machine learning & knowledge extraction

Systematic Review

Digital Assistance Systems to Implement Machine Learning in Manufacturing: A Systematic Review

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Abstract: Implementing machine learning technologies in manufacturing environment relies heavily on human expertise in terms of domain and machine learning knowledge. Yet, the required machine learning knowledge is often not available in manufacturing companies. A possible solution to overcome this competence gap and let domain experts with limited machine learning programming skills build viable applications are digital assistance systems that support the implementation. At the present, there is no comprehensive overview over corresponding assistance systems. Thus, within this study a systematic literature review based on the PRISMA-P process was conducted. Twenty-nine papers were identified and analyzed in depth regarding machine learning use case, required resources and research outlook. Six key findings as well as requirements for future developments are derived from the investigation. As such, the existing assistance systems basically focus on technical aspects whereas the integration of the users as well as validation in industrial environments lack behind. Future assistance systems should put more emphasis on the users and integrate them both in development and validation.

Keywords: machine learning; systematic literature review; manufacturing; digital assistance systems; work-based learning

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Citation: Rosemeyer, J.; Pinzone, M.; Metternich, J. Digital Assistance Systems to Implement Machine Learning in Manufacturing: A Systematic Review. *Mach. Learn. Knowl. Extr.* **2024**, *6*, 2808–2828. https://doi.org/10.3390/make6040134

Academic Editor: Anna Helena Reali Costa

Received: 27 September 2024
Revised: 15 November 2024
Accepted: 26 November 2024
Published: 4 December 2024

1. Introduction and Background

Caused by latest innovations such as a strong decrease of computing times of processors as well as advances in algorithms, Machine Learning (ML) applications yield high potentials for manufacturing companies [1,2]. Yet, a survey by the World Economic Forum identifies a mismatch between ML capabilities and operational needs as well as insufficient skills at the intersection of ML and operations leading to a poor dissemination in practice [3]. Indeed, most initiated ML projects fail due to unstructured project management and a lack of prerequisites such as ML knowledge, infrastructure and data [4,5]. Despite all technical advances, implementing such applications still relies strongly on the expertise of different specialists like domain experts, software engineers and data scientists [6,7]—as well as external experts not familiar with specific processes [3]. Nevertheless, recent publications show that data scientists and their required ML expertise are missing in many companies, especially in small and medium enterprises (SMEs) [8–10]. Although SMEs usually have a high level of manufacturing knowledge, the lack of programming skills hinders the implementation of ML applications [9,11,12]. However, employees think in causal chains and make connections from existing knowledge and experiences [13]. The ability to abstract and transfer them to new situations underlines their importance for successful implementation of ML.

In their literature review, Aggogeri et al. [14] identify various possible applications of ML in manufacturing processes. They finally state that ML models are currently used to determine vibrations on equipment, roughness estimation and prediction, quality assurance, modeling the behavior of machine tool components and parts, and machine and tool condition monitoring. Mypati et al. [15] investigate approaches to specific production processes (casting, machining, molding, welding, etc.). They also arrive at similar use cases. In the context of assembly, ML applications are suitable for predicting overall equipment effectiveness [16], for supporting employees in identifying the right components [17] and for process planning [18]. Other production-related approaches use ML to simplify root cause analysis [19], for human-machine interaction [15], for robot control [20], to ramp up production [21] or to monitor energy consumption [22].

A large number of process models have been developed in recent years to support project management. Probably the best known is the CRISP-DM [23]. The KDD [24], SEMMA, DMME [25] and the CRISP-ML(Q) [26] have also become popular.

Beyond that, authors addressed the gap between potentials and actual distribution by developing easy-to-use software-based digital assistance systems (DAS), which assist domain experts in implementing ML applications without demanding programming knowledge. Those assistance systems exhibit the following properties [27]:

- They provide an end-to-end ML pipeline in a generic and structured way.
- They contain technical details and application scenarios and thereby allow use in arbitrary ML tasks.
- They provide performance measurements indicating the models' performance.

Such DAS have already been developed and diffused in other domains than manufacturing. For example, Wöstmann et al. [28] created an architecture for the process industry by which data collection from several databases and the subsequent performing of machine learning tasks are simplified without having to write program code. Several models are trained and evaluated automatically. Diamantis and Iakovidis [27] developed a framework based on Deep Learning for obstacle recognition in images in several health use cases. The application simplifies the ML pipeline by pretrained models whereby coding tasks are externalized from the user. Martín et al. [29] described an architecture called Kafka-ML that manages the pipeline of ML applications through data streams. By writing few lines of source code in a graphical user interface, users can create an ML model and control the ML pipeline, create configurations to evaluate different ML models, train, validate, and deploy them. Likewise, numerous commercial systems such as KNIME [30], WEKA [31], or Orange [32] have been launched previously. Rosemeyer et al. [33] provide a detailed description of published applications of communal use, including a classification of strengths and weaknesses.

Notwithstanding their potential in supporting manufacturing managers and workers during the implementation of machine learning on the shop floor by providing a step-by-step guide and support in numerous decisions [34,35], examples of DAS are still limited. Therefore, for researchers and manufacturing managers interested in this topic and willing to increase the spread of ML applications in manufacturing, it is of paramount importance to gain an overview over software-based DAS existing in literature. However, to the best of the authors' knowledge, no systematic review exists that parses the current state of research regarding corresponding DAS and analyzes them in depth. Hence, this publication aims to shed light over the research landscape by conducting a systematic literature review (SLR). Based on the findings, requirements for the development of future DAS are derived. This publication thereby allows researchers to easily identify research gaps in the description of existing DAS and serves as baseline for future research.

The remainder of this paper is thus structured as follows. In Section 2, the research methodology including research questions, search term and investigation criteria is described in depth. The findings of the SLR are then outlined in Section 3. In Section 4, the findings are discussed as well as requirements for future research derived. Section 5 finally summarizes the contribution of the paper.

2. Systematic Literature Review Methodology

An SLR was considered an adequate method to provide the intended overview of the current state of research and to identify existing gaps. The guidelines proposed by Kitchenham [36] and Page et al. [37] were applied. For the sake of ensuring reliability within the SLR, all conducted steps including search term, inclusion and exclusion criteria and interim results for reaching the overview are described in the following paragraphs [38]. Given the aim of the study, a bibliometric analysis and a content analysis were performed. In terms of bibliometric analysis, publication year, region of origin of the authors, author keywords and publication medium (e.g., conference proceedings or journal) were analyzed. As for the content analysis, the ML use cases regard in existing DAS were investigated. Besides, three further research questions (RQs) were posed, which are named in the following and briefly described thereupon.

RQ1: Which ML use cases are addressed by the identified DAS?

In a first step, the ML use case addressed in the identified DAS were analyzed and thereupon classified in a previously published scheme. Thus, it was explored whether the articles take monitoring, quality prediction or anomaly detection into consideration. Following, the use cases were categorized into the classes given by Nti et al. [39]. In addition, an analysis of integrated algorithms was conducted. In particular, it was determined whether there were any focal points in the choice of algorithm.

RQ2: To what extend are shortcomings of SMEs considered in identified DAS?

Second, it was investigated whether the shortcomings described in Section 1, namely lack of ML knowledge, lack of information technology (IT) infrastructure and lack of data are targeted in the papers. In this context, it is of question, whether those hurdles as well as other prerequisites are addressed or whether observed articles solely concentrate on the infrastructure of described DAS. In order to deliver an adequate answer, the five factors for organizational artificial intelligence (AI) readiness first proposed by Pumplun et al. [40] and later outlined by Jöhnk et al. [41] and their respective sub-factors were adopted and extended with two factors proposed by Hamm and Klesel [42]. A brief explanation of each factor is presented in the following.

Strategic alignment: The factor describes the condition that the use of AI technologies is in line with the business goals of a company and that one's customers are also prepared for product-integrated applications. Corresponding sub-categories are *AI-business potentials*, *Customer AI readiness*, *Top management support*, *AI process fit and Data-driven decision-making*.

Since the factor Strategic alignment is outside of the scope of this paper, it was dropped.

Resources: The factor comprises all resources that have to be considered when implementing AI technologies: *Financial budget*, *AI personnel* (meaning domain experts with basic understanding of AI serving as translators) and *IT infrastructure*.

Knowledge: The factor describes any knowledge about AI that employees in different positions need to have encompassing *AI awareness* (awareness of prerequisites for AI applications like high-quality data), *Upskilling* (upskilling of existing employees), *AI ethics* (adherence to ethical standards like gender bias).

Culture: The factor relates to any influence on company's culture dealing with *Innovativeness* (ability to taking risky decisions), *Collaborative Work* (capability to collaborate in teams from several departments) and *Change management* (competence to deal with fears of employees).

Data: The factor encompasses all aspects that are related to data that are needed to train and test the AI application focusing on *Data availability* (quantity of data), *Data quality* (high-quality data), *Data accessibility* (access management to several data sources) and *Data flow* (pipeline to move data from source to application).

Industrial validation: This aspect investigates whether authors validate their models in real industrial validation. Optionally, they might either use an open-source data set, focus on learning factories or have no validation at all.

Target group validation: This factor focuses on a validation with the target group, e.g., manufacturing employees with decision-making competency but no deep programming knowledge.

RQ3: Which focal points for next development steps can be outlined in the publications?

Lastly, emphasis was laid on the research outlook that is presented in the articles. In order to present the results compactly, they were classified into the three categories Human, Technology and Organization by Strohm and Escher [43].

The research was conducted on the Web of Science in February 2024. The following keywords were searched in abstract, title and author keywords for finding proper publications: ((AI OR "artificial intelligence" OR ML OR "machine learning" OR "data science" OR "data analytics") AND (production OR manufacturing) AND ("digital assistan*" OR "cognitive assistan*" OR tool* OR guide*)).

In the following, a description is delivered how articles for deeper investigation were selected. An overview over inclusion and exclusion criteria is applicable in Table 1, whereas their description is delivered thereupon. Besides, the selection process according to PRISMA-P [37] is displayed in Figure 1 at the end of the description.

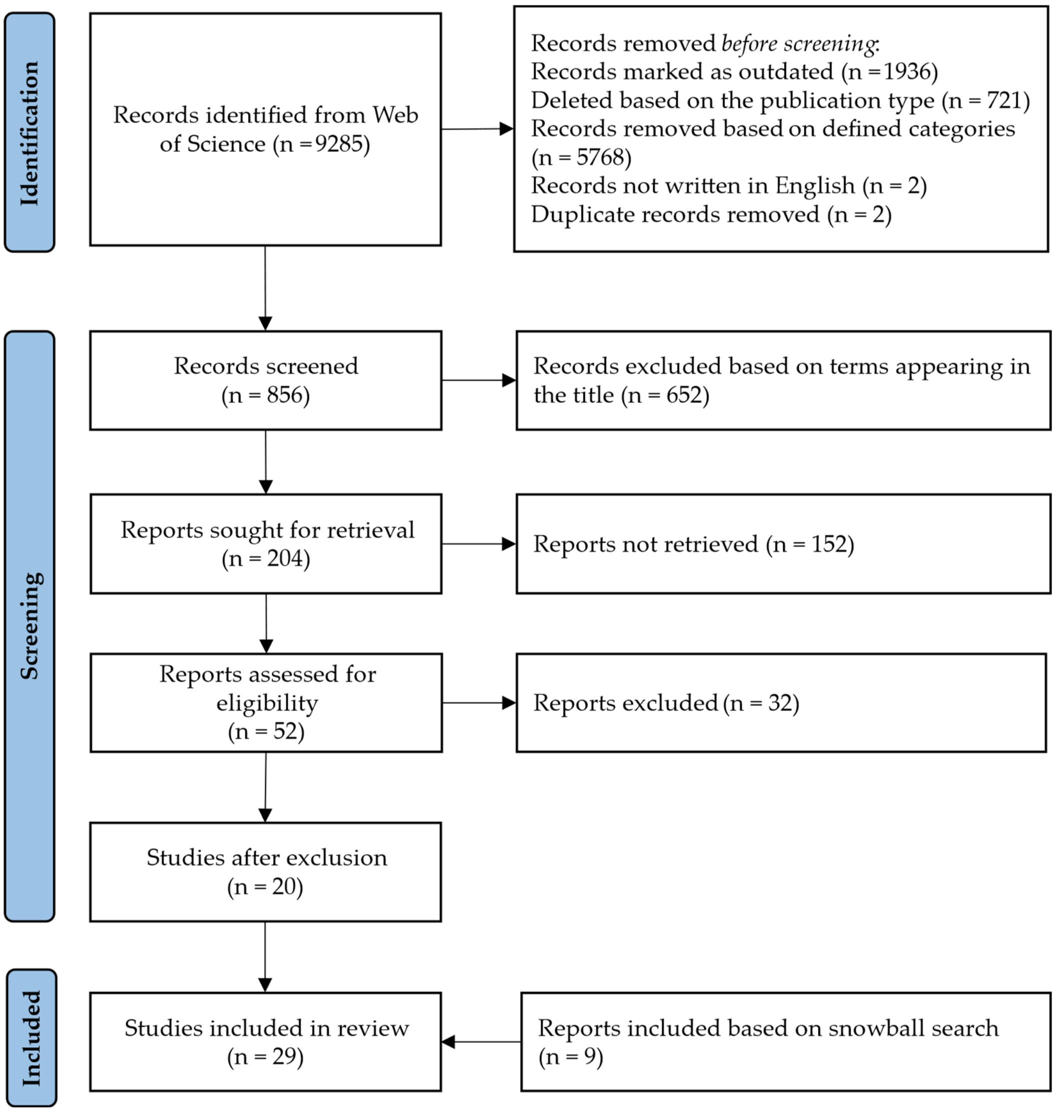

Figure 1. Publication selection process; own illustration based on Page et al. [37].

Table 1. Inclusion and exclusion criteria.

Inclusion Criteria	Exclusion Criteria
• Publication date: 2015–2024 • Document type: Articles, conference proceedings and book chapter • WoS Categories: ◦ Engineering Manufacturing ◦ Engineering Industrial ◦ Engineering Mechanical • Publication language: English	• Duplicates • Titles and abstracts containing the terms “2D”, “3D”, “additive*”, “AGV”, “bio*”, “blockchain”, “CAD”, “chemical”, “digital twin”, “empirical”, “fluid”, “green”, “health*”, “lean”, “medicine”, “process industry”, “review”, “robot*”, “safety”, “secur*”, “simulation”, “strategic”, “supply chain”, “survey”, “sustainab*”, • Titles and abstracts that contain specific ML algorithms, processes or products such that models are not universally applicable • Papers focusing on theoretical models without technical realization • Papers, whose full text was not accessible

An analysis by means of the search term results in 9285 papers. In the first step, papers published before 2015 were excluded to find latest innovations (1936 publications). Second, the document types were limited to articles, proceeding papers and book chapters (5768 papers). Next, the categories offered by Web of Science were limited to discrete production engineering applications (721 papers). Thereupon, a limitation was conducted to papers written in English and duplicates removed (4 articles). Thus, the titles of 856 records were screened.

In the context of the title investigation, articles that contained terms such as “3D”, “chemistry” or “health*”, among others, which were not in line with the review goals and questions, respectively, were excluded (see also Table 1). Likewise, publications whose titles indicate that developed models therein could only be used in very specific application scenarios (e.g., by naming the process (“on a milling machine”), product (“in the turning of automotive parts”) or algorithm (“using neural networks and support vector machines”)), violated the criteria introduced by Diamantis and Iakovidis [27] (see chapter 1) and consequently eliminated from further analysis. The reports sought for retrieval result in 204 articles.

Subsequently, an investigation of the abstract was made. Since the frame of this review is on versatile DAS with a focus on operative implementation and targeting domain experts in manufacturing environment when implementing ML applications, articles providing decision support for ML use cases in manufacturing or algorithm selection for respective use cases were not within the scope of this paper and therefore excluded. Particular attention was paid to whether the assistance systems are suitable for arbitrary ML tasks or merely focus on one isolated solution. Publications that only focus on one application once again violate the criteria by Diamantis and Iakovidis [27] listed above and were therefore discarded. The condition for this was that the use cases were already named or described before the actual development steps. In contrast, publications that describe the use case only from the evaluation were not affected by the sorting, as it is assumed that no focus on the specific application was undertaken. In this context, 152 articles were excluded, resulting in 52 publications.

This was followed by an analysis of the full text with the same questions. Besides, papers only describing purely theoretical models were not further regarded. Consequently, another 32 articles were excluded, whereby 20 papers remain. Finally, a snowball search was conducted whereby increasing the number of relevant publications to 29. The resulting papers were finally explored in depth. The entire research process and the in-depth analysis can be found following the link provided in the Data Availability Statement.

3. Results of the Review

Firstly, this section provides an overview over the bibliometric information of the identified articles. Subsequently, a report about the findings of the content analysis by answering the three research questions posed in Section 2 is given. A detailed presentation of the results can be found in the Supplementary Materials.

3.1. Descriptive Analysis

To gain an overview over the state of the art on the subject, the publication year, continent, and country of the authors were analyzed in a first step. This makes it possible to make a statement about possible distortions. In case of cross-continental work, the continent of the corresponding author was considered. It is apparent, that no relevant publication was found in 2015 and 2016 and that no year-related trend is applicable (see Figure 2). Moreover, it can be seen that most publications are originated in Europe (20 papers, and here especially from Germany (8 publications)) followed by Asia (four papers) and North America (three papers). Only one paper each can be located in Africa and Australia.

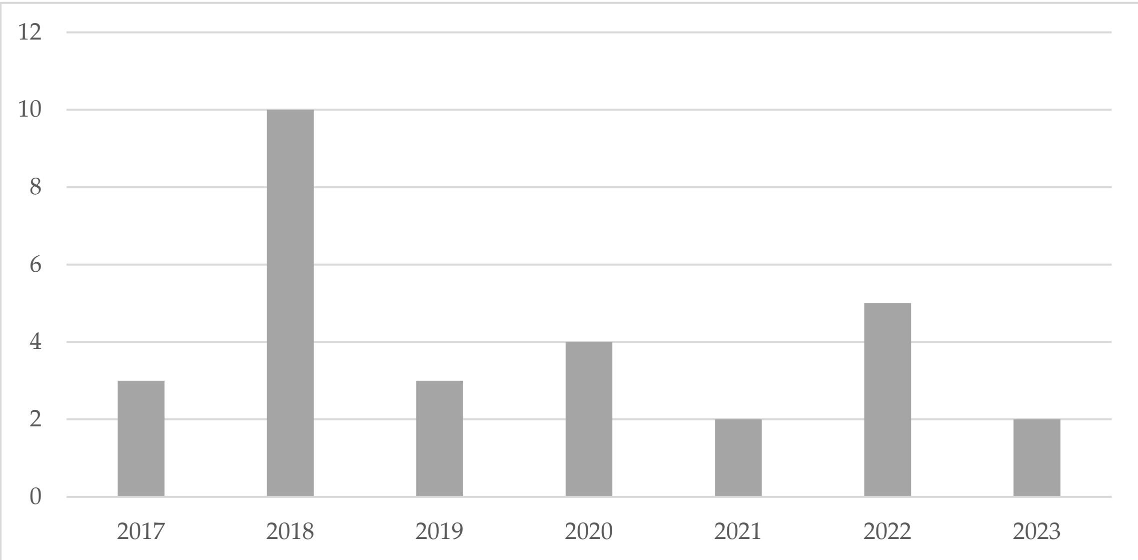

Figure 2. Distribution by publication year.

In addition, it is apperent that 16 papers were published in a journal, 11 presented during a conference and two are book chapters. To investigate most relevant mediums, a more detailed analysis of the single journals and conferences was performed. As such, cited authors published their articles in 18 different books, conferences, or journals. Thereby, the most frequently used ones are the Journal of Manufacturing Systems, Procedia CIRP and The International Journal of Advanced Manufacturing Technology. Other citing media can be seen in Table 2.

Table 2. Most relevant journals and conferences.

Publication Medium	Number
Journal of Manufacturing Systems	4
The International Journal of Advanced Manufacturing Technology	3
Procedia CIRP	3
Computers in Industry	2
Journal of Intelligent Manufacturing	2
IFIP Advances in Information and Communication Technology	2
Procedia Manufacturing	2

Additionally, an examination of author keywords was undertaken using VOS viewer. The findings of the co-occurrence network analysis are depicted in Figure 3, with temporal trends illustrated in Figure 4. Figure 3 highlights that "Industry 4.0" and "machine learning" form the primary clusters, followed by "artificial intelligence" and "cyber-physical systems". Meanwhile, Figure 4 demonstrates a growing research focus on the development and integration of AI systems in manufacturing over time. Furthermore, recent years have witnessed the emergence of keywords related to skills, human-centered approaches, and assistive systems, signalling the need of incorporating human in the AI loop and a growing interest in supporting industrial stakeholders—managers, professionals, and operators—in leveraging the advantages offered by AI.

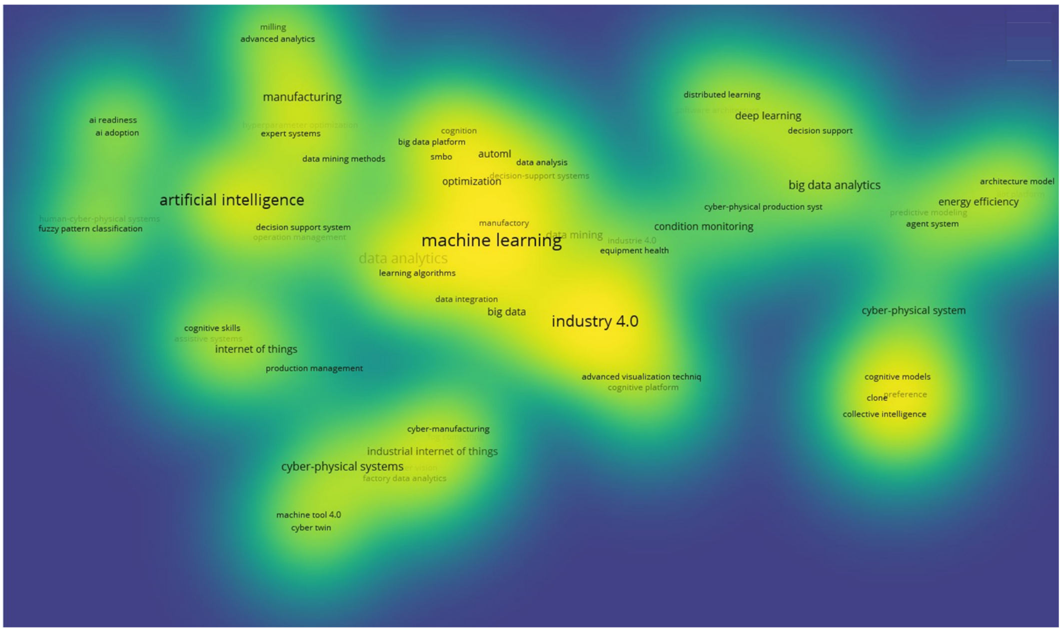

Figure 3. Clustering of co-occurrence keywords network using VOSviewer.

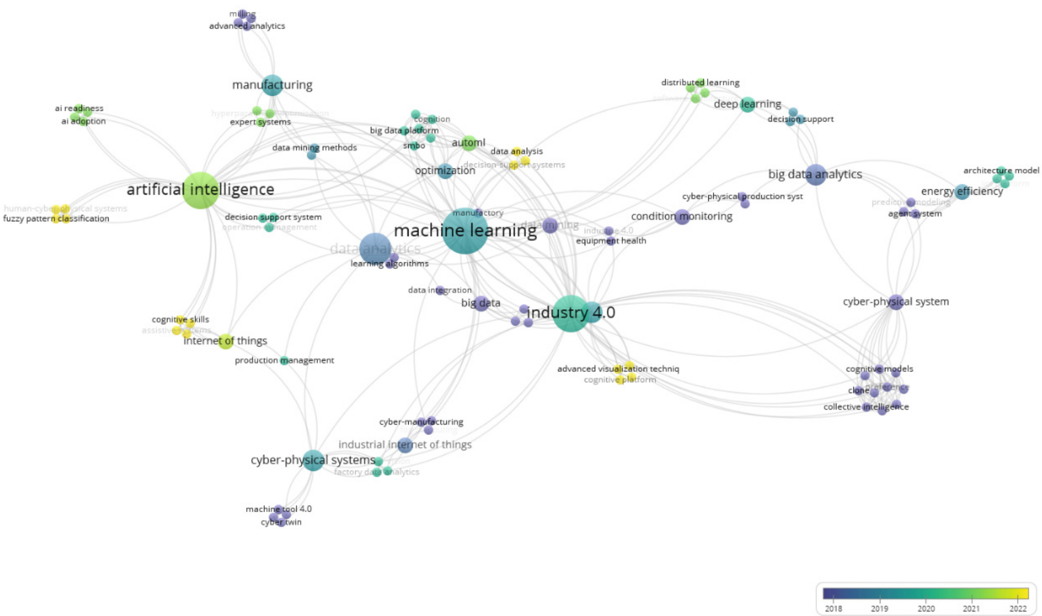

Figure 4. Overlay visualization using VOSviewer.

3.2. Content Analysis

3.2.1. Results of RQ1

In the context of the first research question, the ML use case addressed in each paper was analyzed. They were then categorized into the classification scheme provided by Nti et al. [39]. The analysis reveals that most of the articles focused on manufacturing monitoring, cost and power consumption (although costs are not of importance) as well as wear and tear monitoring (seven publications each). Slightly less important were anomaly detection and predictive maintenance (five papers). This was followed by machine vision and fault diagnostics (two papers each). In five of the papers the use case could not be classified into the framework or remains unclear. The results are also displayed in Figure 5.

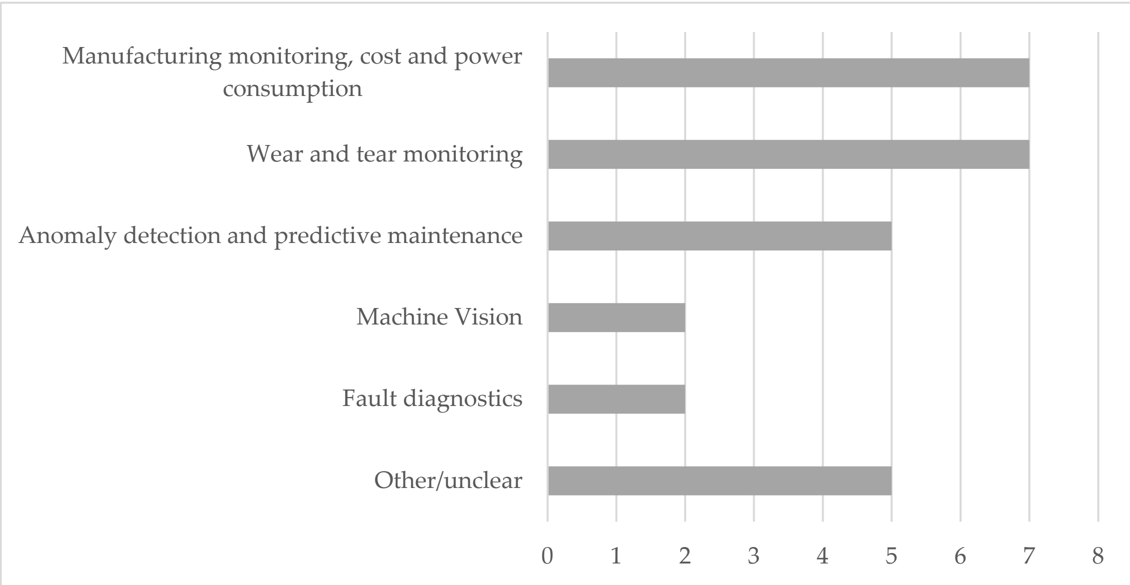

Figure 5. ML use cases.

In order to determine how the individual use cases were approached in practice, algorithms used were also analyzed. This shows that the articles examined rely on numerous different algorithms. In particular, decision trees and random forests are made use of. Specifically, eleven publications included one or both models. Another focus is on artificial neural networks, which occur in various forms (convolutional neural network, recurrent neural network, long-short term memory). A third focus can be identified in the application of automated machine learning. Four authors focus on corresponding solutions. Lastly, the investigation demonstrates that most authors rely on a number of algorithms. In return, six articles only include one model An overview of the algorithms used in each case can be found in the research data (see Data Availability Statement).

3.2.2. Results of RQ2

To answer the second research question, the factors for AI adoption as described in Section 2 were considered within the articles. For this, each paper was ranked regarding its extend against the single criteria. A summary is reported in Table 3. Unless otherwise stated, a paper is assigned an empty space if the respective factor is not mentioned at all. In case of naming without deeper description of a fact, papers are given a semi-filled circle. If a detailed description over several sentences can be found, papers are ranked with a filled circle. In case of the latter situation, a brief introduction about the realization within the respective paper is presented thereupon.

Table 3. Overview over the publications in alphabetical order of the titles.

Source	Personnel	IT Infra-Structure	AI Awareness	Upskilling	Collaborative Work	Data Availability	Data Quality	Data Accessibility	Industrial Validation	Target Group Validation
[44]	○	◑	○	○	○	◑	○	◑	○	○
[45]	○	●	○	○	○	◑	○	●	◑	○
[46]	●	◑	●	○	●	◑	●	◑	◑	○
[47]	◑	○	◑	○	○	◑	●	◑	◑	○
[48]	○	◑	◑	○	○	◑	○	○	◑	○
[49]	◑	○	◑	○	◑	◑	●	◑	◑	○
[50]	○	◑	◑	○	○	◑	◑	○	○	○
[51]	◑	●	◑	○	○	◑	◑	●	◑	○
[52]	◑	○	◑	○	○	◑	◑	○	●	●
[53]	●	◑	●	○	○	◑	○	◑	◑	○
[54]	●	○	◑	◑	○	○	○	○	◑	○
[55]	○	○	●	○	○	◑	○	○	◑	○
[56]	◑	◑	◑	○	◑	◑	◑	◑	◑	○
[57]	◑	●	◑	○	○	◑	●	◑	●	○
[58]	○	●	●	○	○	◑	○	◑	◑	○
[59]	○	○	○	○	○	○	○	○	○	○
[60]	◑	●	◑	○	○	●	◑	○	◑	○
[61]	◑	◑	○	○	◑	◑	◑	○	●	○
[62]	●	○	◑	○	◑	◑	○	○	◑	●
[63]	◑	◑	○	○	◑	○	○	○	○	○
[35]	●	◑	●	◑	○	◑	◑	◑	◑	○
[64]	○	◑	◑	○	○	◑	○	◑	◑	○
[65]	◑	◑	◑	◑	◑	◑	○	○	●	●
[66]	○	●	◑	○	○	◑	●	●	●	○
[67]	●	○	◑	○	○	○	○	○	○	○
[68]	●	◑	◑	●	○	○	○	○	◑	●
[69]	○	○	◑	○	○	○	○	○	◑	○
[70]	◑	◑	●	◑	○	◑	●	○	●	●
[71]	○	◑	◑	○	○	◑	○	◑	◑	○

First, the extent of needed *Personnel* was regarded. Eleven papers did not mention required employees and competencies. Only technical requirements and functionalities were described. Eleven authors briefly introduced the work of affected employees, and seven papers describe affected roles and their tasks in more detail. As such, Villanueva Zacarias et al. [46] introduce a framework where domain experts are responsible for the problem definition, whereas data engineer and data scientist take over algorithm-related tasks. Kranzer et al. [53] follow a different approach. They describe the user's interaction with the system which is realized by a tablet PC and augmented reality. Senna et al. [54] subdivide their development steps into three pillars, out of which human-machine interaction is one of them. Indeed, the authors aim to display relevant information to decision-makers in a human-centered way. Yet, its realization is not outlined. Bocklisch et al. [62] put strong focus on the later user by testing his interaction with the developed system and subsequently collect his feedback. Neunzig et al. [35] introduce an assistance system aiming at employees from development and planning departments. To address user requirements' they develop three different interaction modes that are based on different skill levels. Angulo et al. [68] describe the development of a cognitive assistance system that interacts with its user. To achieve appropriate interaction, the authors additionally collect user's feedback by empirical methods and respective scales. Wellsandt [67] develop a DAS that is able to interact with its users by text-to-speech methods. The user is thereby equipped through additional information.

The next aspect deals with the *IT infrastructure* on the shop floor and connectivity towards the presented assistance systems. It should be noted that the aim here is not to show the extent of IT within the systems, but the connection to IT systems on the production floor. From the results, it is apparent that 31% of the authors did not mention the IT infrastructure needed by a company interested in the developed system. 48% of the publications at least named requirements or described them in few words. Another 21% of the papers gave further descriptions about how to connect the developed model to existing IT infrastructure. For example, Rousopoulo et al. [57] make use of a data acquisition module that is connected to factory machines and cloud services using an open-source hardware system as well as a Message Queuing Telemetry Transport (MQTT) broker. Liu et al. [51] integrate several industrial ethernet, fieldbus and serial communication protocols as well different communication protocols which allows data collection from numerous sensors directly implemented in a machining process. Wu et al. [45] list a number of communication protocols that is used in their application to interact with physical devices in the production hall. As such, several wireless communication technologies (e.g., Wi-Fi, and 4G LTE) enable network connectivity whereas MTConnect ensures interoperability. Likewise, Deshpande, et al. [58] also make use of MTConnect and use Hypertext Transfer Protocol (HTTP) for data transport. A similar approach follow Woo et al. [60] who connect their platform to a manufacturing execution system (MES) using MTConnect. Heimes et al. [66] connect their platform to several open source and commercial databases, such as Hadoop, Open Shift, Microsoft Azure or Amazon Web Services.

As described by Jöhnk et al. [41], a basic requirement for successful adoption is the *AI awareness* of its functionalities. Hence, the third factor analyzes the amount of knowledge about ML that affected employees need to have. The review reveals that in six of the papers high knowledge is needed, especially about several algorithms, metrices, among others. 17 articles present a model that requires some basic knowledge about ML or statistics, deeper knowledge is taken over by the framework. The remaining six papers describe easy-to-use models in terms of required background knowledge. As such, the system developed by Villanueva Zacarias et al. [46] allows users to give instructions in a language they are familiar with. ML-based tasks are then overtaken by respective experts. The model described by Senna et al. [54] requires little ML-knowledge due to an expert system that deals with numerous steps of the ML-pipeline and therefore simplifies its use. As the system described by Kranzer et al. [53] requires little interaction with the user, it is also assigned a full circle. Data is collected via an interface from the Supervisory Control and Data Acquisition (SCADA) system and output given to users finally. Fischbach et al. [55] develop a model where many steps from the ML-pipeline is transferred to the assistance system. The user is basically responsible for data generation and result evaluation. Users of the model presented by Garouani et al. [70] require little previous ML knowledge due to the high number of automated tasks such as data ingestion, algorithm selection and tuning as well as provision of recommendations based on a knowledge-base. Due to the focus on visual inspection, the DAS by Deshpande et al. [58] allows users to perform ML applications more easily and intuitively. Theoretically, the system developed by Neunzig et al. [35] has to be attributed different ratings to as it integrates three different skill modes (beginner, advanced and expert). Those user modes thereby differ in the scope of the instructions and in the variety of functions. Given the beginner mode, within this publication, a full circle indicating little required ML knowledge was considered most appropriate.

Jöhnk et al. [41] furthermore state that "*upskilling* enables employees to learn and develop AI or AI-related skills". In this context, papers within the review at hand were investigated regarding its ability to function for a so-called work-integrated learning. Papers were rated with a full circle if a detailed description of procedures and background knowledge and thereby methods for non-formal learning were provided, with a semi-filled circle in case of a brief explanation and an empty one otherwise. Precisely, one paper contains an in-depth knowledge support, four articles provide at least some ideas and 24 publications do not contain any deeper knowledge description at all. Other than described above, also papers with a half-filled circle are to be described here. Angulo et al. [68] make use of a cognitive module that analyzes its environment and extracts information. This information is provided to the user for learning reasons. Another possible method for realization of upskilling deliver Garouani et al. [70] by the integration of explainable AI, whereby facilitating the interpretability of algorithms. Likewise, Terziyan et al. [65] transfer human knowledge to their system and use this to support the decision-making in later steps. As described earlier, Senna et al. [54] aim to enhance users' cognitive abilities by their assistance system. However, they do not describe a realization of this goal. As described before, Neunzig et al. [35] make use of different user modes depending on the previous experience of the users. They describe that, i.e., the length of instructions varies in this context. Thus, beginners are given longer text to introduce them in the subject and explain in more detail what to do and what will happen in the DAS.

Not only an explanation of stakeholder was under examination, but also their *Collaborative work*. The analysis demonstrates that 22 of the articles do not provide a description of different functions/departments (e.g., manufacturing operators, information technology or human resources). Six of the papers at least briefly mention or describe the role of several stakeholders. Only in one paper, a detailed description with roles and integrative work is explained. As already introduced above, Villanueva Zacarias et al. [46] indicate that domain experts are responsible for the problem definition and model evaluation in terms of applicability in manufacturing, whereas data engineer and data scientist are in charge for algorithm-related tasks. Hence, a delimitation of tasks is described.

An essential prerequisite for ML models is the *Data availability*. Thus, both the quantity and quality were investigated. The review demonstrates that six papers do not address at all in what way data was used. Some of them neither validate their models. Twenty-two of the articles validate the model by either using open-source data or by using a complete data set from learning factories or industrial partners. Only one publication generates data when using the model developed and demonstrate practical applicability in that context. As such, Woo et al. [60] use their framework for energy prediction on a milling machine. In the context of the prototype implementation, they record data with a given set of work piece, machine tool and operation. In contrast, the other articles follow different approaches. Therein, they collect their data within an existing learning factory [55], set up a demonstrator specifically for the evaluation [71], augment collected demonstrator data by additional data points [50] oder simulate real manufacturing lines [69]. A different approach is the usage of open source data, for example from Kaggle, such as in [35]. Optionally, authors can draw on historical data recorded in previous projects [66].

Also, *Data Quality* can be considered to be crucial for ML implementation. Nevertheless, 55% of the articles do not outline in what way data quality is ensured. 24% of the publications briefly describe methods to improve data within their model. Six articles extensively ensure that data quality is considered and improved. The model described by Villanueva Zacarias et al. [46] consists of four sub-modules out of which one is meant for increasing data quality. It also allows to summarize a profile of the later to be used in later steps. Zhang et al. [47] describe in detail and over several paragraphs necessary steps for ensuring high data quality and how it realized in their assistance system. Similarly, Rousopoulou et al. [57] included data cleaning with i.e., missing value handling and normalization as well as remove low variance features as both decrease the model performance. Equal steps are taken by Garouani et al. [70] who also conduct a robustness test in order to ensure the applicability of the model in the long-term. Lechevalier et al. [49] include a data pre-processing module in their system aiming to clean, reduce and transform data as necessary. Heimes et al. [66] place a filter to maintain data quality at the beginning of their DAS. In this way, they ensure that only high-quality data is used and that, in case of doubt, adjustments are made to the data set at an early stage. To achieve this, they rely on various visualization tools.

As stated by Jöhnk et al. [41] *Data accessibility* should also be considered. It can be outlined that slightly half of the papers (15) do not provide information about access to data. Further eleven articles only mention accessibility, while three articles elucidate in detail the access to data that they used within their model. In the validation of those papers listed here with a full circle, data must be collected directly from a machine. Otherwise, the accessibility cannot be proven. Liu et al. [51] describe several sensors and connectors to allocate data directly from machines. In consequence, their system allows data analytics in real-time. Wu et al. [45] make use of MTConnect and Open Platform Communications Unified Architecture (OPC UA) to gather data directly from the shop floor and then store it in a local data base. As previously shown, Heimes et al. [66] link their assistance system with various cloud platforms and can therefore easily access data. They then divide the data into different categories so that their DAS can analyze it precisely.

In addition, a focus was laid on the *validation in industrial environment*. Papers were rated with a full circle if the validation was indeed conducted in manufacturing environment and with semi-filled if the validation took either place on an open-source data set or in a learning factory. In case that there was no validation at all, papers were rated with an empty circle. The research reveals that five research ideas were validated in the manufacturing environment of partner enterprises. Another nineteen of the articles validated their models on open-source data sets and learning factories, respectively, and five developments were not validated at all. Frye et al. [61] perform wear and tear monitoring and vibration prediction in a milling process of a real product. After conducting necessary steps, they outline next steps for long-term deployment. Terziyan et al. [65] use their assistance system to facilitate decision-making in the absence of actual decision-makers at a company site in Ukraine. It simplifies the decision-making process for non-experts. Rousopoulou et al. [57] perform anomaly detection on six injection molding machines of an anonymous company site and extract relevant information for a high-quality machining process. Jun et al. [56] conduct condition monitoring in an injection company. They extract data from an MES and feed it into their assistance system. González Rodríguez et al. [52] solve a hybrid flow shop problem in an industrial production planning process. There, they aim to control the stocks at a tactical level. Heimes et al. [66] validate their solution in two use cases of an automotive battery production for electric vehicles. In this context, they record data from several sensors and try to investigate whether there exists a correlation.

Lastly, it was investigated whether the validation was carried out only by the authors of the papers or whether the *target group* was actively involved. Deviating from the previously described classification, a paper reporting a validation with non-ML experts was rated with a full circle, an empty one otherwise. From the findings, it can be seen that the target group was directly involved in four of the 29 papers. In the other 25 publications, only the work of the developers was described. González Rodríguez et al. [52] for example assign specific tasks to several users that are relevant for the validation in practice. Yet, from their description, it can be concluded that the authors themselves still strongly support the users during execution. As described above, Bocklisch et al. [62] test their assistance system with one user, observe him while execution and thereupon collect his feedback. Terziyan et al. [65] point out that three employees from a targeted company were involved in the validation. Nevertheless, it remains unclear what their specific tasks were. Angulo et al. [68] describe how an operator can collaboratively work with the system, especially what his tasks are and in what way he can overrule the proposals made by the assistance system. Garouani et al. [70] perform interviews with the target group after execution for collecting feedback when working with their system. A detailed description of the feedback is given subsequently.

Finally, it can be highlighted that the sub-factors *Financial budget*, *AI ethics*, *Innovativeness*, *Change management* and *Data flow* were not considered in the papers.

3.2.3. Results of RQ3

Within the frame of RQ3, the outlook for future research presented in the papers were investigated and categorized into the classes Human, Technology and Organization [43]. It must be noted that the classification is not disjoint, as authors might present more than one outlook. The research reveals that seven publications describe improvements and necessary adjustments for the users. Here, emphasis is mostly laid on collecting users' feedback as well as improving the user interface for better interaction. Most effort is attributed to the technology, as 23 papers contain respective delineations. The respective articles either describe improvements regarding the algorithms selected as well as extensions to other algorithms or outline adjustments in the assistance system infrastructure. Ten publications contain specifications for organizational aspects, most often indicating the need to transfer the model developed to other manufacturing use cases, and to industrial implementation, respectively. Two articles provide no outlook at all. In sum, it can be concluded that future effort is mostly assigned to technical improvements of developed DAS, whereas the impact on the users as well as the organization usage in manufacturing environments are poorly regarded. Figure 6 summarises the findings and presents them graphically.

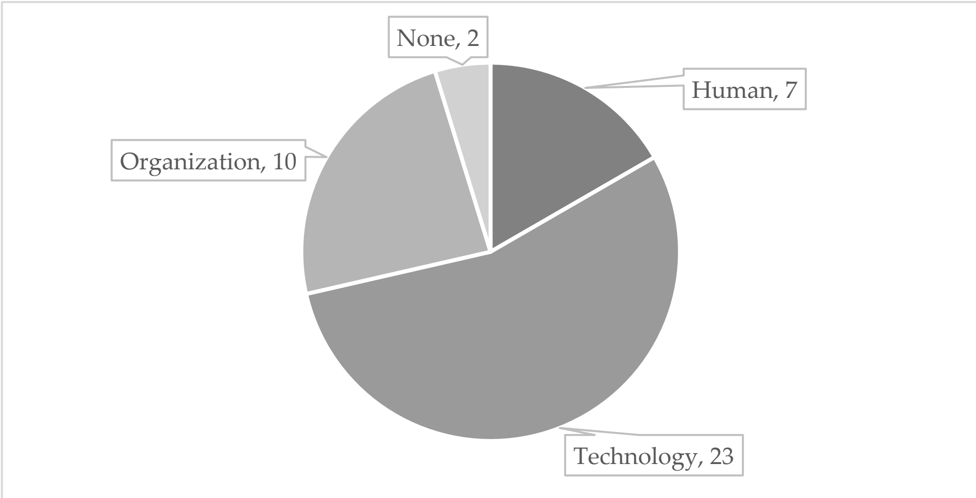

Figure 6. Presented research outlook.

4. Discussion of the Results and Research Outlook

In this section, the previously obtained and described findings are first further discussed. This is followed by recommendations for future research.

The review shows that increasing effort has been put on the development of DAS supporting users with little programming knowledge in designing ML use cases for manufacturing environments especially in the last years. In return, no relevant publication could be found in 2015 and 2016. This finding is not unexpected as research on ML technologies is conducted in particular in recent years [72]. Especially authors from Europe concentrate their effort on the design of such applications, which leads to a European bias in the publications.

In addition, six key findings (KF) can be derived from the results of RQ2 (extend of AI readiness) and RQ3 (focal points in research outlook), which will be outlined here and discussed in more detail subsequently:

As displayed in KF1 most emphasis is laid on technical aspects and technical improvements. In fact, almost 80% of the articles describe future advances in additional algorithms or improvements of ML-common performance indicators (e.g., accuracy). The focus on technical aspects and technical improvements can be attributed to the novelty of the research field and to the fact that technical developments are of high importance in the peer-review process of high-ranked journals and conferences.

KF1: The focus of development and improvement steps is laid on technical issues.
KF2: Despite the focus on technical issues, little emphasis is laid on data acquisition and access.
KF3: The user is only regarded marginally both in development steps and practical usage.
KF4: Learning on the side of the users to work with the systems independently is not ensured.
KF5: Developed DAS are mostly validated in laboratory settings and not in manufacturing environments.
KF6: The shortcomings of SMEs described in section 1 of this article have barely been addressed.

Despite the previously described focus on technical developments, regarded articles only roughly concentrate on data generation, quality and access (KF2). In contrast, it is often supposed that sufficient data are already available and only need to be loaded into the respective system. It can be assumed that this behavior is due to the difficulty of accessing data sets by researchers. Even if data is generated during the evaluation phase, they often come from demonstrators [50,71] or from existing production lines in laboratories [55]. Indeed, application projects in industrial companies face considerable challenges, as they are usually both extensive and lengthy. One particularly demanding aspect is the recording of data, which is time-consuming and resource-intensive due to the complexity of corporate structures and the heterogeneity of the data landscape. However, researchers are under pressure to publish, which traditionally focuses on the development of new systems. On the other hand, the application of practical work only rounds them off. Consequently, findings from these are often given secondary consideration. As a result, in many cases either public data sets from learning factories or synthetically generated data sets were used. Even if researchers have their own production environments, giving them greater control over data generation, the problem of large volumes of data remains.

Although the integration of users is considered a success factor [73,74] only few publications also focus on them (KF3). Firstly, the targeted personnel is marginally described and the validation is mostly not performed with the target group. Secondly, only few articles describe future human-centric development plans. In fact, special attention to the users is only given by Villanueva Zacarias [46], Garouani et al. [70], Senna et al. [54], Bocklisch et al. [62], Wellsandt et al. [67], Neunzig et al. [35], Kranzer, et al. [53] and Angulo et al. [68]. The authors mentioned address various potential roles (employees, IT, ML expert) and describe their specific tasks. Profiles are also created, which increases the usability of users, as explanations are based on their level of knowledge. Interaction with the developed DAS is also simplified. A special focus on the users is placed by Bocklisch et al. [62], who evaluate the application of their assistance system in a user-centered manner through an empirical study and collecting feedback from them. Notably, many of the articles point out in their introduction that solutions for non-experts are needed. Nevertheless, only five papers also include the target group in the final validation. Besides, the low consideration of possibilities for non-formal learning leaves the question unanswered as to whether domain experts can operate independently with the models in a comparable situation in the future (KF4). Corresponding approaches are only very briefly described by Senna et al. [54], Terziyan et al. [65], Angulo et al. [68] and Garouani et al. [70]. The cited authors pursue two strategies. Either they try to increase the interpretability of the results of their DAS by using explainable AI approaches. Users thus gain a deeper understanding by being able to mirror results against their input. Optionally, various user or competence profiles are explained in referenced publications. These differ primarily in the amount of explanation required. In consequence, users who consider themselves to have very little prior knowledge receive more information than advanced beginners. However, a more detailed description is pending.

A consideration of consecutive *Change management* with respect to the use of ML is therefore difficult to implement. Moreover, the deployment of models is rarely regarded (KF5). Indeed, a technology readiness level (TRL) of five can be attributed to most applications, meaning that models were tested in laboratory settings and not in real production environments and are therefore in particular not deployed. The investigation allows to conclude that most papers perform a support evaluation and possibly application evaluation [75]. A success evaluation is hardly evident and can only be attributed to those five articles that carry out the validation with the target group. Rather, the validation is carried out by the authors themselves. This observation can be attributed to the fact that the development of corresponding assistance systems is a novel topic and thus few real industrial applications are expected but more industrial pilots or industry-related environments such as learning factories. However, the marginal validation in industrial practice also hinders the consideration of *AI ethics*.

Considering the key findings, it can be concluded that the answer to RQ2 is that SMEs' shortcomings (lack of ML knowledge, lack of (high quality) data and lack of IT infrastructure) as described at the beginning of this article are barely addressed (KF6). It remains open to what extend employees from SMEs can use the DAS analyzed in this paper.

However, this publication cannot provide an in-depth analysis of the systems themselves as software code was barely accessible. Likewise, an evaluation of the applicability in industrial environments from the user's point of view was outside of the research frame. Thus, only the descriptions within the publications were considered in this work and not the assistance systems themselves. This limitation may result in individual DAS being more usable than described by the authors. For example, they could be intuitive for users to operate. This applies all the more to the learnability of the systems, which, as shown, was only marginally described. Further research is necessary in this regard.

Subsequently, requirements for future research projects are pointed out. These follow an ideal situation in which all the criteria described above are integrated completely. The corresponding key findings are referenced at the appropriate points to simplify understanding. Consequently, the shortcomings for ML in SMEs are regarded in particular and employees from SMEs are enabled to use the systems. At this point, the discussion and recommendations are enriched leveraging on the available (extended) literature and the experience of the authors. Here again, four requirements, which can be derived from the analysis, are listed first and then explained in more detail.

REQ1: Relevant stakeholders are considered both in development and validation to ensure acceptance and usability.
REQ2: Assistance in data and IT infrastructure generation is provided to overcome existing technological gaps in SMEs.
REQ3: Legal and ethical requirements are addressed to increase trustworthiness.
REQ4: Theoretical background knowledge is supplied such that knowledge building and non-formal learning on ML is simplified.

Just as the DAS described in this article, newly developed assistance systems contain a detailed description about functionalities and sub-systems. But it becomes necessary that they put the actual target group and their requirements in the center of development (KF3) [73,74]. Due to the criticality of users' acceptance [76], they should be regarded in detail. To this end, researchers can take advantage of several methodologies that have been proposed for integrating human factors in engineering design [77], user-centered design and human-centered design elements [78,79]. Here, it is in particular necessary to develop user interfaces that meet the expectations of the users. Established quality criteria are usability and user acceptance. Furthermore, future research requires a comprehensive description of how relevant data can potentially be obtained from the use cases under consideration. Depending on the use case, suggestions can be made on the basis of existing publications as to how data can be generated. A focused consideration of the data protocols and storage systems used is suitable for this purpose. From the descriptions, technical requirements on the side of the shop floor thus become evident. To increase practical relevance, it needs to be indicated how access to data is realized (KF2). However, in complex ML systems, data quality should be monitored throughout the entire life cycle. This applies to data preparation, training and testing as well as the validation of ML models [80]. Besides, legal and ethical requirements are to be elicited and addressed to improve transparency, fairness, and trustworthiness of ML applications throughout the entire lifecycle [81–83]. Users should be involved in the individual steps.

Moreover, the DAS itself automates as many steps of the ML pipeline as possible and, according to possibility, encompasses a cognitive module from which explanations about results can be drawn. For the sake of simplified use of such assistance systems as well as for independent future applicability, relevant background knowledge, such as explanations of functionalities and other non-formal learning opportunities are to be integrated (KF4). For instance, Clement et al. [84] and Naqvi et al. [85] provide an overview of Explainable Artificial Intelligence techniques that have been implemented in the manufacturing domain. Furthermore, if applicable, coaches in the form of supervisors or colleagues, respectively, can be considered, such that the systems can be used for competence development among the users. Since ML-projects require company-wide collaboration and change management efforts [86], support in the construction of an interdisciplinary and innovative team is of advantage. Thus, not only the main target group should be analyzed and involved, but also other affected stakeholders such as IT and HR units. When it comes to the validation phase, use cases with respective data from real industry processes are considered (KF5). The systems should not (only) be validated by the authors themselves or colleagues of theirs but by the considered target group. This allows a success evaluation, in which it can be finally stated whether the original goal, the development of an easy-to-use assistance system on the topic of ML for non-experts, has been achieved. An optimal case is the application of the users in their real production environment. This makes it easier to make statements about the practicality of the solutions.

In summary, the requirements and the criteria examined by Jöhnk [41] will be compared and the extent to which they are addressed will be explained. Subsequently, more precise statements can be made about the extent to which future solutions can close the gaps identified in this review. If the users are systematically included in the development and validation process as an example, this will result in a detailed description of the personnel. This also makes it easier to design systems that require less prior knowledge. If DAS focus more strongly on the needs of SMEs, consideration is given to the design of the IT infrastructure and a comprehensive description is provided of the sources from which data was obtained and how it was processed. The final comparison is shown in Table 4.

Table 4. Comparison of analyzed criteria and requirements.

	REQ1	REQ2	REQ3	REQ4
Personnel	X		X	
IT Infrastructure		X		
AI Awareness	X		X	X
Upskilling	X			X
Collaborative Work	X			
Data availability		X		
Data quality		X		
Data accessibility		X		
Industrial validation	X	X	X	
Target group validation	X		X	

5. Conclusions and Outlook

In this publication, 29 software-based digital assistance systems focusing on the implementation of ML applications in manufacturing environment and targeting non-ML-experts with limited programming knowledge were reviewed and analyzed in depth. A special emphasis was thereby laid on an examination of the systems regarding organizational AI readiness previously defined in literature [40,41].

The review shows that this topic is especially addressed in European countries. Within development steps, articles focus on technical aspects. Algorithm improvements, performance improvements, among others are considered in detail and represent the essential focus for future improvement. In contrast, human-centered matters lack behind—despite the relevance described by most of the authors themselves. Besides, many assistance systems have not been validated in industrial practice and even if they were, validation was carried out in most cases by the developers themselves. The most frequently considered ML use cases are manufacturing monitoring, cost and power consumption as well as wear and tear monitoring.

The conducted research provides a summary and points out future research directions to researchers interested in this field and companies interested in assisted implementation and use of ML in their manufacturing environment. In consequence, suggestions for future research projects were provided in detail. They are designed in such a way that also SMEs with their lack of ML specialists can profit from them.

In addition to the integration of the described requirements in newly developed systems, future research is necessary on the effects of such digital assistance systems on the users. As such, a more detailed analysis of user requirements has to be performed and the described DAS rated against them. For this, an in-depth investigation using the systems is necessary.

Supplementary Materials: The following supporting information can be downloaded at https://www.mdpi.com/article/10.3390/make6040134/s1.

Author Contributions: Conceptualization: J.R. and M.P.; methodology: J.R. and M.P.; formal analysis: M.P.; investigation: J.R.; resources: J.R. and M.P.; data curation: J.R.; writing—original draft preparation: J.R. and M.P.; writing—review and editing: J.R., M.P. and J.M.; visualization: J.R. and M.P.; supervision: J.M.; project administration: J.R.; funding acquisition: M.P. All authors have read and agreed to the published version of the manuscript.

Funding: The study has been partially supported by the HumanTech Project financed by the Italian Ministry of University and Research (MUR) for the 2023–2027 period as part of the ministerial initiative "Departments of Excellence" (L. 232/2016).

Data Availability Statement: The original data presented in the study are openly available in TUdatalib at URI: https://tudatalib.ulb.tu-darmstadt.de/handle/tudatalib/4368 (accessed on 6 March 2024).

Conflicts of Interest: The authors declare no conflicts of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results.

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