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Value Contributions of Artificial Intelligence Applications in Production – A literature-based Assessment

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Abstract

The manufacturing industry is undergoing a fundamental transformation, driven by the ongoing digitalization of all stages and processes across value chains. The extensive collection and subsequent automated analysis of data with the help of artificial intelligence (AI) not only enables a higher degree of automation of manufacturing processes, but also a significant increase in their efficiency. AI pilot applications are increasingly being brought into industrial settings, demonstrating the potential benefits of adopting AI as a technology for production systems. However, pilots are primarily being trialed either by major companies with access to vast resources or by research institutions. In contrast, small and medium-sized companies are faced with the challenge of identifying the most beneficial uses of AI applications for their individual production systems while facing limited resources for the actual implementation. An objective assessment of the cost-benefit ratio is required to select and implement the most promising use cases. In addition, interactions between decision-relevant parameters must be considered in the selection process, which are often only recognized in the course of implementation. This paper aims to identify and evaluate value contributions of current AI applications in production. A literature-based assessment using the PRISMA method encompasses discriminative AI use cases in the manufacturing industry and highlights distinct types of value contribution with a focus on the main dimensions time, costs, quality and flexibility.

Keywords

Manufacturing industry; Industrial Production; Artificial Intelligence; Value contributions; Machine Learning

1. Introduction and Practical Relevance

The rapid development of artificial intelligence (AI) and its increasing integration into industrial production processes presents companies with numerous challenges and at the same time opens up considerable potential for optimization [1]. AI-based applications, in particular, promise significant improvements in areas such as efficiency, cost reduction, and productivity [2]. However, small and medium-sized enterprises (SMEs) in particular, are faced with the difficult task of selecting suitable AI applications and evaluating their specific value contributions while simultaneously experiencing a lack of resources needed for the implementation [3][4][5]. Potential types of value contributions of AI are mostly unclear, which makes it difficult to make informed selections prior to implementation [6].

This paper seeks to identify, categorize, and evaluate the value contributions of AI applications in industrial production, focusing on time, cost, quality, and flexibility. While generative AI models have shown promise

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in design and simulation applications, their integration into core production processes remains in its early stages. Therefore, a focus is laid on discriminative models. By analyzing already implemented AI applications, common use cases are categorized and examined for value contributions based on the basic targets for value contribution in industrial production. The relationship between different types of AI use cases and their achieved types of value contributions is quantified, and therefore a basis for implementation decisions is aimed to be provided.

The structure of this work is based on the research procedure of applied science according to ULRICH, which includes the practice-orientated development of inductive rules and models [7]. This ensures that the research results are directly related to practice. The validation of these rules and models forms the conclusion of the research process. As part of the objectives described above, a literature analysis is carried out to identify the value contributions of AI systems. To this end, AI applications are differentiated and categorized. Subsequently, distinct value contributions are identified and defined on the basis of the application. On this basis, the value contributions are allocated to the AI systems and hypotheses about their allocation are derived.

2. Fundamentals

The primary scientific domains of this work include the theory of manufacturing, and more specifically the management of manufacturing processes. This chapter sets out the theoretical foundations for this paper and addresses central aspects of production management, including the dimensions for value contribution of production processes and the influence of digitalization on modern manufacturing. Subsequently, the development of AI is briefly summarized.

2.1 Production management

Production is the systematic process of converting raw materials into finished products using manual or mechanized techniques. The aim is to add value to the materials and ensure efficient production processes [8]. Production management is responsible for controlling and monitoring production. Operational resources are planned and controlled in order to manufacture products in the required quantity and quality. To this end, quantitative and qualitative control variables are defined and passed on to the operative functions. Targets are used to determine adjustment requirements for production. These are based on management variables, the so-called overall objectives, which are specified from outside the production system [7]. A production system consists of two main units: the control unit and the execution unit. While the steering entity is responsible for planning and controlling operational resources, the execution entity carries out the actual physical production. Both instances are embedded in an environment that is influenced by economic, legal and political circumstances [7]. In the context of industrial production, three target categories are established: *Time*, *costs* and *quality*, which are described as the "magic triangle" [9]. Time describes the intervals it takes to manufacture a product or, for a more customer-centric approach, the end-to-end order to delivery time of a product. *Costs* refer to the minimization of production costs, including the optimal use of resources such as personnel, machines and materials. *Quality* encompasses compliance with production standards and the reduction of defects [10]. In the development of manufacturing enterprises, methods for optimizing and harmonizing these targets have been the focus of development and a means to achieve economic competitiveness. Lean manufacturing, for example, is a user-specific methodical design principle which aims to continuously optimize processes in production by eliminating wasteful activities (time), establish process standardization (quality) and subsequently increase profitability of the production system (cost) [11].

However, this traditional approach, which strives to attain the greatest economies of scale through mass production, is no longer aligned with contemporary market realities, as customers are still looking for the lowest possible costs with high demands in terms of quality and availability, but at the same time customization [12]. In addition, industrial production and its environment are characterized by volatility, uncertainty, complexity and ambiguity, which is also referred to as a VUCA environment [13]. To include these challenges, *flexibility* is increasingly recognized as a critical fourth dimension in volatile and customized production environments [14]. Flexibility expresses the ability of production systems to adapt to changes in requirements and external factors, e.g. market requirements and product specifications [11].

2.2 Digitalization of industrial production

In addition to optimizing efficiency through Lean manufacturing, the digital networking of production in the form of Industry 4.0 plays a pivotal role for further efficiency increases. Industry 4.0 describes the horizontal and vertical integration of machines, people and objects for the dynamic control of complex systems as real-time capable and intelligent networking [15]. The core of the Industry 4.0 is the complete networking of the entire value chain, which enables optimization through largely self-organizing production. The technical basis for this is connecting production machines and stakeholders on all levels through digital technology. At full implementation, machines, systems, products, and people are envisioned to communicate and cooperate directly with one another [16]. At this level of automation, all internal and external elements of the value chain are connected in real time [17]. These elements include ordering, development, production and the provision of customized product requirements. Based on real-time monitoring of the relevant information of all integrated objects in the value chain, precise forecasts of capacity and requirements are enabled. This makes it possible to determine the optimum value flow along the entire value chain. On the basis of these predictions, processes can be optimized according to management criteria such as costs, availability and resource consumption [18,19].

2.3 Artificial intelligence

The vast amount of additional process and product data generated by networked systems in the Industry 4.0 framework requires new and effective methods for making these forecasts. Traditional, manual data analysis methods are often inefficient and time-consuming, as identifying patterns in large datasets can be difficult or too complex for human operators to manage [20]. AI refers to the ability of machine systems to perform tasks that traditionally require human intelligence [21]. The term was first introduced by John McCarthy in 1956 [22]. Modern AI systems are distinguished by their ability to process vast amounts of information efficiently and identify patterns that enable optimization across various domains [23]. This makes them particularly valuable in industrial production. A key area of AI is machine learning (ML). ML enables AI systems to learn from experience by recognizing patterns in data and making predictions from them [23]. An advanced sub-area of ML is deep learning (DL), which is based on artificial neural networks that mimic the structure of the human brain [22]. Discriminative models, such as support vector machines (SVMs) or decision trees, are mainly used for classification and regression of data [24].

3. Methodology

This section outlines the methodology on which the research work is carried out with. A literature research of scientific publications was carried out, based on the PRISMA method according to MOHER ET AL [25]. The method comprises defining research criteria, presenting sources, describing the search strategy, selecting procedures for identifying relevant studies, and detailing methods for extracting pertinent data [25].

Subsequently, the approach for this work is laid out along three consecutive steps, which are visualized in Figure 1. Firstly, the literature analysis is conducted according to the PRISMA-method, secondly identified applications are categorized according to their type of AI use case and target criteria for value contributions in production are specified. Lastly a quantitative evaluation of the results is carried out.

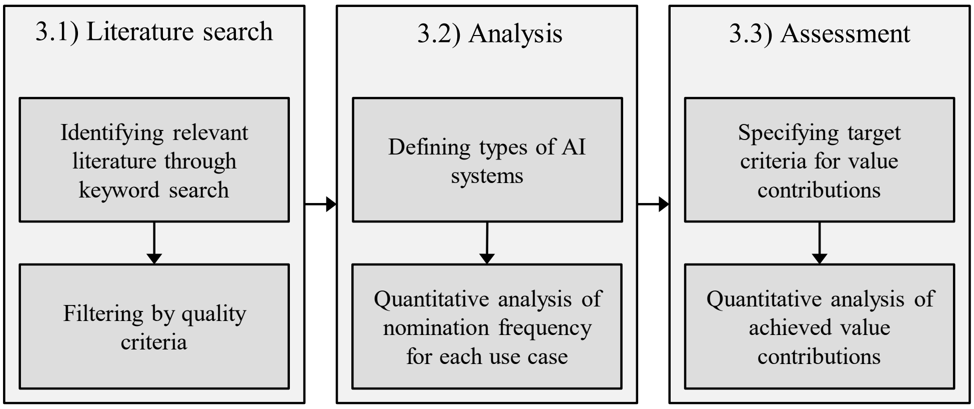

Figure 1: Approach for the analysis of value contributions of artificial intelligence use cases in production

3.1 Literature search

The literature search was conducted systematically based on the PRISMA method [25] in order to identify relevant research results that serve as a basis for analyzing AI systems and their value contributions. First, relevant scientific databases such as Google Scholar, IEEE Xplore and ScienceDirect were searched. A special focus was placed on current studies in the field of AI in production. The search terms included topics such as “artificial intelligence use cases”, “machine learning use cases in production”, “AI models in production” and “production optimization artificial intelligence”. The time frame was limited to the years 2019 to 2024 to ensure that recent advancements in the technology are included. It is important to note, that compilating studies could include more than one case of an AI application.

The identification step included a total 580 studies from above stated databases. After an initial elimination of duplicates, 480 studies where screened (see Figure 2). The aim of the screening was to confirm the domain affiliation of identified AI applications to production.

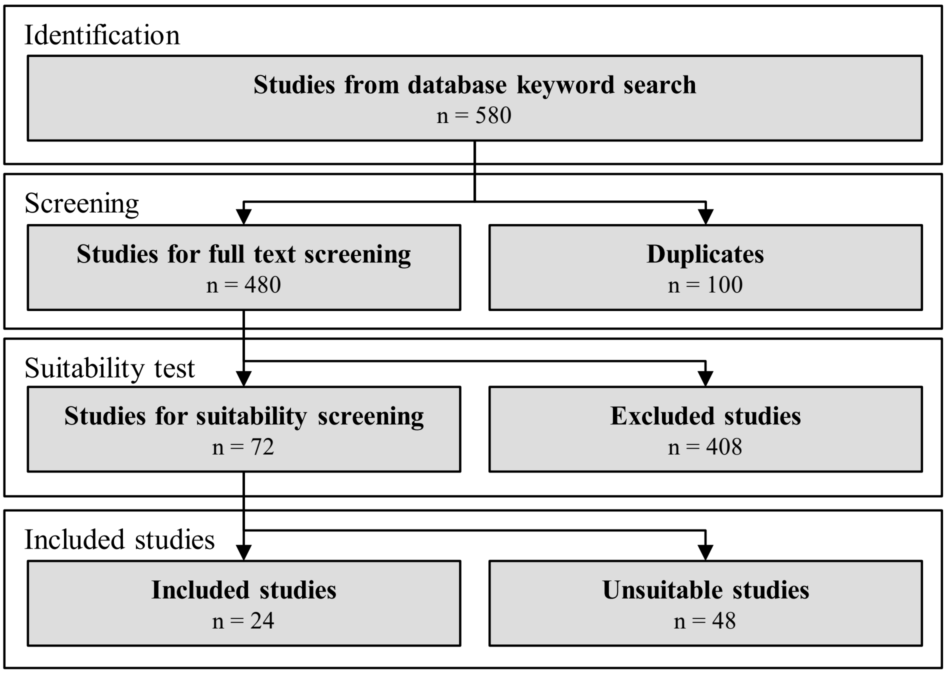

Figure 2: Included literature according to the PRISMA approach

After screening for duplicates, 72 studies remained. In the following test for suitability, the extent to which the studies systematically record and describe value contributions was analyzed. The filtering of relevant studies is visualized in Figure 3. In the 24 included studies, a total of 127 implemented applications have been identified. The in-detail analysis of each study and application was conducted subsequently.

3.2 Analysis

For the further analysis of the studies, differentiating classes of the subject matter must be established – types of AI use cases in production and their value contribution.

3.2.1 Classification of AI use cases in production

The classification of AI use cases in production is necessary to ensure a rough classification of the original objective of the applications. Relevant approaches already exist in the literature and industry. However, a standardized classification of AI use cases in production is not yet available. In order to be able to classify them nevertheless, the authors considered common works for typifying AI use cases in production [14,26,27,28]. Additionally, differences in classification within the approaches were considered. The approach with the most comprehensive structure by SCHOLZ derives use cases from the comparison of two dimensions: the goals of Industry 4.0, environmental perception, exploration, forecasting, reorganization and self-organization as well as the goals of lean management – the reduction of waste caused by waiting time, transportation, unnecessary processing steps, movements, scrap or rework, overproduction and inventories. This comparison results in 16 use cases, which are shown in Table 1 [14].

Table 1: Overview of assessed types of AI use cases [14]

		Extended goals of networked, adaptive production				
		Perception	Exploration	Prognosis	Reorganization	Self-organization
Waste types in Lean Management	Wait times			6) Time prognosis		
	Transport				12) Production procedure planning	
	Processing steps	1) Wear & tear assessment 2) Anomaly detection	4) Increase in process understanding	7) Process parameter prognosis 8) Predictive maintenance	13) Process planning	
	Movements				14) Planning of movements	
	Scrap & rework	3) Detect. of product defects	5) Error-cause analysis	9) Product quality prognosis	13) Process planning	15) Process optimization
	Over-production			10) Sales prognosis 11) Cost prognosis		
	Stocks					16) Resource optimization

3.2.2 Assessment of value contribution criteria

For evaluating the value contribution of AI applications, a distinct range of evaluation criteria is introduced. As highlighted in section 2.1, the target dimensions of time, cost and quality, supplemented by flexibility, provide the basis for this range. However, individual criteria within the dimensions must be selected for a more in-depth analysis. It is obvious that multiple effects and qualitative, hard to measure, value contributions, e.g. knowledge gains or strategic gains, are also achieved through AI use cases [29]. In order to objectify the present analysis, the focus lies on distinct target variables given in the present target system of time, cost, quality and flexibility. To define a manageable evaluation system, distinct criteria for each of the dimensions are established. However, as described in section 2, the individual criteria can influence each other. For example, a measure to increase product quality can have a negative impact on the manufacturing costs of a product. For this assessment, value contributions are only assessed in terms of their primary effect, which is being mentioned foremost by the authors of the specific application. For example, a reduction in the processing time of a product mentioned in the literature is not rated as an additional reduction in manufacturing costs, although a decreased throughput time usually also leads to lesser manufacturing cost, due to hourly rates of production resources. In Figure 3, an overview of all categories and criteria for value contributions is shown.

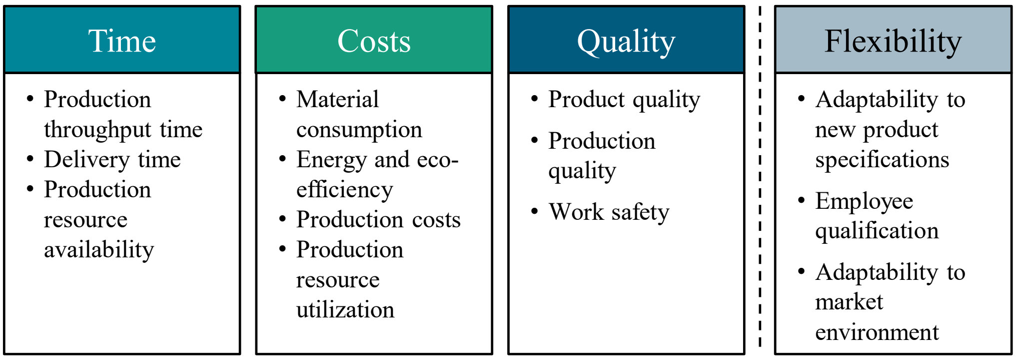

Figure 3: Overview of categories and criteria for value contribution in production [19-30]

The definition of **production throughput time** describes all individual times needed for the manufacturing of a product, including manufacturing times, set-up times, process times and tool change times [30]. By **production resource availability**, an accelerated provision of production resources, e.g. through improved maintenance effects is denoted. Machine and worker availability are included within the criterion, with the focus being on operational availability [32].

For the definition of a positive contribution to the **cost structure** of the user, the perception of costs of a product manufacturer or producing company and not of a product user is established. Depending on the company’s definition, cost of goods sold can be viewed from different perspectives [33] . In order to separate the effect of an AI system on production costs from the effect on production times, cost subcategories are established. The **material consumption** criterion aims at the reduction in the use of materials and consumables by increasing efficiency in the production process. Cost reduction induced by primary optimization of maintenance and servicing of machines is also included. **Energy efficiency** entails applications in which AI systems have accomplished a reduction of the energy consumption per unit of output in production [34]. Miscellaneous **production costs** cover overall aspects of cost reduction [35,36]. Finally, the **production resource utilization** criterion describes applications in which AI models are used to bring the utilization of production resources closer to their capacity limits [35].

ISO 9001:2015 defines **quality** as the degree to which a set of inherent characteristics of an object fulfils product requirements [36]. The main elements of the Total Quality Management approach are employees, processes and customers [37]. In our assessment of AI systems, we simplified these three categories into production quality and product quality. Therefore, **product quality** describes AI-enabled measures to reduce the defect rate, rework requirements or increase the detection rate of product failures [11]. The **production quality** criterion describes AI-enabled measures to improve production parameters and their variance [36]. The criterion **work safety** is especially relevant in human-machine collaborative environments and describe ways to use AI to enhance work safety, thus driving production quality [38].

In the category of **flexibility**, the capability of production systems to adapt to changing boundary conditions within a short time frame at reasonable cost is evaluated [39]. **Adaptability to product changes** is understood as the ability of any components of the production system to change in response to the introduction and modification of the goods to be produced. **Adaptability to market changes** in contrast, describes the ability of production systems to make extended changes in production in response to changing external factors, e.g. ramping up or manufacturing an entirely new product in a new production environment [40]. Lastly, **employee qualification** covers all aspects of how AI can increase the flexibility of the human resources, e.g. through knowledge transfer or trainings [41].

Subsequently, these four categories of value contributions with 13 distinct criteria are used for the quantitative analyses of the identified literature.

4. Results

In the following section, the results of the literature analysis are shown using the types of AI use case established in section 3.2. First, the frequency of use case types analyzed are evaluated. Subsequently, the types that appear most frequently in the literature selection are subjected to a more detailed analysis of their value contribution types.

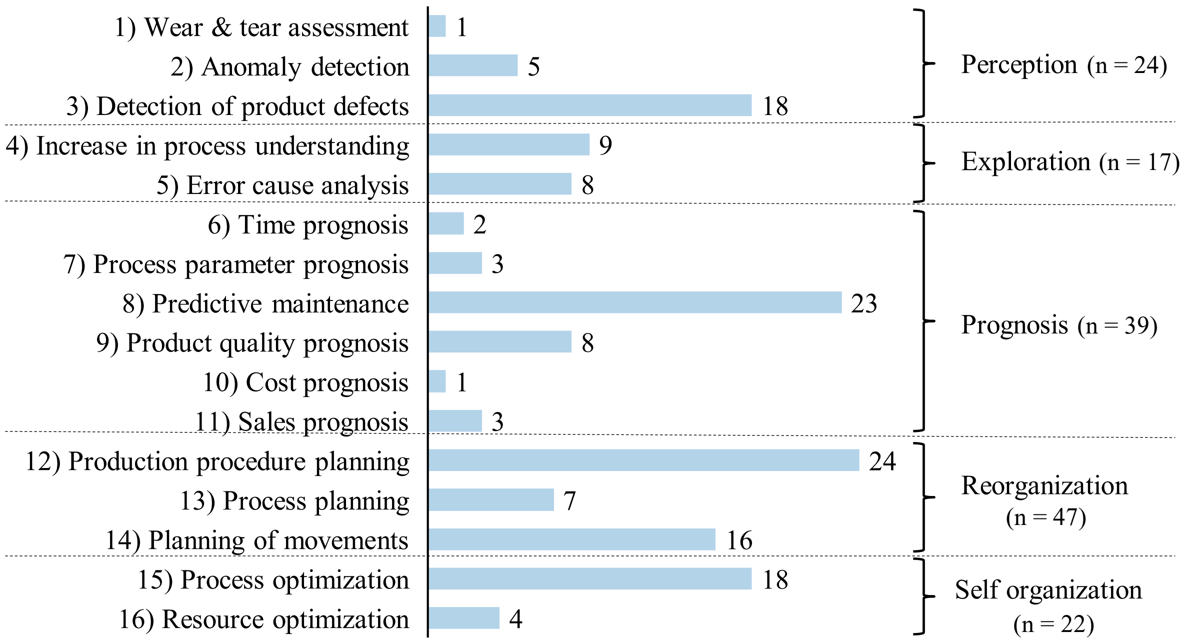

Figure 4: Literature frequency analysis for AI applications

Figure 4 shows the distinct types of use cases which were included in the literature analyses. The comparative analysis highlights the types, which are mentioned most often in the literature. An individual analysis of the types in each capability field that were mentioned most frequently in their field and therefore have a higher significance is conducted: *Detection of product defects*, *Increase in process understanding*, *Predictive Maintenance*, *Production Procedure Planning* and *Process Optimization*.

In the first capability field, *Detection of product defects* is the most cited application type (18 out of 149 applications) next to anomaly detection and wear and tear assessments, concluding a focus on perception-based use cases on products (next to process anomalies and production machinery). In the context of production, AI enabling technologies such as machine vision are used to automatically label a product as faulty [42]. Considering the advanced technological maturity of vision systems as indicated in the analysis of AI-centered technologies by GARTNER [43], which is a prerequisite for the application in real-life production environments, the high number of applications of this type shown in this paper's analysis is deemed plausible. Figure 5 displays the result of the first capability field. For comprehensiveness, the inner circle diagram depicts the total mentions of each value contribution category (time, cost, quality and flexibility), the outer circle displays the in-detail view of the distinct criteria.

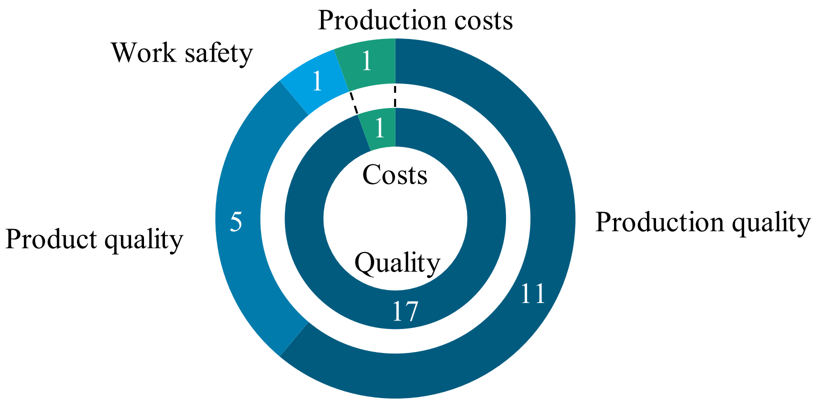

Figure 5: Detailed analysis of the use case type 3) Detection of product defects

As demonstrated in Figure 5 the main value contribution of these AI use cases is on improving production and product quality rather than decreasing overall production costs. The analyzed applications in literature focus on the increase of production quality as the main value contribution. Secondary achievements in cost reduction are considerable, although the main driver of cost reduction of this use case type is the replacement of manual quality checks. Notable examples for AI applications in this use case type include MCMAHON ET AL. [44], who cite an up to 90% higher error detection rate in AI systems compared to error checking done fully manually. Other sources cite that an AI-based system is already achieving an 88 to 98% error detection rate in raw material analysis and in one example of rail production [45,46].

In the capability field *Exploration*, which serves the primary purpose of reducing uncertainty about the modes of action and dependencies within a production system, the use case *Increase in process understanding* was mentioned most often [47]. The use case of increasing process understanding (9 of 149 applications analyzed) concerns the utilization of AI to permeate complex production processes, thereby providing insights that may inform potential reductions in process inefficiencies. The aggregation of data across multiple production facilities can also contribute to the generation of new insights into value generation processes.

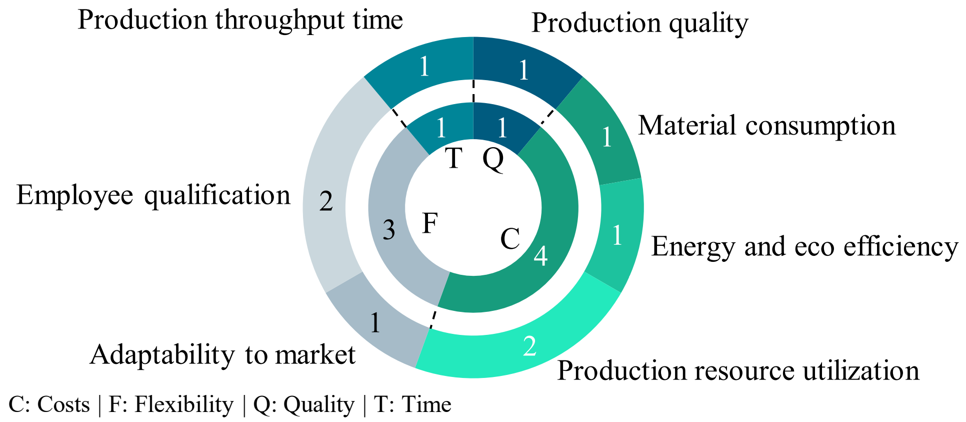

Figure 6: Detailed analysis of the use case type *4) Increase in process understanding*

The analyzed literature contains a notable example by KREUTZER ET AL. [48] for this use case type. In this application, the industrial manufacturer BOSCH reports a doubling in productivity through enhancing process understanding with AI and subsequent sharing of knowledge in facilities around the world. Internal company knowledge management can also significantly be enhanced using AI, increasing productivity by 100%. The distribution in different types of value contribution shown in Figure 6 indicates a heterogenous effect of this type, ranging from cost reduction in energy and eco efficiency to flexibility improvements.

Predictive maintenance, the application of AI to monitor production machinery and equipment to predict potential failures before they occur represents a key use case, is represented with a large number of mentions in our analysis (23 out of 149 applications). According to the analysis, this use case type mostly aims to minimize downtime and secondarily, maintenance costs (see Figure 7) [49]. Typically, methods for detecting early signs of wear and tear or operational inefficiencies are employed [49]. Starting from this and by aggregating data from multiple machines across various facilities, organizations can anticipate failures and therefore optimize maintenance schedules and extend the life of their assets, moving from preventive maintenance schedules based on experience to predictive schedules. Predictive maintenance is particularly valuable in industries with complex machinery, where unplanned downtime can lead to substantial losses [50].

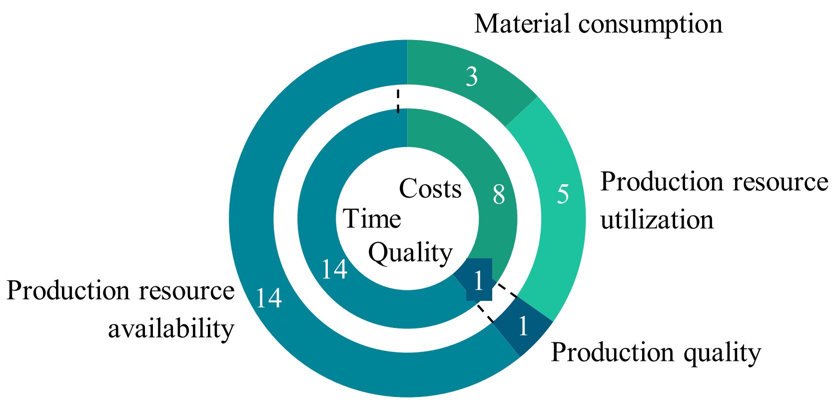

Figure 7: Detailed analysis of the use case type *8) Predictive maintenance*

Notable examples of Predictive Maintenance are presented by CHRYSSOLOURIS ET AL., who show that AI-enhanced predictive maintenance can reduce machine downtime by 15 hours per week with an average cost saving of $20,000 per minute [1]. Other sources cite a reduction in machine downtime by up to 50% while decreasing maintenance cost by 40% [46].

In the context of the application of this paper, *Production procedure planning* describes the decision making process about the order in which products are produced as well as the order in which certain production jobs are scheduled [51]. In the capability field *Reorganization,* which enables a production system to adapt to its environment [52], it is the most mentioned type, before *Process planning* and *Planning of movements.*

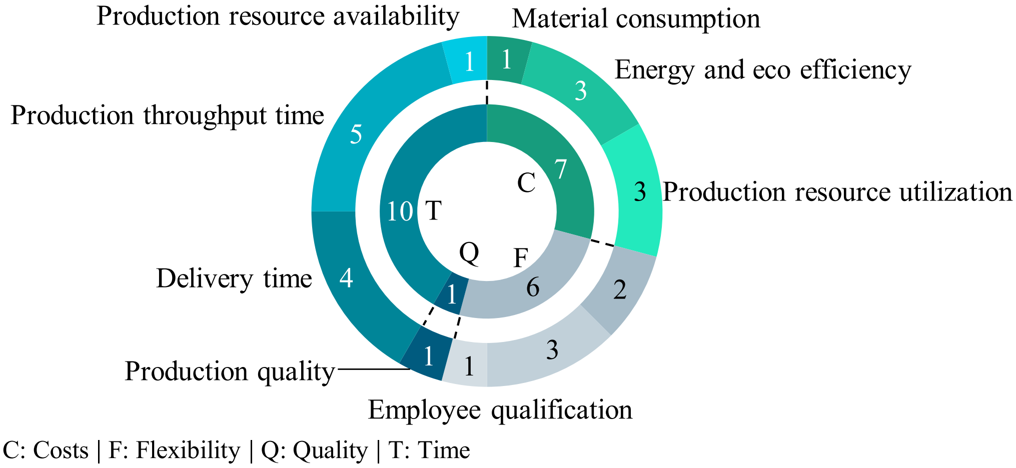

Figure 8: Detailed literature frequency analysis for the use case type *12) Production procedure planning*

As shown in Figure 8, this use case shows a diverse profile in terms of value contribution, enabling mostly improvements in terms of cost, flexibility and production time with a minor majority on time savings (10 of 24 mentions), mainly in production throughput time (5 mentions). This is due to the overall impact that such scheduling decisions have on the entire production process. The product or production quality is not affected by the procedure planning use cases. Notable applications include using AI to build a dynamic real-time decision-making system, that schedules orders based on a continuous update of production parameters [53,54]. In the capability field *Self organization,* the use case type *Process optimization* refers to ways in which AI is used to optimize the processes needed in all stages of manufacturing (see Figure 9). This field also shows a diverse profile in terms of value contribution type, with a slight emphasis on cost-related value contribution (38.9 % of mentions).

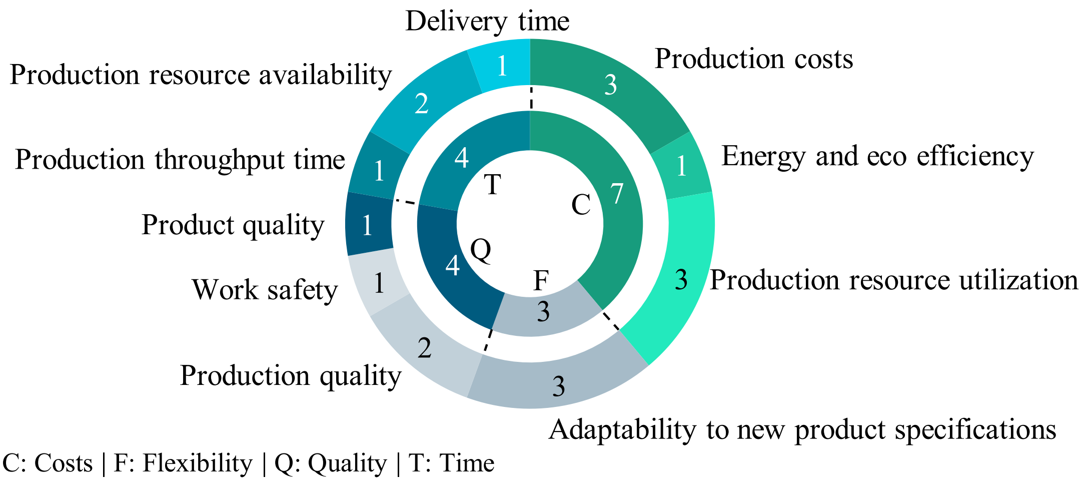

Figure 9: Detailed analysis of the use case type *15) Process optimization*

Notable examples include a 45% reduction in energy consumption in carbon fiber production [2]. In a paper published in 2022, TRUMPF reported that through their AI-enhanced platform called "Axoom", they were able to supervise 15 machines with just two people [48]. Special emphasis is also laid on the potential of AI to improve on real-time decision-making by using the data collected by the Internet of Things (IoT) [55].

5. Study limitations

While this study provides valuable insights into the value contributions of AI applications in industrial production, several limitations should be acknowledged to contextualize the findings and guide future research. The literature analysis was confined to studies published between 2019 and 2024, which ensures a focus on recent advancements but may omit valuable earlier works or long-term data on AI implementation effects. Furthermore, the analysis is limited to 127 AI applications across 24 studies. Although these were selected systematically using the PRISMA methodology, the sample size remains a subset of the broader body of AI research in production.

The evolving nature of AI technologies means that new applications or refinements to existing ones may not yet be represented in the analyzed literature. The categorization of AI use cases and value contributions relies on frameworks derived from existing literature and expert judgment. Given the absence of a universally accepted taxonomy for AI applications in production, the classifications applied here may oversimplify complex, multidimensional use cases. Furthermore, value contributions were assessed based on their *primary effects* as reported by the authors of the studies, potentially overlooking secondary or indirect impacts. For instance, while throughput time reductions were not additionally classified as cost savings, in practice, such effects are interrelated.

The identified AI applications predominantly stem from larger enterprises or research collaborations with substantial resources. Small and medium-sized enterprises (SMEs), which often face unique operational constraints, might exhibit different implementation patterns or value contributions that are underrepresented in this analysis. As such, the generalizability of the findings to SMEs or specific industrial sectors may be limited. AI technologies and their industrial applications are rapidly evolving. The findings presented here reflect the current state of research and industrial deployment but may quickly become outdated as new algorithms, hardware, and integration strategies emerge. For instance, while this study focuses on discriminative AI models, the increasing adoption of generative AI in production environments is likely to introduce new value contributions and implementation challenges not covered here.

6. Summary and outlook

This paper highlights the transformative potential of AI in enhancing the efficiency and automation of production processes. A systematic literature review was conducted, identifying 127 implemented AI applications from 24 studies, categorized into 16 types based on their objectives and value contributions. The analysis revealed that AI applications contribute to improving production and product quality, reducing costs, and increasing production flexibility. Notable use case types include defect detection, process understanding, predictive maintenance, production procedure planning, and process optimization. Detailed insights into the most frequently mentioned use cases, such as defect detection and predictive maintenance, highlight their specific value contributions and real-world examples from the literature. This retrospective analysis, methodological frameworks for evaluating AI applications prior to implementation can be refined to better target specific areas of analysis. For future research the authors focus on exploring the potential of generative AI models in manufacturing, as well as developing standardized frameworks for evaluating AI use cases. Standardized frameworks for evaluating AI use cases are crucial to ensure consistency and comparability across different applications. The proposed frameworks aim to consider various dimensions, including technical feasibility, economic impact, and implementation complexity.

Finally, future research should emphasize scalability of pilot applications for AI. Scalability encompasses not only the expansion of AI pilot applications to full-scale production environments but also the adaptation of models to diverse production settings, ensuring interoperability with existing systems, and addressing infrastructure and workforce readiness. Research should address strategies for managing the transition, including the adaptation of AI models to larger datasets, integration with existing IT infrastructure, and training of personnel. By focusing on these areas, research can provide valuable insights that will help manufacturing companies of all sizes leverage AI to its full potential.

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