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Frameworks for data-driven quality management in cyber-physical systems for manufacturing: A systematic review

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Abstract

Recent advances in the manufacturing industry have enabled the deployment of Cyber-Physical Systems (CPS) at scale. By utilizing advanced analytics, data from production can be analyzed and used to monitor and improve the process and product quality. Many frameworks for implementing CPS have been developed to structure the relationship between the digital and the physical worlds. However, there is no systematic review of the existing frameworks related to quality management in manufacturing CPS. Thus, our study aims at determining and comparing the existing frameworks. The systematic review yielded 38 frameworks analyzed regarding their characteristics, use of data science and Machine Learning (ML), and shortcomings and open research issues. The identified issues mainly relate to limitations in cross-industry/cross-process applicability, the use of ML, big data handling, and data security.

Keywords: Quality Management; Artificial Intelligence (AI); Cyber-Physical Systems (CPS); Framework; Systematic Literature Review

1. Introduction

The advent of advanced technologies in the manufacturing industry such as Internet of Things (IoT), Machine Learning (ML) and distributed ledger in the context of digitization and Industry 4.0 is transforming today's manufacturing lines into Cyber-Physical Systems (CPS). In the context of this paper, the term CPS describes a new generation of manufacturing systems with interconnected computational and physical capabilities that can interact with human operators through new modalities [1]. The prevalent manufacturing industry is characterized by increasing competitive pressure and customer requirements with regards to product and process quality as well as low prices. Concurrently, the complexity of the manufactured products is rising through ongoing optimization, customization, and the use of high-tech engineering in products working at the physical limits of the respective materials such as in offshore wind turbines and aerospace products [2, 3]. Companies in the manufacturing sector thus strive for continuous improvement, optimization and increasing efficiency of their processes to cope with the increasing quality requirements and to keep up with the competition. Coincidently, the growing availability of data related to quality aspects yields the potential of enhancing process and product quality using data analytics [4]. Quality is here seen from the manufacturing perspective and relates to conformance to technical requirements [5]. Quality Management is defined as "an integrated approach to achieving and sustaining high quality output, focusing on the maintenance and continuous improvement of processes and defect prevention at all levels and in all functions of the organization, in order to meet or exceed customer expectations" [6]. Process and product quality optimization using acquired production data has distinctly emerged as a prominent subject of research in the last two

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decades [3] and is becoming more feasible in practical applications due to the deployment of CPS. The introduction of data-driven quality management in companies is still challenging though, due to the novelty of the respective technologies. Frameworks have thus been introduced in the literature to guide the implementation of quality management in CPS, providing a structured architecture to connect physical production systems and digital services. As this is a topic of active research, multiple such frameworks have been introduced, cf. Table 1, which focus on various aspects and industry sectors. To gain an overview as well as to identify the benefits and shortcomings of these frameworks, a structured review is needed. To the best of the authors' knowledge, no such review exists and shall thus be provided here. The main contributions of this work are our answers to the following research questions (RQ):

RQ1: *What are the characteristics of existing data-driven frameworks for quality management in CPS?*

The first research question investigates the characteristics of the identified frameworks. The focus with respect to the manufacturing process and industry should be identified, as well as similarities and differences of the frameworks. Finally, the level of abstraction e.g., product/ single machine/ production line, should be classified, together with the benefits that are achieved by the implementation of the framework.

RQ2: *How are data science and ML techniques used for quality management?*

The second research question focusses on the use of data science and ML for quality management within the frameworks. Thus, it should be identified what the data-based components of the frameworks are used for and which specific algorithms are employed. Further, it is of interest, what kind of data e.g., synthetic/ real data as well as which metrics/ Key Performance Indicators (KPIs) are used for training and evaluation. In the context of interaction with human operators, it is of special interest how ML KPIs e.g., accuracy, can be translated to manufacturing KPIs e.g., parts per million (ppm), and whether the frameworks can provide statistical guarantees like traditional Statistical Process Control (SPC).

RQ3: *What are the deficits and open research questions?*

Finally, the deficits of the available frameworks shall be identified. This is done to highlight open research questions and opportunities for future work.

2. Methodology

We conduct a systematic literature review (SLR) following the guidelines from [7, 8]. With the context and research questions presented in Section 1, we describe the criteria for selecting the primary studies. Then we explain our search and selection process that yields the final set of primary studies.

Inclusion criteria. Papers which present a framework or a software architecture for CPS and that address quality in manufacturing were selected.

Exclusion criteria. We discard non-peer-reviewed papers, unpublished papers, and non-English papers. We exclude papers that do not provide technical details about the respective framework and surveys or literature reviews. We also do not consider papers having less than 4 pages double column or 6 pages single column. We keep the journal version and exclude the conference version of the same work. We also exclude papers outside the time range from 2010 to February 2021.

Search and selection process. We first search for potential primary studies from the four most popular publication databases IEEE Xplore, ACM Digital Library, ScienceDirect, and Scopus. Scopus and ACM DL already index SpringerLink [9]. Following the guidelines from [8], based on the research questions and keywords utilized in related articles, we define our search keywords. The following search string is adapted to fit each of the search engines of the publication databases: *(framework OR software architecture) AND (manufacturing OR industry OR industrial OR production) AND (quality) AND (cyber-physical system OR CPS OR digital twin OR DT) AND (artificial intelligence OR AI OR machine learning OR ML)*.

We merge the search results returned from all four databases (673 papers) into one Excel file and remove any duplicates based on paper titles and DOIs. For every candidate paper in the search results, we first review the paper's title and abstract, followed by skimming through the contents.

3. Results

Data from the primary studies are extracted and synthesized to answer the research questions. Table 1 provides the complete list of the 38 primary studies.

RQ1. Figure 1 shows the distribution of the papers per year, from 2010 to February 2021. An increase in the number of frameworks for CPS related to quality in the last 5 years, with a strong growth trend (compound annual growth rate of 63% from 2017 to 2020) is clearly noticeable. From the 38 papers, 63% (24) were published in journals, and 37% (14) in conference proceedings. Based on the papers' authorship the number of papers per country was calculated. In papers with authors from *n* countries, the papers were assigned as *1/n* to each country. China (29%) and USA (23%) account for most publications. South Korea, United Kingdom and Germany are represented with 11%, 7% and 6% of the papers, respectively. 84% (32) of the papers validated the proposed frameworks with use cases.

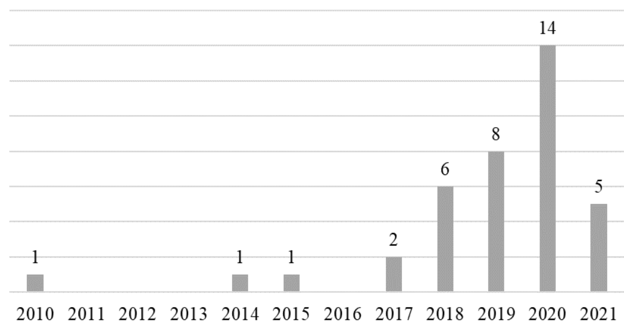

Figure 1. Number of papers per year

Table 1. Primary studies

#	Year	Title	DOI
S1	2021	BiDrac Industry 4.0 framework: Application to an Automotive Paint Shop Process	10.1016/j.conengprac.2021.104757
S2	2021	Maintenance and digital health control in smart manufacturing based on condition monitoring	10.1016/j.procir.2020.05.216
S3	2021	Data-driven cyber-physical system framework for connected resistance spot welding weldability certification	10.1016/j.rcim.2020.102036
S4	2021	A digital twin-based flexible cellular manufacturing for optimization of air conditioner line	10.1016/j.jmsy.2020.07.012
S5	2021	A big data-driven framework for sustainable and smart additive manufacturing	10.1016/j.rcim.2020.102026
S6	2020	Digital Twin-enabled Collaborative Data Management for Metal Additive Manufacturing Systems	10.1016/j.jmsy.2020.05.010
S7	2020	A Conceptual Framework for AI-based Operational Digital Twin in Chemical Process Engineering	10.1109/ICE/ITMC49519.2020.9198575
S8	2020	Architecture model proposal of innovative intelligent manufacturing in the chemical industry based on multi-scale integration and key technologies	10.1016/j.compchemeng.2020.106967
S9	2020	Six-Sigma Quality Management of Additive Manufacturing	10.1109/JPROC.2020.3034519
S10	2020	A Requirements Driven Digital Twin Framework: Specification and Opportunities	10.1109/ACCESS.2020.3000437
S11	2020	Digital twin-driven supervised machine learning for the development of artificial intelligence applications in manufacturing	10.1080/0951192X.2020.1747642
S12	2020	Machine Learning-enabled feedback loops for metal powder bed fusion additive manufacturing	10.1016/j.procs.2020.09.314
S13	2020	Research on on-line Monitoring Method of Automatic Production Line based on Industrial Internet of Things	10.1109/IAAI51705.2020.9332863
S14	2020	Virtual quality gates in manufacturing systems: Framework, implementation and potential	10.3390/jmmp4040106
S15	2020	A digital twin-based big data virtual and real fusion learning reference framework supported by industrial internet towards smart manufacturing	10.1016/j.jmsy.2020.11.012
S16	2020	Contributions of lean six sigma to sustainable manufacturing requirements: an Industry 4.0 perspective	10.1016/j.procir.2020.02.044
S17	2020	A hybrid predictive maintenance approach for CNC machine tool driven by Digital Twin	10.1016/j.rcim.2020.101974
S18	2020	A Quality-Oriented Digital Twin Modelling Method for Manufacturing Processes Based on A Multi-Agent Architecture	10.1016/j.promfg.2020.10.044
S19	2020	Digital twin for cutting tool: Modeling, application and service strategy	10.1016/j.jmsy.2020.08.007
S20	2019	Visual Analytics Framework for Condition Monitoring in Cyber-Physical Systems	10.1109/ICSTCC.2019.8885611
S21	2019	Mímir: Building and Deploying an ML Framework for Industrial IoT	10.1109/ICDMW.2019.00065
S22	2019	A digital twin framework for performance monitoring and anomaly detection in fused deposition modeling	10.1109/COASE.2019.8843166
S23	2019	A Conceptual Framework for Cyber-physical System in Connected RSW Weldability Certification	10.1016/j.promfg.2020.01.055
S24	2019	The framework design of smart factory in discrete manufacturing industry based on cyber-physical system	10.1080/0951192X.2019.1699254
S25	2019	Machine Learning based Digital Twin Framework for Production Optimization in Petrochemical Industry	10.1016/j.ijinfomgt.2019.05.020
S26	2019	Cyber-physical-based PAT (CPbPAT) framework for Pharma 4.0	10.1016/j.ijpharm.2019.06.036
S27	2019	Proposition of the methodology for Data Acquisition, Analysis and Visualization in support of Industry 4.0	10.1016/j.procs.2019.09.370
S28	2018	Digital twin-based smart production management and control framework for the complex product assembly shop-floor	10.1007/s00170-018-1617-6
S29	2018	A study on the integrations of products and manufacturing engineering using sensors and IoT	10.1007/978-3-319-99707-0_46
S30	2018	Implementation of cyber-physical production systems for quality prediction and operation control in metal casting	10.3390/s18051428
S31	2018	IDARTS – Towards intelligent data analysis and real-time supervision for industry 4.0	10.1016/j.compind.2018.07.004
S32	2018	Data-driven smart manufacturing	10.1016/j.jmsy.2018.01.006
S33	2018	Integrated Cyber Physical Simulation Modelling Environment for Manufacturing 4.0	10.1109/IEEM.2018.8607696
S34	2017	A Framework of a Smart Injection Molding System Based on Real-time Data	
S35	2017	Framework and development of fault detection classification using IoT device and cloud environment	10.1016/j.jmsy.2017.02.007
S36	2015	Cyber-physical Systems Architecture for Self-Aware Machines in Industry 4.0 Environment	10.1016/j.ifacol.2015.06.318
S37	2014	Towards a domain-specific framework for predictive analytics in manufacturing	10.1109/BigData.2014.7004332
S38	2010	Research on Intelligent Process Quality Control System under Network Environment	10.1109/ISME.2010.29

The frameworks in most of the papers (53%) are implemented and validated in a research setting, e.g., in testbeds. The remaining papers (37%) implement and validate their approaches in real industrial use cases. The presented use cases are from a variety of industries, as presented in Figure 2. The industry sectors were taken from the Global Industry Classification Standard [10]. The category “Multiple” refers to use cases that can be applied to a variety of industry sectors, for example, additive manufacturing, that can be utilized in, among others, the Aerospace & Defense sector as well as in Household & Personal Products. The Electrical Equipment and Automotive industries are most strongly represented with 7 and 6 papers, respectively.

Metal additive manufacturing [S5, S6, S9, S11, S12, S22] is the most frequent use case. Followed by milling [S1, S3, S5, S27], cutting [S17, S19, S36], battery production [S2, S14, S16], air conditioner production line [S4, S38], assembly [S18, S35] and welding [S3, S23]. When analyzing the abstraction level of the frameworks, 26 of the 38 papers (68%) developed the frameworks for the production line level (in some cases incorporating previous phases from the product development). 10 papers (26%) presented frameworks for specific machines (for example machine tools with cutting use cases, or selective laser melting machines for additive manufacturing). Only 2 papers (6%) developed a framework for the produced parts.

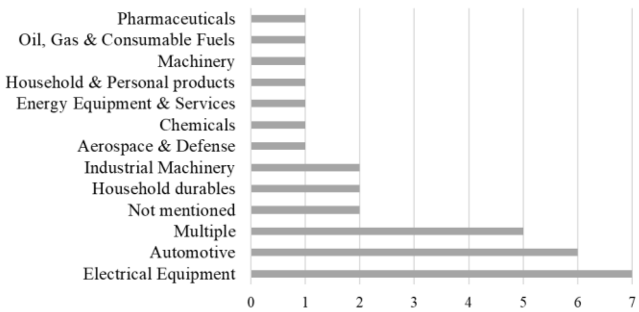

Figure 2. Number of papers per industry sector

Regarding the architecture, most of the frameworks are implemented using a combination of cloud-edge technologies (24%) as shown in Figure 3. Cloud computing was the most used technology with a combined presence of 56%. IoT technologies were present in 24% of the architectures.

Some papers (16%) did not provide information about the technologies used in their architecture design.

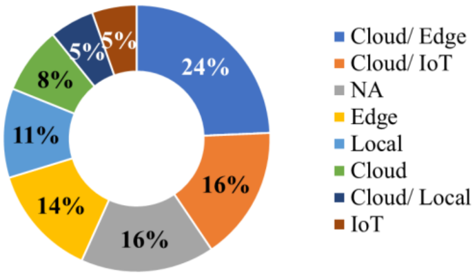

Figure 3. Architecture type

The existing frameworks focus on bridging the physical and digital worlds by establishing data transfer and interactions between layers in the production environment. In 30 of the 38 papers "quality" is mentioned as a goal or focus for the framework. Predictive Maintenance is also considered a part of the broader concept of quality in CPS, as it is often cited in the context of process quality. For the remaining eight papers quality is part of the framework, but not the focus. We identified nine main benefits that can be achieved by adopting the proposed architectures, namely: Optimization of processes and decision making, detection of deviations and quality issues, decision support for domain experts, automation and reduction of the need for human intervention, scalability of the proposed data processing solutions, adaptation to changing conditions, integration of the value chain at different levels (local, subcontractors, etc.), assessment of production KPIs, generation of simulation data for quality assessment.

RQ2. In 50% of the studies (19 papers), ML is part of the framework and used as the data analysis tool. The papers that do not implement ML make use of classical statistical methods (e.g., SPC) and visualization techniques for assisting the decision-making process. 17 papers mention that ML can be used for the data analysis, but do not provide concrete implementations or provide algorithms that may be used. These papers were not considered in the following analysis regarding RQ2.

In the frameworks ML has been used for classification, regression, clustering, creation of digital twins, optimization of parameters, and scheduling. The most frequent use of ML is to perform regression (9 papers), where dependencies between product quality, machine data and process data are established. 7 articles perform classification of sensor data, images, process, as well as internal machine data to predict defects, recognize parts, detect anomalies, and predict product quality. Finding optimal parameters such as machine and process configuration has also been explored [S5, S34] using multi-objective optimization methods such as heuristics combined with supervised learning. ML models have been used to create digital twins [S6, S11, S17, S19, S25, S28], for instance, to fit a simulation and create a surrogate model using machine and sensor data [S7]. Clustering [S14, S31] in manufacturing has been used to group machine conditions based on machine and sensor data as well as to explore and understand the data. The input data, the ML algorithms and the output data can be seen in the Sankey diagram in Figure 4.

Input data. We differentiate between time-series sensor data (14 papers), image data [S6, S9, S11] and shop-floor data [S14, S28]. Time-series data refers to measurements from sensors (e.g., temperature, pressure, and vibration) either installed in the machines or along the production process. Image data are photos of the manufactured product (e.g., of the layers in additive manufacturing or the final product). Shop-floor data are data from systems such as the Manufacturing Execution System or the Enterprise Resource Planning System. Shop-floor data can be for instance from personnel, logistics, equipment operation, inspections, etc. It is noticeable that most papers that adopted ML methods make use of time-series sensor data (both historical and real-time data).

Output data. The output data shows more variety. Classification of product quality between a range of pre-defined classes [S6, S13, S21, S24, S30, S35] and between conform and non-conform (OK, NOK) [S3, S14] account for most classification tasks. For continuous variables, the prediction of product quality [S14, S21, S23, S25], e.g., the yield of a chemical product [S25], is the most frequent output format. In two papers the output of the prediction tasks was the cutting tool wear [S17, S19]. Also, the prediction of energy demand [S1] and future states for a shop-floor configuration [S28] are among the outputs. The probability of failure [S31] and the defect probability [S9] appear in one paper each. The optimization of process parameters appears in two papers [S5, S34]. And finally, unsupervised learning techniques combined with expert knowledge are also used for data understanding [S1].

ML algorithms. The most used algorithms fit into the category of supervised learning: Artificial Neural Networks - mainly Fully Connected Neural Networks [S3, S5, S13, S14, S24, S30] and Convolutional Neural Networks [S6, S9, S11] for image processing for time-series data, Random Forest [S3, S14, S17, S21, S25, S30], Gradient Boosting [S1, S21, S25], Lasso-lars regression [S14, S21], Decision Tree Regressor [S1, S17, S30] and Classification and Regression Tree [S3, S23], among others listed in Figure 5. K-Means Clustering [S1, S31], k-Nearest Neighbor [S3, S21] and Principal Component Analysis [S1] are the unsupervised learning techniques implemented in the analyzed studies.

Automation level. Another point of interest for this study is the level of automation that the identified frameworks provide with regards to the use of ML algorithms. We differentiate between "Assisted Decision Making" and "Autonomous Decision Making". Assisted Decision Making applies to scenarios where the framework provides information and suggestions that can be used or applied by the machine operators but are not executed autonomously. The framework thus has no direct control over physical equipment.

Examples for this are indicators regarding the probability of quality problems, anomalies in the production process, suggestions for optimal process parameters as well as tool condition estimates for predictive maintenance.

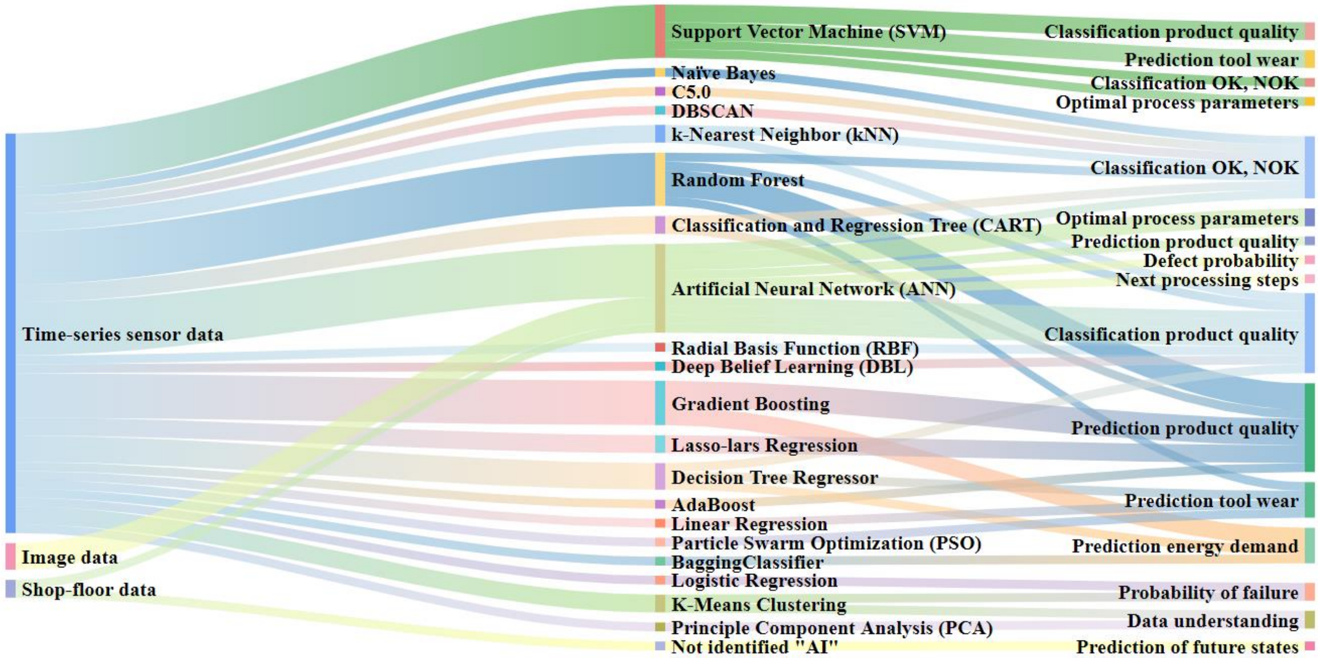

Figure 4. Sankey diagram linking input data, ML algorithm and output data

In contrast, Autonomous Decision Making describes scenarios, where the framework directly executes control decisions such as scheduling decisions. The review shows, that most frameworks (93%) that specify the automation level fall into the category of Assisted Decision Making while only two frameworks support Autonomous Decision Making.

For further analysis of the deployed ML systems, the use of metrics and KPIs is investigated. Only a small number of studies (10 papers, 26%) provide information regarding the metrics used in the frameworks. Out of these, the most popular metric for classification problems is Accuracy (5 papers), followed by Precision and Recall (3 papers). For regression problems, metrics focusing on the magnitude of the absolute deviation between target and prediction values are most popular such as (Root-)Mean Squared Error (RMSE), Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE) (5 papers).

A further point of interest in this study is the origin of the data used for validation of the ML systems. Most of the reviewed studies used real data to test their implementations (71%). Some studies validated their implementation using simulated data (8%) and others used a combination of simulated and real data (13%).

RQ3. In the following section, open research questions and deficits in current frameworks are identified, based on the acknowledged limitations and opportunities for future work in the primary studies. We coarsely group the identified issues into scope-related, machine learning-related, data security/privacy-related, as well as data handling/cloud-related. Starting with the scope of the frameworks, it is often noticed, that the framework is specific to a single industry [S3, S9, S11, S14, S25, S27] or even to a specific process, e.g., milling [S1, S3, S5, S27] and may be extended to cover different processes and industry sectors to facilitate a broader usage. Similarly, a higher abstraction level, e.g., production line instead of a single machine, is mentioned as a possible extension in [S11, S20, S22, S28]. Further, the frameworks may be adapted to support not only the production process but also the supply chain or even the complete product lifecycle [S5, S16, S27, S29, S30]. Finally, practical implementations as a proof-of-concept [S7, S34] as well as an analysis regarding the economic costs and benefits of using the framework [S14, S25] are considered as possible extensions.

Regarding the use of ML, multiple frameworks only vaguely describe what ML may be used for within the framework and often acknowledge that the use of ML must be more concrete and may be extended to further parts of the framework and more advanced use cases such as parameter adaptation/optimization and automated decision making [S2, S6, S16, S17, S25, S26, S28, S31]. Further, ML-based virtual sensor may be used to estimate quality-related variables that are hard to measure physically [S4]. Another gap concerning the use of ML in current frameworks is the lack of uncertainty estimation and online evaluation acknowledged in some of the studies [S7, S17]. Manufacturing environments are strongly dynamic, which may degrade the accuracy of static ML models over time. ML models thus need to be adapted in case of changes to the environment [S14, S27].

An important issue in data-based quality management that is often mentioned is the potential for data security vulnerabilities that should be explicitly analysed by future frameworks [S14, S20, S23, S30]. Process and quality data are sensitive assets of manufacturing companies and thus must be protected. This issue is especially prominent in cloud-based applications [S10]. Nevertheless, future data protection and anonymization measures should not render the data useless to ML models [S23]. A possible solution is seen in the use of blockchain or distributed ledger technology (DLT) [S7, S8].

Lastly, the issue of big data handling and cloud technologies is recognized by the primary studies. In general, the use of cloud technology is seen as a possible way to tackle growing amounts of data and local storage limits [S17, S26]. New ways of effectively managing big data in real-time applications need to be developed, especially when using cloud technology as issues with latency and bandwidth may arise. A possible solution is seen in the usage of edge devices for pre-processing of the data [S2, S17, S22, S28, S32, S35]. Further, the heterogeneity of data sources and communication protocols raise integration efforts and costs of frameworks. Thus, standardized formats and protocols should be developed and utilized [S30, S32]. Finally, a simulation may be used as an additional data source [S15, S30, S32].

4. Discussion

Following the description of research gaps that are acknowledged in the primary studies (RQ3), we critically discuss the frameworks in the following section.

One of the major shortcomings we found is the superficial description and lack of detail of the presented frameworks. Oftentimes the system overview, the interconnection of different layers of the CPS and information about the data integration is missing. Many articles (14 papers) mention ML or Artificial Intelligence (AI) but do not specify what type of ML algorithm they use. We identify the need for studies that provide a concrete description on how to implement the framework, to guarantee its transferability and use in research and industry for additional use cases.

A special focus of RQ2 has been the investigation of ML KPIs and metrics for evaluation of the algorithms used in the frameworks and how they may be translated to KPIs of the manufacturing sector. Very few of the frameworks describe the use of ML KPIs in detail and none of the studies describe the transformation into shop-floor-related KPIs. This result highlights an opportunity for further research, as the explainability and practicability of KPIs is a significant factor in the practical adoption of ML systems in industrial applications [10].

ML algorithms are primarily used for supervised learning (17 papers). 4 articles use both supervised and unsupervised techniques. Our observations indicate that there is a gap in the use of unsupervised and reinforcement learning methods in the CPS frameworks for manufacturing. Also, the use of ontologies and knowledge-based solutions is explored in only one paper [S37]. Domain knowledge representation has the potential to contribute to the explainability and acceptance of AI for realizing flexible manufacturing systems [12].

5. Conclusions

This study investigates the existing frameworks for data-driven quality management in cyber-physical manufacturing systems by means of a systematic literature review. The review identifies gaps and shortcomings from 38 frameworks. Concerning the implications for practice, this work provides an overview of the existing frameworks, the benefits provided by them, and how AI-technologies are being used as data analytics tool. This can provide general support for improving quality management principles and implementation in certain industries. For academia, the literature review presents the open research questions and gaps regarding quality management in cyber-physical manufacturing systems, indicating further research directions in the field. The identified issues mainly relate to limitations in cross-industry/cross-process applicability, the use of ML, big data handling as well as data security. Unsupervised, reinforcement learning, and ontology-based techniques are less explored when compared to supervised learning. AI model update and uncertainty estimation are not sufficiently discussed in the existing frameworks. Blockchain and DLT should be explored to tackle data security issues.

This study has its limitations. First, academic databases are constantly updated, and the sample collected for this review refers only to the period in which the study was conducted. Finally, we also might have missed potentially relevant frameworks, despite the efforts presented in the methodology section.

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