuitive and productive. Tests with a combination of hand guiding of a cobot and voice control show up to 46 percent decrease in teach-in time for simple pick and place operations (Ionescu/Schlund 2021). Besides the productivity increase, flexible set-ups of different interaction modes, such as textual and graphical user interfaces, hand guiding, gesture and voice control, or even brain-computer interfaces are possible. The integration of these different interaction modes has been made easier by open libraries, such as (Zhang 2017). Most of these approaches to the interface are adaptable, e.g., the user can adapt the voice-user interface to return voice information in either male or female voice, adjust the speed, or train personal commands for brain-computer interface. In order to upgrade from adaptable to adaptive and even personalized human-machine interfaces, automated recognition of the user context and the context in the actual workplace setting has to be considered.

4.4. Challenges towards designing adaptive and personalized work systems in manufacturing

Following a socio-technical approach in designing and implementing the presented use cases, we address some challenges encountered during the design of adaptive and personalized work systems. Overall, there is an evident lack of implementation standards and dedicated open datasets for the retrieval of user context, e.g., for activity recognition in manufacturing. For example, the dataset for the gesture control utilised in example 5.1 had to be created from scratch. As a consequence of the lack of open datasets and standards, data generation and system development are time-consuming. This makes the transfer of these applications into industrial settings difficult. Data privacy and data security pose further challenges. As adaptive work systems rely on data collected by sensors integrated in the environment, they could potentially expose the privacy of workers, if not secured through the use of appropriate processing techniques. Furthermore, while employees expect to have control over the data they provide to the employer, company-related data is also under threat in the event of a security breach. This poses a potential risk to internal know-how. Due to a lack of experience and established implementation solutions, there are reservations in many companies about fully exploiting the advantages of digitalisation to the extent that is technically possible.

5. Conclusion

Within the context of sensor integration, ubiquitous computing, and real-time-capable over-the-air communication of large data streams, adaptive work systems have already become feasible within small, isolated applications. Adaptivity can be triggered by changes in the context in the work system or individual characteristics and preferences. Adaptive and personalized work systems have the potential to implement human-centricity and therefore to fulfil one of the oldest imperatives of ergonomics: to adapt work systems to the workers. However, in order to design and implement adaptive and personalized work systems on a large scale, modelling approaches of different domains (engineering, human factors, human-computer engineering) have to be brought together to create a common framework. This paper introduces first steps in this direction in enlarging the work system model of DIN EN ISO 6385 towards the integration of further elements and to show the relevant direction of future development towards adaptive and personalized work systems in manufacturing. However, the conceptual work is far from being finished. To date, reference models for human-centric manufacturing approach this goal from a more production-technology related angle (cf. Lu et al. 2022). As the topic per se is transdisciplinary, shared or at least known agreed and mutually accepted models across the disciplines of engineering, human factors, human-computer engineering are needed.

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Human-Centered Design of Hybrid Cyber-Physical Production Systems

Use of Human Autonomy Teaming as a Future Way of Working

Hendrik Stern, Michael Freitag

1. Motivation

Many production processes are changing toward hybrid cyber-physical production systems (CPPS) in which physical and computational elements and humans are interconnected (Spath et al., 2013). In such hybrid CPPS, humans work together with intelligent and automated or autonomously acting systems (hereafter in this section collectively referred to as automated systems). The allocation of tasks to automated systems enables economic advantages through more efficient processes, error reduction, quality improvements, or easier work for operators. Consequently, it contributes to sustainable production, preserving resources (e.g., by reducing waste or saving energy due to error prevention and increased efficiency). Besides, it positively impacts operators (e.g., by eliminating physically demanding tasks or by reducing cognitive workload through assistance systems) (Chen et al., 2020; Santochi & Failli, 2013).

An important design question of automated systems is the distribution of tasks among the different actors. With respect to the type and extent of the automated tasks compared to human work tasks there are different approaches of system design (Parasuraman et al., 2000), e.g., allocation of tasks according to feasibility and costs (Manzey, 2012; Salvendy, 2012). Beyond these rather technical and economical motivated approaches, other ideas consider humans and automation as a complementary, hybrid system in which humans take the role of supervisory control (Sheridan, 2012) or operate as partners (O'Neill et al., 2020). Here, various design guidance is available such as the creation of active involvement of people, access to complete and real-time information on automated tasks to create adequate situational awareness (Endsley, 1995), and the consideration of both operators and automation as equal and independent actors of the overall system (Manzey, 2012; Sheridan, 2012). Additionally, further research work considers the role of humans in CPPS in general as that of a partner of automation, which takes a central role in a partially automated, human-centered production system (Operator 4.0) (Rauch et al., 2019; Romero et al., 2016).

But how do these different approaches and principles of designing hybrid CPPS affect the overall system performance and, in particular, the operators in detail? The knowledge of these effects is of significant importance for the usability of

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these concepts (Rauch et al., 2019) and will be crucial for their success. Therefore, this paper deals with how these systems must be designed to achieve both economic and human-centered goals (e.g., overall system performance, work performance, workload, human work perception, or sustainability). We first present the results of a first literature review on the state of the art regarding the interaction of humans and autonomous systems in production systems and the associated division of work (Human Autonomy Teaming, HAT). Here, we especially emphasize autonomously acting systems. On this basis, open questions regarding system design are derived (e.g., in terms of degree of autonomy or interface design). Finally, we propose and discuss preliminary ideas and starting points to solve these design issues. These shall serve as a basis for future research work.

2. Human Operators in CPPS

Work design addresses measures that contribute to a change in existing work systems or the creation of new ones. A work system consists of humans, workplace, work equipment, work environment, and work organization (Spath et al., 2012). From a human-centered perspective, work design is concerned with creating work systems that enable safe work that is neither physically nor mentally exhausting (Wegge et al., 2014). Hackman and Oldham (1976) have described various motivational effects for operators in this context, e.g., through task variety, comprehensiveness, and meaning (Oldham et al., 1976), which continue to be an essential basis of work design nowadays. Autonomy in execution and feedback on the task outcome were also identified as beneficial (Hackman & Oldham, 1976).

Implementing CPPS will bring profound changes within work systems in many manufacturing work domains (see Section 1) and thus put the applicability of existing principles in the focus of research. A human-centered design of the new work plays a crucial role in determining the extent to which targeted quality or performance improvements are achievable. A central challenge here is the design of interfaces between operators and machines. Only if operators working with and on the CPPS can control and comprehensively understand its actions, adequate decisions in line with the CPPS are possible (Hirsch-Kreinsen, 2014). In Stern (2020), based on a study-based investigation with 68 participants, the authors showed that different design elements of work in CPPS (e.g., level of information display and type of user interface design) have significant effects on work performance and work perception (Stern, 2020).

Although the ideas regarding CPPS based on Industry 4.0 concepts have not yet been finalized or fully established, we are already starting to look at the subsequent Industry 5.0 (Nahavandi, 2019). Industry 5.0 focuses on the interaction between humans and autonomous systems, while Industry 4.0 is primarily based (only) on interconnected, automated systems. In Industry 5.0, humans and machines act together to bring human capabilities (such as creativity or cognitive skills) to fruition through the collaborative support of machines while liberating humans from tedious, repetitive tasks (Nahavandi, 2019). In this way, efficient and value-added production is possible, which can also be resource-efficient (e.g., in terms of material waste or energy consumption during production). Industry 5.0 can thus contribute to current sustainability and environmental goals (Nahavandi, 2019).

In summary, the concept of Industry 5.0 is based on intelligent assistance systems and tools, and intelligent automation or autonomous systems that enable collaboration between humans and machines. In this context, trust and reliability are decisive criteria. As a result, significant increases in efficiency are possible, including error-free production (Nahavandi, 2019).

Linked to considerations on Industry 5.0, there are also already initial characterizations of the role of people within these systems. Operator 5.0 describes a human operator in production systems who interacts with machines (in this case, robots, automated and intelligent systems) in a trusting manner and utilizes the potential of CPPS (Romero & Stahre, 2021). The authors assume that this will result in levels of efficiency, productivity, and resilience of CPPS that neither fully automated nor classic manual systems can achieve (Romero & Stahre, 2021). Such systems can be, for example, the interaction of humans with intelligent cognitive assistance systems or collaborative robots. Figure 1 depicts examples of such systems: (1, 2) show cognitive assistance systems based on a smartphone (1) and data glasses (2), which display context-dependent Augmented Reality (AR) virtualizations for assembly and maintenance support based on image recognition methods (Quandt et al., 2020; Stern et al., 2021). (3) shows a collaborative robot system that supports the unloading process of containers by autonomously performing unloading operations under human supervision (Petzoldt et al., 2020; Rolfs et al., 2020).

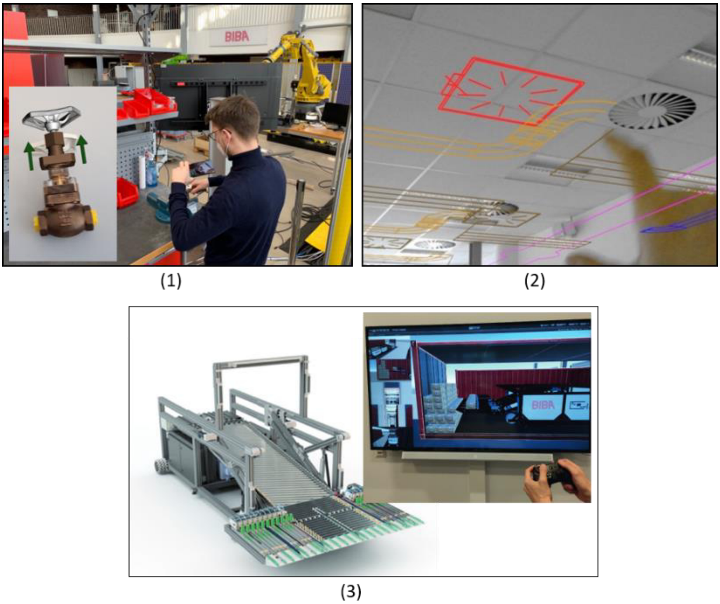

Figure 1: (1) cognitive AR assistance system (smartphone), (2) cognitive AR assistance system (data glasses), (3) interactive robot unloading system

Involving operators in the design of CPPS can be done by applying Human-Centered Design (HCD) approaches, which provide for an intensive alignment of the development process with the users' requirements (Boy, 2011). One example of HCD is Contextual Design, a method that considers the context and the requirements of a system to be developed. Here, requirements are elicited via interviews, the obtained information is consolidated and analyzed, and an idea is derived. The idea again is evaluated with users at the prototype level. The approach emphasizes the importance of a clear picture of user requirements, which designers cannot replicate independently. For this purpose, user input is required (Holtzblatt, 2009; Jacko, 2012).

In summary, the change of production systems towards CPPS according to the Industry 4.0 and, in particular, the Industry 5.0 concepts evoke new forms of cooperation between humans and machines. In Stern (2020), the authors could show the effectiveness and positive effect of HCD on work performance and work perception for CPPS for a collaboration of humans and (partially) automated systems (Stern, 2020). Going further, it now seems necessary to adapt and transfer previous findings for a human-centered work design to CPPS according to the Industry 5.0 concept, i.e., in the sense of collaboration between humans and autonomous systems as HAT.

3. Human-Autonomy Teaming in Manufacturing and Logistics

The implementation of CPPS often requires intelligent and autonomously acting systems (Schelble et al., 2020). Examples of this are predictive maintenance, cognitive assistance systems, or collaborative robots based on artificial intelligence (O'Neill et al., 2020). In the case of interaction between humans and machines, this is referred to as HAT (Demir et al., 2019; Schelble et al., 2020).

HAT describes an interaction between (multiple) humans and (multiple) autonomous systems with mutual dependencies regarding work actions and the achieved work results. All team members (both humans and machines) have clear roles and pursue a common goal in completing the task (Demir et al., 2019; O'Neill et al., 2020). A distinction is made between the concepts of automation and autonomous systems. Automation is the execution of a task by a machine that was previously fully or partially executed by humans (McNeese et al., 2018; Parasuraman et al., 2000). The degree of this task takeover (automation level) was described by Parasuraman (2000) by the level of automation (LOA) continuum. It ranges from fully manual tasks to low and medium LOA, where basic tasks are performed by the machine, to full automation, where the machine alone decides and executes. At the same time, the human operator has a passive role (Endsley, 2017; O'Neill et al., 2020).

According to Parasuraman (2020), O'Neill et. al (2020) made a transfer to autonomous systems as an adaptation of the LOA continuum. Here, the original LOA was transferred into three groups of autonomous systems (no autonomy, partial autonomy, and high autonomy). Figure 2 shows this continuum. According to O'Neill et al. (2020), for a human-machine-system to be designated according to the concept of HAT, there should be at least partial autonomy (corresponding here to level 5 on the original LOA continuum, where the machine performs a spontaneous action after confirmation by the human operator) (O'Neill et al., 2020).

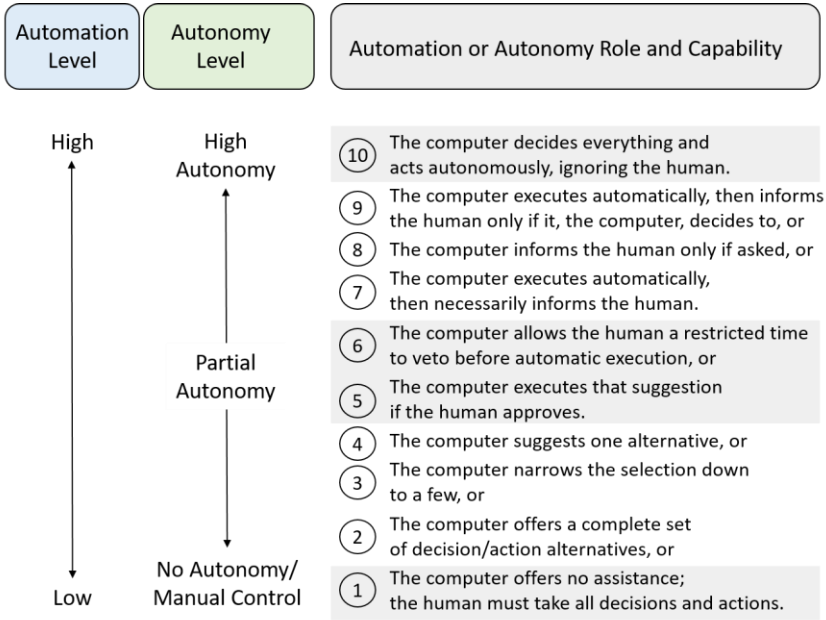

Figure 2: LOA continuum for autonomous systems according to O'Neill (2020) and Parasuraman (2000)

The concept of HAT has many overlaps not only with the ideas of Industry 5.0 (4.0). Still, it can also be found within the ideas of Smart Factory or Smart Production, Ubiquitous Manufacturing, and Digital Manufacturing (Mabkhot et al., 2018). For example, the role of humans is also discussed in the Smart Factory and described as that of a highly skilled operator who is not only involved in the manufacturing process in a traditional way but is also responsible for monitoring and supporting the autonomous systems (Mabkhot et al., 2018).

Overall, the interface between humans and machines is addressed in many research works investigating use cases within CPPS, even without an explicit focus on HAT (Stern 2020). For example, (Mabkhot et al., 2018) describes an assembly work system in which necessary tools, work steps, and the complete CAD model of the product can be visualized. In addition to classic displays or handhelds, projection or AR can also be used as hardware (Mabkhot et al., 2018). The human-machine interface design in CPPS is as a crucial challenge (Hirsch-Kreinsen, 2014; Siepmann & Graef, 2016).

Furthermore, a human-oriented work design in CPPS also leads to sustainable production systems. Besides its beneficial impact of resource consumption and energy usage mentioned in Section 1, sustainable production can also be achieved through sustainable work in terms of physical and mental health, satisfaction, working conditions, or opportunities for learning and training (Santochi & Failli, 2013). This requires minimizing employee stress through knowledge and involvement, trust, and ergonomics (social, mental, and physical). Sustainable work can be achieved, for example, by providing information in the direction of the operator (e.g., about products, processes, and scheduling) and in the direction of the autonomous system (e.g., about difficulties, errors, suggestions) (Santochi & Failli, 2013).

In summary, a central role of humans in the production systems of the future is postulated by many sources. In a paper by Zhou et al. (2019), the term Human Cyber-Physical System (HCPS) is used for this purpose. It refers to an intelligent production system that consists of humans and digital and physical systems with the aim of achieving production goals in an optimized way (Zhou et al., 2019). Here, the CPPS are based on intelligent, autonomous systems (Gronau, 2016; O'Neill et al., 2020; Schelble et al., 2020).

4. Design Issues for Applied Human Autonomy Teaming in CPPS

To answer design questions around HAT in CPPS, we first look at existing findings from other application areas. In an extensive systematic literature review, O'Neill et al. (2020) examined existing research on HAT. Due to their comprehensive and systematic approach, this publication is used as the central and main source for a depiction of the current state of the art regarding HAT in this work. The authors evaluated 76 papers on this topic, which included studies that addressed HAT in the sense of collaborative task completion, i.e., that involved teams consisting of humans and machines. The machines acted at least partially autonomously. The studies examined were thereby categorized by the authors into their input factors (1), which go through mediators (2) and ultimately lead to outputs (3). Thus, within the studies, various independent variables were used as input factors (such as task type, task difficulty, team composition, and degree of autonomy) and led to effects to be studied on various dependent variables as outputs (such as performance, confidence, situational awareness) (O'Neill et al., 2020). Mediator factors, such as communication, have been examined in only a few studies. Figure 3 provides an overview of the inputs, mediators, and outputs studied.

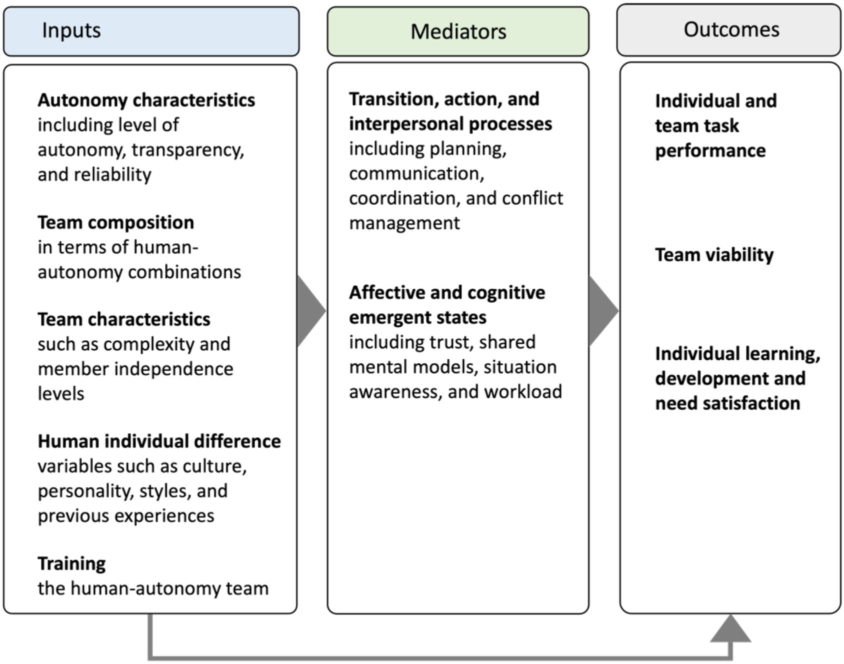

Figure 3: Inputs, mediators, and outputs studied in HAT performance research examined by O'Neill et al. (2020)

The authors were able to draw the following conclusions (among others) during the evaluation and derive open research questions (O'Neill 2020):

Level of autonomy: Overall, a high level of autonomy has a predominantly positive effect on employees and task completion. Regularly, this is also accompanied by higher development costs. However, the available studies have not been conducted under field conditions but only under laboratory conditions (O'Neill et al., 2020). This leads to the following open research question: When is which level of autonomy beneficial, e.g., depending on specific task types?

HAT system performance: in existing studies, a HAT was generally inferior to a human-human team in terms of work performance. However, there is a need to identify the mechanisms that act on the system performance of a HAT. The authors expect that with knowledge of these mechanisms, underlying potentials can be unlocked (O'Neill et al., 2020).

Agent interdependence: Studies indicate that interdependence among agents within a HAT is beneficial to achieving good system performance (O'Neill et al., 2020).

HAT for complex work tasks: The theoretical expectation that HAT, or the use of autonomous systems, leads to superior system performance for particularly complex work tasks could not be confirmed (O'Neill et al., 2020). The authors suggest at this point that the autonomous systems were not sufficiently well designed for the tasks they were given. In principle, complex tasks should be performed by autonomous systems to reduce human workload (O'Neill et al., 2020).

Communication in HAT: Communication between humans and machines within HAT should be organized differently from that between humans. In HAT, (relevant) information should be given to humans in the right way (push principle) instead of offering it only on demand by humans, as this creates delays (pull principle) (O'Neill et al., 2020). There is a need to find out what is the impact of the form of communication used and the way information is shared, e.g., in terms of transparency, reliability, the form of communication, or level of information (O'Neill et al., 2020).

Effect mechanisms of HAT: Many of the studies examined refer to typical input factors and outputs but neglect the effect mechanism that takes place in between. For example, out of the studies reviewed only communication between actors within a HAT was examined but no other mediators, such as how teams coordinate within the HAT. Moreover, mediator factors were often treated as outputs (O'Neill et al., 2020).

Training for HAT: The training of actors within HAT is seen as a significant influencing factor. Since the collaboration with autonomous systems is new to many operators, a steep learning curve can be assumed. This should be taken into account in studies. Furthermore, the training itself, e.g., the choice of the correct form of training for HAT, should also be the subject of research (Demir et al., 2019; O'Neill et al., 2020).

Long-term effects of HAT: There have been no long-term surveys of HATs (longitudinal studies) up to now. Therefore, no conclusions can currently be drawn about the development of the system performance of HAT over time (cf. also Training for HAT) (O'Neill et al., 2020).

Human-centered design of HAT: Autonomous systems must be designed for use as actors within a HAT. This design differs from the general design of an autonomous system, as interaction with humans poses special requirements. This is reflected, for example, in the poor performance of HAT compared to purely human teams. If the autonomous systems are to take over a role that has so far been assigned to humans, improvable system performance is to be expected. Instead, such a role should already be considered at the early stages of the development process and be suitable for an autonomous system's requirements. Future research should thus jointly address the needs posed by the work task, the associated role, and the appropriate design of autonomous systems (O'Neill et al., 2020). This includes the question of how autonomous systems are designed in terms of their technological basis (Demir et al., 2019).

The authors conclude by pointing out that HAT is very likely to be a relevant form of work in the future. Therefore, primary research around this area is of particular importance (O'Neill et al., 2020). As a first step towards a solution to these open research questions, Schelble et al. (2020) worked on deriving a framework for the design of autonomous systems within HAT for CPPS based on application-oriented studies. The framework is intended to enable users to make informed decisions about the development and integration of autonomous systems within Industry 4.0 applications leading to better, more efficient, and customized HAT. Figure 4 shows their framework.

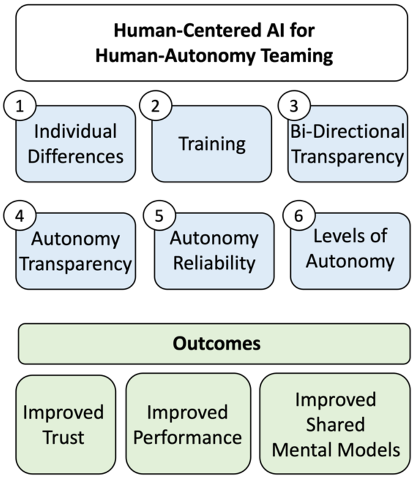

Figure 4: Framework on design factors for HAT in applied settings of CPPS and their outcomes (according to Schelble et al. 2021).

The factors of the framework are intended to be interpreted in the order of individual differences, training, bi-directional transparency, autonomy transparency, autonomy reliability, and levels of autonomy. They can help achieve outcomes in the form of improved trust, improved system performance, and improved shared mental models. Table 1 provides an overview of the content and design recommendations related to each factor (Schelble et al., 2020). The framework provides an essential and helpful basis for the development of autonomous systems for use within HAT.

Factor	**Content**	**Design Recommendations**
Individual Differences	Operators have different characteristics, e.g., due to culture, background, or life experiences.	Conduct user studies prior to developing and implementing a HAT to determine the existing characteristics in the current workforce so that a suitable system can then be developed.
Training	Training operators and autonomous systems to work together leads to better system performance.	Conduct training and familiarization activities for operators with autonomous systems to create transparency about how they work.
Bi-Directional Transparency	Both the employees and the autonomous system should be transparent to the other agent to enable adaptive collaboration.	Development of the HAT using appropriate interfaces that generate transparency for the operator and use of sensors, e.g., about the physiological state of the human that generates transparency for the autonomous system.
Autonomy Transparency	Knowledge of the operator about the autonomous system, including capabilities, intention, decision making, and state.	Generation of knowledge through training. Finding an appropriate level of information to convey relevant information but avoid information overload.
Autonomy Reliability	The reliability level of the autonomous system directly affects the system's performance.	The goal in developing the autonomous system should be to optimize reliability (>70 percent). Additionally, combined with training and transparency, a positive effect on system performance can be achieved even with lower reliability.
Levels of Autonomy	The Level of Autonomy describes the distribution of tasks and competencies within the HAT (1-10, 1: manual system, 10: fully autonomous system).	The choice of the Level of Autonomy is of crucial importance in the development of the autonomous system/design of the HAT. In particular, it should be ensured that adequate situational awareness is maintained for the human, i.e., the human remains in the loop, thus avoiding errors.

Table 1: Contents and design recommendations regarding the framework's on HAT design factors (according to Schelble et al., 2020)

In line with the authors' conclusions, both at (O'Neill et al., 2020) and (Schelble et al., 2020), we agree on the need of further research on the open research questions as pointed out and on a further detailing of the framework. Consequently, this could improve its usability for different use cases (e.g., work areas in manufacturing and logistics, use of purely cognitive or (also) physical autonomous systems).

5. Towards Design Guidance for Applied Human Autonomy Teaming in CPPS

Outside of CPPS, there are various examples of HAT. One application example for physical autonomous systems are self-driving vehicles. These are characterized by different levels of automation. According to a classification by the Society of Automobile Engineers (Society of Automotive Engineers International (SAE), 2018), such vehicles can be divided into levels from 0-5, where 0 means "no driving automation" and 5 means "full driving automation" (Society of Automotive Engineers International (SAE), 2018). The corresponding intermediate levels are described by driving assistance systems, conditional or partial autonomous driving, as in the case of distance assistance systems or driverless parking (Mercedes-Benz Group, 2020). According to a transfer to the levels for the classification of HAT according to O'Neill et al. (2020), self-driving vehicles can be described as HAT at level 3, i.e., as soon as the control is autonomous and the human driver only intervenes when asked to do so (Hagemann & Rieth, 2021). In addition to self-driving cars, the idea of a self-driving vehicle in the sense of a HAT also includes the idea of non-personal usages, such as truck platooning (ADAC, n. d.), self-driving buses (Hansen, 2018), subways, or transport vehicles from the military and space sectors.

Digital assistants such as Apple's Siri, Amazon's Alexa, or Microsoft's Cortana, which can now be found on many mobile devices and smart home devices, are an example for cognitive autonomous systems (Brill et al., 2019). Such an Intelligent Personal Assistant (IPA) is an application that uses the user's voice, the field of view, or contextual information to assist by answering questions, recommending actions, or performing actions (Hauswald et al., 2015).

These examples can already be transferred to application scenarios within production and logistics. As already described in Section 1, collaborative robots, autonomously driving floor vehicles in intralogistics, or intelligent cognitive assistance systems, for example, can fulfill the definition of a HAT. They show implementations of Industry 4.0/5.0 concepts that include autonomous systems and thus HAT. Thereby, an increasing tendency of this kind of collaboration between humans and machines can be assumed for the future. The consideration of previous findings on HAT in the context of this research work shows that basic research and initial design principles are available but that there is a need for further research with regard to interface design and the human-oriented design of autonomous systems.

Overall, in particular, a transfer of the approaches to different CPPS use cases seems necessary to achieve a detailing of the existing design recommendations, e.g., according to Schelble et al. (2020). This includes the following research goals and questions:

1. As outlined in (Quandt et al., 2022, in print), user involvement ensures that the system represents the users' activities and considers the users' needs (Preece et al., 2015). This involvement leads to an increased sense of responsibility of the users for the system design, a higher user loyalty to the developed system, and a resulting higher system acceptance (Wagner & Piccoli, 2007). In this sense, a HAT should be easy to learn, useful, functional for the particular work context, and at the same time easy and enjoyable to use for the operators. To achieve this, an early focus on users and tasks, empirical measurement, and iterative design are necessary (Gould & Lewis, 1985). These three principles are considered the widely accepted fundamentals for human-centered system development (Preece et al., 2015). We assume a similar beneficial effect for the design of HAT in CPPS. Explicit integration of human factors or existing human-centered design (HCD) approaches opens up the potential for improving HAT system performance, e.g., in the areas of transparency or degree of autonomy.

2. As outlined in (Stern & Becker, 2019), a standard research method of human factors are experimental studies (Jacko et al., 2012). These methods can be used to show whether there are causal relationships between the design of a HAT and resulting effects on operator or the system itself. Therefore, in an experimental study, one or more variables are modified in order to induce observable effects studies (Jacko et al., 2012; Wickens et al., 2014). Thus, conducting laboratory studies (and later field studies) for CPPS use cases could help to improve the data foundation and derive more focused design recommendations for HAT.

3. HAT in CPPS could contribute to resource and energy savings in terms of sustainability goals and should therefore be included as a goal early in the development process. In addition, an improved division of labor between humans and machines allows operators the opportunity for creative development and further process improvement since they are released from the cognitive workload of tasks that can be automated, for example.

4. The use of VR environments could promote the use of HAT and the development of corresponding potentials. For example, the utilization of a VR environment instead of an actual test setup is promising for the implementation of studies, which are necessary for a more focused individual design of HAT according to a particular use case. Thus, a pure VR

implementation could significantly reduce development efforts and eliminate the need to develop an actual HAT for testing purposes. Furthermore, such a VR environment could be used for training in using case-specific or higher-level setups to generate knowledge within the workforce for working with autonomous systems.

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Advanced analytics applications in smart manufacturing – A systematic literature review on their perspectives, effects, and sustainability

André Ullrich, Michael Buchmin

1. Introduction

Advanced analytics applications in smart manufacturing provide manufacturers with benefits in areas such as product design, production processes, maintenance, service, and recovery (Ren et al. 2019). These benefits include the predictive maintenance of industrial robots and machines to avoid production outages, quality prediction of products, and the optimization of production processes to reduce energy consumption or waste (Meng et al. 2018). An advanced analytics application in smart manufacturing is understood as a sophisticated quantitative method to reveal previously unknown patterns, make predictions, or provide optimizations in the production environment (Boobier 2018). The beneficiary effects of advanced analytics applications in smart manufacturing are well researched (Meng et al. 2018). However, their effects and implications for sustainable development of production and thus also society are not well elaborated. Neural networks for example have come under criticism because of the complex mathematical operations, which lead to a high demand for computational resources and thus for energy (García-Martín et al. 2019). The Internet of Things (IoT) has been critically evaluated because of the required investment and operation costs, its energy consumption during operation, and a diverging lifespan which can be quite short (Routray and Sharmila 2017) and is thus rather non-sustainable.

The concept of sustainability refers to enduring and changing over time, and is commonly deconstructed into the social, environmental, and economic sustainability spheres (cf. Barbier 1987). The environmental sphere primarily affects the usage of natural resources, whereby not only the consumption is in focus but also the residuals and waste that inter alia result from using technologies. In this light, pollution prevention includes natural resources such as air, water, land and waste. Therefore, environmental sustainability addresses both production and consumption aspects (Lozano and Huisingh 2011). Social sustainability deals with crucial aspects such as the standard of living, education and community supporting opportunities, including in terms of equity and equality. Furthermore, environmental justice as well as stewardship of natural resources both locally and globally link social sustainability to the environment. However, as Goodland (1995) highlights, social and environmental sustainability are connected in a quite more fundamental way, since "environmental sustainability or maintenance of life-support systems is

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a prerequisite for social sustainability". Following a market-based view of production and consumption, profit, cost savings, economic growth as well as research and development are all crucial aspects of economic sustainability. In this vein, economic sustainability refers to the capacity of fostering the mentioned aspects, thereby enabling an entity to endure over time.

To address the challenges and thus create a basis for sustainable development for people and the environment, the United Nations (UN) has formulated 17 Sustainable Development Goals (SDGs) as part of the 2030 Agenda for Sustainable Development (United Nations 2022). The SDGs are a central component of the 2030 Agenda for Sustainable Development, which was adopted by all member states at a UN summit in 2015. The agenda pursues the common goal of transformation towards a world in which everyone acts in an ecologically compatible, socially just and economically efficient manner (UN General Assembly 2015). The indivisible and interdependent 17 goals are primarily concerned with five core aspects: people, planet, prosperity, peace and partnership, which serve as guiding principles for action and concretize the relationships between the goals.

The sustainability perspective is important for advanced analytics applications in smart manufacturing. Firstly, advanced analytics applications in smart manufacturing often require IoT devices as data sources. Moreover, advanced analytics applications include complex mathematical operations such as neural networks and increasingly use cloud computing (Tao et al. 2018). Therefore, these applications are affected by the current research debate about the sustainability of certain information and communication technologies (ICT). Secondly, ongoing discussions on climate change, resource depletion, or social inclusion in the public and scientific debate point to a growing interest in the sustainability of ICT (Ullrich 2022). Consequently, non-sustainable ICT might be impacted by a shifting acceptance, potentially hindering their adoption. This allows to address its weaknesses and adjust them accordingly.

Advanced analytics applications are often seen as a subset of technologies for smart manufacturing so that little specific attention is dedicated to them (e.g., Caiado and Quelhas 2020; Meng et al. 2018; Qu et al. 2019). Consequently, the research field is characterized by many single applications with little conceptual synthesis (Fay and Kazantsev 2018). Therefore, the research questions address both a systematization of the field and an identification of specific sustainability themes in this field:

Which advanced analytics applications exist in smart manufacturing in the scientific literature?

Which sustainability themes are represented in the literature on advanced analytics applications?

The contribution to the scientific community is an overview of existing advanced analytics applications in smart manufacturing and of sustainability themes, that emerge in this context. The research questions are answered through a systematic literature review (SLR). The results will be systematized in a concept matrix. The analysis furthermore revealed 27 sustainability themes which holistically cover all pillars of sustainability, with a focus on the social and economic spheres.

This chapter will be structured as follows. Section 2 presents the underlying methodology of this study. Section 3 describes the results according to the effects and research perspectives of the SLR. Section 4 continues with the identified sustainability themes in the body of literature. Section 5 discusses the results in more detail and provides conclusions.

2. Methods and Materials

Three steps were executed based on the PRISMA 2020 (Moher et al. 2015) statement and vom Brocke et al. (2009) to find publications for answering the research questions.

2.1. Step 1 – Search string definition and scope

To identify keywords for the SLR, existing literature on Big Data technologies in the context of sustainability was analyzed to gather a deeper understanding of the key concepts. Based on the read literature and the research questions three blocks of keywords emerged. The block *Advanced Analytics*, comprising the terms *Advanced Analytics*, *Artificial Intelligence*, *Big Data Analytics*, *Data Analytics*, *Data Mining*, *Machine Learning*, *Prescriptive Analytics*, and *Predictive Analytics*. The second block *Smart Manufacturing* with the terms *Factory*, *Industrial Internet of Things*, *Industry 4.0*, *Manufacturing*, and lastly, the block *Sustainability* with the terms *Clean*, *Green*, and *Sustainabl**.

The first block covers keywords about advanced analytics. The second block includes keywords about smart manufacturing and the last block comprises keywords related to sustainability. On this basis, a narrow search string was developed which was used in all databases (Table 1). The search string uses logical operators. Keywords inside a block are connected via an OR operator so that all keywords were searched synonymously. Moreover, the blocks were linked with an AND operator so that only publications which matched all three blocks were shown as hits.

Search String
((“advanced analytics” OR “artificial intelligence” OR “big data analytics” OR “data analytics” OR “data mining” OR “machine learning” OR “predictive analytics” OR “prescriptive analytics”) AND (“factory” OR “industrial internet of things” OR “industry 4.0” OR “manufacturing”) AND (“clean” OR “green” OR “sustainabl*”))

Table 1: Search string

The PRISMA guidelines require the definition of inclusion and exclusion criteria (Table 2) to ensure focus of the investigation.

Inclusion criteria	Exclusion criteria
Original work, published in a journal or conference proceeding	No manufacturing context
Focus on sustainability	Not written in English
Focus on Advanced Analytics	Not per-reviewed
Published in English	

Table 2: Inclusion and exclusion criteria

2.2. Step 2 - Journal, conference proceeding and database selection

The topic sustainability of advanced analytics applications is situated in several research subjects. Smart manufacturing is located in engineering and technology, while advanced analytics is often covered by information systems and informatics disciplines. In contrast to this, publications in sustainability are mostly covered in specific sustainability outlets. To find a representative selection of advanced analytics applications in smart manufacturing with a sustainability focus, four databases were selected. The *IEEE Xplore* database represents a vast number of publications in engineering and technology related subjects. The AIS eLibrary database offers access to journals and conference proceedings in the field of information systems. The EBSCOhost and Web of Science databases provide a collection of a broad range of publications, including sustainability and informatics outlets. The data was retrieved between 28.5.2021 and 03.06.2021.

2.3. Step 3 – Data analysis

The SLR resulted in 1.537 hits (Figure 1). The most hits were found in AIS eLibrary, followed by IEEE Xplore, EBSCOhost, and Web of Science. In total, 65 duplicates were removed, so that 1.427 unique hits were achieved. After scanning the hits based on the eligibility criteria, 65 final hits were identified. This marks a matching ratio of 4,6 %.

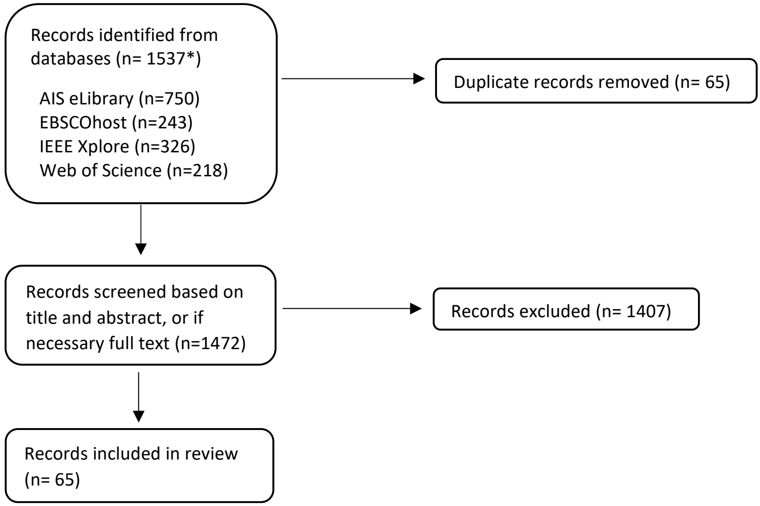

Figure 1: PRISMA flow chart

Interestingly, the AIS eLibrary database showed 747 hits, but only 3 publications qualified for final hits. Consequently, research about advanced analytics applications in smart manufacturing is rarely thematized in information systems research. In contrast to this, IEEE Xplore provided 37 final hits. Even the general databases, EBSCOhost and Web of Science had 15, respectively 19 final hits, before the removal of duplicates.

37 final hits (57%) were published in journals. The leading journals, based on the number of final hits, were the Journal of Cleaner Production (8 final hits), the IEEE Access Journal (7) and the Journal of Intelligent Manufacturing (6). 28 publications were published in conference proceedings. The year with the highest number of final hits was 2020. There is a significant increase in final hits since 2018 which shows a growing interest in the research subject. While 2015 (4 final hits), 2016 (4) and 2017 (4) had rather few final hits, 2018 (13), 2019 (16), and 2020 (18) show substantially more, with 2021 showing only 6 final hits yet.

The identification of sustainability related themes was conducted by analyzing the respective themes, their coding book, and respective text fragments with the previously mentioned sustainability literature. A sustainability theme was given if it impacted at least one pillar of sustainability.

3. Results

The final hits were grouped by their research perspective and aimed effect in a concept matrix (Table 3). In this paper, the research perspective shows the motivation of the publication according to their authors and its position in the research debate. As every research publication should justify its relevance and its relation to other publications, this perspective provides information about the contribution of every publication and its application to the respective research discussion. This allows to understand the current research streams in the research subject by analyzing why research efforts were conducted. Ultimately, enabling to see the current state of the art through the research motivation and its distribution.

The effect shows the practical purpose for which an advanced analytics application in smart manufacturing was developed. This means the contribution offered by an application to a particular real-world problem such as an application to predict the quality of products, the need to maintain a robot, or the optimization of production schedules. Ordering the applications by aimed effects allows to directly compare the proposed solution for the same or a similar problem. As every advanced analytics application in smart manufacturing can be unique in its design and particular setting, this is a meaningful way to classify them, and common in this research field (e.g., Meng et al. 2018; Ren et al. 2019). Moreover, this perspective allows to understand the coverage of the beneficiary effects by the analyzed research publications.

Publications in the category *application* focus on contributing to the research community by developing new applications which were not covered by the scientific literature yet. This mostly implies applying known beneficiary effects such as energy consumption prediction for new machine types or manufacturing environments. Yu et al. (2017) for example developed an energy consumption optimization application for the semiconductor industry. However, instead of focusing on the energy consumption of the production facility, they investigated the production tools which are responsible for 41% of the power consumption. Zhang et al. (2020) developed an energy-efficient bi-objective manufacturing scheduling approach. They justify their research by the fact that flexible multi-task scheduling problems were already extensively investigated, however energy-related objectives were rarely considered. Therefore, they developed the application to incorporate this issue. Another example is Vijayaraghavan et al. (2016) who developed a data-driven approach for modeling turning processes of Inconel 718 alloys. While previous research covered wear mechanisms and chip formation, their research focused on understanding the cutting force and power consumption. Publications in this category can also include detailed descriptions of the implementations, however this is not their justification for their research.

Research perspective \ Effect	Author	Energy insights	Energy prediction	Energy optimization	Process insights	Process prediction	Process optimization	Predictive mainenance	Quality prediction	Scheduling optimization	Material prediction
Application	Vijayaraghavan et al. (2016)		x			x					
	Pereira and Lima (2018)		x							x	
	Yu et al. (2017)			x							
	Wang et al. (2018)			x							
	Park et al. (2020)			x							
	Zhang et al. (2015)				x						
	Fang et al. (2020)				x						
	Xu et al. (2021a)			x		x	x				
	Xu et al. (2021b)					x					
	Gao et al. (2019)					x					
	Leng et al. (2021)						x				
	Deng et al. (2018)			x			x				
	Hong and Lee (2018)						x				
	Liu et al. (2017)							x			
	Borgi et al. (2017)							x			
	Unnikrishnan et al. (2020)								x		
	Jo et al. (2020)						x		x		
	Ren et al. (2019)								x		
	Qu et al. (2015)									x	
	Jiang and Zhang (2019)			x						x	
	Lei et al. (2017)			x						x	
	Lu et al. (2019)			x						x	
	Tian et al. (2019)									x	
	Zhang et al. (2020)			x						x	
Framework	Qin et al. (2017)	x	x								
	Zhang et al (2018)	x						o			
	Bhinge et al. (2017)		x	o							
	Li et al. (2017)		x								
	Burow et al. (2019)			x							
	Ma et al. (2020)			x							
	Lin et al. (2020)				x	x					
	Mi et al. (2020)						x				
	Tong et al. 2020)			o	o		x				
	Zeng et al. (2019)							x			
	Villalonga et al. (2018)							x			
	Saez et al. (2018)							x	x		
	Apiletti et al 2018)							x			
	Kaparthi and Bumblauskas (2020)							x			
	Schmitt and Deuse (2018)								x		
	Feng et al. (2020)			x						x	
	Li et al. (2015)									x	
	Qu et al. (2016)									x	
	Wang et al. (2016)									x	
	Penumuru et al. (2020)										x

	Kang et al. (2020)	x	x	x				o		
	Mulrennan et al. (2020)		x							x
	Silveira et al. (2020)							x		
Implementation	Rudolph et al. (2020)							x		
	Ingemarsdotter et al. (2021)							x		
	Li et al. (2019)							x		
	Tong et al. (2018)								x	
	Khelil et al. (2019)					x		x		
	Mehdiyev and Fettke (2020)				o	x				
	Cheng et al. (2021)					x				
	Efkolidis et al. (2019)					x				
	Neef et al. (2018						x		x	
	Wanner et al. (2019)							x		
	Cheng et al. (2019)							x		
Design	Huang et al. (2019)							x		
	Wang et al. (2020)							x		
	Wen et al. (2018)							x		
	Calderisi et al. (2019)								x	
	Hsu et al. (2019)								x	
	Yuan-Fu and Min (2020)								x	
	Qu et al (2019)									x

Table 3: Concept matrix

The research perspective *framework* includes publications which justify their motivation with the need of approaches to implement specific advanced analytics applications. Consequently, their research is motivated by the facilitation of implementation through theoretical elaborations. Therefore, they primarily aim to provide guidelines that support the implementation. A characteristic of publications in this research perspective are thus frameworks or methodologies. Villalonga et al. (2018) for example were motivated by the fact that small and medium sized enterprises were rarely adopting a cyber physical system (CPS) although there was a strong interest in the scientific community. Therefore, they concluded that there was a need for a systematic approach to implement CPS. In a similar way, Apiletti et al. (2018) argued that real-time data poses challenges for manufacturers so that they saw the need to develop an approach that facilitates implementation of predictive maintenance applications. As a last example Qu et al. (2016) described issues concerning real-time processing capabilities, this time relating to scheduling problems. Consequently, they developed a generic framework to solve this issue. Interestingly, publications within this perspective do not always present case studies to proof the feasibility of their approach such as Mi et al. (2020) but sometimes only test their framework on publicly available data sets (e.g., Apiletti et al. 2018; Kaparthi and Bumblauskas 2020; Penumuru, Muthuswamy, and Karumbu 2020).

In contrast to the previous research perspective, publications with the perspective *implementation* are motivated by the need to present detailed descriptions of comprehensively realized real-world applications. Silveira et al. (2020) for instance justified their work by pointing to the absence of detailed and replicable descriptions of implemented case studies. They criticized that most applications do not explain how their application is assembled and structured or that only certain stages of the data lifecycle are explained in detail such as the used algorithm. Therefore, they provided a pilot project with lessons learned and design decisions so that readers can benefit from it. Rudolph et al. (2020) elaborated that data processing is not a trivial task and therefore explained their preprocessing and feature engineering from data of a grinding machine in detail. Tong et al. (2018) reviewed the literature about quality prediction applications in the semiconductor industry and concluded that many publications would not pre-process their source data, select the most useful features or did not prove the feasibility of algorithms with theoretical analysis. Therefore, they completed a comprehensive semiconductor quality control problem application including data preprocessing, feature selection and practical testing.

Lastly, the category *design* includes all publications which justify their work with an improved approach in respect to its design. Their goal is to make an application for example more effective, more affordable, or more socially inclusive. Wanner et al. (2019) for example explained their predictive maintenance use case with the aim to design it as socially inclusive as possible to increase the acceptance of the users. It includes a rule-based system for the machine learning algorithms so that the users can understand the algorithms' reasoning and decisions. Moreover, the application informs users via dashboards and alerts on their mobile phone about important events. Hsu et al. (2019) justified their application with the use of convolutional neural networks to identify defects on images. They criticized that neural networks tend to use too many learning parameters and thus lead to a high need of computational resources. Therefore, they developed a machine learning approach that uses less learning variables and consequently requires less training time and computational resources. Mehdiyev and Fettke (2020) were motivated by providing "an innovative explainable process prediction solution". They explained that too many approaches would use a black-box machine learning approach which limits the interpretability for human users. Consequently, they developed an algorithm which presents its learning steps in more detail so that human users can interpret them and consequently gain more trust and acceptance.

The highest number of final hits belongs to the research perspective *application* (24 final hits), followed by *framework* (20), *design* (14), and *implementation* (7). This distribution shows that most publications are concerned with expanding the research subject with new applications or by explaining frameworks to implement the applications. Consequently, sustainability in the research field is still more focused on achieving sustainability effects than having a sustainable design for the respective applications. However, when taking the temporal perspective into account, publications in the category *design* have just been published since 2018. A similar pattern is visible in the category implementation. The publication dates in the categories *application* and *framework* are more distributed. This may indicate that *design* and *implementation* are of growing interest in the research community.

Furthermore, ten effects were identified. The effects represent consolidated categories with similar effects grouped into one effect in order to facilitate the analysis. The composition of the effects is elaborated in every corresponding part. Moreover, some publications propose applications which provide beneficiary effects in more than one area. The main focus of the publications is indicated by "X" and can include more than one mark. In case, a publication has a focus on more than one beneficiary effect, it is ordered by the effect in the concept matrix, which is described in more depth. Furthermore, if a certain effect is only mentioned but not the focus of the publication, it is indicated with "O". The most mentioned effects are *predictive maintenance* (16), *scheduling optimization* (13), *energy optimization* (12) and *quality prediction* (10). The least mentioned effects were *material prediction* (1), *energy* and *process insights* (both 3 times).

Predictive maintenance is referring to the capability to detect, for example a machine failure, before it occurs and impacts the production process. Borgi et al. (2017) present an application which is able to predict the maintenance need of an industrial robot based on current data and a regression analysis. Wang et al. (2020) used production data to develop a neural network which predicts the maintenance need of complex equipment. Zeng et al. (2019) trained their algorithm on vibration signals so that it was capable to predict the faults for rolling bearings of a rotating machine. Furthermore, *predictive maintenance* is shown for example for machinery (Liu et al. 2017), a machine tool (Li et al. 2019) and a grinding machine (Rudolph et al. 2020).

Scheduling optimization encompasses applications which aim to perfectionate the use of machines or production facilities based on a manufacturer's multiple objectives and various production constraints. Applications with this effect often refer to scientifically embedded and well-known scheduling issues such as the hybrid flow shop scheduling problem (Lei, Gao, and Zheng 2017), the flexible multi-task scheduling problem (Zhang et al. 2020) or the flexible job shop problem (Tian et al. 2019). Feng et al. (2020) for example used process variables and sensors to develop an energy consumption optimized scheduling of flexible workshops. Li et al. (2015) applied production data to improve the efficiency of a shop floor. Jiang and Zhang (2019) developed an algorithm which is able to provide an energy consumption optimized scheduling for hybrid flow shops with limited buffers.

Quality prediction describes applications which predict the properties of a product and consequently its quality. It also includes the prediction of defects of products as this impacts the quality. Hsu et al. (2019) for example developed a machine learning algorithm which can detect defects on a substrate's surface for semiconductors. A similar application for the semiconductor industry was developed by Tong et al. (2018) based on production data. Ren et al. (2019) predicted the quality of engines by detecting bubbles through images.

Another major focus of the publications is energy consumption. Three effects *energy insights*, *prediction,* and *optimization*, within 20 publications, are dealing with this particular benefit. *Energy insights* includes applications which aim to reveal previously unknown information about energy consumption. Qin et al. (2017) developed a framework which allows to estimate the energy consumption of an AM machine during its different operations. Zhang et al. (2018) revealed the energy consumption of ball mills in a pulp workshop through a regression and neural network. Kang et al. (2020) developed an integrated energy data analytics approach for machine tools and were able to reveal the energy consumption.

Applications with *energy prediction* are focusing on predicting the energy consumption of a process, factory, manufacturing environment, or machine. Pereira and Lima (2018) predicted the total energy consumption in job shop systems by applying machine learning techniques. Mulrennan et al. (2020) used historical manufacturing data to model the electrical energy profile of a production facility. Vijayaraghavan et al. (2016) trained an algorithm to predict the energy consumption for the turning process of Inconel 718 alloys.

Energy optimization summarizes applications which perfectionate the use of energy. This encompasses scheduling optimization with energy as an objective but also processes, and machines. Jiang and Zhang (2019) and Feng et al. (2020) for example developed scheduling optimization algorithms which also takes energy consumption optimization as a goal. Yu et al. (2017) used production data to reduce the energy consumption of production tools. Park et al. (2020) applied a neural network based on among others sensor data from IIoT to optimize the energy consumption of a dyeing process. Wang et al. (2018) developed an assessment method with association rules to increase the energy efficiency of industrial robots.

Applications with relation to production processes are another major group of effects with 15 publications relating to *process insights*, *prediction*, or *optimization*. *Process insights* includes applications which enable manufacturers to better understand their production processes or operations. Zhang et al. (2015) and Fang et al. (2020) implemented radio frequency identification (RFID) technology to enable real-time status monitoring of workpieces in manufacturing workshops. Lin et al. (2020) used big data to better understand production line issues.

The effect *process prediction* summarizes applications which predict outcomes of production processes or operations. Efkolidis et al. (2019) for example predicted the thrust force and torque during drilling of a workpiece. Xu et al. (2021a) estimated the tool wear of coated tool during cutting operations. Gao et al. (2019) predicted the material removal based on acoustic sensing for robotic belt grinding of Inconel 718. Mehdiyev and Fettke (2020) used production data from a factory to predict different production process parameters such as the average duration per process step.

Process optimization encompasses applications which perfectionate the execution of production processes, except scheduling problems. Deng et al. (2018) elaborated an optimized cutting process for a machine tool depending on the material to be cut. Hong and Lee (2018) used sensors to detect the need for a cleaning operation. Leng et al. (2021) developed an application which perfectionates the order acceptance decisions of mass- individualized printed circuit boards.

Applications with the effect *material prediction* aim to identify and classify different materials. Penumuru et al. (2020) present a methodology for automated material identification through machine learning to enable an industrial machine to perform an appropriate operation on the respective material.

The identified effects cover the two application areas intelligent production and intelligent maintenance and service. In this respect, all effects, except *predictive maintenance*, relate to the aspects of intelligent production. Effects related with energy consumption aim to enable a better understanding, prediction, and optimization of energy use. *Quality prediction* supports in automating defect detection and quality measurement. Effects related to processes focus on providing a better understanding, predictions, or optimizations of operations. *Optimized scheduling* applications perfectionate the use of available resources in the production facilities. *Material prediction* automates production processes.

Moreover, the applications can be grouped according to their scope (Table 4). Most publications were dealing with effects in predictive (42 publications), followed by prescriptive (25), and diagnostic analytics (6). Predictive analytics applications include the prediction of energy consumption, material, product quality, processes, and maintenance needs. Prescriptive analytics encompasses applications with the optimization of scheduling, processes, and energy consumption. Diagnostic analytics covers the revealed insights about energy consumption and processes. Moreover, some applications could also be grouped into the category cognitive analytics which refers to human-like capabilities. In this selection of analyzed publications three applications meet this requirement.

Scope	**Number of publications**
Diagnostic analytics	6
Predictive analytics	42
Prescriptive analytics	25
Cognitive analytics	3

Table 4: Scope of effects by analyzed publications

Penumuru et al. (2020) made use of images to enable a machine to recognize different materials and then execute appropriate operations on it. Hsu et al. (2019) and Yuan-Fu and Min (2020) both trained neural networks based on images to identify defects on materials for the semiconductor industry. Consequently, machines were able to autonomously adjust their operation based on the present material, and production systems were able assess the quality like human quality inspectors.

4. Sustainability themes

In total, 27 themes related to sustainability were identified, based on the content analysis. These themes are affecting all stages of the data lifecycle and the design of advanced analytics applications (Table 5). If a theme affects more than one stage, it is listed in brackets in the following stages.

Data lifecycle stage	**Theme**
General	Transferability, implementation time, performance
Data acquisition/recording	Equipment costs, energy consumption equipment, requirements acquisition
Data processing	Complexity data sources, challenges big data, processing efforts, data quality, data accessibility, familiarity software, open source, preprocessing efforts
Data management	Knowledge sharing, (challenge big data), security, remote control, latency, energy consumption cloud
Modeling/analysis	Expert knowledge, prerequisites model-building, algorithm efficiency, comprehensibility, computing complexity, updatability, (challenge big data)
Interpretation	Interactivity, visualization

Table 5: Themes ordered according to data lifecycle stages

The data life cycle stages with the most different themes are the *data processing* (8), *modeling/analysis* (7) and *data management* (7) stage. Only two themes can be assigned to the stage *interpretation*. Of all themes, only *challenges big data* is affecting more than one stage so that all other themes are uniquely connected to one particular stage. Consequently, the handling of the acquired data to extract knowledge is well represented by the themes. An overview with a short explanation is shown in Table 6.

Performance evaluates an advanced analytics application concerning its accuracy in making a prediction, optimization, or providing insights. It consequently refers to the quality of an application in its respective context. This means that a high performance for example equals a high prediction power and therefore has a high usefulness for its users, and vice versa. Apiletti et al. (2018) for example stated that a low accuracy deteriorates the trust and acceptability of the application for its users. Jo et al. (2020) stressed the economic relevance of the *performance* theme by pointing to the fact that the desired cost reduction is only achievable with a corresponding accuracy. Kaparthi and Bumblaukas (2020) pointed to the relevance of the accuracy of the algorithm to the decision-making capabilities in general.

Theme	**Explanation**
Performance	Accuracy in making a prediction, optimization, or providing insights
Computing complexity	Required mathematical calculations of an algorithm to deliver results
Expert knowledge	Required expertise on manufacturing environment for model-building
Challenges of big data	Issues caused by high volume, velocity, and variety of data
Data quality	Accuracy of the data
Equipment costs	Costs for acquiring data acquisition/recording equipment
Comprehensibility	Interpretability of the decision-making process of an algorithm

Complexity of data sources	Required efforts to integrate data from multiple data sources
Prerequisites of model-building	Properties of data set required to build a model
Visualization	Visual tools to facilitate interpretation for users
Interactivity	Tools to facilitate active interpretation for users
Security	Issues related with use of cloud resources in respect to crime prevention
Knowledge sharing	Exchange of data, information, and knowledge between different locations to enlarge data basis
Algorithm efficiency	Efficient use of resources by algorithm to deliver result
Familiarity with software	Previous experiences of the users with the software
Open source	Publicly available source code of the software
Preprocessing efforts	Required efforts to preprocess data, e.g. detection of missing values
Processing efforts	Required efforts to prepare additional values, e.g. calculations
Data access efforts	Required efforts to access data

Requirements acquisition	Conditions that have to be fulfilled to enable acquisition of data
Transferability	Possibility to apply application in another manufacturing environment
Updatability	Capability of algorithm to adjust itself with new data incrementally
Latency cloud	Time required by cloud computing until real-time data is received
Equipment energy consumption	Energy consumption through data acquisition and recording equipment
Cloud energy consumption	Energy consumption through cloud computing usage
Remote control	Accessibility of production processes/data through cloud computing
Implementation time	Required time to install application and deliver first valuable results

Table 6: Overview of the themes

Computing complexity deals with the mathematical calculations of the algorithms to deliver a result. Depending on the applied algorithm different mathematical operations have to be conducted. Therefore, algorithms differ in their required *computing complexity* and thus required computing resources to perform computation tasks. A high mathematical complexity leads to a high demand in computing resources, and vice versa. *Computing complexity* impacts the economic-environmental pillar. Penumuru et al. (2020) for example state that a long computation time is equivalent to high computation costs. The computation costs result partially from the energy required to power the corresponding ICT. Therefore, the environment is concerned as well because energy is still produced by burning fossil fuels. Tong et al. (2018) and Lei et al. (2017) for example have pointed towards the high and thus expensive computation needs of neural networks and genetic algorithms respectively.

The theme *expert knowledge* refers to the required expertise to understand the manufacturing environment in order to model advanced analytics applications. In this context, knowledge about processes, machines, and or causal relationships is needed so that data can be meaningfully used for the modelling. In this respect, Schmitt and Deuse (2018) for example stressed the relevance of process knowledge in selecting input variables for the modeling. Qu et al. (2016) also argued that *expert knowledge* about the manufacturing system is needed to design effective algorithms. Li et al. (2015) praised the experience which comes from many working years. *Expert knowledge* impacts the social pillar because it demands a corresponding expertise from developers. Consequently, need of *expert knowledge* limits the *accessibility* to human beings.

Challenges of big data deals with all issues which are caused by the use of a high variety, volume, and velocity of data. Zhang et al. (2018) stressed the challenges that big data constitutes for traditional architectures and infrastructures. Tong et al. (2020) pointed to the need of adequate technologies to store big data. Fang et al. (2020) mentioned the necessity to apply appropriate techniques for preprocessing and Apiletti et al. (2018) elaborated on the need of machine learning algorithms which can deliver convincing results based on big data. Consequently, big data impacts the social and economic pillar. Wanner et al. (2019) stressed that big data can overwhelm human workforce because of the "sheer amount of data". From an economic perspective big data thus requires the acquisition of software and hardware which can handle it (Wanner et al. 2019).

Data quality is concerned with the fidelity of data accessed through equipment such as sensors and RFID. In this context, fidelity and thus data quality is defined by the reliability of the data representing real events. Fang et al. (2020) noted that data from RFID readers is heavily impacted by noise and errors with "up to 30% of sensor readings is noisy data". Zhang et al. (2015) concluded that RFID raw data is "inherently unreliable due to physical device limitations and different kinds of environmental noise." Consequently, Rudolph et al. (2020) noted that a low data quality negatively affects the accuracy of an algorithm, and thus the decision-making capabilities. The social pillar is affected as human workers have to assess the quality of data (Fang et al. 2020), and consequently deal with it accordingly (Tong et al. 2018).

Equipment costs deals with the required investment to purchase data acquisition equipment such as sensors, cameras, and RFID readers. Borgi et al. (2017) pointed to the high costs of laser tracker systems and Ma et al. (2020) stressed the high cost of real-time sensors which can be higher than the potential energy saving of applications for which these sensors should be acquired. Zhang et al. (2015) and Wang et al. (2016) praised the low costs of RFID readers. Consequently, this theme deals with the economic pillar and potential costs of hardware.

The theme *comprehensibility* deals with the interpretability of the decision-making process of algorithms for human beings. Jo et al. (2020) for example explained that neural networks generate complex structures which are hard to understand. For this reason, Apiletti et al. (2018) decided to choose machine learning algorithms such as random forest, support vector machines and regression because these allow humans to interpret the algorithms and their computations. Wanner et al. (2019) argued that if users cannot understand the decision making of algorithms, this would decrease the trustworthiness and acceptance of those systems. Therefore, this theme is impacting the social pillar and the accessibility for users.

Prerequisites of model-building evaluates an application concerning the properties of the data set required to train a model. It encompasses the difficulty to acquire sufficient data for the particular algorithm but also if the data for the training has to be labelled. Yuan-Fu and Min (2020) explained that for the neural network often a large amount of data is required. Cheng et al. (2019) stressed the need to have sufficient labeled data for their predictive maintenance applications. In a similar way, Ingemarsdotter et al. (2021) summarized that a technical challenge of predictive maintenance is to acquire enough data representing failures. This theme is impacting the economic and social pillar by posing a challenge to developers who have to collect enough data for the model-building.

Interactivity relates to any tools which inform a human being directly about relevant events or developments in the manufacturing environment. It includes messages, warnings, and alarms which provide a user with information to take precautions or actions. Wang et al. (2016) described these tools as a "user-friendly interaction" and Villalonga et al. (2018) as a guidance for users to take corresponding measures. However, Ingemarsdotter et al. (2021) also noted that too many alarms would overload support technicians. *Interactivity* deals with the social pillar and the accessibility by facilitating the interpretation.

Complexity of data sources deals with the efforts to integrate data from multiple data sources. Integrating data from different sources is considered as a challenge because it requires to transform data from the different sources into a common format so that it can be processed (Saez et al. 2018). Mehdiyev and Fettke (2020) stated that it constitutes a "vital challenge" for users. Therefore, this theme impacts the social pillar by posing challenges to humans and has influence on the economic pillar by requiring accordingly human workforce.

Visualization includes tools which support users through visual means such as dashboards or graphs in order to facilitate the interpretation of results from the application. The theme is influencing the social pillar by facilitating the interpretation of information (Villalonga et al. 2018), providing users "with a direct overview of the nature of the problem" (Wanner et al. 2019) and enhancing "the efficiency of information illustration and exchange" (Tong et al. 2020).

Security deals with issues relating to the safety of data and remote control through the use of cloud technologies. The concern is that sensitive data might be exposed (N. Wang et al. 2020) or that remote control might be misused (Silveira et al. 2020) which might impact the economic, social, and environmental pillar by theft of sensitive data, manipulation of machines which might harm workers, and sabotage of production processes which might waste resources.

Another theme in the *data management* stage in relation to cloud technologies is *knowledge sharing*. This theme encompasses the exchange of data from machines for example in order to enlarge the available data sets to improve the modelling of algorithms. Mi et al. (2020) praised the advantage of exchanging data as it facilitates the acquisition of failure data. It thus impacts the social and economic pillars by following the principles of openness and knowledge sharing and facilitating the acquisition of data for businesses.

Algorithm efficiency as a theme is concerned with the efficient use of resources to deliver a result. It differs from *computing complexity* by focusing on whether the applied algorithm is the most efficient way to deliver the most accurate solution (Leng et al. 2021) and thus deals with the economic and environmental pillar by taking the consumption of resources, especially energy, into account.

Familiarity with software regards the advanced analytics applications concerning the software used to conduct processing tasks. A familiar software such as WEKA (Jo et al. 2020) or coding environment as RStudio (Rudolph et al. 2020) facilitates the work of the development team (Silveira et al. 2020), and thus impacts the social pillar. Another example for the social pillar is the theme *open source* which is concerned with the regime under which software is usable during the *processing* stage (Silveira et al. 2020). By providing publicly available source code, and being mostly for free, this theme also has relevance for the economic sphere.

The themes *processing efforts* and *preprocessing efforts* relate both to the *processing* stage. However, *preprocessing efforts* is concerned with the work to prepare data for the model building in terms of the traditional data cleaning tasks (Rudolph et al. 2020) such as the detection of missing or out-of-range values. *Processing efforts* in contrast deals with time and work intensity of additional processing tasks such as the calculation of certain values which are required for the model building as input. Both themes impact the social and economic pillar by posing challenges to development teams (Mulrennan et al. 2020) and requiring work time, in terms of preprocessing tasks for example about 80% in many projects according to Rudolph et al. (2020).

Data access efforts deals with the efforts to access data from a source for the processing and model building tasks. While data stored in databases or from sensors is directly available electronically, data from hand-written sources is difficult to assess as it has to be digitized (Mulrennan et al. 2020). Another theme in relation to the data sources, is *requirements acquisition* which encompasses the set-up requirements to collect data properly. Penumuru et al. (2020) elaborated that taking images through has several requirements. For example, it is very important to keep a strict lightening provision to ensure that the images have a similar illumination so that the machine learning algorithm can detect these. This requires corresponding investments in the manufacturing environment and efforts by the developers.

Transferability is concerned with the possibility to apply the application in another manufacturing environment. It thus deals with the resource efficiency in terms of transferring the described advanced analytics application (Bhinge et al. 2017). This impacts economic and environmental resources.

Updatability is referring to the capability of the application to adjust the model with new data incrementally. The theme is only mentioned by Bhinge et al. (2017) by labeling this as a particular advantage of the applied Gaussian process regression algorithm. Consequently, this theme has an impact on the decision-making capabilities as it determines whether decision-makers can use the latest data. Another theme which was mentioned once is *implementation time* which refers to the required time resources to install an application and collect enough data to deliver "valuable results" (Silveira et al. 2020).

The two themes *equipment energy consumption* and *cloud energy consumption* are both dealing with the respective data lifecycle stages and the energy consumption of the respective technologies. They impact the economic and environmental pillars. The cloud technology use is also evaluated through the two remaining themes *latency* and *remote control*. By using cloud technologies, the real time decision-making is impacted by the latency until data is transmitted through the cloud so that the economic pillar is affected (Feng et al. 2020). The theme *remote control* is concerned with the accessibility of the production processes through cloud computing from the temporal and spatial perspective. It impacts the social and economic pillar by providing access to workers from anytime and anywhere and providing transparency for decision-making (Wang et al. 2016).

All themes are affecting at least one pillar of sustainability (Table 7). Interestingly, there is no theme which is only affecting the environmental pillar alone. However, there are two themes which impact all pillars at the same time. Moreover, 22 of the 27 themes have an impact on the economic pillar in some way. Consequently, economic concerns are the most represented sustainability pillar in this analysis. The environmental pillar is the least represented with seven themes while the social pillar is influenced by 16 themes.

The economic concerns relate in four themes to energy consumption costs. This includes energy consumption for the computation of the algorithms (*computing complexity* and *algorithm efficiency*) and for the operation of hardware (energy consumption for equipment and cloud). Moreover, the economic pillar is also impacted by costs for software and hardware to execute the advanced analytics applications such as open source software or costs for equipment for example sensors. A major aspect of economic sustainability are costs for workforce. Several themes are related with this aspect as many applications require complex and challenging tasks such as preprocessing, the integration of different data sources and the prerequisites of model-building. Moreover, one theme is dealing with the required costs to enable the acquisition of data in the manufacturing environment (*requirements acquisition*). Lastly, the economic sustainability is also represented by the decision-making capabilities. These are impacted by the performance of the applications, the data quality and latency of the cloud to enable real-time decision- making.

Pillar of sustainability	**Theme**
Economic	Equipment costs, requirements acquisition, latency cloud, updateability, remote control, implementation time
Social	Comprehensibility, interactivity visualization, familiarity with software, expert knowledge
Economic-social	Challenges of big data, complexity of data sources, processing efforts, preprocessing efforts, open source, prerequisites of model-building, knowledge sharing, data access efforts, data quality
Economic-environmental	Computing complexity, algorithm efficiency, equipment energy efficiency, cloud energy consumption, data quality, transferability
Economic-social-environmental	Performance, security

Table 7: Themes ordered by sustainability pillar

The environmental sustainability is represented in four of the seven themes by aspects of energy consumption and thus CO2-emissions. These are *computing complexity*, *algorithm resource efficiency* and energy consumption for equipment and cloud. Moreover, there are themes which are dealing with resource efficiency and thus the relationship between in- and output. In this respect, *performance* for example represents the usefulness of an application and thus also indicates what the invested input can deliver in value as output. In a similar way, *transferability* shows whether the invested resources can be used to apply the application in a different manufacturing environment.

Social sustainability is represented by several aspects. *Knowledge sharing* and *open source* adhere to principles of openness and knowledge sharing in general. *Challenges big data*, *complexity data sources*, *processing efforts*, *prerequisites model-building* and *data accessibility* constitute themes which pose challenges to developers which require time to find solutions or execute these tasks. Another aspect of social sustainability is the accessibility of the decision-making of the algorithms (*comprehensibility*), the model-building in the respective manufacturing environment, (*expert knowledge*) and the interpretation of results (*visualization* and *interactivity*). Lastly, *performance* and *data quality* impact the trust of the developers in the applications.

5. Discussion and conclusion

This study aimed to forward the research subject of the sustainability of advanced analytics applications in smart manufacturing. The goal was to provide an overview of existing advanced analytics applications in smart manufacturing and to identify sustainability themes in the scientific literature.

Therefore, a SLR was conducted and 65 different applications were identified, which cover ten different effects in the two application areas intelligent production, maintenance and service, namely energy consumption insights, prediction and optimization, process insights, prediction and optimization, predictive maintenance, quality prediction, scheduling optimization and material prediction. The applications represent diagnostic, predictive, prescriptive as well as cognitive analytics. Moreover, four research perspectives were identified. The publications were motivated by providing new applications, theoretical frameworks to implement them, descriptions of implementation projects, and more sustainable designs.

Furthermore, the analysis resulted in the identification of 27 sustainability themes, which can be used to evaluate advanced analytics applications in smart manufacturing regarding their sustainability. These themes cover the pillars of sustainability holistically. Social aspects were represented by criteria such as the comprehensibility of the computations of applied algorithms for human users, and the interactivity of interpretation tools to facilitate the analysis for users. The economic pillar was covered by data acquisition and recording equipment costs and energy costs for computations of complex algorithms for example. The environmental aspects were only impacted by energy consumption and thus criteria such as the energy consumption of sensors. In general, the identified sustainability themes had a strong economic focus, with 22 out of 27 being related with economic concerns. Social issues were represented by 18 themes, and seven were dealing with the environmental pillar.

This study came to the following conclusions. Firstly, the research about the sustainability of advanced analytics in smart manufacturing is still at its beginning.

Efforts in this area are more focused on providing sustainability effects with new applications and frameworks to implement them. Moreover, the analysis of application areas showed that publications still have not covered all applications areas and that some cutting-edge technologies are underrepresented when it comes to verify the proposed applications. Consequently, it is expected that more research will be conducted to close these gaps.

The identified sustainability themes show that there are critical issues for the design of advanced analytics applications in smart manufacturing. For example, the energy consumption through the computational complexity and the comprehensibility of the decision-making process of algorithms might represent issues which could surpass a critical issue of awareness, once advanced analytics applications are more commonplace.

This research has several limitations. The analyzed publications do not exhaustively cover the subject due to the applied keywords, search string, selected databases, and publication date during the SLR. Consequently, publications with advanced analytics applications that cover additional effects in smart manufacturing could be missing. Moreover, the SLR might be impacted by a selection bias, which refers to the fact that final hits were identified by the authors so that certain publications might have falsely been excluded. However, by defining and applying eligibility criteria, this bias should have been minimized. More specifically, a subset of possibly available data was presented here. This leads to a potential reporting bias. The presented transparency of the applied methodology, however, allows the reader to assess validity of the results, which are reproducible.

Future research should focus on a more comprehensive and critical investigation of sustainability themes. This is important to ensure that the applications do not harm the pillars of sustainability and thus enable a broad adoption of advanced analytics applications in smart manufacturing.

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A regional remanufacturing network approach

Modeling and simulation of circular economy processes in the era of Industry 4.0

Norbert Gronau, Edzard Weber, Paul Wander, André Ullrich

1. Introduction

The natural resources on our planet are exhaustible and most processes in the creation and processing of products cause emissions. Furthermore, in many areas, including consumer goods, more products are currently being manufactured than are necessary (Marte-Wood 2018; Varga 2020). In design and production of goods, the focus is often still not on a long life of a good or a product or its individual components. This leads to several critical aspect on both, consumption and production side of goods. Waste of products by cause of e.g. optical reasons, leads to increasing market prices due to continuous – and mostly not necessary – scarcity of resources (see Barnett and Morse 2013), environmental pollution (Rathore, Kota, and Chakrabarti 2011), or increasing carbon footprint (Lewandowski and Ullrich 2022), to just name a few negative external effects. The concept of disposable products for single use violates the idea of sustainable behaviour and development - which guided humanity for thousands of years - and inherently weakens society. Of course, economical aspects of production such as value creation, securing employments, or filling societal needs cannot be ignored. However, economic growth against the background of resource depletion, environmental burden, and rising societal pressure demand a radical shift in market strategies and production/consumption behaviour of the actors (Rathore et al. 2011). On the other hand markets, legislation, and a growing societal awareness for responsible consumption and behaviour drive remanufacturing (Steinhilper and Brent 2003). Remanufacturing refers to a "life cycle renewal process that is recognized as one of the most effective green strategies to attain sustainable manufacturing" (Ngu, Lee, and Osman 2020). Within this process, products that consist of assemblies or several individual parts can be disassembled and reprocessed and then refurbished and, if necessary, partially replaced so that they can be re-mounted to the finished product. This way, the entire assembly or dismantled individual parts can be reused. However, manufacturing companies still have relatively few points of contact with the circular economy and are unaware of its potential (Kumar et al. 2019; MacArthur 2013). Furthermore, often cost-efficient assessment of the condition of the individual parts is problematic and assessment procedures after individual part separation are technically complex (e.g., scanning and testing procedures) (Zhang et al. 2019). Furthermore, these assessment procedures are usually only

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available after the disassembly process has been completed. This is where conceptualization, data acquisition and simulation of remanufacturing processes can help. Advance information about product use via feasibility analysis can relieve the disassembly effort in advance and provide information about installed individual parts and their condition. Furthermore, advance information, if accessible, also enables the use of components from non-manufacturers, so that greater interoperability can be ensured. Advance information can thus make the remanufacturing process cost-effective and also provide information on future product design to facilitate the remanufacturing of new product variants. One major constraining aspect is reducing logistic efforts, since these also have negative external effects on the environment. Thus regionalization is an additional but in the end consequential challenge for remanufacturing processes and approaches. In accordance with the problem outlined, this article aims to fill a gap by providing an ex ante approach to local remanufacturing, in particular the design of local remanufacturing chains and the simulation of alternative courses of action, including feasibility study and economic assessment.

This chapter is structured as follows. Section 2 introduces and elaborates on circular economy in general and remanufacturing specifically, thereby, focusing on the remanufacturing circle and its phases. Section 3 presents the local remanufacturing network approach and its phases. The haptic scenario modeling approach and the Centre Industry 4.0 Potsdam (CIP4.0) that are used for scenario specification including feasibility and operating efficiency study will be introduced in Section 4 and 5 respectively. The application of both steps will be illustrated in Section 6, using the example of local remanufacturing of a trailer, instead of scrapping the existing and buying a new trailer. The focus lies on both, implementation of the haptic workshop and a requirement analysis regarding data that needs to be harvested and analyzed according to specific process steps. Section 7 provides a discussion and conclusions.

2. Theoretical Background

2.1. Circular economy

Circular economy is understood as an economic system that replaces the "end-of-life" concept through reduction, remanufacturing, recycling and recovery of materials in production/distribution and consumption processes. In the circular economy, a distinction is made between two types of basic principles (Kirchherr, Reike, and Hekkert 2017). There are the R-frameworks and the systems perspective. In practice as well as in science, different R-frameworks have been used for a long time, ranging from four over six to nine or even ten R (Fig. 1).

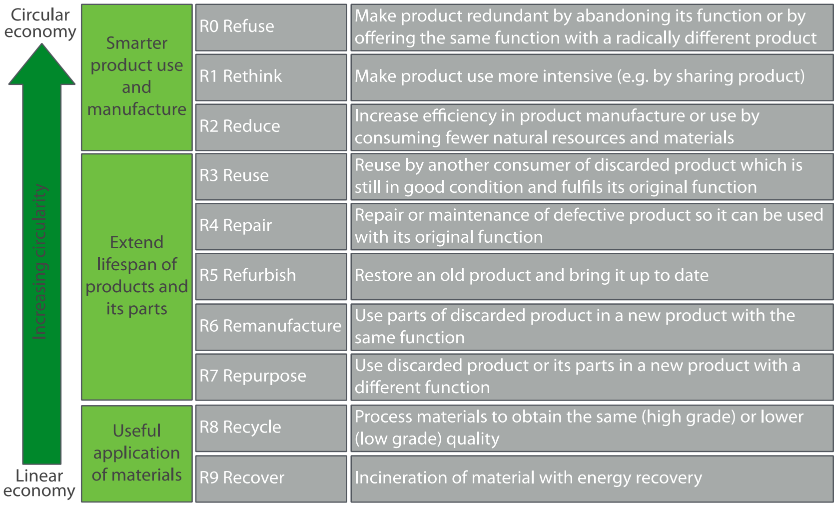

Figure 1: The 9R Framework (following Potting et al. 2017)

All variants of the R-framework have a hierarchy as a main feature, where the first R (which would be “reduce” in the 4R framework) is considered to have priority over the second R and so on (Potting et al. 2017; Sihvonen and Ritola 2015; Van Buren et al. 2016).

From the systems perspective, three systems are identified within the circular economy. Fang et al. (2007), Sakr et al. (2011) and Jackson et al. (2014) differentiate the macro, the meso and the micro system. The macro system responds to the industrial composition and structure of the entire economy. From the meso system perspective, industrial parks are identified as systems or regional level systems (Shi, Chertow, and Song 2010). Here, the process is specifically optimized to increase the local circular economy. Within the micro system perspective, on the other hand, products or individual companies are considered (Jackson et al. 2014; Sakr et al. 2011).

2.2. Remanufacturing

Remanufacturing refers to the repair or replacement of worn-out or ”no longer in use“ components and modules. According to Johnson and McCarthy (2014) it refers to “the rebuilding of a product to specifications of the original manufactured product using a combination of reused, repaired and new parts”. In general, it is the industrial reprocessing of used end-of-life parts and is uniformly defined in the literature in terms of its essential characteristics. Remanufacturing can be characterized by four major aspects (Lange 2017):

(1) The term refers to an industrial remanufacturing process of used parts.

(2) An end-of-life part is remanufactured using standardized process steps, and its original function is restored to it.

(3) The product performance added back to the old part is equal to or of an equivalent to new production.

(4) The same quality assurance measures as in the production of new parts and a guarantee ensure that the remanufactured product or the remanufactured product unit corresponds to the quality of a new production.

Sundin (2004) summarizes the remanufacturing process as an industrial process, through which end-of-life parts are refurbished for reuse. At the end of the process, it must be ensured that the remanufactured product meets the standards of the remanufacturing originals. Remanufacturing is described as a physical measure that restores the function of a defective unit (component, device, subsystem etc.) (Ijomah 2002). In comparison to remanufacturing, the wear stock is not renewed. The term "defective unit" describes the condition in which a unit is incapable of fulfilling a required function.

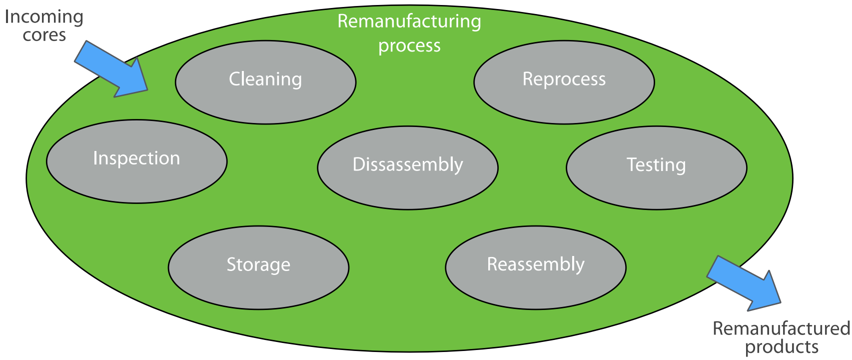

Figure 2: The generic remanufacturing process (Sundin 2004, p. 61)

Figure 2 summarizes the individual steps of the remanufacturing process. The used product that is to be remanufactured usually goes through 7 steps. The sequence of the remanufacturing process depends on many factors such as product design, working environment, volume etc.

Remanufacturing does not start with the product itself, but with the selection of cooperation partners and the organization of work to remanufacture the product. A particular challenge is when remanufacturing is to be established as an element of a regional closed-loop system and when it relies on distributed competencies. This is because it is an ideal and special case if a company can implement all remanufacturing sub-steps efficiently (time, cost, quality) on its own. This is probably only true for very specialized equipment or for large companies. At the same time, it is possible that several regional companies with different competencies can mutually establish a remanufacturing process regionally. This should at least be the goal if one wants to achieve remanufacturing as a standard for many products and not only for a few.

For the diverse and cross-company dissemination of remanufacturing, it is necessary to identify regional networks that can map and embed the regional process for a specific product class. In the case of new initiations, a large number of actors will be relevant who are not aware of the feasibility and economic viability. At this point, participatory group processes are (unusually) suitable to demonstrate the interaction of subtasks distributed among different actors in a remanufacturing process.

3. A regional remanufacturing network approach

The process model for a regional remanufacturing network (RRN) must cover tasks that go beyond the generic remanufacturing approach. The intention is that the remanufacturing is carried out by and with actors from a specific region. For this, the right competencies and respective specialists have to be identified. Specialists and customers must be convinced to participate in such a network by demonstrating feasibility and economic viability. The actual remanufacturing process is embedded in a joint planning for the entire regional network. The process model (see Fig. 3) thus includes tasks of production planning, supply chain management, quality management and stakeholder management, which are ensured by a company in the role of a network manager.

1. A potential trigger for the regional remanufacturing process can be a customer request. Her request is evaluated along with all other requests to identify trends or acute focus orders that should be prioritized or handled with particular systematicity. The customer contact can be initiated at any partner company in the network. Likewise, the needs analysis is shared by all partner companies. The network manager is responsible for the central maintenance of customer data, customer inquiries and analysis routines.

2. Maintaining and expanding contacts with partner companies for the network is another central task for the network manager. The network checks whether the necessary competencies are available to fulfill acute or potential orders. The later planning and execution is not self-organized. The individual business objectives and framework conditions of the participating companies are too dominant for this. Central planning works on the basis of the data that the network participants in turn provide to the network in a self-organized manner. Each company must be aware that involvement in a remanufacturing job is more likely if the information about its own availability and performance is better updated. The network can focus, for example, on specific industries, fail-safety and regional self-sufficiency. These strategic considerations must be understood and supported by all partner companies. For this reason, special network

meetings are held to run through various scenarios and actor constellations. Here, new potentials and effective relationships within the network are uncovered and discussed. The network manager maintains the provided master data of the partner companies and initiates strategic networking.

3. In the feasibility check phase, the technical implementation of the remanufacturing process is reviewed. Central questions concern the correct decomposition of the remanufacturing process and the necessary product and actor data to make this process controllable at all. The verification is carried out by means of a simulation. In the case of a cyber-physical simulation, partner companies are shown directly what workload they have to adjust to or what information still has to be supplied. In addition, problems in the network can be simulated and it will be determined whether they can be handled with the information available in each case. Partner companies should gain confidence here and recognize the need to exchange information with companies that may be competitors beyond and within the network. If it turns out that a certain product cannot be remanufactured or cannot be remanufactured economically, it is jumped back to the first phase. The customer need and the network setup are considered again by the partner companies, so ideally new and missing competencies and information are shared. The network manager organizes the feasibility check and is responsible for monitoring and reworking orders that cannot be implemented.
4. In the distribution phase, the basic feasibility of the remanufacturing process is confirmed. Here, concrete process planning and optimization is carried out. Again, this is done with information about capacities, availabilities and costs from the partner companies. As a result, a concrete remanufacturing process and offers for the workpiece, specifying the companies involved, quality standards, total costs and total completion date will be presented to the customer. If no solution can be created or the offer is not accepted, it is jumped back to phase 1 so that the partner companies can revise the performance of the network.
5. The execution phase includes the actual remanufacturing process. The subtasks will most likely be spatially distributed and processed over several network partners. Thus not only the subtasks but also the transports of the disassembled workpiece must be coordinated. This is done by the network manager.
6. Finally, the delivery and the evaluation of the distributed overall performance in the remanufacturing process take place. Here also the phases 1 to 4 are considered. The compliance and adequacy of costs, times and result quality are checked and considered for future processes.

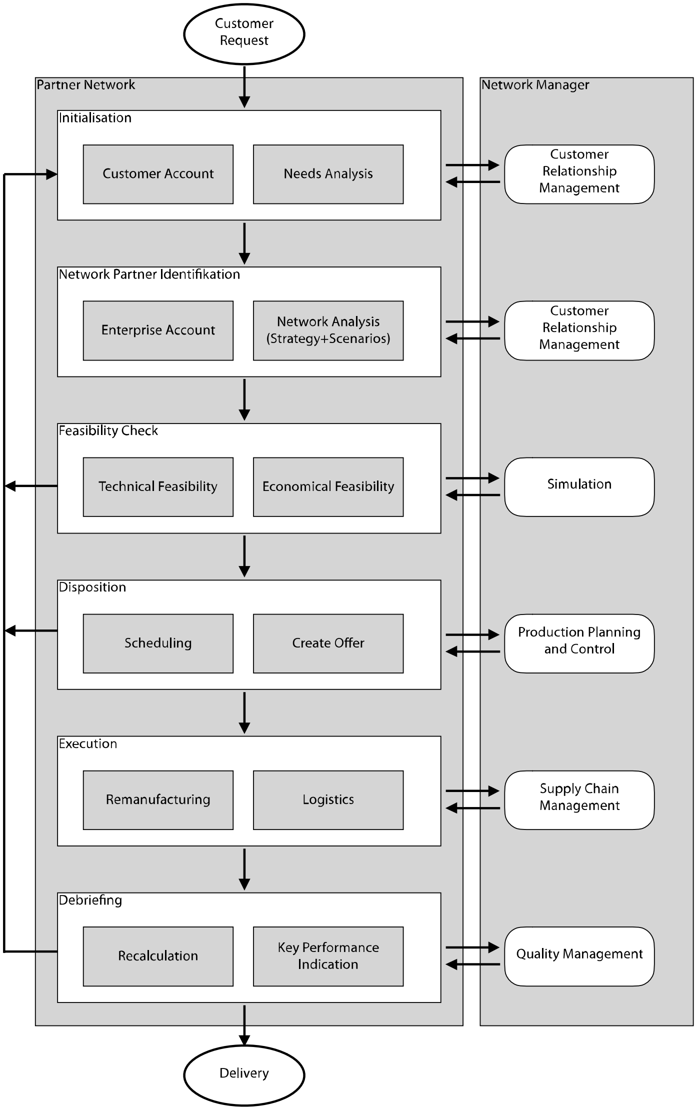

Figure 3: General procedure model for the regional remanufacturing network

The network manager is responsible for operating the application systems required by the network partners in the remanufacturing network. S/he integrates functions and data for the overall process. In operational terms, this means that s/he ensures the availability of data and the executability of the subtasks by the network partners. The network manager is not the central decision-making authority. The initial customer contact goes through the network partners. The network manager only ensures a central customer database and enables evaluations of products and competencies in demand. S/he requests and maintains relevant data from the network partners. The companies themselves decide which data is made available to the network. The same applies to feasibility analyses, scheduling and execution. Many of the network manager's tasks can be automated: Renewal of analyses, data exchange, reminders, scheduling, cost calculations, and performance metrics reporting. Thus, customer contact does not normally have to exist at all. Intensive contact with network partners only takes place in the "Feasibility Check" step. These are strategically important tasks (simulation workshops) in which the network partners, under the moderation of the network manager, determine the partner structure (scenario modeling) and the technical feasibility of the remanufacturing. This sub-step is only complex if new product categories or new partners are included by the network. The network manager is needed as an independent and autonomous actor in the network. S/he has no personal interests in the actual fabrication process and can ensure that critical data from partner companies is used only for planning but not passed on directly to the other network partners.

4. Scenario development workshop using haptic modelling

In the network identification phase, an exchange of knowledge takes place with and between the actors from the region. The aim is to identify potentials and effective relationships. A common understanding of the production network and the various roles of the partner companies involved and to be involved will be generated. To ensure that individual perspectives, concerns, unique selling propositions, advantages and disadvantages can be worked out transparently and presented in a comprehensible way for all participants, a system modeling will be carried out. For this purpose, a participatory approach and a haptic type of representation will be used (Hoffmann 2020). This is based on a synthesis of current methods of haptic thinking (Grunwald 2009).

4.1 Haptic modelling in general

Haptic thinking and modelling methods are hands-on methods in which tacit knowledge and skills are brought into 3D space by modeling with the hands (Harrigan, Kues, and Weber 1986). Lego® Serious Play®, PlaymobilPro®, Design Thinking, Rapid Prototyping and other new techniques are based on the principle of Haptic Thinking (Nerantzi, Moravej, and Johnson 2015).

Thus, the system under consideration is physically mapped so that spatially inspired changes in perspective can be made. Likewise, spatial relationships can be mapped more effectively. System or model elements can be moved or rotated in relation to each other without any problems in order to be able to observe dynamic changes even of actually static system structures. From an experienced-based learning perspective, this haptic modelling fosters a deeper understanding of both, the problem and the solution. The mutual discussions in each phase furthermore enable different ways of approaching the content and thus a deeper penetration of the content, which ultimately leads to internalization of the developed solution.

From a practical point of view, the following advantages for haptic modeling are mentioned (LEGO Serious Play 2022):

- New findings from psychology and neuroscience suggest that cognitive processes such as learning and memory are strongly influenced by how our bodies interact with the physical world.
- Through the creative process of modeling, the brain is enabled to work in a different way. This opens up new perspectives.
- Thoughts, feelings and experiences are made visible and comprehensible in order to recognize room for maneuver.
- Existing thought patterns and thought processes are broken up and questioned, allowing new or different information to rise to consciousness.
- The haptic modeling of contexts that are difficult to grasp can be an important aid in reflecting on difficult or particularly complex topics.
- Visual reminders of important aspects of an issue can support thinking skills.
- By creating objects that can be seen and grasped, the brain reduces the amount of things that need to be considered at the same time. Neuroscientists call this process "reduction of mental workload".

An important design feature of haptic modeling methods is the level of abstraction used. System properties, elements, and relationships can be represented concretely, figuratively, or strongly metaphorically. Model elements in a concrete figurative notation provide a direct recognition value of the modeled object (e.g. model cars for real vehicles). System models created in this way are easier to understand for people who only see the modeling result and were not involved in the modeling process. This usually involves working with predefined modeling elements. Metaphoric modeling makes it possible to create more profound model elements. These are only created during the modeling process and the modeler consciously or unconsciously provides the design features of the element. In order to understand these models, participation in the modeling process and in the accompanying explanation and discussion sessions is necessary. Uninvolved model viewers can only understand the sometimes complex metaphors and model evolution with a lot of effort. A simple, uncommented viewing of the model is not enough to be able to understand the embedded metaphors.

4.2 Concrete implementation

The modeling of regional remanufacturing networks focuses on regional settings. The existing infrastructure, spatial distribution of partner companies, the social environment and landscape specifics are relevant influencing factors for the integration of actors in regional networks. All these aspects are integrated into the model, layer by layer and step by step. The individual sub-steps are always subdivided by explanation and discussion phases of the system modelers involved, so that the group always continues to work with a common understanding and consensus of the scenario presented. As a result, the scenario developed provides all strategic information for a conceptual implementation of remanufacturing cycles in the region under consideration.

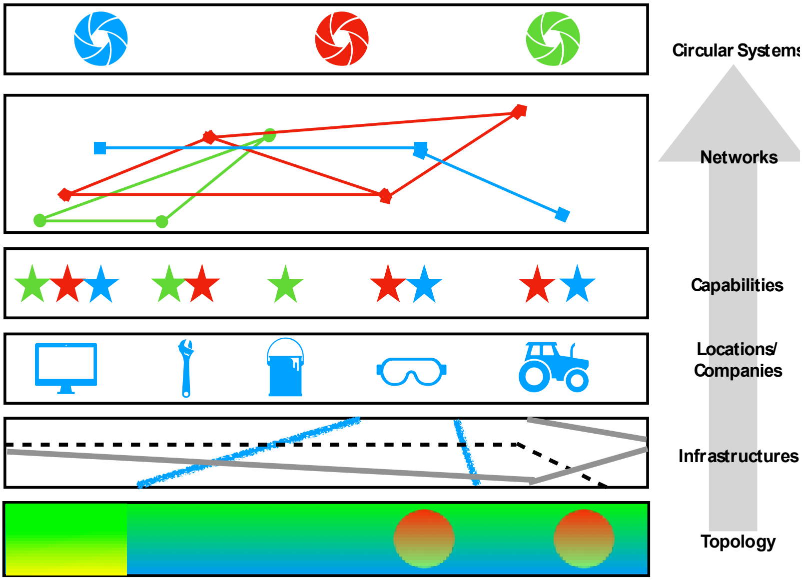

Figure 4: layers of the scenario model

Regional actors that the network manager considers relevant for the upcoming main topics are involved in the scenario modeling. They may be experts in the relevant technologies, people who know the region or those affected by the remanufacturing process. In turn, these can be manufacturing companies or craft enterprises that can technically carry out sub-steps in the remanufacturing process. At the same time, logistics service providers, trade, administration or potential/current customers can also be considered relevant and involved.

The step-by-step scenario modeling takes place in eight phases, of which one is a preparation and introduction phase and another is a post debriefing phase (cf. Fig.

4). Thereby, modeling materials are used in all phases, which allow a most direct figurative representation (cf. Fig. 5).

- Briefing: Begin with an introduction of the participants. This is intended to make transparent the expertise, perspectives, and interests present.
- Phase 1 (topography of the region): In this step, participants create literally the underground for the model. It represents a shortened image of the given topological situation in the considered region. Landscape and agricultural areas, settlement and commercial areas, forest and water areas are designed. It should not and must not be a direct image in the form of a true-to-scale map. It is only concerned with aspects of general land use, the degree of development and urban sprawl, and special natural features in the region.
- Phase 2 (infrastructure of the region): In this step, the main transport routes are added: roads, railways, waterways. Likewise, enterprises and institutions of generally great importance for this region can be added (large enterprises, administration, universities etc.).
- Phase 3 (commercial landscape of the region): In this step, companies are placed in the scenario which, in the view of the participants, may be of importance for remanufacturing work. Prepared overviews with companies from the region are suitable for this. The participants decide for themselves how many companies are to be modeled. Additional modeling can be carried out in later phases.
- Phase 4 (capabilities of the regional companies): In this step, the necessary competencies and capabilities are placed in the scenario that are required for the remanufacturing of specific products. The participants select a product or a product class and analyze its components. The relevant technical competencies are identified for each component. The identified competencies are assigned to the previously modeled companies. Competencies can be modeled redundantly. Unplaced competencies are noted as services to be sourced supra-regionally.
- Phase 5 (networking): The relevant competencies are now networked to a concrete processing sequence. Logistical aspects must be taken into account (transport, intermediate storage, assembly stations). Alternative networking can be designed to optimize routes, fail-safety or work distribution.
- Phase 6 (cycle extraction): In this step, the enterprise network developed for the product category under consideration is transformed into a separate model. The generic remanufacturing cycle (cf. Fig. 2) is applied. If the participants recognize that central actors, competencies or connections are missing, the scenario model can be improved.

- Debriefing: In this step, the modeling process is reflected upon. Participants consider the resilience and practicality of the model created. This can result in measures that the network manager has to implement: active integration of relevant companies into the real partner network, inclusion of the product group in the remanufacturing portfolio of the partner network, elimination of unsolved competence gaps.

By jumping back into phase 4, more than one product group can be worked on within one workshop and in one scenario model.

Figure 5: Modelling material

A landscape modeling technique was developed that uses inexpensive, easily procurable materials on the one hand and self-designed special building blocks on the other (see Figure 5). With the help of a laser cutter, for example, transport elements such as cars, ships, airplanes, and trains are provided. When selecting the different materials, it was important on the one hand that the materials fit coherently into the design of the model. On the other hand, the materials should inspire the participants to model, by being of high quality and therefore pleasant.

Certain technical and interdisciplinary concepts are introduced into the model development process via predefined special elements. This modeling approach fulfills the essential requirements such as modeling speed, expressiveness, traceability, material availability, haptics, modeler interaction and systematic procedure.

Due to the fact that all participants model simultaneously, there are no dominating actors in the designing phases who can drive the entire model in a certain direction. And in the concluding explanation rounds, each participant gets similar time shares to present their ideas and model extensions.

5. Scenario specification in the Centre for Industry 4.0 Potsdam

5.1. Centre for Industry 4.0 Potsdam

The *Centre for Industry 4.0* comprises a hybrid simulation environment, which combines the benefits of virtual and hardware simulation and components in order to design or analyse industrial manufacturing processes or value-adding networks (Lass and Gronau 2020; Teichmann et al. 2018). The main physical components are the work pieces and the machine tool demonstrators as well as transport lines which connect various machine tool demonstrators. The demonstrators with their ability to communicate in different ways and the flexible transport system provide an effortless integration of hardware components into the overall system. Additionally, digital technologies and Internet of Thing (IoT) devices such as AR/VR glasses, tablets, smartwatches, robots, smart products and machines are integral elements (Ullrich et al. 2019). The software is designed for a quick integration of sensors, actuators, and other devices using standard communication protocols such as OPC UA. The hardware components provide the interfaces for an easy connection and integration of new hardware. This simulation environment is used to investigate process layouts and identify alternatives (Gronau, Theuer, and Lass 2013; Lass, Theuer, and Gronau 2012) or as teaching and learning environment in which workers can experiment with new processes, new technologies, and thus acquire new skills (Gronau, Ullrich, and Teichmann 2017; Teichmann, Ullrich, and Gronau 2019). Learning scenarios can be implemented via process models (Thim, Ullrich, and Gronau 2020) and are used to convey skills and competencies (Gronau et al. 2017; Ullrich, Teichmann, and Gronau 2020; Vladova et al. 2022).

The CIP4.0 allows the design of different processes and scenarios that create the required learning situations with the help of the didactic concept and specifically promote the intended knowledge of the individual learning modules. If the hybrid model factory is now explicitly supplemented by a didactic concept, a flexible learning factory emerges which, as an immersive learning location, follows learning-theoretical methodology and greatly reduces the theory-practice gap for learners.

5.2. Simulation in the Centre for Industry 4.0 Potsdam

The simulation environment of CIP4.0 uses a hybrid approach for factory modeling. This approach combines a physical model factory with computer-aided simulation. For each component of the simulation, the most suitable form of model implementation can be selected in each case. In this way, necessary production objects (machines, workpiece carriers, etc.) can be configured, which - regardless of whether realized as a physical original, as a physical model or in virtual form - are integrated into the necessary variant of the production process and provide the desired scenario in the model factory.

A practical implementation of this hybrid concept consists of physical and computer models, which form the main elements, the so-called demonstrators (Lass 2018). The interaction of demonstrators enables the construction and simulation of an entire production process. A demonstrator consists of a box configured with the parameters of a particular production object. Interface and communication modules enable interaction with other components and allow various additions, e.g. further modules (such as additional sensors or actuators). Figure 1 illustrates the basic structure. The visualization of the machining process takes place on both sides of the demonstrator. The user interface for human-machine interaction is located on the top of the demonstrator and displays relevant product, process and job information (Teichmann et al. 2022). The demonstrators exist in stationary form as well as in mobile design (Fig. 6).

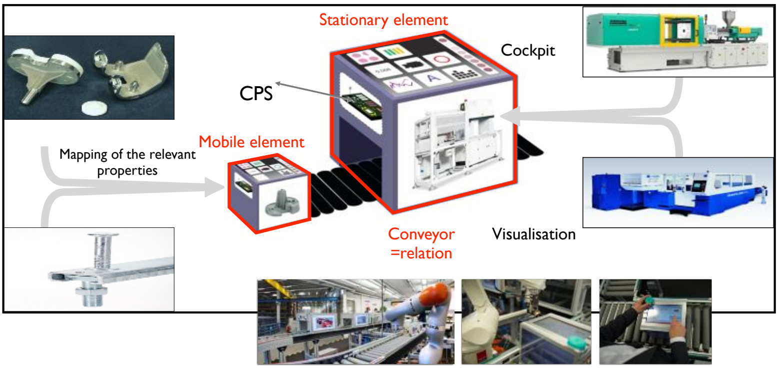

Figure 6: Principle of hybrid simulation

Using transport devices (e.g. roller conveyor) a real material flow in different layouts is possible. Experiences show that the transport by roller conveyor is perceived as very typical for a factory and has a positive effect on the immersion. Furthermore, numerous components from the Industry 4.0 toolkit are available as elements for modeling. For example, assistance systems can easily be configured that use mobile technologists such as tablets or AR glasses and allow the actors to experience the functions and advantages of modern and future production systems interactively in the middle of the production process or train them in their use.

The hybrid approach and its implementation in the CIP4.0 model factory have already proven themselves in competence and skill development (Vladova et al. 2022), testing of IoT-technologies (Bender, Teichmann, and Ullrich 2017) and have proven to be a suitable basis for use within continuing education (Gronau et al. 2017; Teichmann et al. 2019), simulation of production process alternatives (Gronau et al. 2013) or value networks (Lass 2012). Thereby, both general feasibility and economic efficiency of the processes can be investigated. For this purpose, feasibility studies can be conducted to assess the practicality of a specific process layout, configurations, or settings within a manufactory or within manufacturing networks, emphasizing especially respective strengths and weaknesses. Using distinctive manufacturing key performance indicators and realistic numbers for prices of refurbishing, replacement, and labour costs specific alternatives can be evaluated and therewith developed from conceived to feasible and lastly to economically efficient local remanufacturing alternatives. Therefore, the specific remanufacturing scenario is modelled and then simulated in the hybrid simulation environment, focusing on the good to be remanufactured and its components, all the associated actors in the remanufacturing process, their specific characteristics and relations.

6. The case of regional trailer remanufacturing

The strategic network planning and the work-preparing feasibility analysis represent the innovative methods within the general process model. Their application is therefore illustrated by a small case study on the remanufacturing process of agricultural trailers.

6.1. Specific haptic Workshop

The (fictitious) initial situation is that actors from a rural region want to ensure the remanufacturing of agricultural machinery. They do not want to rely on supra-regional manufacturers/ OEMs, but to use the competences and structures distributed in their own region. The method of scenario modeling is used to identify the necessary competencies for the remanufacturing of agricultural machinery and the corresponding partner companies. The remanufacturing process must be modeled technically and logistically in the region and with actors from the region.

According to the procedure model for scenario modeling, all phases have been conducted by the participants. Step by step, the scenario had developed. And at the end of each phase, there was an exchange of ideas on the newly added elements. As a result, a common understanding of the region and the remanufacturing network was successively developed (see Fig. 7).

After creating the overview of the remanufacturing cycle, the workshop participants discussed in detail the most effective and efficient process for remanufacturing the agricultural trailer, the consequences and results of which were then simulated haptically using scenario modeling.

- Through the modeling and discussion in the group format, new views and insights could be developed.
- Actors previously considered irrelevant could be identified as options for special tasks within the remanufacturing project.
- The spatial arrangement of the work sites could be directly included in considerations, so that alternative routes and sequences could be identified.
- The professional complementarity or redundancy of network partners could be structured.
- Experiences of cooperation among network partners could be exchanged.
- The regional distribution of workloads and tasks could be discussed.
- Technical competences that are missing in the region could be identified. Supraregional or alternative solutions could be discussed.

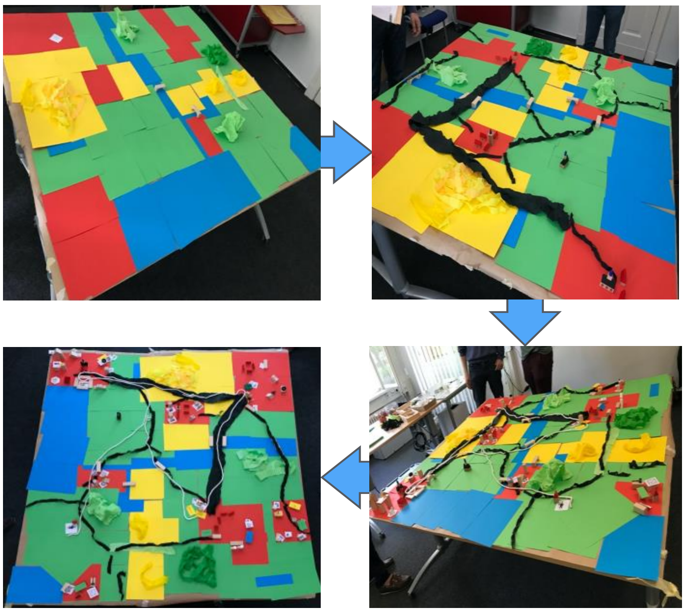

Figure 7: Insights into the haptic modeling workshop

Discussions on the aforementioned aspects were triggered by the scenario modeling. As a result, the participants additionally exchanged and linked their individually bound contextual knowledge about the region and its companies. A single network manager would not have been able to take these hidden potentials and sensitivities into account for a centrally implemented network planning.

6.2. Requirements for simulation in ACI4.0

How to plan a factory for regional remanufacturing networks when the network is not yet fully established? How to show the advantages and possible challenges to avoid a cost-intensive ramp-up phase? To answer these questions a simulation is the appropriate method of choice. Simulation as a method for mapping production processes and investigating effects that cannot be studied to the same extent in reality is widely used in engineering (Richter 2017; de Sousa Junior et al. 2019). There exist several requirements for simulation of regional remanufacturing networks (see Table 1).

The cyber-physical simulation of the remanufacturing network offers different insights into technical feasibility than classical planning systems. MES and production planning and control systems are designed to use provided order data to optimize overall planning. In regional production networks with several, loosely coupled players and constantly new product classes, optimization has a downstream significance. The focus is on the many imponderables which, unlike in a purely internal production line, cannot be controlled centrally. The danger of incomplete data from individual network partners, of failures of network partners and of technically induced changes in the remanufacturing steps primarily require confidence-building measures. The network actors (companies and customers) must be convinced that the network is sufficiently resilient or capable of change to be able to deal with such influences.

Requirements
Support of real-time decisions
Adaption to fast changing environments
Prediction of material flows
Usage of data from digital manufacturing systems (databases, traceability systems, process models)
Reusable generic remanufacturing algorithm

Remanufacturing information model
Access to data collected in manufacturing by sensors

Table 2: Requirements for the simulation of regional remanufacturing networks (Goodall, Sharpe, and West 2019)

Classical production assumes that all parts are in pristine condition. This is not given in remanufacturing processes. So the much higher degree of autonomy which comes with cyber-physical systems allows to flexibly reroute parts and assemblies according to their state and designation dynamically. This is where cyber-physical simulation concept can show its strength. Both purely virtual and cyber-physical simulation approaches initially require an internal model of the production process and a set of rules for controlling the production process. CPS approaches, however, have higher degrees of freedom in introducing disturbances. Disturbance scenarios do not have to be planned in advance and started according to schedule, but can be brought about at any time by direct physical interaction: Workpieces disappear, are delayed, are misrouted or are damaged; production facilities are overloaded, work incorrectly or fail completely. Network partners can jointly participate in such a hybrid simulation. In this way, each individual participant can act out his or her highest-rated hazardous moments. And the network partners together can see how the control concepts created for the production network independently deal with such disruptions.

The regional remanufacturing processes will not occur in large numbers and will always be carried out in different constellations. Thus, it does not make sense to learn exclusively from errors that have occurred. Structural deficiencies, faulty planning, lack of information and capacity bottlenecks can be largely uncovered by CPS simulation and eliminated before they actually occur.

We will collect data from exemplary remanufacturing processes and bring them together in a virtual remanufacturing network to show the advantages of this approach.

7. Discussion and conclusion

Inefficient production processes, the economical need of growth and throw-away society unnecessarily shorten limited natural resources. Globalization, additionally, has negative external effects on the environment. In semi-conductor industry e.g., a wafer is transported three times around the world before it is delivered to the customer. Such kinds of local optimizations of production processes in value creation networks lead to overexploitation of the environment. A promising and rising – yet the underlying principle is already hundreds of years old – approach is the remanufacturing of goods. Under the umbrella of circular economy, this approach allows for decreasing resource consumption. For being consequent, this approach needs however be implemented in a local context to decrease logistic efforts and thus negative effects on the environment.

In this paper, we presented a local remanufacturing approach that allows for reducing resource consumption, fosters local companies, and efficiently provides solutions for regional re- and further usage of goods. Therein, a particular focus was on identification of local networks and feasibility study of the remanufacturing process. Therefore, haptic modelling for identification and hybrid simulation in the Centre Industry 4.0 in Potsdam for feasibility study was presented. The approach to substitute a usually solely technical planning process with open workshop formats is new. This is, however, particularly helpful for the participants and affected persons to understand the existing complexity of such processes. Furthermore, the simulation of remanufacturing networks for conducting feasibility study and identify not just conceivable but practically implementable options in hybrid simulation environment is also new.

In principle, the RRN approach is suitable for a wide range of products. In particular, however, this is strongly dependent on both the regional demand and the existing competencies. If there is a large regional demand for a certain product category, it makes sense to build up an RNN, even if supra-regional competencies have to be included. If there are good regional competencies, an RRN can be created, even if the demand for this product category comes less from the region but supra-regionally. Example of extreme cases are cheap mass-produced appliances (e.g. coffee machines) on one side and large custom-made products (e.g. production equipment) on the other side.

That the competencies are composable within an RRN is a necessary criterion. The sufficient criterion is then the economic efficiency. The challenge of the network manager is to fathom out over time how large the order volume and the product complexity must be or may be in order for the network to cover its costs.

The RRN approach can be scaled down, so that production networks for certain product categories are not elaborately simulated, but are implemented directly without any claim to profitability. However, this only works if there are network partners who carry out certain activities on a voluntary basis (e.g. small equipment remanufacturing in open workshops).

Especially if the CIP4.0 approach is realized, it probably makes sense to start with large, medium-complex products. As experience is gained, the RRN can then be extended to more complex items or to mass-produced items. For both orientations, it makes sense to also consider non-economic remanufacturing scenarios (reprocessing of low-cost items for citizens with the primary goal of waste avoidance. Or reprocessing of special machines that are existentially important for the regional economy). This would then even be an advantage for regional resilience, so that one can help oneself better in extreme situations.

A detailed listing of the potentials and challenges of regional remanufacturing networks is shown in Table 2.

Potentials	**Challenges**
Strengthening of regional economic and business relations	Additional coordination effort
Independence from supra-regional supply problems (material, knowledge, transport)	Additional IT infrastructure is required
More transparency in value creation	Sometimes too close interdependencies
Regional ties as a performance incentive	Regional performance (quality, costs, capacities) usually lower than that of supra-regional companies
RRN experience remains in region and grows	In case of small markets there is only little demand
Better traceability of costs, deadlines, and quality	Each region needs a method-competent network manager, if central RRN services are to remain regionally located
Process experience, methodology and IT architecture can be transferred to other regions and does not need to be rethought	Willingness of network partners to communicate necessary information
Networking of regional partners to remanufacturing services with supra-regional unique selling point	Dependence on good data from network partners
Uncovering regional synergies and emergences	Network partners need infrastructure to be able to transmit data

Systematic collection of experiential knowledge	Sensitivities in regional competitive situations have a greater impact
New business models for regional companies	Exposure of company internal key figures and structures to other network partners
Independence from supra-regional manufacturers / OEMs	Dependence on IT and network managers to manage complexity efficiently
Potential to integrate semi-professional actuators (hobbyists)	
Scalable for many/few products and for large/small products	
Degree of own contribution can be determined and implemented	
Regional optimum is in the foreground	
Existing organizational concept, in case supra-regional supply totally fails or is overloaded (e.g. emergencies)	

Table 3: Potentials and challenges of regional remanufacturing networks

Haptic modeling of socio-technical systems is not the norm in business informatics or production science. However, it offers several advantages over digital models and two-dimensional representations, which can be directly experienced in any modeling workshop. These advantages could also be confirmed for the application context of remanufacturing.

- Scenario modeling is a strategically significant negotiation process. There are individual interests and personal sensitivities. Personal presence of the actors involved is thus basically advantageous. Points of view, ideas and opinions are not only expressed through words, language and facial expressions. The way in which certain aspects of the model are designed with the hands also sends out tacit signals to the other participants.

- Because placing elements and establishing supply connections implies affirming business relationships, working with haptic elements is analogous to making "tangible" statements that are placed in the model.
- Modelers can change geospatial perspective at any time. Models have a different effect on the viewer depending on the angle of view or distance. Zooming in digital models does not correspond to the usual physical, intuitive movements and then distracts from the object of observation.
- Likewise, conflicts (technical but also economic) between the actors are directly revealed and dealt with in a playful context. More formal meeting scenarios tend to escalate opposing positions.
- Since regional networks are involved, the balanced selection of the involved competence carriers also plays a role. Their appropriate spatial distribution in the region can be a key acceptance factor in ensuring that this service model is perceived and used by customers from the region. This is because each network partner acts as it were for customer acquisition.
- The modelling process is immensely efficient and effective. This is because all actors work on the model at the same time and initially no time has to be invested in negotiating design decisions.
- Model creation is not dominated by those who have the writing cursor, greater market power or rhetorical competence. In fact, the model becomes useful only when the smaller companies or niche competencies are integrated into the model.
- These workshops are about a service from the region for the region. Even independent of this business model, the network partners form an economic community due to their spatial proximity to each other. Bringing regional companies into conversation with each other is always a sensible measure. This also initiates other opportunities for cooperation. From the point of view of the remanufacturing network, these meetings and the "playful" cooperation are an important measure for making the players personally known to each other and building trust.

Future research activities comprise modelling and simulation of further goods to enrich the process library, the implementation of a deeper detail planning to also assess intra logistic and remanufacturing process variants within the network participants.

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Disruption Management in One-Off Production with Collaborative Digital Assistance Systems

Benefits of an Integrative Approach with a Generic Data Model

Niklas Jahn, Tim Jansen, Robert Rost, Hermann Lödding

1. Introduction

Disruptions inevitably occur in the project execution of complex one-off projects (Fischäder 2007). They cause effort and costs and, in many cases, delay the progress of the project. Nevertheless, in practice, disruption management is often inadequate because disruptions are only recorded locally and disruption information is not documented in a structured manner. A large part of the disruptions is solved by the interaction of several operational roles, such as workers and foremen (Gruß 2010). However, access to disruption information is not easily available for all affected roles. One-of-a-kind manufacturers are also confronted with a lack of information between the operational level and project control (Wandt 2014), so that disruptions can rarely be related to the overall progress of the project.

By using digital assistance systems, disruptions can already be reduced or even avoided on the operational level. The reason is an improved presentation of information (Friedewald et al. 2016). Nevertheless, unavoidable disruptions occur, such as quality defects of installed parts or delays due to environmental influences (Steinhauer/König 2010). A potential for improvement is to reduce the effort caused by such disruptions and to reduce or completely prevent consequential disruptions by reacting quickly. Furthermore, information about disruptions and the knowledge gained from them should contribute to future avoidance in follow-up projects and should be transparently available (Gronau et al. 2019).

This article shows how digital assistance systems will play a key role in the future in order to improve disruption management in one-of-a-kind production. The basis is a generic data model that can map different disruptions and enables structured storage for the many participants in disruption management. We assume that digital assistance systems will already be well integrated into the work processes and will thus avoid system and context changes at the operational level, while supporting in disruption management activities.

The paper is structured as follows:

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First, the importance and handling of disruptions in one-off production is exemplified (Section 2). Subsequently, the state of the art in relation to the use of IT systems in disruption management (Section 3) is discussed.

The development of digital assistance systems (Section 4) and data models are examined in regard of disruption management requirements (Section 5). In the process, opportunities and deficits are highlighted. Following, the concept of a generic data model for disruptions is presented (Section 6).

The integration with a digital assistance system and a web application incorporating value-added features is described in Section 7. Especially we show how to use the solutions to improve disruption management.

The paper concludes with a summary and an outlook, which gives a perspective on the use of the obtained disruption information in follow-up projects.

2. Significance of Disruption Management in One-off Projects

Disruptions are any kind of unintentional deviation from the normal process (Lehmann 1992). Typical sources of disruptions observed in one-off projects at different branches of industry are problems with (Rost et al. 2019):

- Construction acceptance, e.g. open items at quality gates
- Complaints in the customer acceptance phase
- Material supply, e.g. a shortage of material
- Assignment of tasks, e.g. unclear task definition
- Resource conflicts, e.g. building site reservations and closures
- Construction ambiguities

These problems cause rework, clarification efforts and waiting times. Good handling of disruptions can increase the quality of a product and thus its longevity. For a more sustainable production, more products can also be produced while using the same amount of resources by reducing scrap and rework efforts.

One-off productions are particularly sensitive to above mentioned disruptions for two reasons:

1. The execution of one-off projects requires a high degree of interdisciplinarity through the interaction of many disciplines and multiple project-to-production interfaces. A disruption in one discipline therefore in many cases affects other disciplines as well as the project management.

2. Different one-off production projects usually share the same production resources at the same time in terms of disciplines and also partly space. This can lead to cross-project disruptive effects due to lack of resources or space as a consequence of a single disruption.

Therefore, high demands are placed on the cooperation as well as on collectively managing disruptions to maintain a smooth project and production execution (Rost et al. 2019). If disruptions occur, they require a rapid response and often also a rescheduling of production. Therefore, up-to-date information about disruptions is just as important as knowing about the current project progress and situation.

Our studies in shipbuilding industry have shown that construction managers and foreman play a key role in communicating and resolving most disruptions. For example, 43 individual disruption cases taking up the majority of working time were observed during a single shift, see Figure 1.

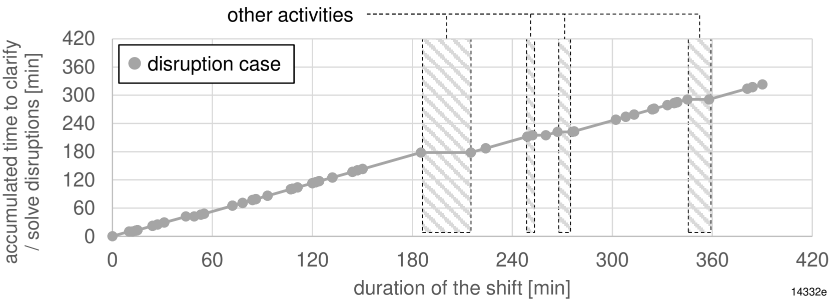

Figure 1: Example of the accumulated clarification time for disruptions of a construction manager during a shift

Figure 2 uses a simplified example from customized aircraft cabin production to show how different types of disruptions are handled with the involvement of different roles. Minor disruptions (1) can be solved bilaterally between a worker and his foremen. Bigger disruptions (2) require further escalation and involvement of superior roles. Our observations show that usually the following activities are performed after a disruption occurs:

1. Initial message by a worker (documentation)
2. Assessment by a foreman, incl. finding a solution
3. Further escalation, if necessary for finding a solution and deciding on a counter-measure
4. Communication of solution instructions from foreman to worker (counter-measure initiation)
5. Documentation of countermeasures and evaluation or feedback on effectiveness from worker to foreman

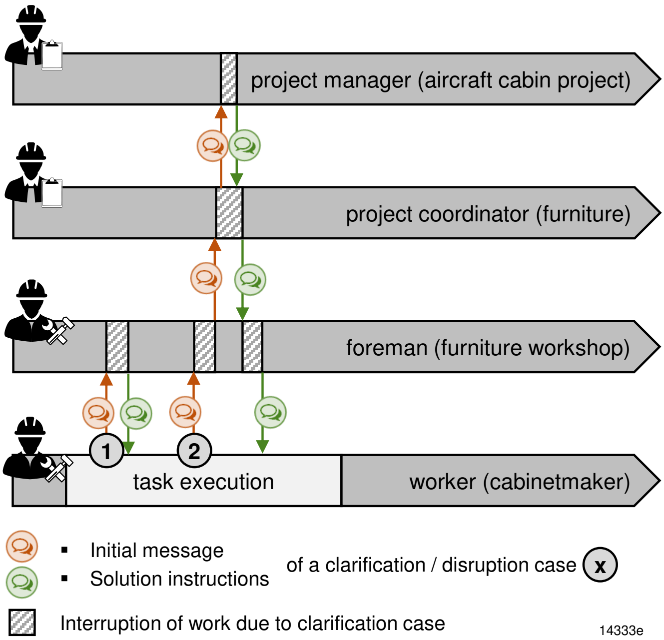

Figure 2: Management of disruptions in one-off production, based on (Rost et al. 2019)

These activities of dealing with disruptions are typical for a reactive disruption management, because they take place after a disruption has happened and aim at reducing their effect. There are two basic strategies for managing disruptions, namely prevention and reaction strategies (Schwartz 2004), see Figure 3.

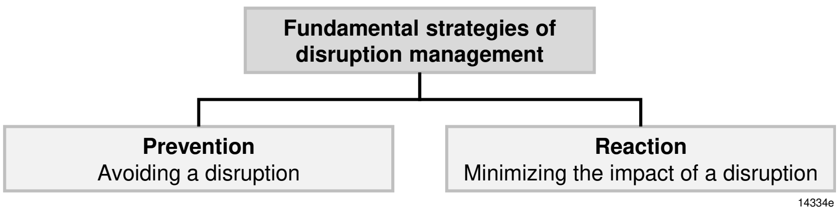

Figure 3: Fundamental strategies of disruption management, based on (Schwartz 2004)

Prevention requires assessment of possible disruptions and implementing measures to either eliminate their cause or protect against their occurrence beforehand (Schwartz 2004). Preventive activities in one-off production are performed mostly within a discipline or on project management level by regular meetings of domain experts. They typically collect potential lessons learned from their discipline-specific disruption documentation solution.

Previous analysis and evaluation of disruptions during planning are however especially challenging in one-off projects since design can occur even late in the production process and there is a constant lack of information, especially in the early planning phases. Disruptions and their treatment are usually not immediately reflected on extensively in the sense of lessons learned, but instead the order contents are further processed so that no further delay occurs. As a result, preventive measures tend to take place downstream, and there is a tendency to postpone a large number of these until the end of the project. The problem is that in the end preventive measures and lessons learned are usually carried out in a rather rudimentary manner, if at all, since a new or parallel project usually ties up the resources immediately. Because preventive disruption management often is rudimentary in one-off projects, reactive activities are especially important.

3. Information Technology Used in Disruption Management

Disruptions are typically managed and tracked individually per discipline with a variety of methods, often with generic IT tools, such as Excel sheets with different layouts, digital Kanban boards as in Microsoft Teams or messenger apps like WhatsApp. Sometimes, instead of IT tools, paper is still used for notes on disruptions and to-do lists are created to keep track of the troubleshooting process.

Usually, reactive activities and underlying disturbances are not transparent and accessible across disciplines and projects. In consequence reaction efforts are slowed down along the communication chain. If a disturbance affects other disciplines, it regularly is observed as an isolated disturbance by this discipline, triggering isolated disturbance management activities where a collaborative approach would be required.

The criticality of a disruption is strongly determined by the scope of consequences, which can be individual, discipline-wide, cross-discipline, project-wide or cross-project. However, when a disruption occurs, often the consequences cannot be determined solely by the person noticing it. Therefore, it is important that disruptions can be easily accessed by all affected parties to see far-reaching consequences. Consequentially a company-wide organizational and IT infrastructure is necessary.

The digital processing and IT support of disruption management in one-off production has been subject of research since the 1990s (Eversheim 1992; Lehmann 1992; Bamberger 1996). IT systems proposed or used for disruption management are adapted shop floor management systems or workflow management systems as well as dedicated disruption management systems, such as assist^{IT} (Wünscher 2010). As a link between planning systems and production, Manufacturing Execution Systems (MES) are also able to identify disruptions and initiate countermeasures (Schumacher 2009). So far, these have mostly been established in the context of highly automated production with extensive use of machines, which can be monitored with sensors and controlled digitally. For companies that perform one-off production, which is characterized by a high number of manual activities within production orders, there is still no suitable MES (Jericho et al. 2022). However, there are already approaches to connecting the shop floor in one-off production with MES systems or with a Digital Twin in particular with the aim of improving disruption management (Jericho et al. 2022). Yet the exact digital integration of the particularly important workers is not described in detail.

We could see that the acceptance for the aforementioned systems is low in practice of one-off production. This is due to different reasons: the systems are not integrated well into standard processes or tools, they are often not designed to be user-friendly for non-experts and they often run on stationary computers, resulting in walking distances and additional work for the user. Our observations show that a natural starting point to report a disruption for the workers is the link with components, product structure, location and ideally a products 3D model. Most disruptions have a component reference and a reasonable link saves workers the search effort when trying to resolve a documented disruption.

Digital assistance systems for production workers are a promising alternative to the systems described before due to their focus on the product and its 3D representation as well as their availability on mobile devices. Unfortunately, they are not entirely adapted to be used in disruption management. In the following it will be shown how adapted digital assistance systems combined with a generic data model can overcome present deficits and lead to more integrated disruption management.

4. Digital Assistance Systems

Digital assistance systems are a special type of information systems, which are designed mainly for use at production level and run on mobile devices such as tablets or mobile phones. They are intended as the main source of information for operators performing their work. Studies show that the use of such assistance systems can reduce assembly errors and improve productivity (Friedewald et al. 2016). The main functionalities provided by digital assistance systems in one-off production are (Friedewald et al. 2016; Halata et al. 2014; Rost et al. 2019):

- Easy and quick access to product and work package related information:
    - CAD model of the product or the relevant parts for a work package
    - Additional attributes, such as geometric measures or process parameters
    - Digital documents, such as data sheets
- Visual 3D deviation check of an installation situation (actual state vs. target state) by means of comparison to reality via augmented reality (AR) or CAD view.

- Basic documentation and feedback of
    - Work progress
    - Disruptions

For several reasons, digital assistance systems for the worker are ideal and useful in disruption management:

- Digital assistance systems reduce the effort required to document because the documentation is made with the same device and software that is used for the value-adding activities. Important points of the documentation can be deduced from the tracking function of the AR function (location) or from the workflow (part numbers of affected parts).
- Studies indicate that digital assistance systems enjoy a high level of acceptance among employees and are therefore likely to establish themselves as the primary information system in manufacturing. They are characterized by high availability and easy accessibility because they run on mobile devices.
- Digital assistance systems bear the potential to sense disruptions (via user input / feedback / context) and reach out to individual users for immediate reaction with counter-measures.
- Digital assistance systems can be connected to an MES or a digital twin and thus integrated into the comprehensive disruption management across several company IT system levels and together with machines.

However, there are still some deficits besides the aforementioned chances that need to be solved in order to achieve a comprehensive disruption management:

- **Vertical integration.** Current digital assistance systems often address only the operative roles and lack integration with information systems for foreman, production and project managers and engineering (see Figure 4).
- **Horizontal integration.** Digital assistance systems currently focus on dedicated disciplines and do not function across them, which would be needed for a bilateral information exchange.

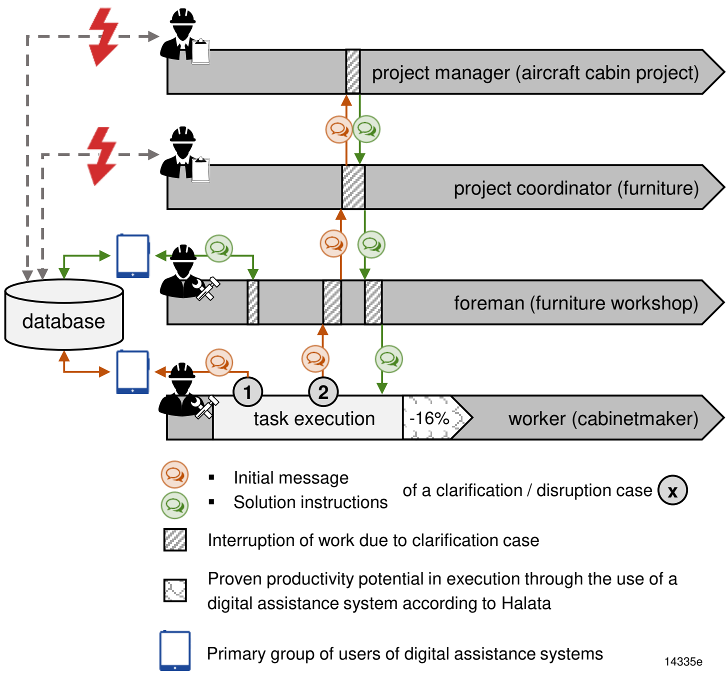

Figure 4: Motivation and improvement potentials for using digital assistance systems in disruption management, based on (Rost et al. 2019)

Moreover, current disruption management functionality in digital assistance systems suits user groups that can share a fixed and standardized data model in a database. In the following, this data model is described in more detail and its problems and limitations are shown as soon as more than one discipline as well as project management and engineering are to work collaboratively with it.

5. Existing Data Models for Disruptions

Data models are the backbone of digital assistance systems. The data relevant for disruption documentation and management can be summarized as follows:

- Identification key, e.g. a GUID
- Textual descriptions and categorizations
- References to product, location and work order
- Processing and meta information (status, dates, author, responsible)
- Descriptive attachment references (documents, images, …)

Rost et al. introduce a data model for documenting issues in 3D with Augmented Reality based on the IFC and BCF formats, which originate from the Building Information Model (BIM) used in the construction industry (Rost et al. 2018). Since most construction projects are similarly complex as production projects in shipbuilding and aircraft cabin modification, the data model can be applied in principle. However, it has a few shortcomings, which are to be discussed.

First, the data models lack flexibility in terms of information content of the topic to match discipline-specific needs, of which some examples are shown in Figure 5. Second, the data models are not integrated into the global project scope, e.g. the project plan but also the global production scope, e.g. the production plan.

Many data models are based on the assumption, that a one-size-fits-all solution in the form of a rigid data model can be explicitly formulated. However, there are multiple situations in which this assumption is wrong, since it requires that standardization is possible with reasonable effort.

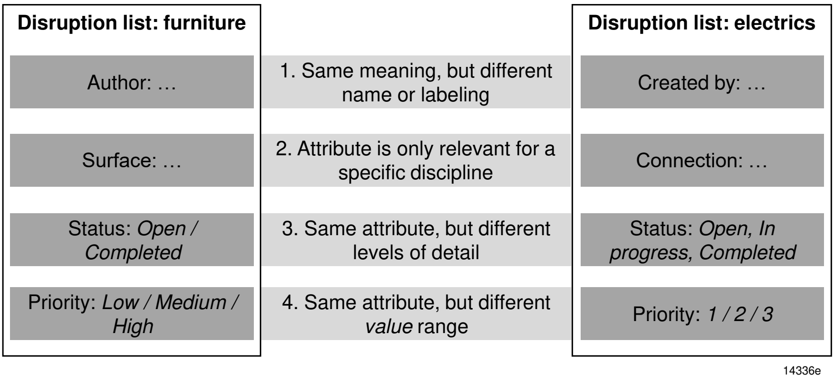

Figure 5: Differences between disciplines in disruption documentation

Reasons that problematize standardization and the aforementioned assumption for one-off production are:

1. Different disciplines have individual requirements regarding the visual presentation of disruption data, e.g. label based on a discipline- or process-specific expression ("author" vs. "created by" vs. "responsible").

2. Different disciplines require custom attributes and categories to document their disruptions, which are not needed by others.

3. Different disciplines require the use of individual status definitions for their disruptions internally, which only partially matches with overall project / production status definitions, because a finer division is required.

4. The same case as in 3., but different division of the status is required.

It is not feasible to combine the lists of the different disciplines into one, since:

1. Different designations are absolutely justified, since they e.g. are common in technical language and are therefore easier to understand.
2. Since there will be too much and also irrelevant additional information when simply merging the lists, the disciplines would have to make an effort through manual filtering to keep an overview, which impedes usability.
3. Having unnecessary additional choices can cause confusion.
4. Same argument as 1. Even with a compromise in which both attributes remain to coexist in a merged list (e.g. priority 1, priority 2) this is at the expense of clarity.

The example shows that, despite initially obvious differences, there are similarities and intersections in terms of content. This favors the plan to find a generic model that meets the different needs of the processes and disciplines and could thus lead to a cross-process standard. A concept for this is developed below.

6. A Generic Data Model for Disruptions

This section presents the concept of a generic data model for disruptions derived from requirements arising from the previously identified deficits in disruption management. The purpose of the proposed data model is to store all data describing and related to a single disruption in a way that serves all stakeholders in disruption management during associated activities.

Requirements for a data model derived from the previously elaborated problems and deficits are:

1. Allowing a definition of discipline-specific disruption types with custom attributes and individual status.
2. Maintaining comparability of different types of disruption records.
3. Being able to derive disruption management performance indicators from the data model for all disruption types from any source.
4. Allowing customization of the visual representation of the disruption data, without the need of changing or extending the data model itself.

The concept of the generic data model for disruption consists of two parts: the first part considers the requirements 1 to 3 and the second part covers the fourth.

Combination of standardization and customizability. The data model consists of a set of default attributes, to allow for comparability and common analysis of different types of disruptions, and a set of customizable attributes, which enable flexible definition of different disruption types in a discipline-specific manner.

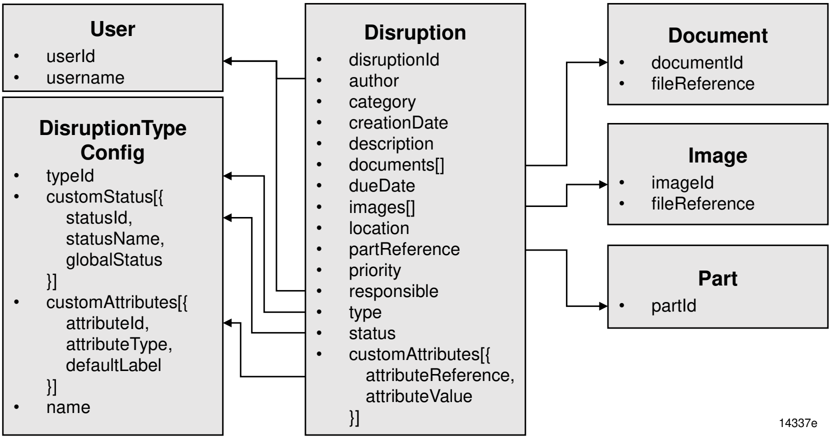

Figure 6: Entity-relationship model of the generic data model (simplified)

Figure 6 shows the entity-relationship model of the generic disruption data model. The properties identified in the previous section as necessary for documenting a disruption are present as default attributes for all disruptions. In addition to a unique identifier and the creator of the disruption documentation, these attributes also include references to a product or part, relevant images and documents, and a location of the disruption. Information on creation and due dates, priorities, and status enable a uniform and joint evaluation of the disruptions regardless of their discipline-specific application.

Every disruption contains a reference to a discipline-specific type configuration that defines custom attributes and status. In this configuration the data type and a default label for the custom attributes are defined. In the model of the disruption itself, only a reference to the attribute definition and the attribute value are stored. The situation is similar with the statuses. Here, too, the discipline-specific statuses are defined in the configuration and only a reference is stored in the disruption model itself. To enable uniform evaluation and derive performance indicators, a type-specific status must be mapped to a global status, e.g. "open", "in work" or "done".

Separation of data model and visualization model. A core idea of the data model concept is making use of the software design pattern called model-view-viewmodel, short MVVM, which separates the business logic related model from the visualization in user interfaces. The reason for this is a gain in flexibility to display the same disruption data in different customizable visualizations and even customize the default attributes of the data model at the user interface layer.

Figure 7 shows the entity-relationship model of the visualization model. It defines which disruption types are to be considered in the visualization. Thereby it is possible to create discipline-specific or combined views of disruptions.

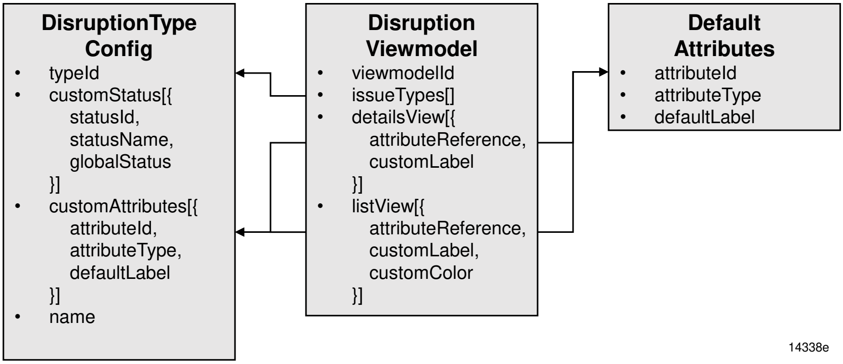

Figure 7: Entity-relationship model of the visualization model (simplified)

Customization of a detailed view of a single disruption and a list view of multiple disruptions can be done independently of each other. In both cases, an array is defined that contains references to the default attributes or custom attributes of the selected disruption types. If a custom attribute label is assigned, it will be used at the user interface layer instead of the default label. As an example, it is possible for the default attribute "author" to have the label "author", "created by" or any other designation for different viewmodels. Furthermore, column colors can be defined for a list view.

7. Integrated Disruption Management with a Digital Assistance System

The integration concept for the generic data model for disruptions addresses native augmented reality based digital assistance systems as well as web-based applications. In total three applications for different purposes have been developed in order to make use of the shared generic data model and to cover support during core activities in disruption management (see Figure 8):

- An augmented reality based digital assistance system on a tablet, which serves as the main work package and production information source for production level (Subsection 7.1)
- A web-based disruption dashboard with additional tools for situational awareness and decision making for disruption management on production and project management level (Subsection 7.2)
- A web-based tool especially for the purpose of disruption documentation and remediation for production level via mobile devices, when the use of AR is unfeasible, e.g. due to a lack of 3D models (not shown here)

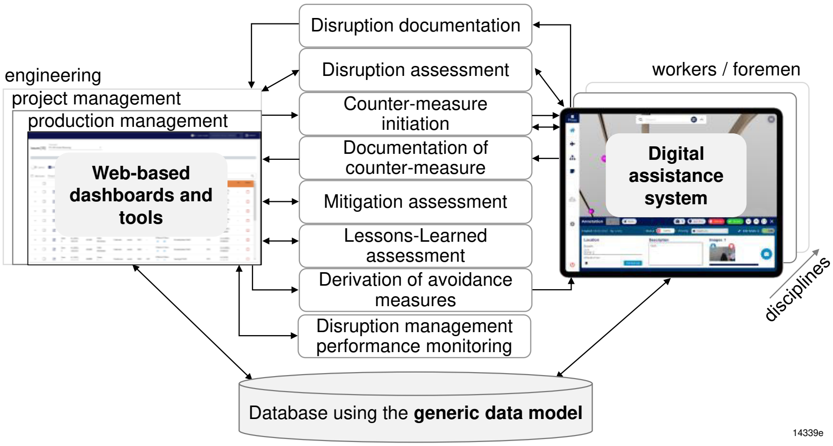

Figure 8: Digital support of core activities in disruption management with an integrated generic data model

7.1. Digital Assistance System with Disruption Management Functionalities

The integration of advanced disruption management capabilities into digital assistance system represents the core idea of this article. The main challenges and solutions which will be presented hereafter lie in user interface (UI) and user experience design, especially when Augmented Reality visualization takes place. On the technical side, the adaptability of the user interface to the generic data model described in the previous section also introduces challenges in software development. However, these will not be discussed in detail but instead the resulting user interface will be presented. The user interface of an existing digital assistance system for manufacturing has been extended by two additional functional areas focused on disruption management:

- a UI for a single disruption that is related to a 3D or alternatively AR view and which can either display an empty state for documenting a new disruption or to review an already documented one, e.g. for processing (Figure 9)
- a UI which presents an overview of all recorded disruptions in a list and includes a 2D layout with the location pins of disruptions, filter functionalities for processing and meta information like author, processing responsible and status (Figure 10)

Figure 9: Individual display and input mask for documenting a disruption

Documenting a new disruption consists of up to 3 steps:

1. Setting a 3D-pin in CAD / AR at the affected location of the product
2. Specifying description and additional information (e.g. priority)
3. Capturing photos of the disruption (optional)

Automated context-sensitive functionalities enrich the quality of the disruption records. Setting the location pin (1.) will automatically detect the related part and derive further information about its location based on the product structure (e.g. zone / deck, parent assembly). The photos (3.) are automatically tagged with information about the parts and disruption it refers to or which are visible in it. These tags are linked to exact 2D positions (markers) on the photo.

As shown in Figure , the digital assistance system supports not only documenting the disruptions but also facilitates processing them until they are solved completely. Solution progress, counter-measures and their success can easily be tracked, documented and reviewed on spot or remotely. A 2D layout and a 3D navigation function accessible in AR help to quickly find locations where disruptions occurred.

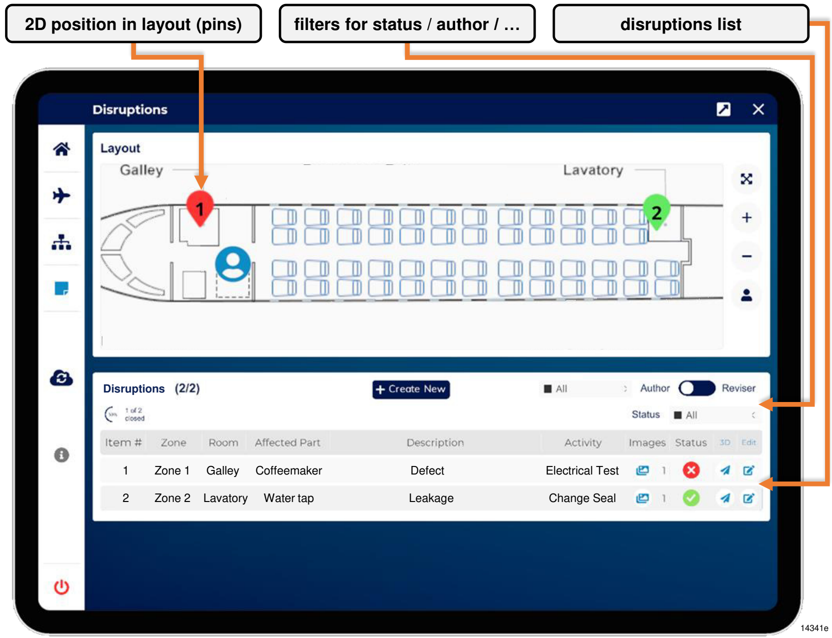

Figure 10: Disruption overview in the digital assistance system for processing

7.2. Web-based Disruption Processing

The developed web-based tools for disruption management use the same generic data model as the digital assistance system described before. However, they are intended for use in decision making by providing an overview and the possibility to review and extend the disruption information for initiation and tracking of reactions. Besides assigning priorities and due dates, users can define countermeasures and delegate them to a responsible discipline, department or employee.

The upper part of Figure 11 shows the overview of all disruptions regardless of their type. In this case, only the default attributes are shown and the global status of the disruptions. In comparison, the lower representation shows the type-specific view for the "Open Items" viewmodel.

Customization allows to define the attributes to be displayed, their order, label and column color for a specific disruption type based on the MVVM approach of the generic data model. For example, the custom attribute "Connection" is only displayed in the type-specific view. Furthermore, the type-specific status definitions and labels for "author" and "status" are used.

Opening the same overview from a tablet or smartphone results in a different layout due to a responsive design, which helps improving the user experience on different devices.

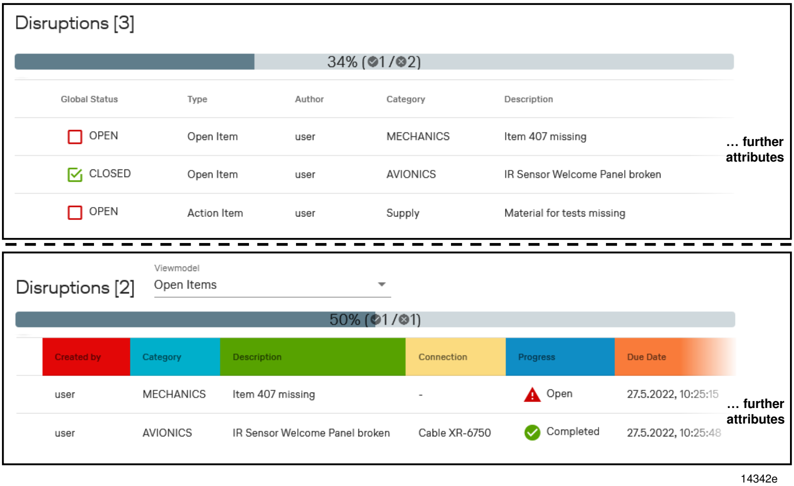

Figure 11: Comparison between the overview of all disruptions regardless of type (upper) and a type-specific view (lower)

7.3. Web-based Disruption Dashboard for Project Management

The disruption dashboard is a web-based application and forms an assistance tool for production and project management for performing analysis and during decision making. It consists of five different tabs in the user interface, each providing a specific toolset to the user for the aforementioned disruption management tasks:

- Overview and disruption distributions
- Disruption management performance indicators: schedule reliability, deviations from schedule and throughput times
- Throughput diagram
- Timeline (project-related)
- Heat map of disruption management activities

The first tab gives an overview of the existing disruptions and their distribution (Figure 12). Besides a breakdown by disruption status, bar charts show the distribution after disruption type and the number of overdue disruptions per project phase including a history over the past calendar weeks. This helps users in production control and project management to deduce trends and to adjust capacities if necessary.

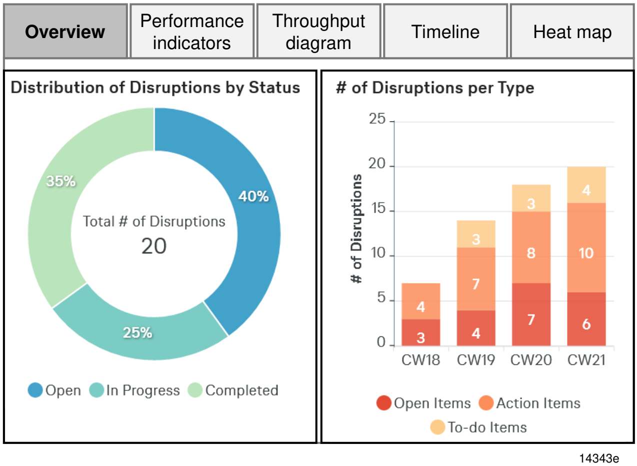

Figure 12: Disruption overview and distribution (excerpt from the web-based dashboard)

A second tab shows management performance indicators like schedule reliability, deviations from schedule and deviations between planned and actual throughput times per disruption type.

It is possible to apply the funnel model of production control to the disruptions as they have the character of an order. In this case, a discipline or department with its employees who process the countermeasures of a disruption form the workstation. As the processing time is not clearly defined for all disruption types, the number of disruptions is used as the work content. The informative value is improved by only displaying disruptions of the same priority and category at the same time. The resulting throughput diagram is part of the third tab (Figure 13).

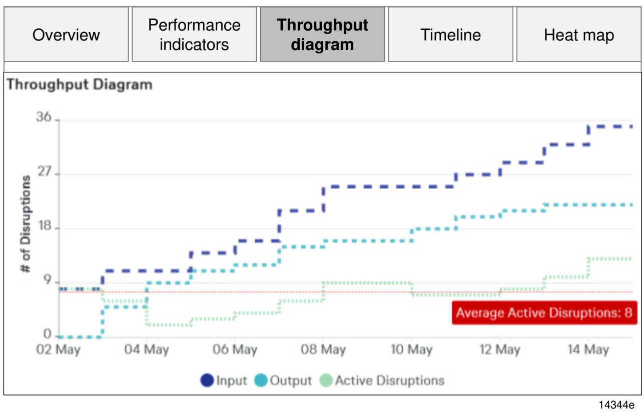

Figure 13: Throughput diagram for disruptions (excerpt from the web-based dashboard)

The disruption timeline in the fourth tab shows the individual disruptions with their scheduled or actual throughput times in the context of the project phases and milestones. Filter and grouping options complete this view.

The last tab contains an activity heat map which shows the disruption-related activities like creation, updating and closing on a timeline. Grouping options help to compare the frequencies of different groups like disruption types or categories.

8. Practical Use and Evaluation Approaches

The approach towards an integrated disruption management with digital assistance systems and a generic data model has been implemented in a demonstrator that includes synthetic data records for an aircraft cabin modification. The solution is to be evaluated via a combination of surveys with production employees, benchmarks of the user experience as well as expert interviews. Some expert interviews as well as a process simulation for the disruption documentation have already been performed, of which some preliminary results as well as expectations regarding results are presented in the following.

Production Level. Several disruption documentation and processing tasks shall be evaluated regarding usability using the User Experience Questionnaire and the NASA Task Load Index. The aim is to achieve a better rating for the digital assistance system for documentation and processing as the current heterogeneous IT landscape (MS Excel, Kanban boards, etc.), so that as many potential users as possible use the system in the sense of end-to-end horizontal and vertical integration.

As mentioned in Section 3, a variety of IT tools have been used to date for documenting disruptions. The presented digital assistance system in combination with the generic data model is able to replace a large part of these IT tools. Redundancies are avoided through the common database and transparency is increased as communication between disciplines is based on the same, up-to-date data.

In customer acceptance processes of several one-off projects, it has been possible to successfully use the digital assistance system, see 7.1, as a prototype in a process-related manner. The system has met great interest for future establishment and acceptance has been high. In addition to the user experience with the application on a mobile device, the increased documentation quality through the direct link to the product and the integration of localized photos was mentioned as advantageous. Only the setup of the tracking required for the use of the AR functionality was recognized as expandable. Therefore, tracking strategies that require even less setup effort are currently being designed and tested. Further the evaluation in customer acceptance processes focused on the documentation, while the processing that is expected to bear a significant productivity impact hasn't been covered yet. This is planned to be checked in future in an overall evaluation.

Production Control Level and Project Management. The practical implications and solution aspects for project management and production control were discussed in an expert interview with a senior project manager. His tasks consist of recording and coordinating internal and external complaints as well as the ensuring the product quality of in-house production and purchased parts.

In general, the senior project manager expresses a positive opinion with regard to a shared generic data model with a common database, since the disruption data provide information that can be decisive for capacity and control adjustments. With live data across all types of disruptions, he sees an opportunity to react more quickly to problems and, in the event of accumulations, to adjust capacities at an earlier stage. At this time, data of different disruption types is gathered manually at certain time intervals which can lead to delays in the reaction. The time histories of the disruption data shown on the dashboard can provide insight into the effectiveness of the countermeasures taken.

Even though the feedback of the senior project manager regarding the disruption dashboard paints a promising picture, the next step is to conduct a quantitative evaluation of this potential at production control and project management level.

9. Summary and Outlook

In this paper the relevance and deficits in the disruption management in one-off projects have been discussed. Further it has been shown why in digital disruption management current rigid data models are not sufficient for cross-discipline working environments.

As a solution it has been shown how a generic data model can represent different disruptions and allows a structured storage. This allows a continuous information feedback to the project management.

Based on this, it is shown how access to disruption information can be improved by a digital assistance system and web-based lists. The digital assistance system enhances information quality by locating it in the project's CAD model and general plan. It provides disruption management seamlessly integrated into the same system used to retrieve work package information and to work in collaboration, thus reducing context switching. Additional web-based tools present the project's disruption situation transparently and support project control in making decisions and gaining knowledge for future projects.

Potential for improvement exists in the form of an addition of functionalities for lessons learned assessment and derivation of avoidance measures via automated support in finding potential lessons learned by a recommender system, which analyzes disruptions for similarities with previous disruptions which were used as lessons learned and ranks them based on their attributes.

Another important aspect is the use of the extensive database of structured disruption data for automated preventive measures, e.g. similarity measurement based on the previous projects' disruption data and the current work package in the digital assistance system in order to automatically suggest and highlight potential problems and disruption risks.

In terms of sustainability, goods should be used for longer, which makes maintenance more significant and good disruption management and documentation all the more important. The data model presented can also be used in the lifecycle phases downstream of production - operation, maintenance and repair - to ensure quality and reduce resource consumption along the lifecycle.

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Digitization of the work environment for sustainable production

How could algae based sink technologies enable a neutral Product Carbon Footprint?

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1. Introduction and motivation

Anthropogenic climate change (Weart 2008) requires a reduction in greenhouse gas emissions in order to achieve the 1.5 degree goal defined in the Paris Climate Agreement (UNITED NATIONS 2015). This requires national regulatory provisions to develop a target path with regard to emission reductions in relevant economic sectors. This development currently poses particular challenges for energy-intensive industries, such as the steel industry (Neuhoff et al. 2016). The long term resulting costs for the economy are strongly dependent on future human behaviour and related decisions on emission limits and adaptation measures (Klepper et al. 2017).

Due to the European Union's commitment to action resulting from the Paris Climate Agreement (cf. UNITED NATIONS 2015), the European Green Deal of net zero emissions until 2050 (European Commission 2019), neutralizing carbon emissions has arrived on everyone's agenda and is proposing major challenges (Qian et al. 2022). This results in economic risks and monetary additional burdens for companies in connection with climate change, which are explained below.

The European Commission established the EU Emissions Trading Scheme (EU ETS) to ensure that climate protection goals are achieved (European Commission). This emissions trading system, known as "downstream", relates primarily to plant operators who emit direct emissions into the environment and affects companies in the energy sector and energy-intensive industries. The aim is to reduce CO_2 emissions and thus achieve the climate targets set in Paris. Emissions trading is based on the cap and trade principle. The system on account of the idea that for every ton of CO_2 emitted, a company must submit a certificate for approval of the emission assessment on the environment and the number of certificates is capped each year. Part of the allowances will be allocated free of charge to the companies involved, while the remaining volume will be purchased at auction. The certificates in circulation are tradable. Companies can sell surplus certificates or purchase required certificates. The available CAP is further reduced every year, with the goal of reducing emissions by 43% by 2030 compared to 2005. (German Environment

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Agency 2021) Through this approach, the degree of technology used to reduce emissions is correlated with the resulting additional monetary impacts. Companies that pursue and actively implement such activities can thus gain competitive advantages. Although this emissions trading currently only applies to energy-intensive industries, such as steel production, a future extension to this area cannot be ruled out due to the major influence of the manufacturing industry.

Due to its global impact, climate change defines an extensive field of conflicts for the processing industry, which is reflected in a variety of challenges. In addition to the legal regulations, the framework conditions within economic activities are changing more and more intensively. This concerns on the one hand the financial economy, and on the other hand the goods economy with regard to the expansion of purchasing decision criteria in the context of climate change. As part of the German government funded research project "CRed", the relationship between climate reporting and the assessment of a company's value was investigated, with the result that companies with particularly high emissions have lower market values. In this framework companies that actively reduce emissions through optimization processes are considered to have a more futureproof, which leads to a better valuation on the capital market. (Schiemann et al. 2019)

The growing ecological awareness among the population confirms the relevance of taking into account one's own environmental impact through economic activities. Addressing climate protection in connection with business activities can result in competitive advantages, as purchasing decisions are increasingly made dependent on this, which can lead to benefits on the market. (Ahrend 2019)

Across all of the above challenges is a remaining CO_2 budget, which defines the amount of emissions still available up to the defined maximum limit. Thus, according to the current state of research, the 1.5-degree target defined in the Paris Climate Agreement is directly related to a remaining CO_2 budget. This remaining budget is regularly recalculated by the Intergovernmental Panel on Climate Change (IPCC) and provides information on the remaining amount of CO_2 emissions worldwide that is still available for an average global warming of 1.5 degrees. Since the beginning of 2020, around 400 Gigatons of CO_2 remain to achieve the goals of the Paris climate agreement. (Allan et al. 2021)

In order to implement national climate protection targets, national budgets will have to be derived in the future, which will make it possible to achieve climate neutrality in the global economy by 2050. (Hornberg et al. 2020)

In summary, multidimensional challenges for companies due to climate change can be identified. At present, it is difficult to predict how these challenges will develop in the future, but it is not possible to predict the general need for action. This is clearly motivated by the remaining global CO_2 budget, which will be consumed over time. Many companies have recognised the situation and set themselves ambitious goals with regard to achieving CO_2 neutrality. An important step is the detailed analysis of CO_2 emissions across the entire supply chain, differentiated by Scopes 1, 2 and 3 (Tamayao et al. 2014). For this purpose, e.g. Siemens AG uses inhouse IT tools to make the individual CO_2 footprint of specific products respectively customer orders transparent. These tools are based on Internet of Things (IoT) and blockchain technologies.

In addition to the transparency of CO_2 emissions along supply chains, carbon capture sinks are very important for success in the context of CO_2 neutrality. The University of Technology Sydney (UTS) can be considered as a pioneer of technical aquatic sinks. The sinks are photo-bio-reactors in various designs and dimensions for the production of microalgae on an industrial scale. In terms of photosynthesis and CO_2 absorption, algae are many times more efficient than forests. The biomass produced serves as a raw material for numerous products that enable the permanent binding of CO_2. The special feature of the UTS laboratory setup for algae production is its design as a highly automated cyber-physical system. The growth of biomass and the associated CO_2 absorption can be recorded in real time or, alternatively, accurately predicted using machine learning models. The IoT middleware enables a direct, virtual coupling of aquatic sinks with globally distributed CO_2 sources and serves as a proof-of-concept for future blockchain connectivity. In this paper, the implementation of the described approach based on a commercial IoT platform will be discussed.

2. The relevance of carbon sinks

Industrial production will always generate CO_2 emissions due to the associated manufacturing and logistics processes. For a product carbon footprint (PCF) neutral production it is therefore essential to compensate these emissions. For this purpose, sinks are needed that storage CO_2 emissions in the amount of the source emission from the atmosphere in order to keep the earth's climate in balance (Lucius et al. 2005). It should therefore be noted that the sinks described below only capture CO_2 from the atmosphere. Other greenhouse gases, whose climate impact is measured in CO_2 equivalents, are not removed from the atmosphere in this process.

Currently, suitable ecosystems are divided into terrestrial and aquatic sinks. Terrestrial sinks include forests, for example. These take up a particularly large amount of CO_2 from the atmosphere during the growth phase. In this development phase there is a high demand for nutrients and thus a corresponding CO_2 withdrawal from the environment. This CO_2 is stored as biomass in the form of wood. (cf. Gleixner et al. 2009; Meyer et al. 2021; Nord-Larsen et al. 2019) However, the sink capacity of forests varies greatly depending on climatic conditions and the tree species used. Furthermore, CO_2 storage is limited by the life cycle of a tree. By decomposition of the biomass of a tree, the bound CO_2 can be partially released back into the atmosphere. In addition, the high area requirement and the difficult to calculate performance of absorption due to the open environment of a forest are further disadvantages (Fuss et al. 2018). Extending this, wildfires can contribute to a large amount of CO_2 being emitted at the same time, significantly shortening the sequestration period. (Luick et al. 2021)

In general, sink technologies of any kind must be as accurately calculable as possible in order to measure their impact in the context of source-sink coupling and to ensure that the right amount of CO_2 is captured. The question is whether the entire CO_2 emission can be compensated or whether the emissions in the atmosphere can be reduced by using a selected technology. This requires well parameterizable and controllable solution approaches, which are to be researched and developed in the future. One possible approach is being pursued by the UTS research group in the field of sink technologies.

Aquatic sinks are available as an alternative to terrestrial sinks. These include algae, which according to current research represent a potential ecosystem for targeted carbon capture. Due to the high photosynthesis performance of algae, a significantly higher efficiency can be achieved compared to forests. On the one hand, the lower area requirement and the strong growth are decisive. In addition, the biomass produced can be used as a raw material for various products. These include, for example, house construction, which results in an equivalent CO_2 bonding time due to the long life cycle of a house. (Rossignolo et al. 2022) In connection with the approach of connecting sinks via IoT described here, the use of algae offers the advantage of a closed system, which enables corresponding monitoring and verification of the sink performance and makes it available in the overall system.

3. The Estainium Association

The complexity of enabling production with a neutral PCF requires interdisciplinary collaboration between industry and academia to create a holistic approach including stakeholders such as customers, suppliers, certification service providers and manufacturers. The Estainium Association (EA) was founded to enable these stakeholders to work together to contribute to sustainable development. The overall goal is to drive industrial decarbonization holistically in a precompetitive, cross sector and cross functional ecosystem that includes universities, SMEs and large companies alike. (Estainium Association 2022)

For this purpose, digital technologies are used to demonstrate scientifically sound ways of identifying, reporting, continuously documenting and compensating for climate negative impacts. There is a particular focus on the exchange of trusted carbon footprint data using blockchain technology and the necessary IoT connectivity. This integrates not only CO_2 sources, but above all certified CO_2 sinks into the platform to be developed. Terrestrial and aquatic sinks, without which the targeted CO_2 neutrality could not be achieved, must be connected in a clearly traceable and tamper proof manner.

The research work of EA takes place within three working groups, which deal with different technological challenges of platform development. The technical background of these is briefly explained below.

- Technology and Infrastructure: Within this working group, solutions for the comprehensive exchange of Environmental Social Governance (ESG) and PCF data along a supply chain are being developed. The overall goal is to create interoperability through common technologies and associated standards and thus to establish a basic infrastructure based on IDunion or GAIA-X, for example. These are architectures for a trusted data infrastructure.

- Standards and Norms: In the second working group, overarching standards and norms are developed, which serve as a basis for the implementation of interfaces between different actors in other working groups. In detail, the work includes the definition of metastandards, manuals and exchange formats for ESG data and the assurance of the interoperability of PCF standards. In addition, approaches for the meaningful and coordinated integration of sinks will be developed.

- Carbon Capture, Use, Storage & Compensation: Within the third working group, the creation of an overarching marketplace is pursued, which transparently presents PCF data and simultaneously enables an exchange of trusted carbon footprint data using blockchain technology. The entire functionality of this marketplace will be provided in the Siemens software SiGreen and will enable, the presentation and exchange of PCF data and the request for certification services for trusted carbon sink services within supply chains. To ensure interoperability, SiGreen is being developed as a web application. In addition, it is planned to develop recommendations for legislation within this working group, which will define the legal framework for the handling of corresponding data and linkages between sources and sinks.

UTS, as a designated founding member of the EA has been part of the third working group since the beginning of the association's work. The goal is to use this sink technology as an efficient tool for carbon sequestration by creating a controlled environment. By linking it to IoT, a valuable contribution can be made to capture carbon in the long term and to reuse the biomass produced as a raw material for numerous products that enable the permanent storage of CO_2.

4. Product carbon footprint transparency

In order to be able to produce products in a CO_2 neutral way in the future, a lot of scientific questions have to be answered regarding the use of sinks to compensate for CO_2 sources such as production. A relevant aspect in this context is the extension of existing methods in the field of PCF allocation. In order to determine the capacitive demand of future carbon capture systems it is necessary to develop accurate methods to determine the real PCF.

According to the current state of technology and research, the environmental impact of products is assessed using the Life Cycle Assessment (LCA) method (ISO 14040; ISO 14044). This method is based on the consideration of the product life cycle and enables the calculation of the resulting environmental impact of a product by using a standardized procedure. LCA can also be used to analyze subprocesses of the life cycle. These studies, known as Simplifield Life Cycle Assessment (SLCA), can, be used exclusively to analyze the production in order to determine its influence on the PCF (cf. Hochschorner/Finnveden 2003).

The LCA calculation of CO_2 emissions is based on statistical data, which is why this method can be described as static. However, especially in the production environment, dynamic aspects have a great influence on production processes. For this reason, there are already some approaches that extend LCA to include dynamic aspects of production. These methods, known as DES-LCA, combine LCA with the Discrete Event Simulation (DES) method. In this way, simulation data of a production area to be investigated are used instead of static data in the context of a classical LCA analysis.

The variances between LCA and DES-LCA have been investigated by Lindskog et al. 2011. The differences between a static SLCA compared to a DES-(S)LCA approach have been compared based on an industrial use case. As a result, the authors show a deviation of about 60% between the two methods in terms of the resulting environmental impact of a product. This discrepancy is largely due to the variation in electricity consumption between static and dynamic process mapping. This highlights the relevance of dynamic approaches and the resulting need for optimization.

At this time, existing DES-LCA approaches only refer to predefined use cases with different accounting framework conditions. Accordingly, the considered PCF influences within production processes are not uniformly defined, since the calculation is strongly dependent on the selected mapping level of the DES method (cf. Sproedt et al. 2015; Brondi and Carpanzano 2011). The Institute for Production Systems from the Technical University of Dortmund is currently researching the development of an interoperable calculation rule in the environment of the processing industry. The goal is to enable a holistic PCF calculation by means of dynamic methods and to develop measures for a PCF reduced process management based on this. This creates the potential for accurate and consistent balancing of the PCF, regardless of the existing product system. In addition, this new approach enables the identification of PCF drivers which can be reduced by an adapted process management and thus products with a reduced PCF can be produced.

With the transparency gained in this way, it will be possible in the future to precisely measure the sink requirement and, based on this, to make a statement as to whether the sink technology used will compensate for or reduce global emissions. In addition, a choice can be made between different sink technologies that are suitable for the purpose. This is of crucial relevance for the future balance of the global climate and the associated production of PCF neutral products. In the long term, these research results will help to determine the real need for carbon capture processes and thus to create a CO_2 neutral production environment.

5. Cyber-physical microalgae farms as a technology for global sinks

Microalgae have proven to be a promising product that can be used in many applications and construction material. In any case, their growth depends on a continuous supply of CO_2, which implies that their production constitutes a natural sink of CO_2. While the demand for microalgae is growing, commercial production is hindered due to their evolutionary history and great biological and physiological diversity (Rawat et al. 2013). The Centre for Advanced Manufacturing of UTS operates an Industry 4.0 laboratory for algae production on an industrial scale. The challenges involved in upscaling the production are investigated by applying promising Industry 4.0 technologies.

The laboratory features two industrial photobioreactors (PBR) for microalgae cultivation and a harvesting machine (see Figure 1). The Subitec LS28 (cf. SUBITEC 2021) harvesting machine has a working volume of 28 litres and the Industrial Plankton 1250L (cf. Industrial Plankton 2022) PBR has a capacity of 1250 litres. While the LS28 can be operated independently, it is used to accelerate the cultivation within the PBR1250L through an increased initial biomass inoculation. The customized built harvest machine is designed to process 350 litres of algae media per usage.

To guarantee the supply of the algae with sufficient CO_2, an air stream enriched with CO_2 is regularly fed into the reactors. The CO_2 is taken from gas cylinders, which can store gas from any potential CO_2 source. In order to measure the CO_2 absorption of the microalgae during cultivation, the PBR has been enhanced with a sensor system consisting of a mass flow controller in the gaseous intake (constant CO_2 percentage provided by PBR control) and a concentration sensor at its output.

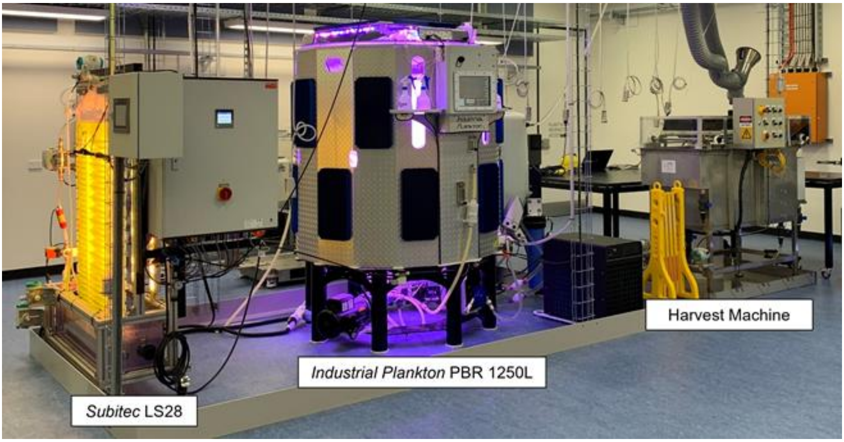

Figure 1: Setup of the UTS CAM Industry 4.0 algae laboratory

The physical components are complemented and connected by an IoT and data science architecture (see Figure 2). All systems are monitored and controlled by a Siemens hardware and software suite, including MindSphere and an S7-1500 acting as master PLC. In addition, a parallel architecture was designed based on Node-RED, MySQL, and Grafana and incorporated as an alternative to MindSphere, as an exploratory, low cost alternative for specific use cases. Rapidminer serves as data science platform in both contexts.

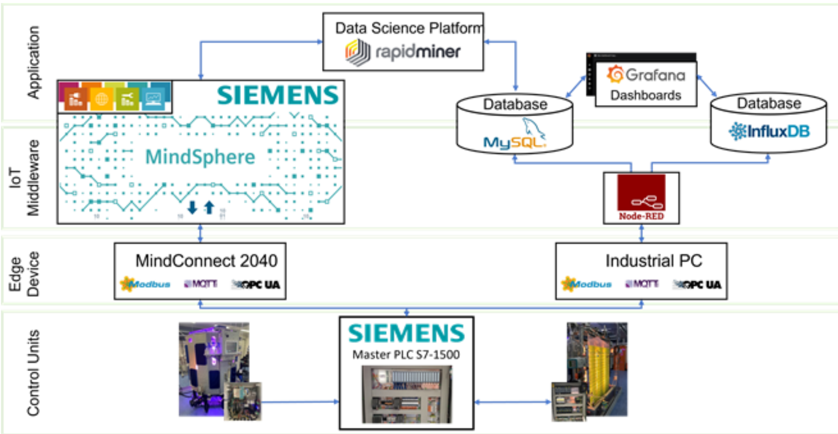

Figure 2: UTS CAM Industry 4.0 algae laboratory IoT/data science architecture

A digital twin is currently being developed to simulate, predict, and optimize the system across the production lifecycle to enable upscaling of algae production.

This will provide an improved understanding of algae behaviour and characteristics in an industrial setting and ultimately enable cost and time efficient algae production.

6. Proof-of-Concept based on algae farming

The inbuilt Industry 4.0 technology provides the foundation for traceability of neutralised emissions via blockchain technology to securely connect carbon source and sink. A current focus of the work is on ensuring accurate calculation of the CO_2 absorbed by the microalgae. This can be measured in several ways using the available sensors on the photobioreactor system. For example, measuring the gas flow of both CO_2 in and out of the system allows the net CO_2 absorbed to be determined. Weighing the total mass of algae produced also allows the absorbed CO_2 to be extracted in another way. The dual approach to CO_2 absorption calculation is deliberate, since it provides some redundancy in the system. This means that if one (set of) sensors fails, CO_2 absorption can still be recorded. The consistency and reliability of CO_2 measurement by these two means is currently being investigated. At the production site, accurate estimation of CO_2 production is not a focus of this work and is a more mature topic of research. However, it is vital that the CO_2 being offset is accurately accounted. Both the CO_2 production and absorption data are being integrated within extensions of existing Siemens software platforms as part of this project. This includes incorporation within MindSphere's Energy Manager, and enabling a connection according to the EA standards. Figure 3 shows an example of how carbon emissions generated by a source in Germany could be offset by the UTS CAM Industry 4.0 algae laboratory.

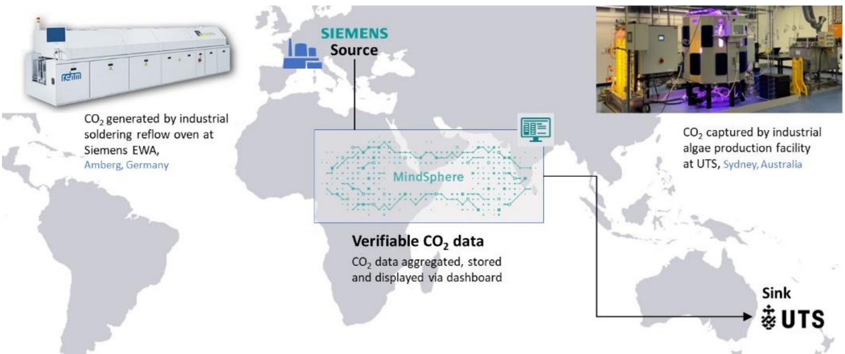

Figure 3: Virtual CO2 pipeline from source to sink

7. Conclusion and outlook

The demonstrated proof of concept represents an efficient approach to reducing CO_2 emissions, which holds out the prospect of a high reduction potential through the use of algae. Due to its full integration into the industry 4.0 environment, the concept enables a connection to technologies for the trustworthy certification of CO_2 data and the sources as well as sinks can be organized in a decentralized manner, which does not limit the strategic options for companies compared to alternative sink technologies. In summary, the described approach offers the potential for end-to-end CO_2 reduction, starting with the source, continuing with data verification, and ending with the technology of a CO_2 sink described in this paper. In doing so, the project can be developed in an overarching manner by integrating it into the Estainium network and creating a holistic contribution to the reduction of CO_2 emission. This paper describes the current state of development in the context of a proof of concept. A current focus of the work is on ensuring accurate calculation of the CO_2 absorbed by the microalgae in a reliable and consistent way, including introducing redundancy in case of sensor failure. In further investigations, the research work is to be centered on the optimization of algae production and to measure the achievable scaling effects. Thereby, methods of simulation and data science support the determination of an optimal operating point. The next step is to embed the data into the SiGreen environment and thus connect the aquatic sink with regard to functionalities such as requesting, calculating and sharing trustworthy PCF data. For this purpose, both the CO_2 production and absorption data will be integrated within extensions of existing Siemens software platforms, such as MindSphere's Energy Manager and a connection of the sink according to the Estainium standards will be enabled.

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Reciprocal Learning in Human-Machine Collaboration: A Multi-Agent System Framework in Industry 5.0

Steffen Nixdorf, Fazel Ansari, Sebastian Schlund

1. Introduction

Recently, the European Commission introduced the term Industry 5.0. Its concept is entirely based on Industry 4.0, while Industry 5.0 provides a vision beyond productivity and efficiency as the sole goals, and reinforces the role and contribution of research and innovation to society (European Commission 2021). The well-being of the worker is put at the center of the production process in order to provide sustainable prosperity beyond jobs and growth. The European Commission defines three main elements of Industry 5.0: i) human-centricity, ii) sustainability, and iii) resilience (European Commission 2021). Human-centric approaches in manufacturing industry explore what the technology can do for the worker than the other way around. In this way, humanistic perspectives and investment in human capital, which is an important factor for economic growth (Goldin 2016), are respected. Thus, human-centric manufacturing emphasizes that novel production systems adapt to worker's individual needs, e.g., guide, assist, and train the workforce (European Commission 2021).

Fostering learning opportunities for human workers directly contributes to the vision of human-centricity (European Commission 2021), specifically by providing skilling and upskilling to increase human capital (Smith 1776). Due to fast evolving technologies, training is a cornerstone of Industry 5.0, because demand of new skills is high, skill gaps are glaring, and unlearning matters. Moreover, industrial practice lacks behind in adoption of novel technologies due to skill gaps in companies' workforces. A study about skills and key technologies pointed out, that skill imbalances significantly diminish growth in technology and employment (CEDEFOP 2019). Therefore, investigating learning opportunities in the process of work may significantly impact the competitiveness of European enterprises.

Where humans and machines collaborate, the term Reciprocal Learning has been coined to describe learning between both agents, i.e., the human and machine. Reciprocal Learning has been inspired by reciprocal teaching (Rosenshine and Meister 1994) and reciprocal altruism (Trivers 1971). Both terms are originating from observing human behavior in human-human symbiosis. Reciprocal Learning has first been introduced by Ansari et al. (2018), motivated by collaboration of learnable technological agents and human agents to form reciprocating learner-teacher interactions.

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Complementing human-centric manufacturing, transformation towards human-automation symbiosis is envisioned (Wang et al. 2019). Human and intelligent agents (machines) will share workplaces and solve complex tasks by combining their complementary competences, i.e., human-machine collaboration. Symbiotic relationship foresees mutual benefits for both agents, such as learning. In this way, the concept of Reciprocal Learning, which describes learning as a bidirectional process between intelligent agents, namely humans and machines, contributes to the notion of human-machine symbiosis. To the best of our knowledge, however, there is neither work that discusses Reciprocal Learning to consolidate its concept comprehensively nor to make it tangible. A first step is taken in this paper, by presenting a work in progress. Therefore, we present a consolidation of a heuristic literature review from various scientific disciplines, e.g., psychology on learning of human(s), computer science on learning of machine(s), as well as human-machine collaboration to form the context of Reciprocal Learning. Thereby, a framework of Reciprocal Learning is provided to outline what it is and what it is not by taking its characteristics, stemming from the human agent, the machine agent, the task, and their collaboration as well as learning processes, into account.

Therefore, the context of human-machine collaboration and human-machine symbiosis is discussed (Section 2, followed by fundamentals of learning and intelligence in humans and machines (Section 3). Further, agent learning divided by single-agent learning (human learning, single-AI agent learning) and multi-agent learning (collaborative human learning, multi-AI agent learning) is discussed (Section 4). In Section 5 the concept of Reciprocal Learning is defined and supported by a framework of Reciprocal Learning in human-machine collaboration, including definitions of characteristics of agents, both human and technology, as well as task and processes of collaboration and learning. Finally, future research objectives are discussed (Section 6).

2. Human-machine partnership in manufacturing

The latest advances in AI technologies and especially collaborative robotics open new horizons for cooperative or collaborative work forms between human and machines as an extension to fully automated production processes. Research on human-machine interaction firstly concentrated on socio-technical systems that contain social (human-related) and technical (non-human) aspects which will interact to pursue a common goal (Avis 2018). Moreover, human and machine components are often referred to as agents in socio-technical systems, i.e., social agent (human), artificial agent (machine). Agents are capable to act independently with an own agenda, i.e., decision-making (Zafari 2020). Throughout this paper, the term "agent" refers to either human or machine actors, if not further indicated.

2.1. Human-machine collaboration

With the development of highly complex and dynamic human-machine systems, comprising of enhanced connectivity, increased autonomy and automation, as well as intelligence, adaptive mechanisms, are emerging. These enable forming independent (active) machine agents for the application in dynamic and uncertain environments to support and assist human workers (Krupitzer et al. 2020), which are, despite the technological enhancement, a significant factor in design of manufacturing systems. Assistance systems aim to compensate human worker's shortcomings in cognitive, physical, or even sensorial capabilities. Besides acting as a mere assistant for human operators, machine entities can actively collaborate with humans on joint activities, sharing and dividing tasks according to the respective strengths and capabilities. Thus, human-machine collaboration is a system of agents which cannot be considered in isolation, but as a team that is formed in order to perform tasks collaboratively. Characterization of human–machine collaboration can be done by the nature of the collaboration, i.e., the distribution of tasks between agents according to their abilities and capacities. In this way, we follow definitions of the fundamental characteristics of human-machine collaboration by Simmler and Frischknecht (2021):

- automation, defining the allocation of situational executive control, ranging from independent human decision-making to fully automated machine decision making and
- autonomy of the machine agent, defining interdependence in completing an assigned task, ranging from deterministic systems to open systems.

Autonomy of the technical system can be assessed by its transparency (i.e., traceability of input/output relations), determination (i.e., same inputs leading to the same outputs), adaptability (i.e., learning from experience), and openness (i.e., expanding input through cooperation with other systems). Openness is considered to be the highest level of autonomy, because the machine is neither limited to specific inputs nor to its own experience. However, input/output relations of open systems become non-transparent. In contrast, autonomy of the human in human-machine collaboration is in general considered superior to the machine's (Simmler and Frischknecht 2021). Still, competence levels of human, such as, novice, competent, proficient, expert, and mastery can be distinguished, which have similar meaning to humans as automation and autonomy for machines (Ansari et al. 2020). E.g., a human at mastery level corresponds to a fully autonomous machine. Multiplicity is distinguished as another characteristic of human-machine collaboration based on the number of agents in a given scenario, i.e., single (human-machine), multiple (multiple of either or both), and team (multiples act coordinated and in consent) (Wang et al. 2017). These three characteristics, namely, autonomy, automation, and multiplicity highlight differences among human–machine collaborations. Competence levels, multiplicity, autonomy and automation, are gradual dimensions that capture a more differentiated understanding of human-machine collaboration in task environments.

2.2. Human-machine symbiosis (HMS)

Symbiotic relationships between human and machine are discussed in human-machine collaboration (Lu et al. 2021; Wang et al. 2019; Wang et al. 2017; Gerber et al. 2020). It defines mutual benefits for both actors (Wang et al. 2019). The symbiotic partnership may also facilitate depth of collaboration, in which both agents are pursuing similar goals, benefit mutually, and become smarter (Jarrahi 2018). Human-machine symbiosis (HMS) has been described in context to manufacturing work environments (Lu et al. 2021; Wang et al. 2019), to achieve previously unattainable goals by merging capabilities and overcoming individual agent's restrictions (Gerber et al. 2020). They form a partnership of agents which is capable of solving problems the individual members alone would not be able to tackle (Wang et al. 2019). Requirements of HMS systems are shortly described in the following, based on Lu et al. (2021), Gerber et al. (2020), and Wang et al. (2019):

- Balanced **autonomy**, all agents are inherently autonomous, i.e., in equal position, they form together a team or group which is responsible for the successful and efficient performance of a set of tasks. Roles of leadership change dynamically, as the actual situation and the task requires.
- Accurate **context-awareness**, all agents are context-aware, i.e., their actions and decisions are grounded on the actual physical and cognitive circumstances. The shared physical work environment tracks and traces the objects, to enable interaction and manipulation in the real world.
- Transparent **representation**, all agents apply at least partially shared representations of the environment to formulate common goals, take roles, execute plans, and solve tasks. The shared virtual representations or mental models are dynamically adjusted in real-time.
- Effective **communication**, all agents continuously engage with each other. Multimodal and bidirectional communication by means of, e.g., voice, physical inputs/outputs, gesture, pose, brainwaves, augmented reality, video, image, text. Communication and exchange of information adapts to content, context, and identity.
- Dynamic **adaptability**, the performance of a symbiotic system improves over time, by adapting to new situations, changing conditions, and learn from failures and successes based on feedback of the environment.
- Natural **human-centricity**, the ability to focus on the human's needs (e.g., safety)
- **Social wellness**, the ability to detect and respond to human distress or fatigue in physical and mental performance to assure well-being.

In conclusion, HMS systems possess the capability of perception, learning, communication, and decision making for context-aware human-machine collaboration. In this way, HMS is a significant extension to the notion of human-machine collaboration for which Reciprocal Learning can be a significant contribution as the core idea of mutual benefit is respected in both concepts.

3. Fundamentals of intelligence and learning from human and machine perspectives and its relevance for manufacturing

Intelligence and learning alike lack consensus and clear definitions. This especially holds true since artificial intelligence (AI) has been emerging and developers pursue their vision to embed intelligence in machines that replicate human's intelligence. Gottfredson (1997) defines **human intelligence** as

> "… a very general mental capability that, among other things, involves the ability to reason, plan, solve problems, think abstractly, comprehend complex ideas, learn quickly and learn from experience."

Thus, human intelligence and learning are closely connected. Human learning has been the subject of various disciplines in human science, inter alia, psychology, pedagogy, didactics, sociology, philosophy, and biology. This is reflected by a wide variety of different definitions of learning. Psychology puts the human individual in the focus of research and has been exploring and examining cognitive processes of humans intensively. However, human cognition is hardly observable. Therefore, theories and hypotheses about learning have been constructed to explain and investigate learning in humans. This notion is fully reflected in behaviorism, a theory which investigates input-output relations of human behavior, neglecting any internal processes (Skinner 1938). In this way, learning is described as changes in human behavior based on conditioning. Contrary, cognitivism is a learning theory focusing on receiving, organizing, storing, and retrieving information, i.e., knowledge (Lefrançois 2015). Another theory, constructivism, is closely related to cognitivism. While cognitivism is limited by the available and provided information, constructivism describes self-directed learning and construction of knowledge from problem-based contexts (Kelly 2003), often enacted in social processes of interaction (Kadam and Vaidya 2021). The learner actively constructs new ideas and concepts based on existing and new knowledge by constructing connections. Additionally, individuals' subjective perception and interpretation of their environment significantly influences their reality, recognition of problems, and behavior (Ertmer and Newby 2013). Notably, the body of knowledge represents several other learning theories, while behaviorism, cognitivism, and constructivism are the most respected. In order to combine the theories mentioned and provide a comprehensive definition of learning, the authors choose to follow Ertmer and Newby (2013) with "learning is a change in behavior, or in the capacity to behave in a given fashion, which results from practice or other forms of experience". However, changes in behavior can also result from processes or be influenced by factors that are not considered learning, e.g., maturation, sensitization, adaptation, and fatigue. All of these are excluded from consideration. Further, it should be noted, that cognitive learning, i.e., changes in learner's knowledge (cf. cognitivism), is inferred from learner's behavior too, thus inherent.

Machine intelligence and AI are used interchangeably. A clear and consensus definition of AI is lacking (Russell and Norvig 2021). In contrast to Russell and Norvig (2021), who propose AI to be an imitation of human intelligence or system of rationality, Wang (2008) defines it as:

> "… the capacity of a system to adapt to its environment while operating with insufficient knowledge and resources."

Machine learning (ML) is a subset of AI, i.e. a method for modeling the ability of human learning and reproduction of human skills by artificial models and computational algorithms (Russell and Norvig 2021). ML is a promising area of computer science that evolved from pattern recognition, and which consists of a manifold range of applicable algorithms and learning strategies.

Both agents' intelligence differs substantially, in terms of definition, application, and measurement. Learning, however, can be described similarly by adopting the aforementioned notion of learning to be a change of behavior, based on practice or experience. This common ground will be needed to establish Reciprocal Learning.

Manufacturing education relies on work-based learning (WBL) as a promising approach for closing skill gaps. WBL defines learning in the context of work, with respect to process-orientation, experiential learning and the combination of informal, non-formal and formal learning that are increasingly prevalent in digitalized work processes (Dehnbostel and Schröder 2017). For manufacturing practice, learning of humans is the cornerstone of competence development of workforces. Due to transformative skill gaps, learning for production, i.e., training of workers for meeting workplace requirements, and learning in production, i.e., work-based learning (WBL), are increasingly important (Abele et al. 2015). Digitalization enables the creation of work environments with new opportunities for workers to learn performing new tasks and enable the creation of innovative learning approaches at the workplace for skilling, reskilling, and upskilling of workforces. High volumes of real-time information from process production data as well as intelligent assistance and production information systems enable WBL. Considering the differences in employee's education, experience, and skill sets, WBL may close skill gaps efficiently, especially if learning is integrated into the actual workplace. Transforming work organization in order to foster (lifelong) learning and implementing training strategies at the workplace conforms the human-centric notion of modern manufacturing. However, innovative approaches to WBL, such as approaches that are integrated at the workplace remain rare (Nixdorf et al. 2021). Investigating learning from perspective of production engineering to integrate learning processes into human-machine collaboration in manufacturing is necessary to enable efficient training opportunities of tomorrow's workforce. Reciprocal Learning as a type of innovative work-integrated learning, may contribute significantly to the continuous training of human capital.

4. Agent learning

This section discusses learning of human and machine individually, starting with single-agent scenarios, i.e., individual agents without any interactions with any other agents, namely human learning (cf. Section 4.1) and single-agent learning (cf. Section 4.2). Furthermore, learning in multi-agent scenarios (cf. Section 4.3 and 4.4), i.e., humans learning from each other (collaborative learning) and machines learning from each other (multi-agent learning) are discussed. As pointed out above, psychology and computer science have similar definitions for learning. Descriptions of learning in multi-agent scenarios is, however, different. Hence, the following section synthesizes commonalities and describes the components of agent learning and multi-agent learning.

4.1. Human learning

Human learning consists of a wide range of subtypes, mostly conceptualized in behaviorism, cognitivism, or constructivism. While the cognitive process of learning itself remains ambiguous, types of learning are characterized by either their inputs (e.g., instruction, observation, etc.) or outputs (e.g., association, representation), regardless of the theory applied. Hence, in the following, the focus lies on the components and characteristics of learning.

Evidently, human individuals have characteristics, which affect learning, that are independent of the task or situation at hand, i.e., motoric capabilities, cognitive capabilities, knowledge, skills, and competences. In other words, these characteristics vary in individuals, affect the individual's behavior in certain task situations and affect limitations of potential changes in behavior from gathered information. E.g., cognitive capabilities affect the interpretation and processing of information, which is provided to the human. Further, task specific and situational characteristics can be identified, e.g., attention, emotion, motivation, goal, and behavior. Attention is a situational characteristic of a human, which limits quality of gathered information and thereby the potential learning (from experience). Similarly, individual's emotion can negatively affect learning due to, inter alia, lack of confidence, fear of failure, previous negative experiences, and the learner's emotional state (Bierema 2008). Motivation of human affects the behavior as well as the definition of a goal. An individual's goal in a specific task can be divided in a performance goal, i.e., aiming at finishing the task, and learning goal, i.e., aiming at effective learning (Hauer et al. 2014). Generally, goal setting affects the behavior of humans.

The task is typically characterized by its complexity, uncertainty, difficulty, predictability, and novelty, which all influence the required capabilities and thus its outcome. In this way, adequate selection and design of tasks can facilitate learning (Hauer et al. 2014). Furthermore, learning scenarios contain information flows, namely, information available before the task, e.g., instructions (cf. instructional learning), feedback to human during the task, e.g., trial-and-error learning, associative learning.

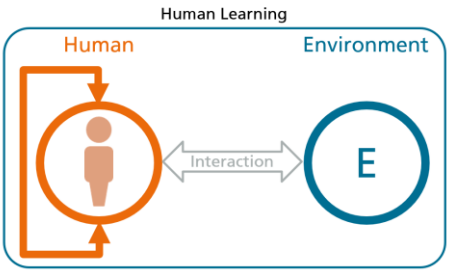

Figure 1: Human learning as a single-agent

The human processes and interprets provided information, which can either be done passively (any information is considered, e.g., associative learning, instructional learning, etc.) or actively, which allows self-directed selection of information to be considered. As depicted in Figure, the human learning scenario contains one human who learns from interaction with the environment, i.e., performing a task and changing its behavior.

4.2. Single-AI agent learning

In AI, an intelligent agent is referred to an entity that is capable of taking decisions from an environment (Russell and Norvig 2021). Weiß and Dillenbourg (1999) define agency, as a matter of distributed AI, to be composed of the following basic components:

- sensors and actuators, which both enable the agent to interact with the environment, e.g., carry out actions or exchange data,
- knowledge base, which contains information about the environment, e.g., regularities, rules, and activities of other agents (in multi-agent systems),
- inference engine, which allows to perform tasks like inferring, planning, and learning, e.g., by deducing information, generating behavioral sequences, increasing efficiency of environmental interaction.

An AI agent is meant to improve its individual skills, irrespective of the domain in which it is embedded (Alonso et al. 2001). Generally, technological agents are distinguished into weak and strong notions. The weak agents are usually independent, i.e., operate on their own without or limited human guidance while imitating human-like intelligence. Pro-activeness and reactivity are both elements of weak agents (Nwana and Ndumu 1998). Strong agents are considered to have mental attitudes, namely, information state (e.g., belief, knowledge, etc.), deliberative state (e.g., intention, commitment, etc.), and motivational states (e.g., desire, goals) (Weiß and Dillenbourg 1999), which is an intelligence considered to be actually human-like. In this way, strong agents do have more commonalities with human beings than weak agents and come closest to resembling them. However, strong agents are not making significant developmental progress. Learning capabilities of agents are necessary to cope with novel situations, which have not been foreseen in the design process, and adapt to the environment (Alonso et al. 2001). Learning of AI agents is subject of ML research, currently encompassing a wide range of learning algorithms, inter alia, (semi-/un-) supervised learning, reinforcement learning, active learning, or deep learning (Russell and Norvig, 2021). Most of ML research has focused on single agents. Machines need to interact with the environment, as depicted in Figure .

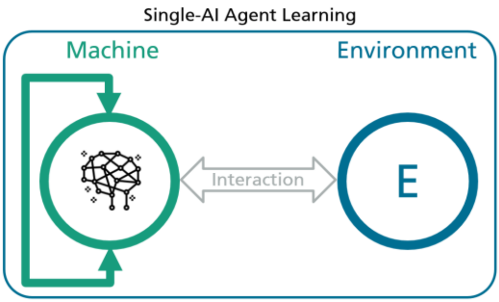

Figure 2: Single-AI agent learning

4.3. Collaborative human learning

Trial-and-error is one of the most fundamental learning techniques humans use. Interestingly, humans can learn by observing trial-and-error learning of other humans without the risk associated with the error. This type of learning is called observational learning (Csibra and Gergely 2009). In social learning, which is often modelled as a learner-teacher (supervision) scenario, the observation is supplemented with active teaching, whose communication allows transmission of knowledge and skills between humans (Csibra and Gergely 2009). Most social learning mechanisms involve some form of observational learning in which behavior is imitated or emulated. Imitation is the repetition of previous actions, while emulation is inferring goals, beliefs, and intentions of the other human. Research suggests that supervision learning, between teacher (supervisor) and learner (supervisee), could be seen as a bidirectional learning process, since the supervisor also learns (i.e., supervision has potential benefits for supervisors and supervisees) (Carrington 2004). In fact, "reciprocal learning" has been mentioned occasionally to describe iterative learning effects between humans (Noël et al. 2013; Carrington 2004; Patrick et al. 2010). It suggests that teaching-learning distribution between humans can dynamically adapt. Importantly, learning results are heavily influenced by the social relationship of the humans and their mutual trust. In group learning situations, observational learning is weighted towards the most skilled individuals of a group. However, information gained from own experience is still considered the most reliable. Supervision learning typically revolves around an unequal relationship between supervisor and supervisee, e.g., one being more knowledgeable than the other, and influence not being mutual (O'Donnell and Hmelo-Silver 2013). Cooperative learning and collaborative learning lean one step further, by introducing learning between humans in equal settings, i.e., groups of equally knowledgeable humans, e.g., a group of students (Davidson and Major 2014). Both concepts originate from education and teaching, occur when (equal) human individuals solve a problem together. In particular, a common shared task, interdependence (i.e., need to rely on each other to achieve goals), individual accountability (i.e., all participants are held accountable for share of work), equal participation (i.e., balanced knowledgeable roles), and simultaneous interaction (e.g., providing feedback, challenging conclusions) are needed (Laal and Laal 2012; Davidson and Major 2014).

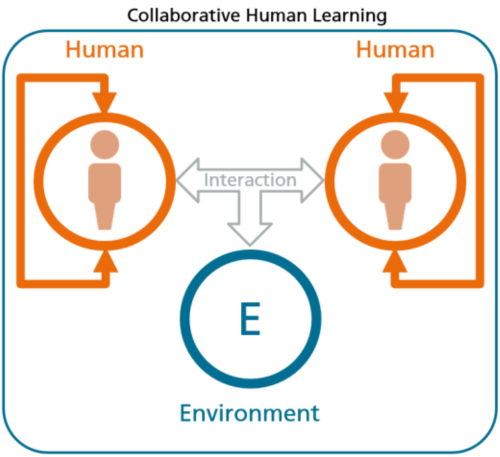

Figure 3: Collaborative human learning

In contrast to cooperative learning, according to Davidson and Major (2014), collaborative learning is open-ended by design, i.e., not limited to only one true approach or response. Additionally, Laal and Laal (2012) highlight adaptability of collaborative learning by pointing to self-assessment of achievements, goals and identification of potential changes to function more effectively as a group. As collaborative learning also qualifies as a type of social learning, it requires trust, leadership, decision-making, communication and conflict management (Davidson and Major 2014).

4.4. Multi-AI agent learning

While AI research mainly concentrates on learning techniques in single-agent environments, distributed AI research concentrates on multi-agent systems (MAS). MAS consists of several interacting agents which are limited and differ in their actuators, sensors, cognitive capabilities, and knowledge about the environment, while their communication, and interaction, i.e., cooperation and collaboration, are relevant to the solution of the task (Weiß and Dillenbourg 1999; Vlassis 2007). MAS can be distinguished by their design (identical or heterogenous agents), environment (dynamic or static), perception (i.e., information and interpretation of the environment), control (e.g., centralized/decentralized decision-making), knowledge of and about other agents (e.g., their actions, perception, knowledge), and communication (e.g., sending and receiving information) (Vlassis 2007). Many MAS implement reinforcement learning algorithms as they enable agents to learn from interacting with the environment (Vlassis 2007), similarly to associative learning (cf. Section 4.1). MAS in some cases aim to maximize a global reward function (e.g., in collaborative reinforcement learning) or own reward functions to find equilibrium (Lin et al. 2021). Design of learning in MAS is a complex matter. Each of the participating agents may learn (i.e., change behavior), thus change the environment and, thereby, affect learning of each agent. Agents need representations of their agent counterparts to reason about them. However, even if an agent is not explicitly aware of other agents, it perceives them as part of the environment and their behavior still affects the agent (Alonso et al. 2001). In this way, learning and teaching in context of MAS cannot be separated (Shoham and Leyton-Brown 2012). In addition, there are three classes of mechanisms that distinguish single-agent learning from learning in MAS, namely multiplication, division, and interaction. Multiplication refers to independent learners in the MAS, where learning processes are isolated, agents may use different learning algorithms and pursue their own goals. In division of multi-agent learning, single tasks or algorithms are divided among agents, which may be due to functional aspects or the data to be processed. Weiß and Dillenbourg (1999) suggest divided multi-agent learning for manufacturing processes, in which each agent concentrates on another step. In interactive learning the interaction is a dynamic activity that concerns the intermediate steps of the learning process. Interaction enables a truly cooperative search for a solution of the task.

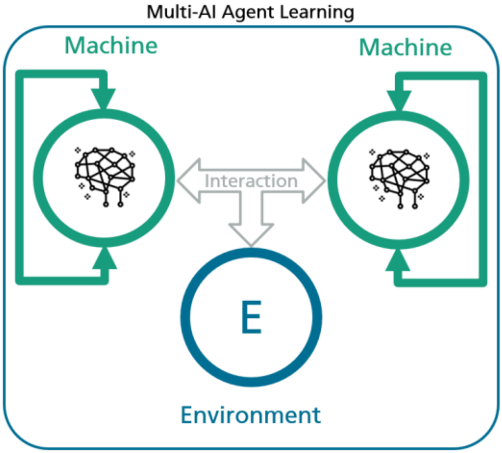

Figure 4: Multi-AI agent learning

Agents involved in interactive learning influence the learning path and synthesize conflicts along the learning process. Imitation learning attempts to train agents to learn from expert demonstrations by means of supervised learning (Lin et al. 2021). Employed learning algorithms to MAS have shown promising results in learning cooperative behavior (e.g., Zhang et al. (2021), Tan (1993)) and have adopted observational learning to MAS (Borsa et al. 2017).

5. Framework of Reciprocal Learning in human-machine collaboration

In the previous section, single-agent and multi-agent learning have been investigated, for humans and machines, comparably. Evidently, interaction of agents in learning scenarios can support achieving agent-specific learning goals. Similarly, collaboration between agents supports achieving mutual learning goals, maximize global payoffs. In the following, findings of Section 4 are consolidated to describe Reciprocal Learning, comprising of characteristics of agents, the task, collaboration, and learning. Based on the definition of Reciprocal Learning, a framework is presented.

Reciprocal Learning between human and machine in the context of human-machine collaboration in manufacturing has been defined by Ansari et al. (2018) as:

> "a bidirectional process involving reciprocal exchange, dependence, action or influence within human and machine collaboration on performing shared tasks, which results in creating new meaning or concept, enriching the existing ones or improving skills and abilities in association with each group of learners."

The concept of Reciprocal Learning has been inspired by reciprocal altruism, in which human behavior is beneficial to others (West et al. 2007) and reciprocal teaching, in which humans learn from each other by switching between trainee and trainer (Rosenshine and Meister 1994). Reciprocal Learning exploits the complementarity and reciprocity of human and machine to achieve mutual benefits.

Any human and any intelligent machine agent, regardless of type of interaction (if any) or task, comprise of basic characteristics that affect learning (cf. Table), namely, a knowledge base (e.g., previous experience, knowledge about the environment, skills, and competence), actuators (e.g., ways to act and interact) , sensors (e.g., ways to receive feedback and information), the general ability to adapt or learn (e.g., change own behavior), a perception of the environment (e.g., interpretation of reality), and autonomous cognition or inference engine (e.g., reasoning, problem-solving), respectively. The characteristics affect the behavior of the agent and are required to learn. Additionally, each agent comprises of situational characteristics that affect learning. These change regardless of any learning effects that may occur in the meantime, e.g., due to fatigue, emotions, or the task environment. Situational characteristics are attention (or data pre-processing), information (or data) selection, motivation, and goals. In Table , human's and machine's characteristics are evenly aligned, however, the underlying morphologies of these characteristics are substantially different, e.g., human's actuators are entirely different to machine's.

A task has several characteristics that affect learning, such as its complexity, difficulty, uncertainty, predictability, and novelty. Moreover, information of required skills is needed to evaluate the task's impact on collaboration and learning processes. Task design, namely defining the characteristics above, can have an impact on learning by choosing design conducive to learn.

	Human	Machine
Basic characteristics	Cognition	Inference engine
	Knowledge base	Knowledge base
	Actuators	Actuators
	Sensors	Sensors
	Adaptability (learning)	Adaptability (learning)
	Perception	Perception
Situational characteristics	Attention	Data pre-processing
	Information selection	Data selection
	Motivation	Motivation
	Goals	Goals

Table 1: Characteristics of human and machine relevant for learning

Human, machine, and task characteristics serve as inputs to human-machine collaboration in order to facilitate Reciprocal Learning. Accordingly, Reciprocal Learning requires multiplicity of agents, i.e., at least one human and one machine agent. Hence, each agent has to deal with a dynamic environment, i.e., changing over time, by mere presence of the other agent(s) (Vlassis 2007). In a MAS environment, organization of the task either by multiplication or division is required for Reciprocal Learning. Further, it foresees collaboration between human and machine in order to gain mutual benefits, similar to HMS. However, HMS goes beyond the concept of Reciprocal Learning. Hence, another level of Reciprocal Learning can be defined, i.e., Symbiotic Reciprocal Learning, satisfying all requirements of HMS, in particular, context-awareness, representation, human-centricity, and social wellness. In the following, these requirements are discussed in Table . Characteristics of multi-agent learning (human and machine agents) also affects Reciprocal Learning, as detailed in Table . Notably, Weiß and Dillenbourg (1999) suggest that humans excel at establishing mutual and shared understanding, by, inter alia, conflict resolution, and explanations. MAS, however, are designed to avoid misunderstandings of any kind, while collaborative human learning is facilitated by resolution of conflict. In particular, humans will likely reach states of disagreement in their collaboration (i.e., conflict), whose resolution can further enhance learning, as also explanations are constructed iteratively.

Collaboration characteristics	For Reciprocal Learning
Autonomy/Competence	Autonomy and competence levels
Automation	Action independence
Multiplicity	Multiples (at least one type of agent each), teams
Communication	Continuous, multidirectional and multimodal
Adaptability	Dynamic change of behavior for improvement
Trust	Mutual trust
Task sharing	Flexible task division or multiplication
	Symbiotic Reciprocal Learning
Context-awareness	Accurate perception
Representation	Adjustable and shared mental models
Human-centricity	Focus on human's condition
Social wellness	Detect and respond to human's condition

Table 2: Characteristics of HMS in context of Reciprocal Learning

Learning characteristics	For Reciprocal Learning
Interdepence	Mutual influence on results
Accountability	Individual accountable for own share of work
Participation	Balanced roles, low skill difference
Conflict management	Understandable explanations
Leadership	Changing teacher-learner

Table 3: Characteristics of learning in context of Reciprocal Learning

A framework of Reciprocal Learning is established (cf. Figure), taking all inputs (i.e., human, machine, and task characteristics) and processes (i.e., collaboration and learning) into account. Hence, Reciprocal Learning is the output of this framework, which is characterized by its inputs' characteristics, characteristics of processes, namely collaboration and learning. Depending on requirements regarding HMS, Symbiotic Reciprocal Learning is characterized as an extension of Reciprocal Learning. In this way, characteristics of both agents are respected. Both agents are defined by a range of basic characteristics that define their states regardless of any given task and situational characteristics (cf. Table). Reciprocal Learning is defined by the agents' characteristics, as well as characteristics of collaboration and learning, as described above. The interaction is characterized by the collaboration of human and machine, as well as the learning process. In addition to the aforementioned characteristics, Reciprocal Learning is distinguished by quality of mutual effects (cf. Table). Learning, i.e., change/adaptation of behavior, needs to be realized in both type of agents in order to label learning to be reciprocal. Additionally, benefits must be mutual, i.e., improved performance, skills, ergonomics may not be imposed on only one of the agents, but both of them. However, the benefits do not need to match in their respective qualities, which allows asymmetrical benefits. In this way, Reciprocal Learning is not present if only one individual agent changes its behavior, or only one single agent benefits from the learning, regardless of the encountered learning mechanism. These may include learning mechanisms, such as: Trial-and-error learning, observational learning, social learning, supervision learning, imitation learning, and collaborative learning.

Benefit	Change of behavior	
	Individual	Mutual
Individual	**No** Reciprocal Learning	**No** Reciprocal Learning
Mutual	**No** Reciprocal Learning	**Reciprocal Learning**

Table 4: Reciprocal Learning defined by mutual change of behavior and mutual benefit

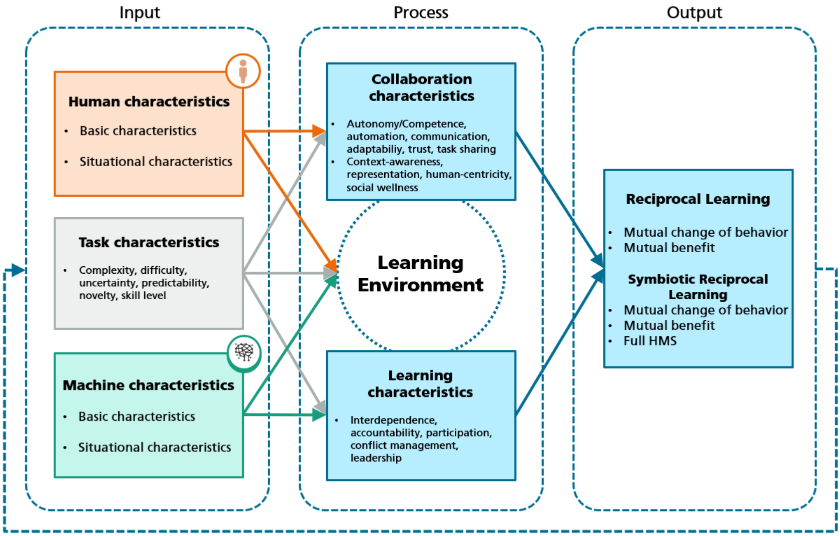

Figure 5: Framework of Reciprocal Learning in human-machine collaboration

6. Conclusion and future research in Reciprocal Learning in human-machine collaboration

In conclusion, human intelligence and AI have ambiguous definitions and are conceptually evolving due to substantial efforts in psychology and computer science. The vision of Reciprocal Learning has been gaining interest due to its innovative approach to WBL. However, the concept has not been clearly defined. Hence, this paper offers intermediate results of a work in progress on Reciprocal Learning by means of outlining inputs, processes, and outputs to characterize Reciprocal Learning.

In future research, characteristics of Reciprocal Learning need to be defined comprehensively, in order to define qualitative and quantitative requirements for Reciprocal Learning. Moreover, research is encouraged to investigate technology readiness to deploy Reciprocal Learning to MAS in manufacturing. Therefore, use-cases and applications need to be investigated in order to leverage potentials of Reciprocal Learning in enhancing WBL and enable empirical research.

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Sustainability is gaining importance and the economy is changing into a circular economy, especially with regard to climate change and the need to create more resilient value chains. The organization of work is meeting these challenges with, among other things, the digitalization of increasingly changeable production. Collecting and understanding data is becoming increasingly complex, as not only internal production data is of interest, but also cross-company sustainability indicators play a role in decision-making. The research results presented under the main topic "Digitization of the work environment for sustainable production" address this problem of compliance with sustainability requirements by means of digitization and its impact on the workplace and workers. The members of the Scientific Society for Work and Business Organisation (WGAB) present innovative concepts and research results for practitioners and scientists and thus provide valuable input for current challenges.

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