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

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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 %.

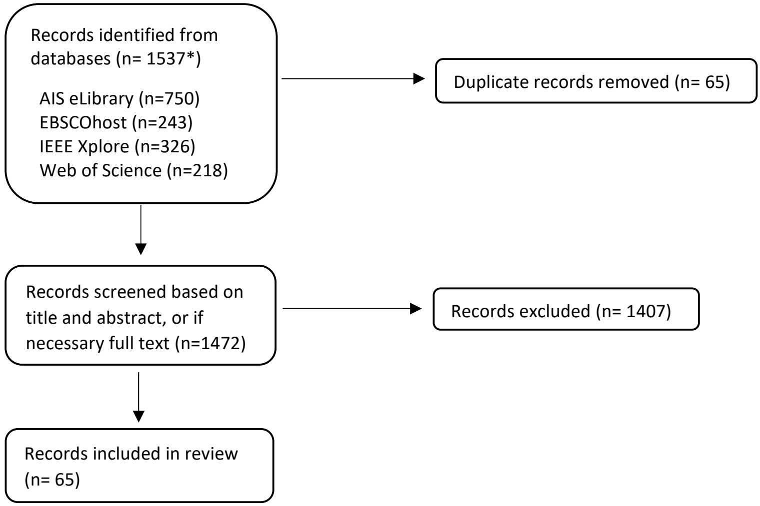

Figure 1: PRISMA flow chart

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

Implementation	Kang et al. (2020)	x	x	x				o		
	Mulrennan et al. (2020)		x							x
	Silveira et al. (2020)							x		
	Rudolph et al. (2020)							x		
	Ingemarsdotter et al. (2021)							x		
	Li et al. (2019)							x		
	Tong et al. (2018)								x	
Design	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		
	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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