sustainability

Review

Artificial Intelligence Applications for Increasing Resource Efficiency in Manufacturing Companies—A Comprehensive Review

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Abstract: Sustainability improvements in industrial production are essential for tackling climate change and the resulting ecological crisis. In this context, resource efficiency can directly lead to significant advancements in the ecological performance of manufacturing companies. The application of Artificial Intelligence (AI) also plays an increasingly important role. However, the potential influence of AI applications on resource efficiency has not been investigated. Against this background, this article provides an overview of the current AI applications and how they affect resource efficiency. In line with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines, this paper identifies, categorizes, and analyzes seventy papers with a focus on AI tasks, AI methods, business units, and their influence on resource efficiency. Only a minority of papers was found to address resource efficiency as an explicit objective. Subsequently, typical use cases of the identified AI applications are described with a focus on predictive maintenance, production planning, fault detection and predictive quality, as well as the increase in energy efficiency. In general, more research is needed that explicitly considers sustainability in the development and use phase of AI solutions, including Green AI. This paper contributes to research in this field by systematically examining papers and revealing research deficits. Additionally, practitioners are offered the first indications of AI applications increasing resource efficiency.

Keywords: sustainability; energy efficiency; material efficiency; water efficiency; greenhouse gas emissions; Green AI; AI; machine learning

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1. Introduction

The results of the latest assessment reports of the intergovernmental panel on climate change (IPCC) unambiguously reveal the need for action concerning the diminution of human-caused environmentally harmful emissions [1]. Based on the year 2010, the industry sector accounts for approximately 21% of the global emissions of greenhouse gases [1]. These emissions occur due to the consumption of resources during production. The emission intensity of resources increases with every subsequent step in the upstream supply chain. Consequently, the saving of every quantity unit of resources prevents upstream ecological impacts. Hence, the reduction in energy and material inputs directly results in significant advancements concerning the ecological performance of the manufacturing industry. Therefore, the increase in resource efficiency is of pivotal relevance in addressing ecological challenges of current and future times. Nevertheless, this progress needs to be accompanied by the widespread implementation of sufficiency and consistency approaches in economy and society [2]. Whatever the reasons for this may be—regulations becoming more stringent or the intrinsic motivation of decision makers, employees, and customers—an increasing number of companies are facing the challenge of becoming more sustainable and, consequently, of reducing their environmental impact.

After an age of economic growth, in which industrial pollution was widely accepted as an accompanying effect, the focus of many companies in recent years did not shift towards reducing environmental impacts [2–4]. Due to this inactivity, the first improvements could easily be obtained when analyzing existing processes by taking the objective of increasing sustainability into account [5]. Many measures identified during such evaluations are commonly referred to as "low hanging fruits", as the necessary effort and investment for implementation is comparably low, while the implications can be significant. After implementing first measures for reducing the ecological footprint of companies, the identification of further potential for improvement often becomes more complex. Here, targeted data acquisition as well as efficient data processing serve as enablers for the holistic and effective optimization of manufacturing environments. Hence, digitization is widely seen as a powerful enabler for improving the economical, ecological and societal performance of the industrial sector. The adoption of information technology in the monitoring of manufacturing systems bears the potential to increase the overall sustainability performance [6]. Apart from basic digitization approaches, such as big data analytics and digital twins, artificial intelligence (AI) represents another promising enabling technology for a sustainable transformation of the manufacturing industry.

While not solely focusing on sustainability in the context of industrial production, Figure 1 illustrates the increasing visibility of "artificial intelligence" in combination with the concept of sustainability in the scientific community. The number of respective scientific publications has nearly exponentially increased during the last 30 years. A prominent example is the work of Vinuesa et al. [7], who assesses potential impacts of AI regarding the Sustainable Development Goals (SDGs), proving both positive and negative effects. Di Vaio et al. [8] explore the influences of AI on business models in the context of the SDGs identifying a research gap for SGD 12 "sustainable consumption and production patterns". Nishant et al. [9] see the potential benefit of AI in enabling effective and efficient environmental governance with a focus on developing resilient sustainable systems. Their comprehensive literature review summarizes the applications of AI in societal matters and aspects of national economics and the design of energy systems. In conclusion, they mention the improvement in "industrial environmental performance" as one out of four promising practical applications of AI [9]. Without a detailed description or specific examples, the optimization of resource consumption in industrial processes is assessed as being beneficial for operations at every scale [9]. The present article addresses these issues by identifying the utilization of AI in this regard by a thorough literature review.

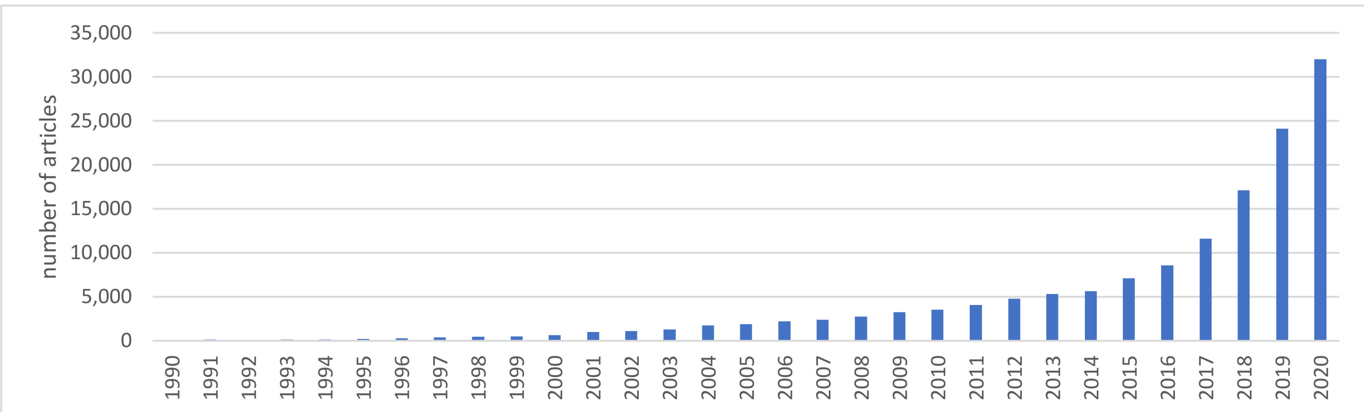

Figure 1. Number of articles containing terms "artificial intelligence" and "sustainability" on Google Scholar since 1990.

While the correlation between general sustainability and AI is discussed extensively in the literature (Figure 1), a holistic review of the implications of AI utilization on resource use in the manufacturing industry does not exist to date. Thus, this paper addresses the research gap by examining the (potential) influence and the current state of AI for improving resource efficiency and answers the following research question: What is the current state of AI used for improving resource efficiency within manufacturing companies?

By providing a comprehensive meta-analysis of existing applications described in the scientific literature and identifying current research deficits, this article contributes to the research field of AI and resource efficiency. Additionally, the identification of typical use cases helps practitioners and researchers to determine possible use cases for increasing resource efficiency within production.

The paper is structured as follows: Section 2 provides definitions for AI and resource efficiency, which are essential for the literature review. Section 3 describes the proceedings and method used in this paper. For the literature review, the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines were chosen. The papers identified are listed and described according to AI tasks, AI methods, resource efficiency, and business unit in Section 4. In Section 5, the results are discussed, analyzed, and typical use cases are identified. Section 6 concludes the findings, states the limitations of this papers and gives an outlook for future research directions.

2. Fundamentals of AI and Resource Efficiency

By defining AI and resource efficiency, this section is the basis for the following analysis. Additionally, the link between AI and resource efficiency is explored, clarifying the possible impact of AI application on resource efficiency.

2.1. Definition of AI

Although AI is seen as a technology with disruptive potential in companies and research, it lacks a universally valid definition and is not clearly distinguished from general IT [10]. Broadly speaking, systems that incorporate AI possess analytical capabilities that emulate human cognition. Nilsson [11] defines AI as "that activity devoted to making machines intelligent, and intelligence is that quality that enables an entity to function appropriately and with foresight in its environment." Various scientific publications discuss the complexity of determining the research domain of AI in detail and provide overviews of different definitions [12–14].

While often falsely equated with AI, machine learning is a subset of AI, comprised of various sub-branches such as deep learning [15,16]. Although various other methods and branches of AI (e.g., expert systems) exist, machine learning is one of the more popular in the public and scientific dialogue [10]. Machine learning deploys statistical methods for advancing the analytical abilities of the respective system [17,18]. This is done autonomously in a predefined framework and without detailed instructions in the form of human programming [10]. Generally, three main categories of learning methods are applied for state-of-the-art AI agents with machine learning algorithms (supervised, unsupervised and reinforcement learning). Supervised learning, as the least autonomous method, utilizes expert knowledge or given regularities to verify hypotheses derived from data analyzation [19,20]. Humans predefine and label the utilized data beforehand [21]. Based on derivations calculated from the correct result, the AI model learns systematically by adjusting parameters [22]. Unsupervised learning lacks this kind of testing circle. Respective models learn without comparing the potential solution to a desired result. Sathya and Abraham [19] describe the operating principle as the identification of "hidden patterns in unlabeled input data". While applicable to use cases where data quality does not allow the implementation of supervised learning, the performance of unsupervised learning models is often difficult to quantitatively evaluate, as the comparison to an ideal result is not possible [21]. Reinforcement learning is also known as semi-supervised learning as it is a mixture of the two learning methods described above. The input data are labelled beforehand; however, it might occur that the labelling is changed over the course of the learning process [20]. The reinforcement is obtained from rewards emitted from the affected environment. The system achieves a maximization of cumulated positive feedback through a systematic and iterative approach [21]. The superordinate task of models based on reinforcement learning is to identify an equilibrium between the exploration of new information and exploitation of existing information [21,23].

Generally, individual or combinations of various AI methods in manufacturing environments are able to analyze unstructured data such as audio or image signals. Consequently, patterns are identified and deviations from the regular conditions of the monitored system are detected rapidly and, in some cases, proactively [24]. These irregularities are informationally processed and provided to decisional entities. Subsequently, measures for improvement are automatically or manually derived and commissioned, depending on the grade of autonomy of the AI solution. The effects of the implementation of AI in manufacturing environments are mostly related to operational efficiencies. However, the potential implications for resource efficiency have not been investigated in detail.

2.2. Definition of Resource Efficiency

According to VDI 4800 [25], resource efficiency is defined as “the ratio of a specific benefit or result to the resource input required to achieve it”. A benefit or result can be the production of a product or the execution of a production process [26]. Resource input in this context can be defined as natural and operational input for production systems. Natural resources represent a “resource that is part of nature. These include renewable and non-renewable primary raw materials, physical space (surface area), environmental media (water, soil, air), flowing resources (e.g., geothermal, wind, tidal and solar energy) and biodiversity.” [27]. Examples include operational input covers, operating and auxiliary materials, materials, energy, capital, personnel, know-how, and time. As is common in the context of environmental science, the present article focusses on the potential contribution of AI to reducing the use of natural resources in manufacturing systems [28]. Therefore, renewable and non-renewable primary raw materials are of special interest, with energy, material and water being used as a resource input in this article.

Consequently, various operational inputs such as, for example, capital, human resource and know-how-related aspects are not considered in particular [26]. Other impact categories, such as, for example, system and product efficiency [29] are neglected due to the focus on natural resources as well as the system boundary of the manufacturing system.

2.3. Link between AI and Resource Efficiency

By identifying patterns and suggesting measures for improving the performance of the observed system, AI bears the potential to play a relevant role in transforming the industry to a sustainable, competitive and future-proof production. An optimized manufacturing system utilizes its infrastructure and inputs to a perfect extent. In the context of industrial manufacturing, the implementation of AI and the associated possibilities for data analysis can, for example, result in optimized production planning. Thus, by taking the introduced definition into account, all impact categories are potentially affected. By reducing attrition and production waste through improved simulation and planning, the material efficiency of the manufacturing system is improved. The same is true for water usage, which often serves as the auxiliary and operating supply. Optimized production planning reduces energy consumption, for example, through schedule and capacity planning. The improved coordination of various production processes and steps bears a large potential to increase energy efficiency. AI supports decision makers in a holistic analysis of the manufacturing system and, thus, in the identification of potential correlations between singular production entities.

AI thus provides support for the evaluation, identification and implementation of improvement measures in manufacturing companies. In this context, digitized knowledge is very important in order to utilize the knowledge that is already available in a company for AI applications and, thus, to create an enhanced knowledge base [30]. However, a sole focus on AI to increase resource efficiency is not reasonable; rather, it should be seen as a promising technology that could be a building block for enhanced sustainability. This technology, however, can only fully contribute to increasing resource efficiency if this objective is clearly formulated during the development and use of AI. In this sense, resource efficiency is a sub-goal of sustainability and the SDG 12 and can, therefore, only make a limited contribution to improving sustainability, but it is nonetheless an essential aspect.

3. Materials and Methods

Figure 2 presents the research process of this paper. By identifying AI methods, relevant business divisions, and relevant resource efficiency terms, it was possible to create a search string for a literature review according to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines and a framework for an analysis of the included papers. The results of the literature review were analyzed to identify their potential to increase resource efficiency within a manufacturing company.

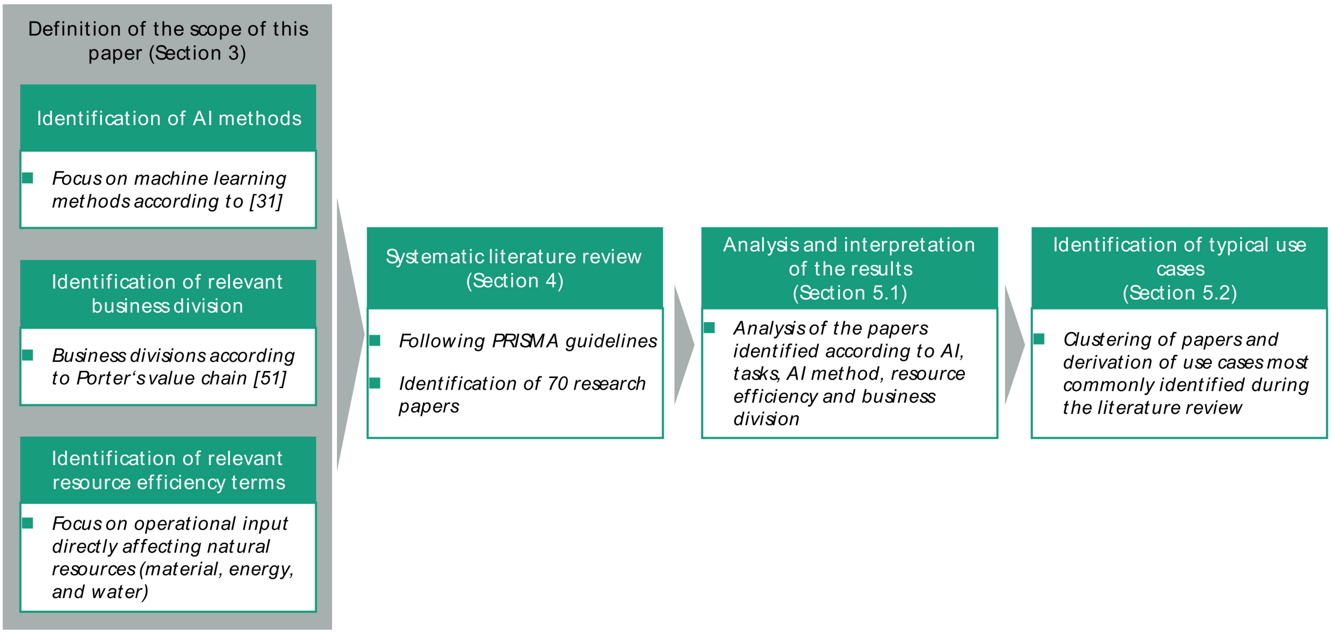

Figure 2. Research process of this paper.

3.1. Identification of AI Methods

The identification of AI methods is based on [19,20,31], focusing on machine learning. Here, various methods were assigned to different tasks and clusters (Table 1) for application as the basis for the subsequent analysis. In total, 21 AI methods were assigned to the AI clusters of supervised, unsupervised and reinforcement learning, as described in Section 2, and to AI tasks. Thus, this paper focuses on machine learning and other AI paradigms, such as expert systems and generic algorithms, are not explicitly included. However, this selection of AI methods is not meant to be conclusive, but rather represents the selection of common AI methods. To include other papers, to which none of the identified AI methods apply, the subordinate term of Artificial Intelligence was integrated in the search string.

Table 1. Identified AI Cluster, Tasks and Methods used for this research paper.

Cluster	Task	Method
Supervised learning	Trend analysis	Linear regression Non-linear regression
	Classification	Decision trees Logistic regression Naive Bayes classification Support Vector Machines (SVM)

Table 1. *Cont.*

Cluster	Task	Method
Supervised learning	Anomaly detection	Isolation Forest Local Outlier Factor
	Image recognition	Convolutional neural networks (CNN)
	Modeling, language processing	Markov chain Pattern recognition Recurrent neural networks (RNN) Transformer Long short-term memory (LSTM)
Unsupervised learning	Clustering	Hierarchical clustering K-means
	Dimension reduction	Principal Component Analysis (PCA)
Reinforcement learning	Learning tasks	State–action–reward–state–action (SARSA) Deep Q-Network (DQN) Double Deep Q Network (DDQN) Q-Learning

Linear regression examines a linear relationship between a so-called dependent variable and an independent variable (bivariate regression) and maps this relationship with a linear function or regression line [32]. In non-linear regression, functions are studied that cannot be written as linear functions in the parameters [33]. Decision trees are used, especially for the classification of data, and consist of nodes, edges, and leaves [34]. (Binary) logistic regression analysis is used for testing whether a relationship exists between a dependent binary variable and one or more independent variables [35]. Naïve Bayes classification is a probabilistic classifier derived from Bayes' theorem. It assigns each object to the class to which it is most likely to belong, or for which the lowest costs are incurred [36]. SVM is a mathematical method of pattern recognition [37]. Isolation forest is an approach in which anomalies in datasets are detected and isolated instead of removed, as occurs in most other machine learning algorithms. [38]. Local Outlier Factor is an algorithm for detecting density-based outliers. It compares the density of the point itself with that of its nearest neighbor to rank the individual datapoints and find anomalies or outliers [39]. CNNs consist of different convolutional layers and one pooling layer, representing a biologically inspired approach. It is most commonly applied for image recognition [40]. Markov chain is a stochastic model describing a sequence of processes in which the probability of each state can be calculated and simulated in relation to the previous states [41]. Pattern Recognition is the ability to recognize regularities, repetitions, or similarities in a set of data [42]. In contrast to feedforward networks, RNNs are characterized by connections from neurons in one layer to neurons in the same or a previous layer. Thus, temporally encoded information in datasets can also be processed [43]. Transformers are applied similar to RNNs in the classification and traversal of ordered datasets and are particularly suitable for recognizing and generating language [44]. LSTM is a specific RNN architecture, which is well-suited to processing times series data [45].

Hierarchical clustering is a method of grouping objects into optimally homogenized sets based on empirical similarity measures and sorting them into hierarchically arranged structures [46]. K-means is suitable for the classification of data into a known number of k groups. It is one of the most frequently used algorithms for the clustering of objects [47]. PCA is used to reduce the dimensionality of datasets, making them easier to interpret without losing information content. This is achieved by adding new, uncorrelated datapoints until the maximum variance is successively reached [48].

SARSA is an algorithm for learning an action-value function. In contrast to Q-learning, however, the agent remains true to its strategy when calculating its subsequent action. DQN and DDQN are variants of Q-Learning [49,50].

3.2. Identification of Relevant Business Divisions

Since this paper focusses on AI applications within manufacturing companies, the definition of business divisions was based on the value chain according to [51]. The following divisions were thus identified:

- Procurement;
- Product development;
- Production planning and optimization;
- Facility management;
- Logistics (internal/external).

3.3. Identification of Relevant Resource Efficiency Terms

To evaluate the influence on resource efficiency within manufacturing companies, this paper focuses on operational input which directly affects natural resources, including material (including operating and auxiliary materials), energy, and water. This proceeding is in line with the above-stated definition of resource efficiency. Hence, material efficiency, energy efficiency, and water efficiency are of interest in this paper. Additionally, the two terms of resource efficiency, as well as efficiency itself, were identified as superordinate terms and included in the search string.

3.4. Literature Review according to the PRISMA Guidelines

The literature review, following PRISMA guidelines, was conducted at the end of September 2020. There were no time restrictions, and it was searched up to the latest issue available. The databases Scopus and Web of Science were searched, with the following search string, consisting of the identified AI methods, business divisions, and resource efficiency terms: (“Artificial Intelligence” OR “Linear Regression” OR “Nonlinear Regression” OR “Support Vector Machines” OR “Logistic Regression” OR “Decision Trees” OR “Naive Bayes Classification” OR “K-means” OR “Hierarchical Clustering” OR “Principal Component Analysis” OR “Isolation Forest” OR “Local Outlier Factor” OR “Convolutional Neural Network” OR “Pattern Recognition” OR “Recurrent Neural Networks” OR “Long short-term Memory” OR “Transformer” OR “Markov chain” OR “ State–action–reward–state–action” OR “ Deep Q-Network”, “ Double Deep Q Network” OR “Q-Learning”) AND (“manufacturing” OR “industrial” OR “procurement” OR “product development” OR “logistics” OR “warehouse management” OR “facility management”) AND (“efficiency” OR “resource efficiency” OR “material efficiency” OR “energy efficiency” OR “water efficiency”)

Figure 3 shows that 1347 papers were identified through database searching within Scopus and Web of Science. Additionally, 49 papers were identified through other sources, including expert recommendations, citations, and cross-references. Subsequently, duplicates were removed, and the title and abstracts of the identified papers were screened. Here, only papers using an AI method for an industrial application were included. A total of 1012 papers not meeting these criteria were excluded, e.g., AI applications, used for environmental monitoring of landscapes, as this application is not suitable for manufacturing companies. The resource efficiency aspect was still of secondary importance in this step and not an exclusion criterion, since resource efficiency potentials were conceivable in many approaches, but these were not explicitly described in the title or abstract. Subsequently, 151 articles were assessed for eligibility. In this step, papers were excluded if no (potential) impact on at least one resource efficiency aspect could be found. At the end of the PRISMA process, 70 papers were identified as relevant to this literature review and for subsequent analysis. In accordance with the exclusion criteria, relevant, in this context, means that these papers address AI applications in manufacturing companies and can potentially impact at least one of the identified resource efficiencies (material, energy, or water).

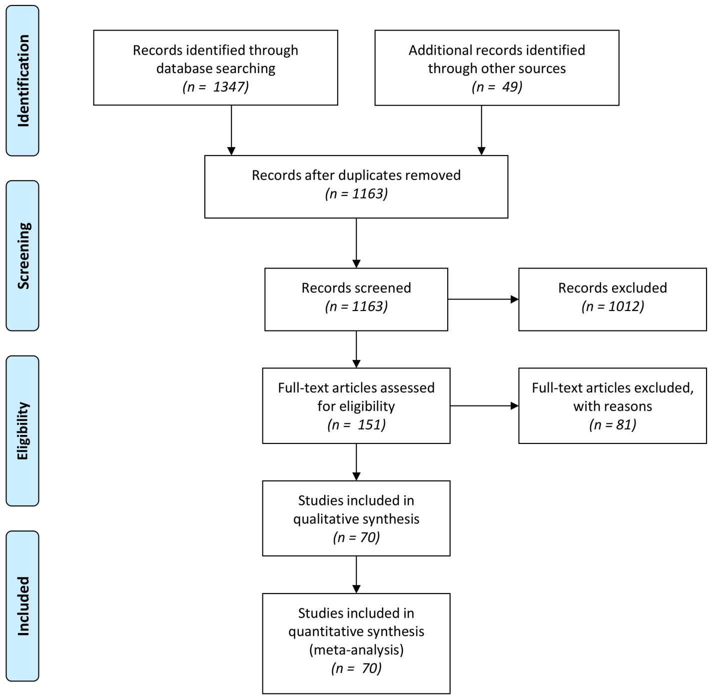

Figure 3. Literature review according to PRISMA guidelines.

3.5. Analysis of the Identified Literature

The included papers were then analyzed regarding the identified AI tasks, AI methods, business divisions, and their (potential) influence on resource efficiency aspects. Due to the high urgency of tackling climate change and reducing Greenhouse Gas (GHG) emissions, a potential reduction in the latter was analyzed alongside the (potential) improvement in energy, material and water efficiency. To objectify the evaluation of the influences on resource efficiency, a scale was developed. This scale includes:

- High influence, if a paper states an improvement in a resource efficiency aspect of 1% or more;
- Potential influence, if the AI application is able to improve a resource efficiency aspect, e.g., by optimizing a process and decreasing product errors. However, no quantification of the improvement is given, or the improvement is below 1%;
- None, if the AI application does not influence any of the resource efficiency aspects;
- N/A, if not enough information is available to evaluate the potential influence.

Furthermore, the papers were categorized according to AI tasks, AI methods, and business divisions.

3.6. Identification of Typical Use Cases of AI Application Increasing Resource Efficiency

When analyzing the identified papers, it became clear that many addressed similar use cases, especially within the business division production. To provide practitioners and applied research with possible starting points for the promising implementation of AI regarding resource efficiency, typical use cases were derived from the approaches. Here, the AI applications itself, their aim of improvement, the addressed resource efficiency aspects, and the improvement object (product or process) were analyzed and, thus, suitable clusters were determined.

4. Results

The 70 research papers identified were analyzed and classified according to their influence on resource efficiency. Table 2 shows the results of the respective classification regarding AI tasks, AI methods, business divisions, and the assessment of the influence on resource efficiency and GHG emissions.

Table 2. Research papers found following the literature research process (green = high influence; yellow = potential influence; grey = no influence; white = N/A).

			Business Divison					Ressource Efficiency + GHG			
AI Tasks	**AI Methods**	**Source**	**Procurement**	**Development**	**Production**	**Facility Mgmt.**	**Logistics**	**Energy**	**Material**	**Water**	**GHGEemissions**
Trend analysis	Linear regression	Rentz et al. (2006)			x			none	pot.	none	none
		Irrek and Barthel 2010)				x		pot.	none	none	pot.
		Bartusch et al. (2012)			x			pot.	pot.	none	none
		Hofbauer et al. (1983)			x			pot.	none	none	pot.
		Gebbe et al. (2014)			x			pot.	none	none	pot.
		Wehle and Dietel (2015)			x			pot.	pot.	pot.	pot.
		Youssef et al. (2019)			x			pot.	pot.	none	pot.
		Adamczak et al. (2020)			x			pot.	pot.	none	pot.
		Kuhlmann and Sauer (2019)			x	x		pot.	none	none	pot.
	Non-linear regression	Johnson et al. (2004)		x	x			pot.	none	N/A	pot.
		Wohlgemuth (2008)			x			none	pot.	none	none
Trend analysis; dimension reduction	Linear regression; PCA	Flick et al. (2017)			x			pot.	none	none	pot.
Trend analysis; dimension reduction	Linear regression; SVM; PCA	Ghaedi et al. (2014)			x			none	pot.	none	none
Classification	Decision trees	Evans et al. (2013)		x				pot.	pot.	pot.	pot.
		Ronowicz et al. (2015)			x			pot.	pot.	none	pot.
		Hsu and Wang (2005)		x	x			pot.	pot.	none	pot.
		Antosz et al. (2020)			x			pot.	pot.	pot.	pot.
	Logistic regression	Yan and Lee (2005)			x			pot.	pot.	none	pot.
		Li et al. (2015)			x			pot.	pot.	none	pot.
		Schmid (2017)			x			pot.	pot.	pot.	pot.
		Yan et al. (2004)			x			pot.	pot.	none	pot.
	Naive Bayes classification; decision trees	Doreswamy (2012)		x				pot.	pot.	none	pot.
	Naive Bayes classification	Adam et al. (2011)			x			pot.	pot.	none	pot.
		Ferreira and Borenstein (2012)	x					none	none	none	pot.
		Prasetiyo et al. (2019)				x		pot.	N/A	N/A	N/A

Table 2. *Cont.*

			Business Divison					Ressource Efficiency + GHG			
AI Tasks	**AI Methods**	**Source**	**Procurement**	**Development**	**Production**	**Facility Mgmt.**	**Logistics**	**Energy**	**Material**	**Water**	**GHGEemissions**
Classification	SVM	Decker (2008)	x	x	x	x	x	pot.	pot.	none	pot.
		Freitag et al. (2015)			x			none	pot.	none	none
		Zendehboudi et al. (2018)				x		pot.	none	none	pot.
		Wanner et al. (2019)			x			pot.	pot.	pot.	pot.
		Deng et al. (2017)			x			pot.	pot.	none	pot.
		Golkarnarenji et al. (2019)			x			high	pot.	none	high
Classification; dimension reduction	SVM; PCA	Pai et al. (2009)			x			pot.	pot.	none	pot.
Classification; modeling, language processing	Naive Bayes classification; LSTM	Zhang et al. (2018)			x			pot.	none	none	pot.
	RNN; LSTM	Cheng et al. (2019)			x			pot.	pot.	none	pot.
	SVM; RNN	Yu et al. (2017)			x			high	none	none	high
Anomaly detection	Isolation forest	Susto et al. (2017)			x			pot.	pot.	N/A	pot.
Image recognition	CNN	Weimer et al. (2016)			x			pot.	pot.	none	pot.
		Bechtsis et al. (2017)			x		x	pot.	pot.	none	pot.
		Scime and Beuth (2018)			x			pot.	pot.	N/A	pot.
		Willenbacher et al. (2017)			x			pot.	pot.	pot.	pot.
		Choi and Kim (2020)					x	high	none	none	pot.
		Liang et al. (2019)			x			high	none	none	high
		Lee et al. (2019)			x			pot.	pot.	none	pot.
		Cui et al. (2020)			x			none	pot.	none	none
		Li et al. (2018)			x			none	pot.	none	none
		Wang et al. (2020 a)			x			pot.	pot.	pot.	pot.
Image recognition; clustering	CNN; hierarchical clustering	Wang et al. (2020 b)			x			pot.	pot.	pot.	pot.
Image recognition; modeling, language processing	CNN; LSTM	Liu et al. (2019)			x			pot.	none	none	pot.

Table 2. *Cont.*

			Business Divison					Ressource Efficiency + GHG			
AI Tasks	**AI Methods**	**Source**	**Procurement**	**Development**	**Production**	**Facility Mgmt.**	**Logistics**	**Energy**	**Material**	**Water**	**GHGEemissions**
Modeling, language processing	LSTM	Zhang and Ji (2020)						high	pot.	none	high
	Markov chain; pattern recognition	Reger et al. (2015)			x			pot.	none	none	pot.
	Markov chain	Abedi et al. (2010)			x			pot.	none	none	pot.
		Jónás et al. (2014)			x			pot.	pot.	none	pot.
		Xu and Cao (2014)			x			pot.	none	none	pot.
		Tsiliyannis (2018)			x			pot.	pot.	none	pot.
	Pattern recognition	Chin (1982)			x			pot.	pot.	none	pot.
		Bhagat (2005)			x			pot.	none	pot.	high
		Dong and Burton (2009)				x		high	none	pot.	high
		O'Driscoll et al. (2013)			x			pot.	none	none	pot.
	RNN; LSTM	Wang et al. (2017)				x		pot.	none	none	pot.
	RNN	Meyes et al. (2019)			x			pot.	pot.	none	pot.
Clustering	Hierarchical clustering	Alper Selver et al. (2011)			x			none	pot.	none	none
		Kain (2018)		x	x			none	pot.	none	none
	K-means	Yiakopoulos et al. (2011)			x			pot.	pot.	none	pot.
		Park et al. (2013)				x		pot.	none	none	none
		Moll et al. (2019)			x			pot.	pot.	N/A	N/A
		Gould et al. (2017)			x			pot.	pot.	pot.	pot.
Clustering; anomaly detection	K-means; Local Outlier Factor	Kanyama et al. (2017)				x		none	none	pot.	none
Dimension reduction	PCA	Lane et al. (2003)			x			pot.	pot.	none	pot.
Dimension reduction; classification	PCA; linear regression	Jagadish and Ray (2016)			x			pot.	pot.	N/A	pot.
Learning tasks	Q-learning	Yang et al. (2020)					x	pot.	none	none	pot.

Rentz et al. [52] applied a regression-based calculation model to the utilization processes of waste products in the metal processing industry. Plans of metallurgical recycling processes were developed and implemented in software tools that drew on problem-adequate mapping the underlying processes. Irrek and Bunse [53] used a regression analysis to select more efficient lighting for a manufacturing plant. The calculation model compares several options and simulates the results, without having to replace the entire lighting of the manufacturing facility contributing to essential energy savings. Bartusch et al. [54] presented an AI-supported intra- and inter-company material flow analysis, which is intended to increase resource efficiency while explicitly considering energy efficiency and CO_2 emissions. Hofbauer et al. [55] analyzed measures for increasing energy efficiency in the heat-intensive industry with the help of linear regression. Gebbe et al. [56] developed a method to estimate the electricity consumption of machines within a factory, although only the aggregated electricity consumption of multiple machines is available. The method uses linear regression to disaggregate the electricity consumption, enabling the consumption to be easily monitored, and thus identifying potential savings [56]. Wehle and Dietel [57] describe a procedure to optimize maintenance processes by evaluating images of possible errors in production in real time. Such a procedure allows for errors to be corrected as efficiently as possible, thus saving scrap and making production more efficient [57]. Youssef et al. [58] developed a model to improve the data-based prediction quality of properties of different materials. By improving this prediction quality, it is possible to find (quasi-)optimal solutions to manufacturing processes, enabling an improvement in material and energy efficiency [58]. Adamczak et al. [59] examined a regression model that analyses data from a ball bearing sensor. Minimization of vibrations can reduce material wear in the long term, as well as energy and, thus, CO_2 emissions, through lower friction [59]. Kuhlmann and Sauer [60] developed a model with linear regression to evaluate energy measures and increase the energetic agility within a manufacturing plant. Johnson et al. [61] used non-linear regression to create a more reliable meta-model and optimize various factors, such as efficiency in manufacturing semiconductors. Wohlgemuth [62] derived analytical equations by applying non-linear regression to test the acoustic compliance of a separation membrane in the galvanic manufacturing process. Thus, more efficient separation membranes can be manufactured [62]. Flick et al. [63] analyzed the energy efficiency of manufacturing systems within the automotive industry. By applying regression analysis and PCA, aspects influencing energy consumption, such as product size or shop area, are identified [63]. By combining SVM, PCA, and linear regression, Ghaedi et al. [64] predicted the adsorption of methylene blue dye.

With the help of a decision tree, Evans et al. [65] created a system that supports the selection of the manufacturing method for a certain manufacturing process. Using historical data, the model is trained to simulate experience and intuition from past decisions [65]. Ronowicz et al. [66] investigated the characteristics of produced pellets using a decision-tree-based model. In this way, the perfect formula per chemical used can be found, in which the respective ingredients can be used as efficiently as possible. As research and development in the chemical industry can be very time-, cost- and energy-intensive, savings in these areas are possible [66]. Hsu and Wang [67] used a decision tree to classify size patterns of the human body for clothing and calculated the amount of fabric needed for garment patterns based on a database of measured data. Applying decision trees, Antosz et al. [68] improved the maintenance approach of manufacturing companies. Yan and Lee [69] used logistic regression for the real-time monitoring of the health status of industrial components. A logistic regression analysis was used by Li et al. [70] to analyze the sound of rotating cutting tools. In this way, even minor inaccuracies can be detected, which prevent increased reject products due to imprecise cutting performance at an early stage [70]. Through a combination of model-based control methods and machine learning procedures, Schmid [71] attempted to improve resource efficiency in process control of industrial printing processes. Yan et al. [72] developed a method for predictive maintenance using logistic regression. Naive Bayes clusters and decision trees are used by Doreswamy [73] to classify datasets of different manufacturing materials. The information gained from these data models enables decisions regarding the use of different materials for specific tasks or manufacturing pieces [73]. Adam et al. [74] applied a Hybrid Artificial Neural Network-Naive Bayes classifier in the identification of reject products in the semiconductor manufacturing. Thus, these products are prevented from being further processed and waste is avoided [74]. Based on a database of past decisions on supplier selections, Ferreira and Borenstein [75] trained a data model. Thus, they developed a system for evaluating suppliers on the basis of a Bayes cluster, also considering resource efficiency and sustainability [75]. Prasetiyo et al. [76] analyzed the energy efficiency of a building with a Naive Bayes cluster. SVM was applied by Decker [77] in order to compensate for variances in process sequences. Freitag et al. [78] trained an SVM model to predict the effects of different process designs, and to evaluate these with regard to logistical performance and technical feasibility. A calculation model based on SVM was applied by Zendehboudi et al. [79] to predict the yield of solar and wind plants. Companies can use this calculation model to plan their own Photo voltaic or wind plant, integrate it into production, or optimize their existing plants [79]. Wanner et al. [80] analyzed machine data to improve maintenance and simplify fault detection, localization and identification. This can ensure smooth production, which, in the long term, reduces the energy costs caused by constant downtimes associated with shutting down and restarting machines [80]. Deng et al. [81] improved the fault detection within manufacturing processes using SVM. By applying SVM, Golkarnarenji et al. [81] increased the product quality and energy efficiency of the production of carbon fiber. Energy savings of almost 45% were realized. Pai et al. [82] applied SVM and PCA to the detection of errors during the production of LCD monitors. Zhang et al. [83] applied LSTM and Naïve Bayes Classification to the prediction of system degradation and the remaining lifetime of a machine. Cheng et al. [84] proposed a model applying RNN and LSTM to optimize the predictive maintenance of machines. By applying SVM, Yu et al. [85] extrapolated the energy consumption of individual tools in production. Moreover, energy savings can be estimated with the help of further simulations.

Susto et al. [86] applied Isolation Forest in a semiconductor manufacturing process, detecting product anomalies and identifying the process which causes the latter.

Weimer et al. [87] designed a CNN for defect detection in industrial inspection. Thus, the feature extraction is automated. In the context of automated guided vehicles, a solution with CNN was described by Bechtsis et al. [88]. Through this approach, the position and possible routes of autonomous vehicles are determined by the data collected at all times, using the Light Detected And Ranging (LIDAR) technology [88]. A CNN is applied by Scime and Beuth [89] to additive manufacturing, to detect anomalies and defects in the interaction of the deposition blade and the powder bed in selective laser melting or laser powder bed fusion. Willenbach et al. [90] combined different AI methods, mainly CNN, to improve the operational material flow management. Choi and Kim [91] developed an "edge AI" using CNN to control the defrosting operation of industrial mobile terminals in logistics. Hence, the energy consumption can be decreased significantly [91]. Liang et al. [92] optimized the machining processes by detecting potential errors with CNN for a dynamic prognosis. The energy efficiency was improved by about 29% [92]. Lee et al. [93] applied CNN for product quality control of steel. Thus, defects can be detected early on within the manufacturing system, and processes can be adapted. Using CNN, Cui et al. [94] analyzed the product quality of additive manufactured metal parts, considering the lack of fusion, crack, and porosity. Li et al. [95] applied CNN to evaluate the product quality during the assembly process. Wang et al. [96] proposed a model for identifying the optimal operation model of manufacturing processes with CNN. Wang et al. [97] designed a method with CNN and hierarchical clustering, enhancing the prediction models of chemical processes. Liu et al. [98] improved human–machine interaction within manufacturing with CNN and LSTM.

Zhang and Ji [99] developed an LSTM method for production error detection and energy-efficient scheduling. Thus, an increase in both energy efficiency, of 21.3%, and in product quality were achieved in a case study [99]. Reger et al. [100] used pattern recognition and Markov chain to classify electric drives in manufacturing plants. Hence, the energy consumption of specific machines can be derived using fewer sensors, and energy efficiency is calculated more easily [100]. Waiting time models (e.g., queues of products in processing lines) were modelled as Markov chains by Abedi et al. [101]. Thus, waiting times at production lines can be reduced or production time can be predicted [101]. Jonas et al. [102] used Markov Chains for the repair process in the industrial electronic sector. Hence, the probability of specific process steps and process time required for the repair can be determined, improving process planning and product quality, and saving resources [102]. Xu and Cao [103] evaluated the energy efficiency and productivity of machine tools based on a Markov chain. Thus, the scheduling of maintenance operations can be optimized [103]. By applying Markov chain, Tsiliyannis [104] improved the forecast of the return of products, which can be used for remanufacturing. Another approach is the Pattern Recognition, used by Chin [105] for automated visual inspection in manufacturing. Bhagat [106] applied pattern recognition to the prediction of heat transfer fouling and to increase tube bundle heat transfer efficiency. Consequently, operation and maintenance times can be adjusted. In order to simulate occupant behavior and usage patterns, Dong and Burton [107] used pattern recognition to evaluate data collected by sensor networks, e.g., temperature and humidity. O'Driscoll et al. [108] applied pattern recognition to characterize different machine components according to their energy consumption. Wang et al. [109] optimized heating systems within buildings, especially offices, in terms of comfort and energy efficiency, using RNN and LSTM. Meyes et al. [110] analyzed the product quality during production by predicting component defects with an RNN.

Alper Selver et al. [111] applied Hierarchical Clustering to evaluate the quality of marble and, thus, automatically sort out unsuitable slabs during the production process. Kain [112] determined the characteristics of biogenic wood filaments produced via additive manufacturing using hierarchical clustering. A k-means clustering was used by Yiakopoulos et al. [113] to automatically inspect ball bearing manufacturing parts and check for defects. When optimizing a sensor network, e.g., to digitize a manufacturing plant, Park et al. [114] used k-means. Thus, the battery life of sensors can be extended, and energy consumption can be reduced [114]. Moll et al. [115] developed a method for investigating the fabrication of workpieces in the Fiber Injection Molding Process with k-means, and hence preventing errors in mold filling. Gould et al. [116] used k-means to optimize the assembly process. By doing this, they achieved improvements regarding assembly time, energy, water and auxiliary material consumption. Water consumption is measured by smart meters by Kanyama et al. [117]. The collected data are analyzed for anomalies using a k-means and Local Outlier Factor [117]. Lane et al. [118] used PCA to monitor a polymer production process and detect anomalies preventing a low product quality. Jagadish and Ray [119] optimized the process parameters of electrical discharge machining using PCA and linear regression, considering aerosol concentration, energy and dielectric consumption. Yang et al. [120] used Q-Learning for a warehouse management system by improving the scheduling system of picking operations.

5. Discussion

This section is divided into two subsections. The first section analyses the identified papers in detail, identifying the applied AI methods and differences within these clusters when addressing resource efficiency aspects. Derived from the identified papers and the analysis, the second subsection determines typical use cases of AI applications, increasing resource efficiency within manufacturing companies.

5.1. Analysis of the Identified Research Papers

In total, 70 research papers published between 1982 and September 2020 were identified during the literature research process. Figure 4 presents the distribution of the identified sources over time. In general, the number of publications increased over time.

The most publications were found for 2017 and 2019. As only the literature from before September 2020 was considered, the lower number in 2020 can be explained. However, the significant decrease in publications in 2016 cannot be explained by the authors. As AI applications become more frequent and available within research as well as industry, and the need for manufacturing companies to improve resource efficiency increases, the trend of relevant sources increasing over time is not surprising.

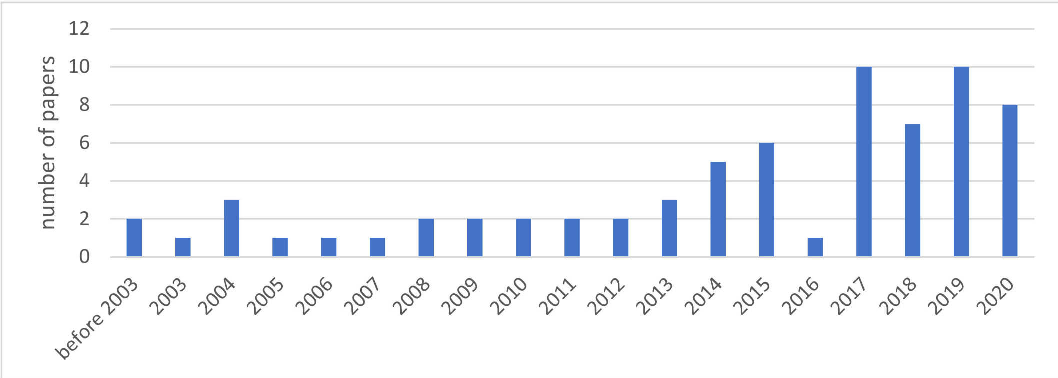

Figure 4. Distribution of sources found by year of publication.

In addition, the distribution of the identified sources can be analyzed regarding the AI method used, and, thus, the AI tasks. Figure 5 illustrates the proportion of methods and tasks. The majority of papers apply CNN (12 papers) or linear regression (12 papers), followed by SVM (9 papers). This result is especially unsurprising regarding linear regression, as linear regression has been used in this context since 1983, by [55]. However, linear regression is also a frequently applied method in current sources.

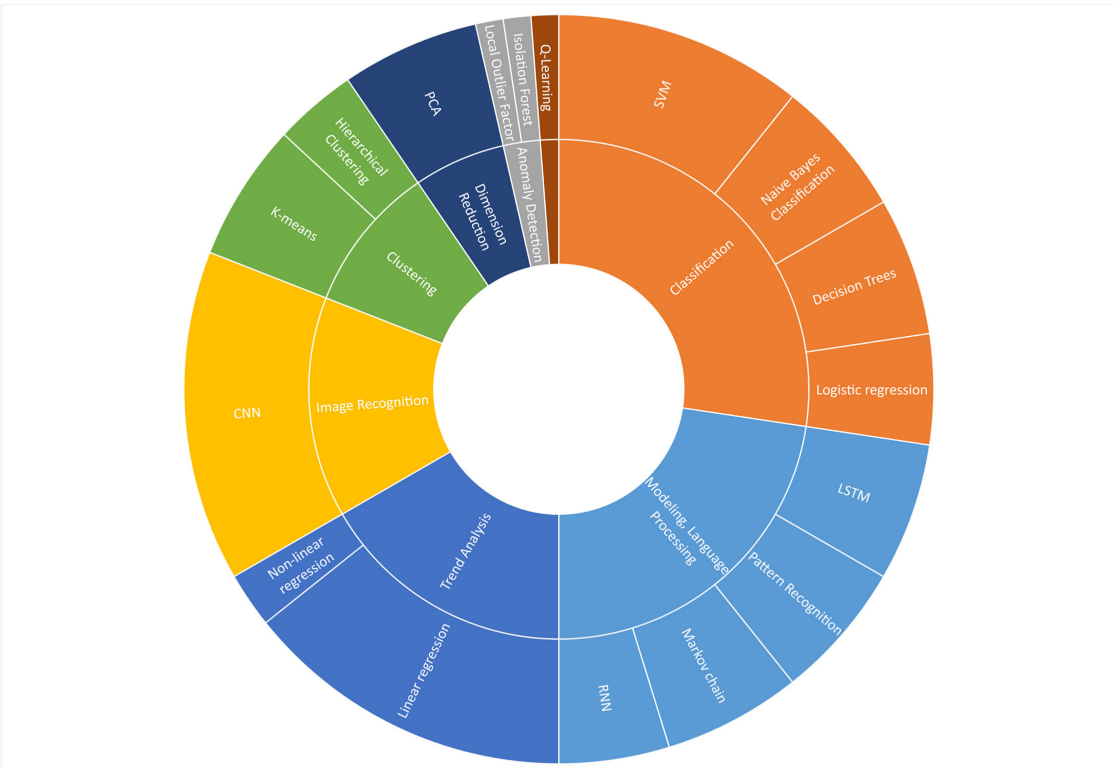

Figure 5. Proportion of research papers with specific AI Tasks and AI Methods.

Other AI methods are not used as frequently, as only five papers apply Naive Bayes classification, decision trees, LSTM, pattern recognition, Markov chain, k-means, and PCA. Isolation forest, Local Outlier Factor and Q-Learning were only used once, while SARSA, DQN, DDQN, and Transformer were not applied at all. Therefore, the most frequently employed AI tasks are classification, with 23 papers, followed by modelling and language processing, with 17, trend analysis, with 13, and image recognition, with 12 papers. Only one paper addressed learning tasks and, thus, reinforcement learning. From the literature review, it appears that papers dealing with reinforcement learning applications are more frequently developed for scheduling problems, robot collaboration, or supply chain problems [121–123]. However, as these papers neglect the aspect of resource efficiency, they are beyond the scope of this literature review and were not further analyzed.

Figure 6 presents the number and distribution of research papers addressing resource efficiency within a specific business unit. The majority of papers look at influences on resource efficiency in production planning and optimization, while only a few papers focus on facility management, development, logistics, or procurement.

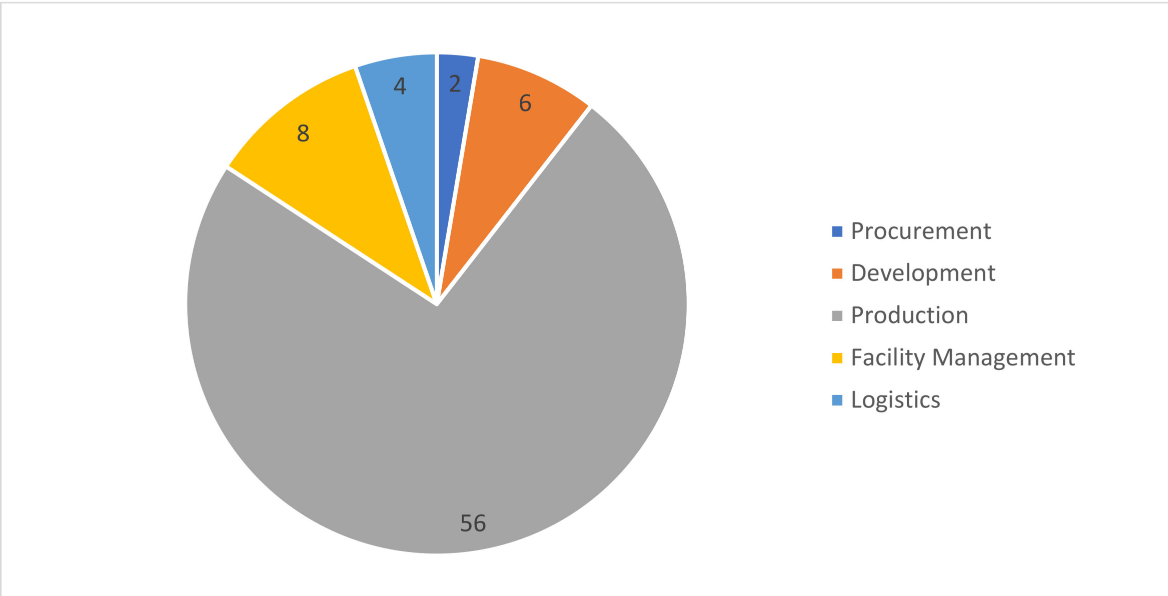

Figure 6. Number of research papers addressing resource efficiency in a specific business unit.

Table 2 also analyzes the influence on resource efficiency within manufacturing companies. As stated in Figure 7, the majority of papers, in total, 60 papers, confirm the impacts on energy efficiency. Papers dealing with influences on GHG emissions are also numerous, due to the fact that GHG emissions and energy are closely related. Only for the latter two aspects could a high potential be determined, meaning an improvement of 1%. A high influence could be found for neither material efficiency nor water efficiency. Furthermore, only 46 papers show a potential influence on material efficiency and 12 papers show an influence on water efficiency. This can be explained by the fact that energy savings count among the resource efficiency improvements that are most frequently addressed by companies. Energy management systems, in particular, make companies more aware of their energy consumption and of potential measures [124]. By contrast, material and water saving measures are usually neither approached nor implemented, due to their having more complex solutions and the nonexistence of comparable management systems.

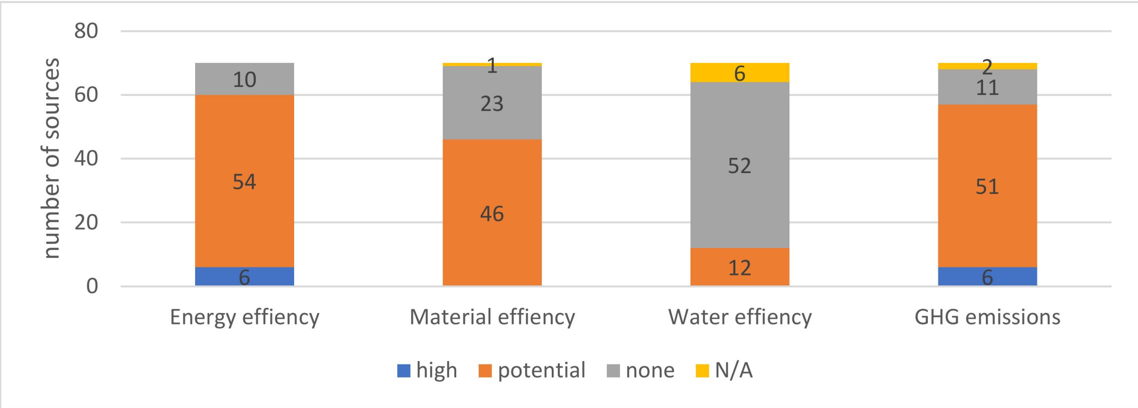

Figure 7. Number of research papers with influence on the different aspects of resource efficiency.

On average, one research paper addresses roughly 2.5 of the predefined resource efficiency aspects. This means that if a source deals with resource efficiency, it usually takes several aspects directly into account. Even if GHG emissions are not considered because of their close relation to energy sources, there is still an average of 1.7 aspects of resource efficiency being addressed.

The identified papers were also examined for the use of AI tasks, AI methods and the potential impact they had. On average, 60% of the resource efficiency aspects are potentially influenced by the identified papers (Figure 8). Small differences between AI tasks can be observed. While papers with AI task classification address 73% of the resource efficiency aspects, trend analysis and learning tasks only address around 50% of the resource efficiency aspects. A possible interpretation of this is that the AI classification task is applied in a wider context, and mostly addresses three out of the four resource efficiency aspects (incl. GHG emissions) at the same time. In contrast, the applications of trend analysis and learning tasks mainly influence two of the four aspects.

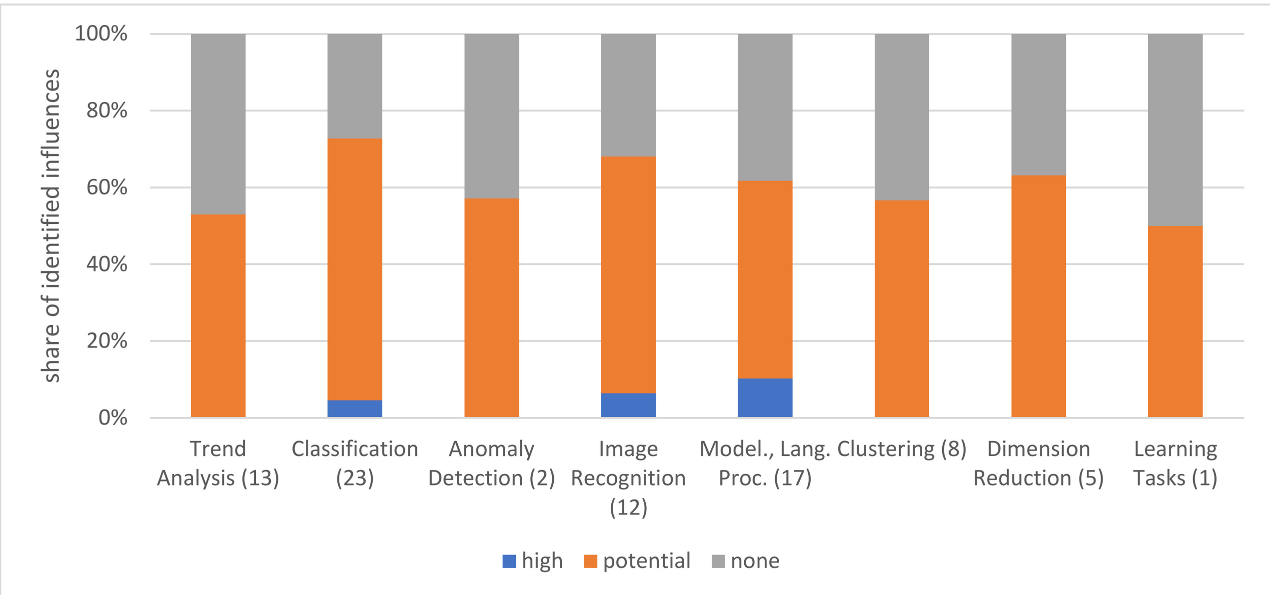

Figure 8. Distribution of identified influences on resource efficiency by AI tasks (the number of identified papers with this AI task is indicated in brackets).

As can be seen in Figure 9, the share of addressed resource efficiency aspects differs more significantly among AI methods than among AI tasks. Only SVM, CNN, Pattern recognition, RNN, and LSTM showed a high potential to influence resource efficiency.

Furthermore, the application of some AI methods addresses all four predefined resource efficiency aspects, such as Isolation Forest, while the found AI application of Local Outlier Factor only addresses one of these aspects. However, due to the small sample size of the two AI methods, it is better to interpret these extreme features with caution. It can still be noted that some AI methods seem to be better-suited to improving resource efficiency within manufacturing companies. However, more research is needed to prove this assumption.

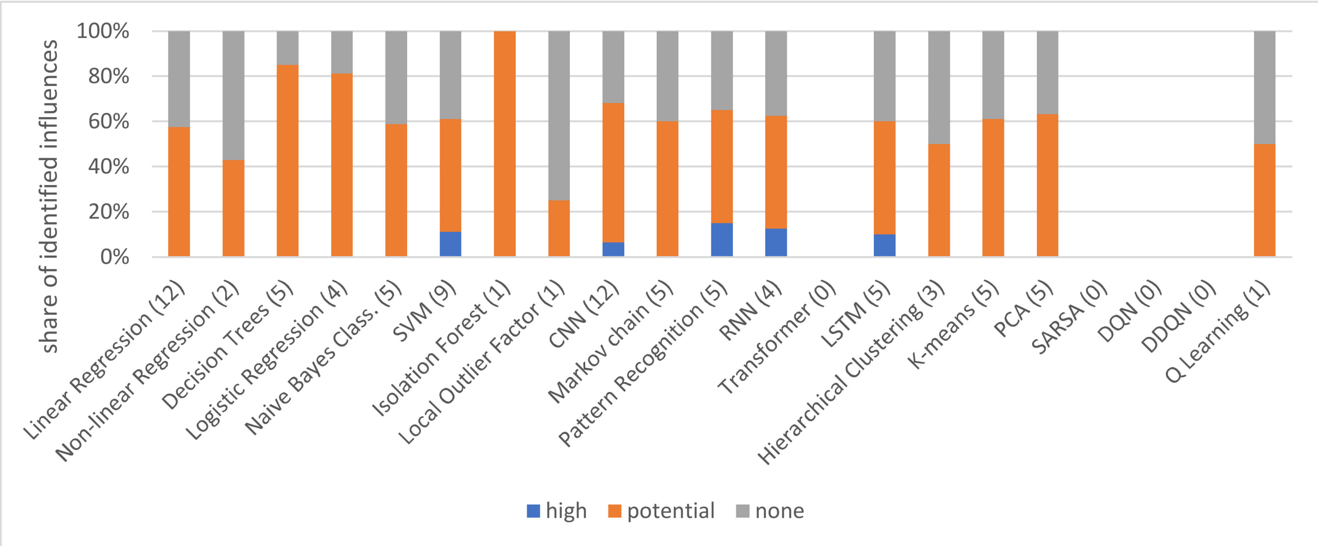

Figure 9. Distribution of identified influences on resource efficiency by AI method (the number of identified papers with this AI method is indicated in brackets).

Although most of a product's environmental impact is determined at the development phase and although there is a high potential for AI applications in materials science (particularly due to the high variability and data availability), this review did not find an AI application which highly impacts resource efficiency during development. However, supporting activities, such as facility management and logistics, seem to use more AI applications that highly impact resource efficiency (see Figure 10).

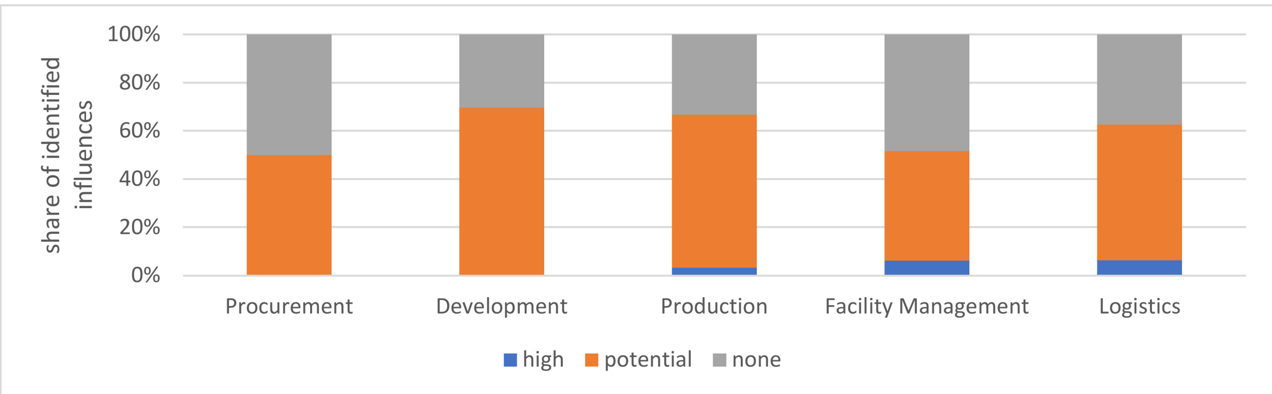

Figure 10. Distribution of identified influences on resource efficiency by business division.

The identified research papers were analyzed with a focus on the objective of intended improvement. It was investigated whether improving resource efficiency is an explicit goal of an AI application, or whether it is only viewed as a side effect by the authors. In total, only 23 papers address resource efficiency improvements as an explicit goal, although only papers related to resource efficiency were included. Within 47 papers, this was just seen as a positive side effect. Energy efficiency is by far the most explicitly considered resource efficiency aspect (Figure 11). This also supports the findings of Figure 7, as well as the relevance and focus of manufacturing companies on energy savings. Only five papers specifically address material efficiency, while three relate to water efficiency. However, material and water efficiency are mainly considered to be part of a holistic approach to improving resource efficiency in general [54,71,116]. Thus, AI applications used solely for improving material or water efficiency are extremely rare, and were only found once by this literature review, in the approach of [52]. The analysis of studies with an explicit objective of reducing GHG emissions is to be viewed with caution, as this was not specifically searched for.

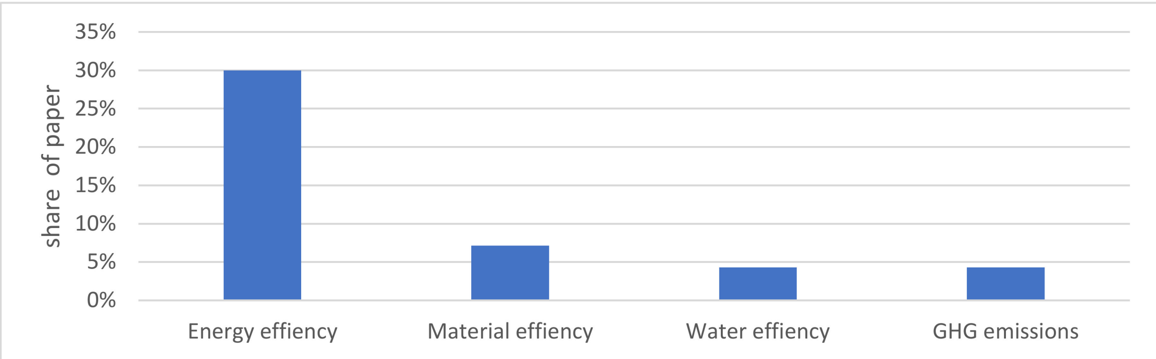

Figure 11. Share of papers having the improvement in an aspect of resource efficiency as an essential objective.

5.2. Identification of Typical Use Cases of AI Application Increasing Resource Efficiency

In general, a high variety of AI applications was found during the literature review; for example, papers dealing with human–machine interaction, material science, or route optimization in logistics. By clustering the identified papers according to their application, typical use cases for AI improving resource efficiency within manufacturing companies can be defined. These are not meant to be conclusive, but rather present an assessment of those AI applications that are currently most commonly used for this purpose in the literature. These typical AI use cases include:

- Predictive Maintenance [57,59,69,70,80,83,84,86,95,113];
- Production planning [52,54,61,65,72,77,78,101,102];
- Fault detection and prediction/predictive quality [58,62,74,82,87,89,93,94,110,111,115,118];
- Increasing energy efficiency in production [56,63,85,99,100,103,108,114,119] and facility management [53,67,76,107,109].

Predictive maintenance, in this context, is made possible by recording relevant time series data over the use phase of a machine. These are intended to map and monitor the condition of the infrastructure being analyzed. The objective is to find patterns, in order to predict failures and prevent them through early maintenance measures. By efficiently maintaining machines, increases in material and energy efficiency can be achieved. Unwanted material and energy losses due to wear and tear on tools and machines are prevented, and components are only exchanged if needed.

Production planning can be supported by AI applications to determine future requirements, and thus to configure optimally designed production lines. Production planning can additionally be supported by analyzing and classifying different production methods, e.g., with regard to efficiency. In particular, classification and trend analysis methods are used for this purpose.

Another typical use case of AI in the field of process optimization is fault detection in production. This can be used for the automated quality control of components and products. In addition, some methods enable fault prediction, which allows for predictive intervention in the production process (process control) to avoid faults. Methods from almost all AI tasks from classification, dimension reduction, and image recognition are used for this application.

The increase in energy efficiency was identified as being the most commonly addressed resource efficiency aspect, and the use cases for the increase in energy efficiency in production and facility management are defined accordingly. These include the optimization of different production processes, such as green electrical discharge machining, and machine components, such as electric drives, via various AI methods. Despite the use of such a variety of AI methods, methods of the AI task Modelling and Language Processing are the most frequently applied. Furthermore, the optimization of building infrastructure, such as heating, cooling and lighting, is identified as typical use case.

The use cases illustrate promising approaches to increasing resource efficiency with AI applications and serve as a starting point for practitioners and applied research, contributing to the diffusion of AI applications, with resource efficiency in mind.

6. Conclusions

To address climate change and the pressing environmental challenges such as biodiversity loss, the integration of sustainability into business operations is becoming increasingly important for companies and a key competitive advantage. In addition, AI applications are becoming more relevant for practice and attractive for companies, due to current developments in the IT field. Therefore, possible contributions by AI applications to sustainability should be included from the beginning. This paper contributes to the necessity of integrating sustainability with AI applications by explicitly examining the aspect of resource efficiency increases caused by AI applications in manufacturing companies.

After analyzing 70 research papers, it was found that only a minority of papers had resource efficiency as an explicit objective. Among those, energy efficiency was the most commonly addressed resource efficiency aspect. Additionally, only a few papers were identified that highly influence resource efficiency, and differences were found in the AI tasks and AI methods used to address the resource efficiency aspects. The focus of some AI applications is very narrow, and they only address two out of four predefined aspects, for example, Trend analysis with linear and non-linear regression or clustering with Hierarchical Clustering. It needs to be taken into consideration that energy efficiency and GHG emissions are closely related and, thus, only a few papers address these aspects separately. Other AI tasks and AI methods consider several resource efficiency aspects at once, and thus have a broader focus, such as classification with decision tree and logistic regression. Regarding business units, in most papers, the (potential) influence on resource efficiency occurs within production planning and optimization.

Providing an overview of current AI applications, typical use cases were identified, including predictive maintenance, production planning, fault detection and prediction/predictive quality, as well as increasing energy efficiency in production and facility management. Moreover, the link between AI and resource efficiency could be displayed in more detail. The identified AI applications showed that there is potential for improvements in both focused applications, such as increasing energy efficiency in lighting, and broad applications, such as holistic process improvement, taking all four impact categories of resource efficiency into account.

6.1. Limitations

This paper presents an extensive literature review, which aims to provide an overview of current AI applications to increase resource efficiency in manufacturing companies. However, this literature review is not without limitations. Through the definition of the search string, methods involving machine learning were selected as the focus of this research. An attempt was made to counteract this selection by including the overarching term AI. However, further work could add to the selected methods, and thus provide a more complete picture of AI applications for resource efficiency. In particular, AI methods such as agent-based modeling, expert systems, e.g., with fuzzy systems or evolutionary algorithms should be investigated for this purpose, since these are common AI methods, but not machine learning methods, and therefore were not assessed in this paper. Additionally, this paper focuses on resource efficiency aspects, which have a direct impact on the natural resources comprising energy, material and water efficiency. Other aspects, such as human resources, system or product efficiency, are not considered in this paper and could be part of further research. The various efficiency aspects should also be placed within a broader context, as, in some cases, it may be more effective to increase resource efficiency in the use phase of a product than in production. Therefore, hotspots for a specific AI application should be identified, e.g., by an evaluation of the environmental impact via Life Cycle Assessment. As well as this, a variety of industry sectors and, thus, production processes, was included in the literature review, as the focus was narrowed down to manufacturing companies only. Therefore, rather heterogeneous industries and production processes were included, from semiconductor manufacturing to textile processing, and from plasma etching to additive manufacturing and materials science. A differentiation and analysis of the suitability of AI applications within a specific industry sector or production process was, therefore, not possible. Further research could focus on these aspects. A similar aspect is the view on rather different levels of a manufacturing company. Improvements in both entire factories and individual components, such as ball bearings, were considered. In the future, detailed analyses could be prepared for such differing levels. Within this research, the majority of papers were identified as (potentially) improving resource efficiency in the business unit of production. For ongoing analysis, it is suggested to further detail the business unit and to specifically classify maintenance and quality management applications. The identified use cases in Section 5.2 present a suitable first approach for such a detailed classification.

6.2. Theoretical and Practical Implications

This paper provides an overview for researchers and practitioners of AI applications and methods for increasing resource efficiency by examining their (potential) influence. It is shown that AI methods have already been applied to increase resource efficiency in manufacturing companies, but only to a limited extent. Future research should, therefore, address more AI applications with this explicit objective. Additionally, this paper offers a first insight for practitioners regarding which AI applications could be beneficial for their specific use case. In this context, the identified use cases can serve as a starting point for practitioners and applied research, and provide a promising approach to increasing resource efficiency with AI applications, leading to more frequent dissemination and consideration of resource efficiency within AI research.

Furthermore, this literature review highlights the fact that only few researchers have taken the direct environmental impact caused by training and implementing AI into account, although this may result in multiple possible savings of energy and resources. For example, training an AI algorithm may consume five times as much energy as a passenger car over its entire life cycle [75]. Furthermore, many data centers are being built because of the large amount of computing capacity required. In the USA, these already account for 2% of total, energy consumption, whereas worldwide, information and communication technologies currently consume about 1% of total global energy and could be responsible for up to 20% of global energy in 2030 [125,126]. Thus, it is strongly suggested that the research field of AI should also consider at least the energy and material consumed by implementing AI applications to increase the transparency of the environmental impact. Taking this a step further, more research is needed that explicitly considers sustainability in the development and use phase of AI solutions. This includes the sustainability improvement of AI applications themselves (Green AI) and by AI (Green by AI), similar to the research fields of Green IT and Green IS [127]. The first approaches can already be found in the literature [128]. Hence, more interdisciplinary research is required, connecting sustainability and AI research fields.

By analyzing 70 research papers, this paper identifies the research gaps and contributes to the scientific discourse on how AI applications can support sustainability and, in particular, resource efficiency in manufacturing companies. To increase resource efficiency and, consequently, sustainability, AI is a promising technology, which helps to identify and improve the products and processes of manufacturing companies. However, it does not lead to greater sustainability on its own, but needs to be embedded in a sustainable framework with specific objectives. Despite the stated limitations, it is our strong conviction that this paper adds significant value to the sustainability research field and AI, and lays the foundation for the further analysis of AI applications for increasing resource efficiency in manufacturing companies.

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