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SURVEY

Unlocking the Potential of Information Modeling for Root Cause Analysis in a Production Environment: A Comprehensive State-of-the-Art Review Using the Kitchenham Methodology

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ABSTRACT Data from production environments is now available in unprecedented volumes, making the problem-solving of incidents through root cause analysis straightforward. However, the root cause analysis process remains time-consuming. This study employs the Kitchenham standard systematic literature review methodology to explore how information models and deep learning can streamline this process. By conducting a comprehensive search across four major databases, we evaluate the current technological advancements and their application in root cause analysis. The aim of this study is to assesses the impact of information models for root cause analysis in a production environment. Our findings reveal that integrating knowledge graphs, association rule mining, and deep learning algorithms significantly improves the speed and depth of root cause analysis compared to traditional methods. Specifically, the use of neural networks in recent literature shows substantial advancements in analyzing complex datasets, facilitating large-scale data integration, and enabling automated learning capabilities. Comparing our findings with other recent studies highlights the advantages of using information modeling and deep learning technologies in root cause analysis. This comparison underscores the superior accuracy and efficiency of these advanced methodologies over traditional manual interpretation methods. The effective implementation of these technologies requires a robust foundation of clean, standardized data, giving rise to the concept of "Production IT." Furthermore, it is crucial for this data to be openly available to facilitate academic research, thereby enabling the development of new methods for more efficient and effective root cause analysis.

INDEX TERMS Data-driven decision making, deep learning algorithms, industry 4.0 technologies, information modeling (IM), machine learning in manufacturing, root cause analysis (RCA).

I. INTRODUCTION

The central objective of this manuscript is to discern the prevailing trends in information modeling (IM), root cause analysis (RCA), and machine learning (ML) within the realm of production. IM serves as the cornerstone for creating, managing, and utilizing data. It provides a structural framework that enables the efficient flow of data, thereby enhancing interoperability and ease of data exchange between different production systems. RCA, on the other hand, is an investigative approach to identify the underlying factors that give rise to problems or inefficiencies within a production environment. RCA methods delve into problems at a granular level, focusing not only on symptomatic problems but also on

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the underlying systemic factors. Despite these advancements, several technical gaps remain that hinder effective integration and application of RCA, IM, and ML in production environments. First, the lack of standardized IM impedes seamless data integration across different systems, which is critical for effective RCA. Furthermore, while ML offers powerful tools for data analysis, existing models often fall short in directly addressing the complex, multi-dimensional nature of industrial data. This complexity requires not only advanced analytical capabilities but also models that are specifically tailored to the nuanced characteristics of industrial processes. Additionally, there is a significant gap in the availability of comprehensive, domain-specific datasets that are crucial for training and validating these models, which limits the potential for widespread application and testing in real-world settings. These technical gaps are stressing the urgency for more efficient problem-solving methodologies. Although there are vast data resources in companies, each problem in a production or industrial process is set in an overly complex environment which needs a multidisciplinary team of experts to solve it. Therefore, this study is motivated by the need to streamline the RCA process using advanced IM and ML techniques to enhance decision-making and operational efficiency in production environments. Hence these studies main contribution in a nutshell are formulated in the following bullet points.

- A systematic literature review, following the Kitchenham methodology, with which we assess current technologies and methodologies, identifying key tools in advancing RCA capabilities.
- We explore how integrating IM with deep learning (DL) enhances the efficiency and accuracy of RCA in production environments.
- Our study provides a comprehensive evaluation of how RCA, IM and ML technologies are applied in practice, focusing on their implementation in diverse industrial domains and their impact on production processes.
- The study contributes to academic and practical understandings by outlining the challenges and barriers in implementing these advanced technologies in a regulated production environment.
- We suggest future research directions based on our conclusion which identifies the gaps in current technologies and methods, particularly in the standardization and integration of data-driven approaches within existing production systems.

The practical implications of this research are profound, positioning RCA, IM, and ML not just as theoretical constructs but as essential tools for the future of manufacturing. By enhancing RCA through advanced ML and IM, industries can significantly improve their operational efficiency, reduce downtime, and optimize production processes. This alignment with industry needs underscores the significant potential for deploying these methodologies more broadly, providing a clear roadmap for integration into existing systems and for ongoing innovation in manufacturing technologies.

To gauge the state of the art, we conducted an exploratory, unstructured pre-study. The insights gleaned from this initial phase lead to the refinement of our research questions and a structured literature review. The query terms deployed in various databases stemmed directly from these research questions. The outcomes of this rigorous search strategy are elucidated in Fig. 1.

In general by integrating IM and RCA methodologies with ML algorithms, the aim is to develop a more cohesive and intelligent production management system. This multidisciplinary approach seeks to harness the predictive power of ML to enhance the accuracy of RCA and the efficiency of IM, culminating in a more robust, adaptive, and resilient production environment. Our research aims at the identification of barriers and current challenges and giving questions for future research.

Our manuscript further endeavors to elucidate how extant norms, specifically cited as [1], can be integrated into contemporary environments employing algorithms from the ML domain. Additionally, we examine the extent to how much an IM and the current frameworks like RAMI [2] are featured in scientific literature. Another frameworks would be reconfigurable production systems [3], [4], or the cyber-physical systems in manufacturing [5]. The remainder of this paper is organized as follows. Section II outlines the hypothesis of the study and discusses the limitations of the applied method. In section III the methodological approach is presented, including the systematic literature review process by Kitchenham [6] and the databases surveyed. Section III-A presents the research questions which were defined after the pre-study. In Section IV, the findings and literature is categorized based on the identified themes and technologies in the relevant studies. The implications of these findings are further explored in Section V. There we delve into the analysis of the current state of the art and its implications for future research and practice. In the final section VI the key contributions of our research are summarized, the encountered challenges outlined, and future study directions in the field of IM and RCA within production environments suggested.

II. HYPOTHESIS AND LIMITATIONS

A. HYPOTHESIS

This study hypothesizes that the integration of IM and DL algorithms can significantly enhance the efficiency and accuracy of RCA in production environments. Specifically, our conjecture is that:

- The use of knowledge graphs and association rule mining will streamline data integration and analysis processes, reducing the time required for RCA.
- Deep learning algorithms, particularly neural networks, will improve the accuracy of identifying root causes by effectively handling complex and large-scale datasets.

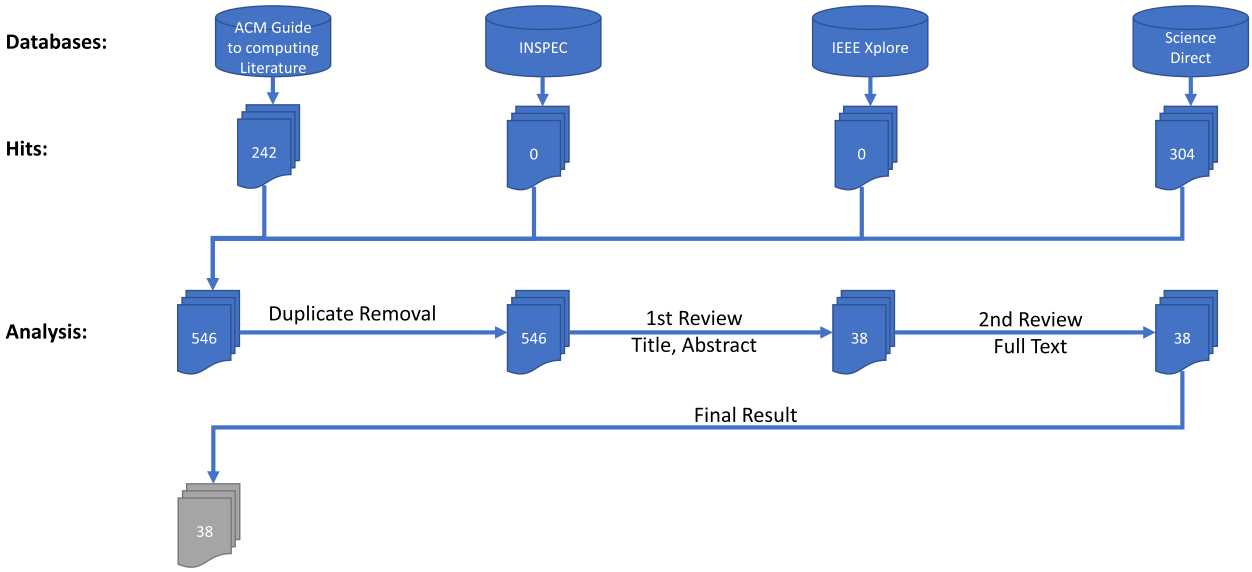

FIGURE 1. The search strategy for our structured literature review.

- The combination of these technologies will outperform traditional RCA methods that rely heavily on manual interpretation and simpler analytical tools.

B. LIMITATIONS

While this study presents promising advancements, several limitations must be acknowledged:

- **Data Quality and Availability:** The implementation of IM and DL technologies requires a robust foundation of clean, standardized data. The availability and quality of such data in real-world production environments can be a significant constraint.
- **Generalizability:** The models and methodologies discussed are developed and validated using specific datasets and production scenarios. Their generalizability to different production settings and industries may be limited without further validation.
- **Computational Resources:** Deep learning algorithms, particularly neural networks, demand substantial computational resources for training and deployment. This requirement may limit their practical application in resource-constrained environments.
- **Integration Complexity:** Integrating advanced IM and DL technologies into existing production systems can be complex and may require significant changes to current IT infrastructure and workflows.
- **Maintenance and Scalability:** Maintaining and scaling these technologies over time, especially in dynamic production environments, can be challenging. Regular updates and retraining of models are necessary to ensure sustained performance.

By addressing these limitations, future research can further refine the integration of IM and DL in RCA, ultimately enhancing their applicability and effectiveness in diverse industrial contexts.

III. METHOD

This study adheres to the methodology outlined by Kitchenham [6] with some adaptations. The schematic representation of our methodology is illustrated in Fig. 1. Prior to the main study, we executed a preliminary study to establish an initial framework of understanding. The multi-faceted search approach spanned Google Scholar, ACCESS Engineering, TEMA - Technik und Management in the WISO-Database as well as Google's gray literature. The search terms where "Root Cause Analysis", "production process", "machine learning", "fault detection" and "industrial internet of things". This yielded a selection of key papers [7], [8], [9], [10], [11], [12], [13], [14]. Based on the preliminary study's outcome, a search protocol was established. Subsequently with this the research questions were defined, see III-A. The following sub-sections elaborate in detail on the multi-pronged methodological approach employed in our research.

A. RESEARCH QUESTIONS

In the scope of this research, we articulate four pivotal research questions:

RQ1. What is the current state of the art for RCA regarding IM in a production environment?

RQ2. What are typical use cases and practical applications for IMs for RCA and in which domain were they applied?

RQ3. Which kind of RCA type based on IEC 62740 [1], framework, software architecture, algorithm, and standards are in use for an IM combined with RCA?

RQ4. What are the main challenges and barriers in implementing academic models related to IM and quality assessment in the manufacturing industry?

In Section IV, the selected publications are taxonomically sorted into four distinct categories. Category 1 elucidates the use-cases where both IM and RCA are deployed. Category 2 zeros in on RCA-centric solutions or those that aim at root cause identification. Category 3 spotlights cases that are primarily focused with pure IM. Category 4 serves as a repository for publications that offer contributory insights for either RCA or IM solutions.

Furthermore, we have undertaken an exhaustive examination of these papers based on their publication dates. This temporal classification permits a dynamic perspective on the evolving algorithms, which are detailed in Section IV-A. In Subsection IV-B, the focus is on papers that serve as review articles, lacking a precise use-case; yet, the domain of application is also noted—for instance, the intersection of aeronautics and information technology for the use-case in aircraft manufacturing. Subsection IV-C systematizes the findings in the following categories: Type of RCA; Framework; Software; Standards. The type of RCA will be designated in accordance with the standard [1]. The Framework section provides an in-depth exposition of the algorithms discussed in each paper, whereas the Software section enumerates the tools or IDE's utilized. Standards encompasses all norms cited in the paper. Finally, in Subsection IV-D, the biggest challenge for academic models is discussed. Besides, the availability of open-source data is analyzed and the implications it has on the broader state of the art are also discussed.

B. SEARCH PROCESS

In this structured literature research we dissected four databases after defining the research questions, as it can be seen Fig. 1. The Databases are ACM, INSPEC, IEEE Xplore and Science Direct. Depending on the database and the queries in table 1 are defined.

The ACM Guide to Computing Literature and INSPEC share the same query. IEEE Xplore had a slightly different query regarding the search structure. A significant difference in the available amount of allowed search terms exists in the Science Direct database. There, the highest search findings were obtained, and also the shortest search query was used. Every database had the same time frame in which the publications are considered, beginning with the year 2000 and ending with the last day of 2022. This means that a timeframe of 22 years is analyzed. This time frame is due to the relative new use of convolutional neural network in 2012 with AlexNet [15] and the more unstructured data available on the internet since 2000.

C. INCLUSION AND EXCLUSION CRITERIA

To find the most related research to answer our questions, it is necessary to define inclusion and exclusion criteria. The criteria for an inclusion of a paper are as follow:

- The study must have full text (e.g. abstract only papers are not considered)
- The study must be in English

The exclusion criteria are

- The study is a duplicate publication
- The study is published before the year 2000 and after 2022

D. QUALITY ASSESSMENT

The quality assessment for this paper had only one criterion. The study must contain at least three of the following search terms in the abstract to be considered for a full-text review:

- root cause analysis,
- manufacturing,
- machine learning,
- information modeling.

If the abstract contains fewer than three terms, it will be categorized into the second class and set aside for future consideration. Papers falling into classes one or zero are immediately discarded from the study. Only papers in class three are considered for this study, resulting in a total of 38 relevant papers.

E. DATA COLLECTION

The study utilized only scientific databases that are most closely related to the topic. These were the ACM Guide to Computing Literature, INSPEC, IEEE Xplore, and Science Direct. The first database researched was the ACM Guide to Computing Literature, which yielded 242 papers based on the derived search query from the research questions. The second and third databases in which the literature survey was conducted were INSPEC and IEEE Xplore. INSPEC used the same search query as the ACM database. For IEEE Xplore, a minor adjustment was necessary to align with the search query. Both databases returned zero results. No adjustments were made to these two databases regarding the search query. The fourth database was Science Direct. The search query had to be modified to fit the search template of this database. Overall, 304 results were found, of which 106 papers are open source. Table 1 lists the three search queries used for the different databases. The extracted data included the following publications as the relevant key finding papers, as seen in table 2.

F. DATA ANALYSIS

The analysis was conducted in a separate Excel sheet. The results were compiled into a final table by answering the research questions. Each research question was divided into smaller sub-questions to facilitate quicker searches through the papers for answers. In Table 3, you can see the sub-questions for each research question.

IV. RESULTS

A. RQ1: WHAT IS THE CURRENT STATE OF THE ART FOR RCA REGARDING IM IN A PRODUCTION ENVIRONMENT?

To comprehensively delineate the state of the art in RCA and IM in a production context, we prioritize the examination of underlying algorithms. We postulate that algorithms recurrently cited or those featured in multiple papers published

TABLE 1. The search term for each database and the results.

Database	Search Term	Result
ACM Guide to computing Literature and INSPEC	[[All: "root cause analysis"] OR [All: rca] OR [All: "automated root cause analysis"] OR [All: arca]] AND [[All: manufacturing] OR [All: modern manufacturing] OR [All: self-adaptive manufacturing systems] OR [All: manufacturing system] OR [All: manufacturing data processing]] AND [[All: product quality] OR [All: quality assessment]] AND [[Keywords: self-healing manufacturing] OR [Keywords: causal inference] OR [Keywords: fault diagnosis] OR [Keywords: industry data analytics] OR [Keywords: internet of things] OR [Keywords: iot] OR [Keywords: industrial internet of things] OR [Keywords: iiot] OR [Keywords: machine learning] OR [Keywords: ml] OR [Keywords: knowledge graph] OR [Keywords: deep learning] OR [Keywords: dnn]] AND [[Keywords: paradigm] OR [Keywords: framework] OR [Keywords: software architecture] OR [Keywords: communication] OR [Keywords: smart manufacturing]] AND [E-Publication Date: (01/01/2000 TO 12/31/2022)]	242 and 0
IEEEXplore	("All Metadata":"Root Cause Analysis" OR "All Metadata":RCA OR "All Metadata":"Automated Root Cause Analysis" OR "All Metadata":"ARCA") AND ("All Metadata":manufacturing OR "All Metadata":modern manufacturing OR "All Metadata":self-adaptive manufacturing OR "All Metadata":manufacturing data processing) AND ("All Metadata":product quality OR "All Metadata":quality assessment) AND ("Author Keywords":self-healing manufacturing OR "Author Keywords":causal inference OR "Author Keywords":fault diagnosis OR "Author Keywords":industry data analytics OR "Author Keywords":internet of things OR "Author Keywords":IoT OR "Author Keywords":industrial internet of things OR "Author Keywords":IIoT OR "Author Keywords":machine learning OR "Author Keywords":ML OR "Author Keywords":knowledge graph OR "Author Keywords":deep learning OR "Author Keywords":dnn) AND (“Author Keywords”:paradigm OR “Author Keywords”:framework OR “Author Keywords”:software architecture OR “Author Keywords”:communication OR “Author Keywords”:smart manufacturing) Filters Applied: 2000 - 2023	0
Science Direct	("Root Cause Analysis" OR RCA OR "Automated Root Cause Analysis" OR ARCA) AND (Manufacturing OR "modern manufacturing" OR "self adaptive manufacturing" OR "manufacturing data processing") AND "product quality"	304

within the last three years constitute the contemporary state of the art. Supplementary to this, to deepen our understanding and contextualize these algorithms, we initially classify each paper by its publication date. As specified in III-B, the defined time span for the literature research is between 2000 and the end of 2022. The first relevant publication was in 2008. We deem a paper as old if it is published before 2020. Up to the year 2019, there were 13 papers published that are considered relevant. These papers were published over a span of eleven years, with 2008 as the first and 2019 as the last ‘‘older’’ paper. This constitutes one third of all the relevant papers. The other two-thirds were published in the years between 2020 and the end of 2022. This means that the other relevant papers are not older than three years and could be considered as newer or recent publications. Overall, there are 27 different algorithms/models identified, with only ten algorithms/models witnessing repeated utilization across publications.

Analyzing the different papers based on the algorithms and used models shows significant use of graphs, as in the papers denoted by IDs 5, 8, 9, 10, 13, 20, 25, 31, and 34. Notably, in the newer publications, graphs are regularly utilized as part of the problem solution. The other algorithms were either popular in the years prior to 2020 or have just recently been used. Older methods focus more on visualization and can be found in early papers, see IDs 1, 11, 12. Additionally, data-mining methods were considered innovative in the papers with IDs 10, 12, 13, which are also older ones. Whereas association rule mining has been used effectively throughout all the years, see IDs 2, 17, 26. DL is a relatively nascent algorithmic approach and has just begun to manifest itself in the current body of work, namely in papers with IDs 19, 25, and 38.

Other algorithms that were applied before 2020 include text mining, case-based reasoning, RCA-methodology, fuzzy set theory, fuzzy logic, rough set, systems theoretic accident modeling and processes, relational tree, multi-criteria decision making, signed digraph model, ranking score with the highest likelihood, anomaly detection, causal testing, principal component analysis, genetic cost-sensitive sparse auto-encoder, and non-revisiting genetic algorithm. These algorithms and models are mentioned only once in a publication and therefore do not fulfill our criteria for representing the state of the art.

B. RQ2: WHAT ARE TYPICAL USE CASES AND PRACTICAL APPLICATIONS FOR IMS FOR RCA AND IN WHICH DOMAIN WERE THEY APPLIED?

Tables 4, 5, 6, and 7 provide an encompassing overview of distinct use-cases. It’s noteworthy that not every pertinent paper delineated a specific use-case. This is due to the criteria definition, which does not exclude other literature studies or mapping surveys. Papers that did highlight a use-case typically delved into highly specialized application scenarios, but they can be coalesced into overarching domains. Fig. 2 illustrates the eight discerned domains into which the use-cases are sorted.This pie chart shows the percentage of each use-case among all the relevant papers in this study. A notable classification is the standalone ‘Production IT’ domain. Even though it is part of the production domain, its distinct emphasis on solutions that amalgamate advanced production facilities, simulation models, and sophisticated information technology solutions warranted its unique categorization. Due to the length of this paper, not all use-cases will be discussed in detail. The exact use-case description of

TABLE 2. The 38 primary studies used in this systematic literature review.

ID	Title	Year	Reference
1	Managing software defects: defect analysis and traceability	2008	[16]
2	An integrated framework for effective service and repair in the automotive domain: An application of association mining and case-based-reasoning	2011	[17]
3	Empirical study of root cause analysis of software failure	2013	[18]
4	Root Cause Analysis of Product Service Failures in Design-A Closed-loop Lifecycle Modelling Approach	2014	[19]
5	Derivation of Diagnostic Models Based on Formalized Process Knowledge	2014	[20]
6	STAMP – Holistic system safety approach or just another risk model?	2014	[21]
7	A fuzzy TOPSIS and Rough Set based approach for mechanism analysis of product infant failure	2016	[22]
8	Risk information formalisation with graphs	2017	[23]
9	Experience report on applying software analytics in incident management of online service	2017	[24]
10	Assisting Developers towards Fault Localization by Analyzing Failure Reports	2017	[25]
11	On the tracking of individual workpieces in hot forging plants	2018	[26]
12	Identifying failure root causes by visualizing parameter interdependencies with spectrograms	2019	[27]
13	Towards a Comprehensive Data Processing Platform	2019	[28]
14	Machine learning based fog computing assisted data-driven approach for early lameness detection in dairy cattle	2020	[29]
15	The seven-step failure diagnosis in automotive industry	2020	[30]
16	Causal testing	2020	[31]
17	Root cause analysis approach based on reverse cascading decomposition in QFD and fuzzy weight ARM for quality accidents	2020	[32]
18	Modernizing risk assessment: A systematic integration of PRA and PHM techniques	2020	[33]
19	Deep learning enhanced digital twin for Closed-Loop In-Process quality improvement	2020	[34]
20	i-Dataquest: A heterogeneous information retrieval tool using data graph for the manufacturing industry	2021	[35]
21	SemML: Facilitating development of ML models for condition monitoring with semantics	2021	[36]
22	Knowledge mapping of digital twin and physical internet in Supply Chain Management: A systematic literature review	2022	[37]
23	Organizational process maturity model for IoT data quality management	2022	[38]
24	Non-revisiting genetic cost-sensitive sparse autoencoder for imbalanced fault diagnosis	2022	[39]
25	PEN: Process Estimator neural Network for root cause analysis using graph convolution	2022	[40]
26	End-to-end industrial IoT platform for Quality 4.0 applications	2022	[41]
27	Machine learning techniques applied to mechanical fault diagnosis and fault prognosis in the context of real industrial manufacturing use-cases: a systematic literature review	2022	[42]
28	Decision fusion for reliable fault classification in energy-intensive process industries	2022	[43]
29	Understanding unforeseen production downtimes in manufacturing processes using log data-driven causal reasoning	2022	[44]
30	Machine learning and deep learning based predictive quality in manufacturing: a systematic review	2022	[45]
31	Large-Scale Trace Analysis for Microservice Anomaly Detection and Root Cause Localization	2022	[39]
32	A Cross-Domain Systematic Mapping Study on Software Engineering for Digital Twins	2022	[46]
33	Comparative analysis of machine learning models for anomaly detection in manufacturing	2022	[47]
34	Root Cause Analysis in the Industrial Domain using Knowledge Graphs: A Case Study on Power Transformers	2022	[48]
35	A framework to enhance predictive maintenance installation in high volume production environments: A case study	2022	[49]
36	Interpretable failure risk assessment for continuous production processes based on association rule mining	2022	[50]
37	Improved root cause analysis supporting resilient production systems	2022	[51]
38	Leveraging on causal knowledge for enhancing the root cause analysis of equipment spot inspection failures	2022	[52]

each relevant paper can be found in the corresponding table.

Navigating to table 4, category 1 encapsulates 13 publications that unify RCA and IM methodologies. Of these, eleven papers include a use-case. Eight of them were published after 2020, and the other five were published prior to 2020. Of the eight published papers, only six had a use-case. The most dominant domain is the production domain, with three use-cases. Each use-case is based on data from a real-world plant or product. The same can be observed for the automotive domain use-cases. The IT domain use-case has one direct real-world problem and one experimental setup with log data from an open-source project. In each publication, except for the studies with IDs 31 and 37, IM and RCA are used to solve the problem. For IM, either an ontology or a graph database was necessary, and for RCA, one specific step from the standard [1] is used. Intriguingly, though, no paper employs the full spectrum of RCA steps.

Table 5 encompasses 15 publications emphasizing RCA. Out of this collection, twelve publications provide specific use-cases. Nine of these publications emerged post-2020, whereas the remainder predate this year. Of the post-2020 collection, seven delineate use-cases. Five of the publications are sorted into the production area, which emerges as the predominant domain. A distinction is observed between use-cases leveraging simulated data (e.g., IDs 6, 24, and 25) and those extracting insights from operational environments (e.g., IDs 4, 7, 12, 14, 35, and 36). Paper ID 14 is a special use-case as it originates from the agricultural domain. Nonetheless, the technology used to solve the problem aligns seamlessly with the study's focus.

Table 6 showcases three relevant publications emphasizing IM. One is prior to 2020 published and the other two are after. All three paper cover exclusively a use case in the domain Production IT. Intriguingly, all three converge on the Production IT domain and devote their attention to real-world scenarios, abstaining from synthetic data.

Table 7 presents seven publications of significance contributing to the overall study but are not particularly emphasizing RCA, IM or both. From these paper only one is published before 2020 and the other six after. From all the papers only four papers elucidate a use case. The use

TABLE 3. The main research questions and the derived sub questions.

Research Question	Sub questions
RQ1 What is the current State of the art for RCA regarding IM in a production environment?	RQ1.1 What is the innovative part or the new aspect of the paper? RQ1.2 How is it related to the topic of RCA? RQ1.3 How is it related to the topic of IM RQ1.4 How can it be used for the production environment?
RQ2 What are typical use cases and practical applications for IM for RCA and in which domain were they applied?	RQ2.1 What is the exact use case and in which domain is it positioned? RQ2.2 What is the direct impact on this exact use case or in other words what did change?
RQ3 Which kind of RCA type based on IEC62740 [1], framework, software architecture, algorithm, and standards are in use for an IM on RCA?	RQ3.1 Which kind of paradigm is used for RCA and IM? RQ3.2 Which kind of framework is used for RCA and IM? RQ3.3 Which kind of software language is used for RCA and IM? RQ3.4 Which kind of software architecture is used for RCA and IM? RQ3.5 Which kind of algorithm is used for RCA and IM? RQ3.6 What kind of standard is used for RCA and IM?
RQ4 What are the main challenges and barriers in implementing academic models related to IM and quality assessment in the manufacturing industry?	RQ4.1 Is the solution based on open source use case data like the Tennesse Eastman Process Simulation Dataset? [53] RQ4.2 Is the solution based on a real life application?

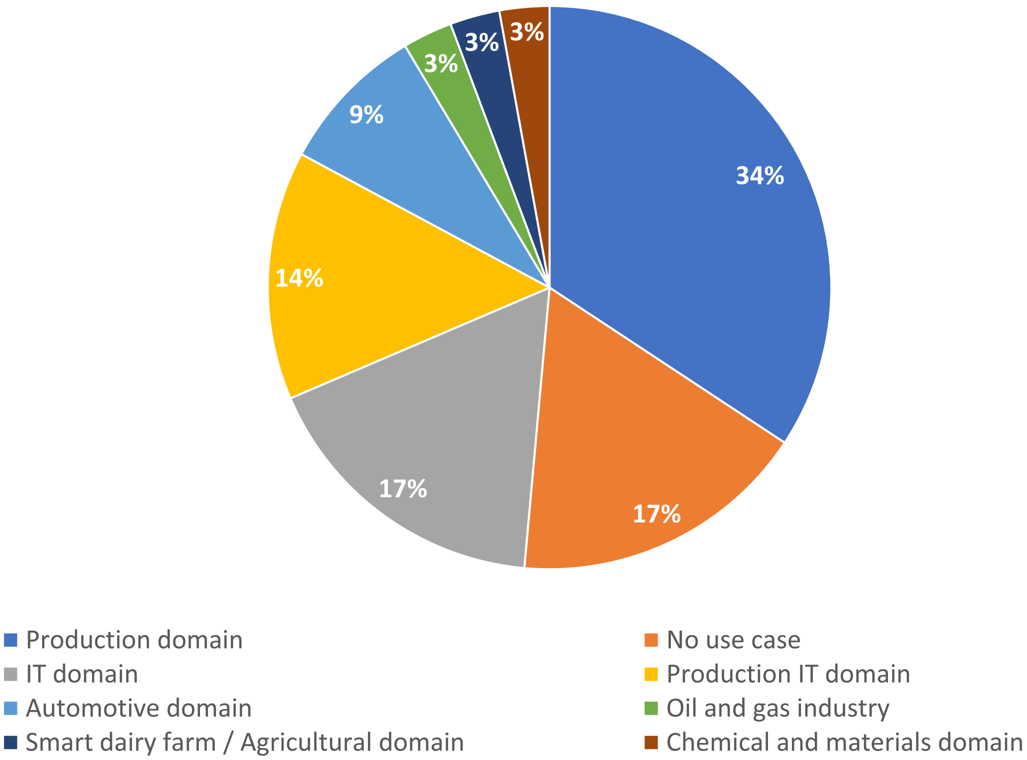

FIGURE 2. The use cases sorted into there corresponding domain illustrated as a pie chart.

cases are more focused on the use of machine log data from simulation models. The target domain of the publications is the Production IT domain, with a substantial subset exploring the algorithmic development.

C. RQ3: WHICH KIND OF RCA TYPE BASED ON IEC 62740 [1], FRAMEWORK, SOFTWARE ARCHITECTURE, ALGORITHM, AND STANDARDS ARE IN USE FOR AN IM ON RCA?

Before answering this question, it is paramount to first elucidate the specific terms and taxonomic rules applied, prior to discussing the results in more detail. Initially, we must explain the annotation used, specifically the notations a), b), c) and d), in regards to RCA. In this paper, a classification based on the RCA - Overview on page 12 of the IEC 62740 [1] has been done. These are the recommended classification classes:

a) There is only one single root cause to identify.
b) There are multiple root causes and eliminating any of the root causes will prevent a focus event from happening.
c) There are multiple root causes and they are all contributory factors for the focus event. Eliminating one of the root causes will only change the likelihood of the focus event occurring but may not prevent it directly.

TABLE 4. Papers Categorized Under Type 1.

ID	Detailed Use Case Description	Domain of Application	Reference
2	Identification of the primary factors influencing repair time for automobiles	Automotive domain	[17]
5	Simulation model of a continuous stirred tank heater	Chemical and materials engineering domain	[20]
8	Aircraft manufacturing	Aeronautics and information technology domain	[23]
9	Addressing software problems related to antivirus configuration corruption	Software analytics in incident management of online services / IT domain	[24]
10	A case study which consists of a series of experiments on six large open source systems	Software maintenance and software development / IT domain	[25]
15	Analyzation of the interference of the stop lamp with body side panel, and functional diagnosis of an engine breakdown at 69.000 Km	Automotive domain	[30]
17	Case study on a washing machine computer board module and it's reoccurring problems within it's product lifecycle management system	Production / Quality domain	[32]
20	Application of graph methodology on a dataset from a drone manufacturing company	Production / drone manufacturing domain	[35]
21	Monitoring quality in an electric resistance welding process by Bosch	Automotive supplier / production domain	[36]
23	Korean cosmetic manufacturing facility which sends sensor and IoT data to a databank and analysis it	Cosmetic industry production domain	[38]
31	No use case	No use case	[39]
34	Knowledge graph about a power transformer	Manufacturing and production domain	[48]
37	No use case	No use case	[51]

TABLE 5. Papers Categorized Under Type 2.

ID	Detailed Use Case Description	Domain of Application	Reference
1	No use case	No use case	[16]
3	Analysis of various software-related incidents	Software domain	[18]
4	Sticky key problem	Automotive domain	[19]
6	Crisis management in a hypothetical oil company	Oil and gas industry	[21]
7	Infant failure, specific example noise vibration harshness (NVH)	Automotive design and development problem from the production domain	[22]
12	An electronic resistance welding for fuel pumps	Production domain	[27]
14	Early detection of lameness in dairy cattle	Smart dairy farm / Agricultural domain	[29]
16	Searching for the RC in the Defects4J benchmark data base	Software testing and debugging / IT domain	[31]
18	No use case	No use case	[33]
19	Remote laser welding process for aluminum doors	automotive production domain	[34]
24	Tennessee Eastman fault diagnosis. Second is a plasma etching process derived from a packaging factory in china	Fault diagnosis of the production domain	[39]
25	Performance check on a 3D point cloud of a CAD model of first-order shell elements. It is an engine hood of an automotive vehicle	Data science with RCA / IT domain	[40]
27	No use case	No use case	[42]
35	Analysis of an extruder screw in an extrusion blow molding machine	Production / Predictive maintenance domain	[49]
36	Carded nonwovens process	Textile industry production domain	[50]

d) There are root causes for successes so to learn by best practice and improve.

Furthermore, we bifurcate our paradigmatic approach to IM. It could either lean on a knowledge-driven or a data driven approach. To classify as a knowledge-driven approach, we must transform expert knowledge into a graph, data bank, algorithm, or some kind of symbolic artificial intelligence (AI). Conversely the data driven approach is based purely on data and the formalization of it. This means that usually a ML or even DL methodology approach will categorize the paper in this category. A mix of both will be categorize as a hybrid approach in our research.

Subsequent tables will be briefly and concisely discussed. The tables are split into the four categories as previously mentioned in the subsections IV-A and IV-B. The focus is set on the framework or model in combination with the used standards. An inherent expectation is that literature post 2015 would predominantly adhere to the IEC 62740:2015 (RCA) standard. However, there are other standards that are helpful and also contributing to finding a root cause or solving a given problem.

Fig. 3 shows the overall distribution of the RCA classes. It is important to notice that paper ID 26 has a special use case which could be split into five different classes of root causes. This explains why the overall amount of classes is higher than the amount of relevant papers. It also shows that the highest amount of root causes cases could be categorized as class c. The second highest number is the amount of unmentioned classes. There, the papers were usually other structured literature research papers without a specific root cause class.

Examining table 8, five articles reveal that they tackle problems classified under the "c" category. The other

TABLE 6. Papers Categorized Under Type 3.

ID	Detailed Use Case Description	Domain of Application	Reference
13	Application of a new comprehensive data processing platform on manufacturing data collected from a real-line automotive parts factory	Automotive production and data processing / Production IT domain	[28]
26	Fashion store which needs to predict the degree of fit of a particular morphotype to a set of body measurements	Production IT domain	[41]
38	Case study based on the metallurgical equipment O&M history and fault investigation	Production IT domain	[52]

TABLE 7. Papers Categorized Under Type 4.

ID	Detailed Use Case Description	Domain of Application	Reference
11	Workpiece tracking within hot forging installations	Production domain / Knowledge management	[26]
22	No Use Case	No Use Case	[37]
28	Simulated data from a pulp and paper plant. Second is a reboiler in a thermomechanical pulp mill which considers the heat recovery network of a thermomechanical pulp mill	Algorithm development for computers in the industry / Production IT domain	[43]
29	Experimental setting with analysis of log-data from a machinery, employing novel methodologies	Production IT domain	[44]
30	No Use Case	No Use Case	[45]
32	No Use Case	No Use Case	[46]
33	Log-data from a real-life machine and a simulation model of a machine with artificial build in machine breakdown logs	Production IT domain	[47]

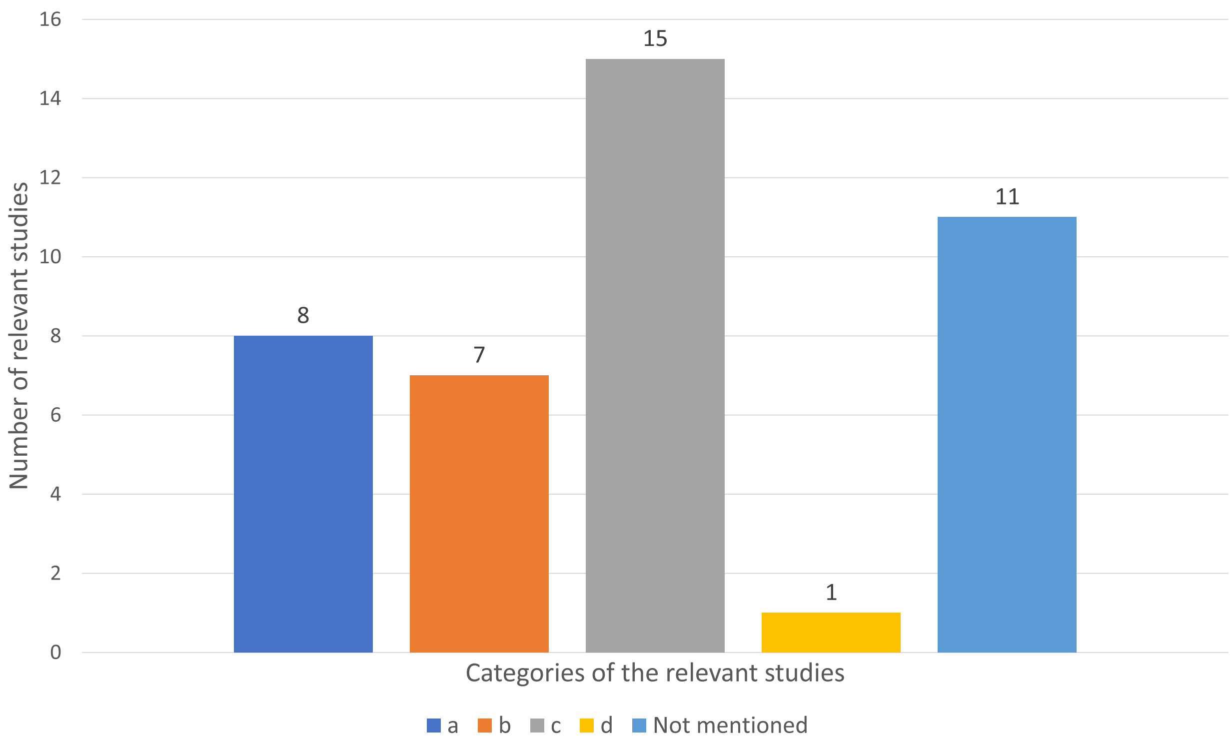

FIGURE 3. The overall distribution of the different root cause classes.

papers are pairwise classified with "a" or "b" or remain unspecified. The underlying paradigm for the IM exhibits a balance between data- and knowledge-driven. paper ID 5 is an extra mention of the paradigm, which is the object-oriented (OO) paradigm from software development.

When scrutinizing the utilized framework, most papers build their frameworks using a standard or norm. This trend is mirrored in the models, with many also relying on established norms or standards. A subset of articles - specifically IDs 2, 9, 10, 20 - utilized frameworks rooted in cloud-based or ontology-based methodologies but did not cite a standard. The exception for this is paper ID 34, which cites the OWL and W3C standard used. Paper ID 15 adopts an internal standard, which is a specific standard for their material analysis. The 7-step approach, also derived from Toyota's problem-solving (PS) approach, couples with it. Notably, paper ID 34 is the only paper that directly uses the RCA standard and the suggested framework.

Transitioning to table 8 and focusing on the software tools, the used software, and in regards to the publishing date and our category for "old" or "new". The publications with the ID 2, 5, 10 are older papers which are using Java. Paper ID 17 uses already MATLAB, and in paper ID 20 is the first mention of Python. This is an important fact because Python is already more than 30 years old (first release was on 20.02.1991) and became recently popular among the software languages.

Table 9 presents six publications which are categorized as a c paper, supplemented by three b and two a classified paper. The other publications have no clear type. Only paper ID 6 uses a knowledge-driven IM approach, whereas the remainder largely adhere to a data-driven paradigm, or in the instances of IDs 14 and 18, employ a hybrid methodology.

Contrary to the previous table, this paper presents models and a framework that is not base on standards. Apart from papers ID 35 and 36, which make oblique references to established standards, most frameworks and models take their methodology from prior scholarly works and notably, paper ID 6 utilizes STAMP. Predominantly, these papers espouse a process-oriented approach over algorithmic intricacies. They primarily aim to enhance operational efficiency by meticulously identifying root causes and applying predictive analytics to anticipate problems or system failures.

Adding another layer of complexity, authors report the software tools employed across these papers unevenly. Specifically, seven out of the 15 papers conspicuously remain silent on this aspect. Recent entries, particularly IDs 16 and 36, demonstrate a preference for the programming language Java and Python. The other papers used more CAD software or were like paper ID 14, 18 and 19—a mix of cloud technology, DL, and or CAE simulation.

Table 10 predominantly centers on IM, yet presents an anomalous instance in paper ID 26, which lacks a clear IM definition despite featuring three distinct use cases and the ensuing problem formulation. Notably, each paper in this set can be categorized under one of the established RCA classifications. Within this context, paper ID 13 employs a GUI as its underlying framework, whereas paper ID 38 has a knowledge graph for its spot inspection used as their model. The used software is the Java-based Neo4J graph database.

In the last table 11 there are two c and one a and b categorized RCA types. The IM is in most cases data-driven or skews towards data-driven methodologies. Paper ID 30 and 33 mention frameworks and models which are based on standards. Paper ID 32 is a comprehensive study on digital twins across different domains, applied implementation technologies, and purposes. Only this and paper ID 22 mention the used software. Moreover, paper ID 32 does reference a standard, its application thereof is implicit rather than explicit. Overall, the papers in this table primarily engage in comparative analysis of various ML models that hold potential utility for RCA.

D. RQ4: WHAT ARE THE MAIN CHALLENGES AND BARRIERS IN IMPLEMENTING ACADEMIC MODELS RELATED TO IM AND QUALITY ASSESSMENT IN THE MANUFACTURING INDUSTRY?

To answer this research question, several key factors need to be examined. The first one is the availability of data for academic research. Domain-specific data is essential for developing accurate and effective models. Without such data, models cannot fully encompass the range of scenarios encountered in specialized use-cases, or meet the necessary criteria to solve a given problem, see [24]. To answer this question, we first determine what kind of data the publication used and whether it relies on an open-source simulation model from the industry, like the Tennessee Eastman Process Simulation Dataset [53]. The next consideration is the data source, specifically whether the data comes from simulations or real-world applications. This is the differentiation meant between a pure simulation model which delivers data, or a real-life physical environment. Even if a model is very complex, simulation data cannot encompass all the intricacies of a real-world environment. In addition, this would directly contradict the intended use of a model. However, we can obtain data from scenarios that are too dangerous for a production environment or not beneficial enough for the user. An example would be scrap parts for very expensive sensors. Finally, we must consider each model's applicability limitations. Each publication is looking at a very specific situation and use case. This means that it is in most cases hard to transfer the knowledge and solution of one use case onto another use case. Therefore, the limitations of each publication must be carefully evaluated.

V. DISCUSSION

In this section, the different research questions are recapitulated and discussed.**RQ1: What is the current state of the art for RCA regarding IM in a production environment?** The conclusion of the research question 1 would be the definition of the "new" state of the art. This is summarized in the three core technologies for graphs, association rule mining, and DL. Specifically, the use of DL algorithms is becoming more common due to better infrastructure for data availability. This infrastructure is enabled through the use of IMs. Still, the workload that is necessary to build an IM, which could be used for RCA, is high. The workload for maintenance is usually not discussed in the paper, but based on the workload to build one, the maintenance workload should also be high.

RQ2: What are typical use cases and practical applications for IMs for RCA and in which domains were they applied? The next research question 2 shows a diverse distribution of domains. Due to the search algorithm for production use cases, the main problems were directly related to production. The only exception is paper ID 14 with its

TABLE 8. The category 1 paper.

ID	Type of RCA and paradigm for IM	Framework or model	Used software	Used standards	Reference
2	b, IM hybrid data driven and partially knowledge based	Association rule mining, case based reasoning and text mining. The IM is ontology based	Java enterprise edition	–	[17]
5	RCA not mentioned, OO paradigm for IM	signed digraphs (SDG)	Java: CAEX/AML	IEC 62424 [54], VDI/VDE-Guideline 3682(2005) [55]	[20]
8	c, knowledge driven IM	failure modes and effects analysis (FMEA), failure mode, effects and criticality analysis (FMECA), fault tree analysis (FTA), fishbone diagram, conceptual graph (IM)	not mentioned	ISO/DIS 31000 [56]	[23]
9	a, IM not mentioned but knowledge based paradigm powered by data driven decision making	Cloud Framework, IM is hidden markov random field algorithm	SQL	not mentioned	[24]
10	a, IM Data driven	Cloud based framework, IM fact extraction Tool-Chain	Java, Amarok, Dolphin, Kopete, Konqueror, GTK+, Nautilus	not mentioned	[25]
15	c, IM data driven	Process called 7 Step unifying step 5 and 6 of Toyota's PS method that are developing and implementing countermeasures in one-step as countermeasures	not mentioned	FCA 52706 [57]	[30]
17	b, IM data driven	heuristic RCI solution based on the fuzzy weighted association rule mining (FWARM) for quality accidents	MATLAB simulation is used to generate 3000 transaction data records in the product lifecycle	not mentioned	[32]
20	c, IM not mentioned	i-dataquest framework which are basically knowledge graphs	Graph storage: Neo4J, Text extractor: Apache Tika, Text from Images: Tesseract, NLP: Stanford CoreNLP, Python Neo4j Library: Py2neo, Python	not mentioned	[35]
21	not mentioned RCA or IM	knowledge driven approach with the reasonable ontology Templates (OTTR) Framework	template processor tool Lutra	ISO 9241-11 [58], ISO 14327 [59]	[36]
23	c, IM not mentioned	Process reference model and a maturity model	not mentioned	ISO 8000-61 [60], ISO 8000-62 [61], ISO 8000-63 [62], ISO 8000-64 [63], ISO 15504-5 [64], ISO 33001 [65] , ISO 33003 [66], ISO 33004 [67], ISO 33020 [68]	[38]
31	RCA not mentioned, IM not mentioned	Not mentioned	not mentioned	not mentioned	[39]
34	c, IM knowledge driven and close world paradigm	Framework by IEC for RCA and for IM it is OWL and based on the Semantic Rule Language (SWRL)	Python with Scikit Learn, SPARQL, RDF/XML as description	OWL and 3W standard, (RCA Standard IEC 62740:2015) [1]	[48]
37	Not mentioned	Not mentioned	not mentioned	not mentioned	[51]

agricultural use case for lameness detection in cows. The overall result shows a growing research field in the area of Production IT. In an academic sense, the main questions will be about developing new methods for more efficient RCA. In an industrial context, the implementation and the reduction of the initial workload for building IMs will probably be the center of attention. **RQ3: Which kind of RCA type based on IEC 62740 [1], framework, software architecture, algorithm, and standards are in use for an IM on RCA?** Research question 3 is showing that the biggest part of all relevant papers focus on solving multiple root causes and they are all contributory factors for a focus event. The complex production environment becomes apparent from this analysis. Authors have provided very specific descriptions of the used models or frameworks in nearly all the relevant papers. This is probably due to the nature of academic research to emphasize the description of the method, model, or framework that leads to a solution. The complete opposite is observed in the description of the used software languages. The used software IDE is most of the time not mentioned. Also, there is a trend towards the software language Python for RCA instead of Java. This should also be attributed to the easy entry level for researchers programming for the first time. A similar situation appears with the standards used. Most of the papers are not following along with any kind of a standard. The lack of standard solutions complicates their integration into the highly regulated production environments. **RQ4: What are the main challenges and barriers in implementing academic models related to IM and quality assessment in the manufacturing industry?** The last question 4 and its

TABLE 9. **The category 2 paper are only focused on the RCA and contain only minor parts about IM.**

ID	Type of RCA and paradigm for IM	Framework or model	Used software	Used standards	Reference
1	b, IM not mentioned	radial analysis chart	not mentioned	not mentioned	[16]
3	c, IM not mentioned	fishbone diagram	CAD and ERP	not mentioned	[18]
4	c, IM not mentioned	inter-loop model which takes information from different phases to determine root causes and corrective actions	CAD	not mentioned	[19]
6	c, Knowledge driven IM	systems theoretic accident modeling and processes (STAMP) model is used for RCA	not mentioned	not mentioned	[21]
7	c, Data driven IM	fuzzy TOPSIS and rough set theory, IM graph based	not mentioned	not mentioned	[22]
12	c, Data driven IM	Framework by Rooney and Vanden Heuvel. Four step approach where the root cause identification is just part of the whole RCA-Process	not mentioned	not mentioned	[27]
14	b, IM hybrid	mix of edge intelligence with pedometer sensor, a fog intelligence for data classification, aggregation and processing and feature selection at the end a cloud intelligence where analytics and machine learning is done	Microsoft Azure, IBM Watson, MQTT	not mentioned	[29]
16	a, IM data driven but used for knowledge acquisition	causal testing which computes minimally different test inputs that, nevertheless, produce different behavior	Java programs	not mentioned	[31]
18	c, IM hybrid	probabilistic risk / safety assessment (PRA/PSA) and prognostic and health management(PHM)	broad range of data sources for the analyzation	not mentioned	[33]
19	Not clear, IM is data driven	closed-loop in process (CLIP) which fuses in-process data, data analytic and physics-driven simulation	CAE simulation tool, DL and a data base for the sensor data	not mentioned	[34]
24	b, IM data driven	non revisiting searching framework for the RCA	not mentioned	not mentioned	[39]
25	a, IM data driven	nonlinear graph convolution neural network which helps to overcome the current linear approaches	not mentioned	not mentioned	[40]
27	not mentioned	not mentioned	not mentioned	not mentioned	[42]
35	not mentioned	Framework of three: analysis of available data and the maintenance analysis, the criticality assessment and the feasibility classification for PdM	not mentioned	IEC 60812:2018 FMEA and FMECA [69]	[49]
36	not mentioned	Framework from IEC 62740:2015	Python	Ishikawa 1996, fault tree analysis IEC 61025:2006 [70], RCA (IEC 62740:2015) [1], failure mode, effects and criticality analysis (FMECA) (IEC 60812:2018) [69]	[50]

corresponding results out of the literature research indicates a big problem with domain-specific data. Usually, it is necessary to have very specific domain knowledge to find a root cause in a production environment. It is also necessary to work in a team of people from different departments, which could be related to the problem's root cause. This means that for academic research it is necessary to develop models which are very complex and specific, based on heterogeneous data sets from different departments. The problem lies with this kind of data because usually it is the know-how of the company. Open data sources from production use cases are difficult to acquire and published papers usually don't provide any data. The study shows that with 38 papers, the general amount of papers of interest is relatively low. In a percentage value, this is only 6.9 % of all the 546 found publications in the database. The reason for this could be the long search terms in the four different database publications. Also the selected databases cannot cover the entire topic. This could be a point for future research to investigate in other databases and to include new databases.

TABLE 10. The category 3 paper.

ID	Type of RCA and paradigm for IM	Framework or model	Used software	Used standards	Reference
13	a, IM data driven	GUI	not mentioned	not mentioned	[28]
26	Predictive maintenance = a, quality management = b, c and ZDM = a, d, IM nm	not mentioned	not mentioned	not mentioned	[41]
38	c, IM data driven	causal knowledge graph-ALBERT which incorporates a spot inspection knowledge graph and a chain relation knowledge into a single model	Neo4J	not mentioned	[52]

TABLE 11. The category 4 paper.

ID	Type of RCA and paradigm for IM	Framework or model	Used software	Used standards	Reference
11	c, data driven IM	Cloud based framework for the IM	not mentioned	not mentioned	[26]
22	RCA not mentioned, Data driven IM	not mentioned	Keyword co-occurrence network	not mentioned	[37]
28	c, IM not mentioned	Multiple ML fault classifier where the output is fused / ensemble learning	not mentioned	not mentioned	[43]
29	a, IM knowledge driven	causal graphical model for IM, RCA it is causal learning	not mentioned	not mentioned	[44]
30	nm, IM nm but predictive quality of manufacturing process	DIN 8580:2003-09 [71], this DIN describes a categorization of processes. The six main groups are: primary shaping, forming, cutting, joining, coating and changing of material properties	not mentioned	DIN 8580:2003-09 [71]	[45]
32	RCA not mentioned, IM not mentioned	not mentioned	For Digital Twin (DT) Maya Simulation Framework, Siemens PLC Sim Advanced, Sinumatik 3D, Verosim, Computer aided design and manufacturing (CAX), Autodesk Revit, CATIA, Delima 3D Experiment, Siemens NX, Solidworks	ISO 16739 [72], ISO/IEC 15288 [73]	[46]
33	b, IM data driven	ML Framework, Scikit-Learn and PyOD, Local Outlier Factor (LOF), Clustering-Based Local Outlier Factor (CBLOF), K-Nearest Neighbors (KNN), Feature Bagging (FB), Isolation Forest, Copula-Based Outlier Detection (COPOD), FAST-MCD, AutoEncoders	Python	Cross-industry standard process for data mining (CRISP-DM)	[47]

The biggest remark or most unexpected realization is the rise in the amount of published papers regarding RCA, IM and AI in production. The main bulk of our relevant papers is from the year 2020 onward. This is an interesting finding as this result indicates the steady incorporation of new technology into a relatively old field. In Fig. 4 the rise of publications is visualized.

VI. CONCLUSION

This study synthesizes the insights gleaned from addressing four pivotal research questions, presenting a unified picture of the advancements and persistent challenges in the field of RCA, IM, and ML within production environments. Firstly, we reaffirm the continued relevance of graphs and association rule mining in RCA and highlight the notable rise in the DL technologies. The increasing availability of data and the accessibility of Python as a programming language have lowered the entry barrier for researchers and practitioners alike, enhancing the analytical capabilities of RCA systems. However, the literature still lacks specific metrics for evaluating these improvements.

Secondly, the emergence of "Production IT" as a distinct domain reflects the evolving nature of production processes from purely mechanical operations to complex, data-driven systems. This transition requires sophisticated IMs capable of handling vast amounts of digital input and managing

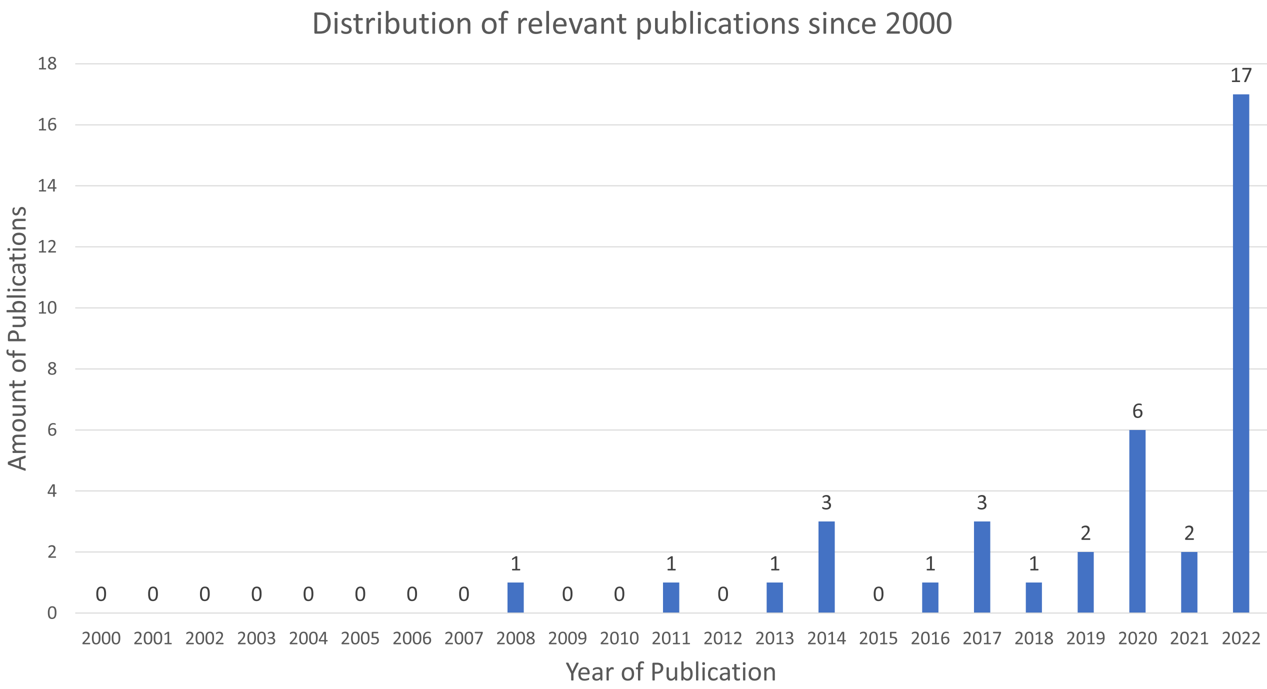

FIGURE 4. The diagram shows that more then 44 % of all the relevant paper where published in 2022.

the intricate dynamics of modern production lines. These changes profoundly influence operational strategies and the RCA approaches employed by industries. The findings of this research underscore the enhanced capability of integrated ML models to refine RCA processes within the production sector. This integration not only elevates the precision of diagnostics but also provides a robust framework for predictive maintenance strategies, thereby significantly reducing downtime and improving operational resilience. Future work should explore the scalability of these models across different industries, potentially broadening the scope of their application.

Thirdly, our analysis shows that the most prevalent form of RCA in production settings involves addressing multiple contributory factors to a problem, rather than isolating single causes. The least common case is the RCA for success, to learn from best practice and improve. This complexity necessitates robust, adaptable frameworks that can accommodate the multifaceted nature of production issues. Yet, the application of standardized algorithms and norms in RCA remains limited, posing challenges to the scalability and reproducibility of these solutions. In addition, the solutions are usually a very specific fit for the use case and not related to a standard or norm.

Fourthly, we identify significant hurdles in implementing academic models, particularly the scarcity of open-source, high-quality, domain-specific data. This limitation critically restricts the development and validation of models tailored to real-world production scenarios. The quality of data not only influences the accuracy of models but also their ability to generalize from training environments to actual operations. While this study provides valuable insights into the integration of RCA, IM, and ML within production environments, it is not without limitations. One of the primary constraints is the reliance on secondary data from published papers, which may not always capture the full range of real-world applications and challenges. Additionally, the specificity of case studies reviewed limits the generalizability of our findings across different industrial sectors. Future research should aim to collect primary data from diverse production settings to validate and refine the proposed methodologies.

Furthermore, the development of more comprehensive, domain-specific datasets is crucial for advancing RCA and IM practices. The lack of standardized, high-quality data sets in certain production domains restricts the potential to fully leverage ML capabilities. Investigating the creation and utilization of such datasets could be a significant area of focus.

Moreover, the integration of these advanced methodologies into existing production systems poses significant challenges due to the variability in technological adoption and infrastructure capabilities among different industries. Future studies could explore strategies for overcoming these barriers, perhaps by developing more adaptable and scalable models that can be customized for various technological contexts.

Lastly, as new ML algorithms and IM techniques continue to emerge, ongoing research will be essential to continuously evaluate their effectiveness in production environments. Establishing benchmarks and creating frameworks for systematic evaluation would provide clearer pathways for integrating these technologies into practical applications.

As no reviewed papers provided quantifiable metrics to gauge the effectiveness of proposed solutions, our study underscores a clear gap in current research. IM is highly dependent on the understanding of the modeler and his experience and skills [74]. This statement also applies to the quality manager, who is responsible for the RCA. If the available data is of lower quality, e.g., bad image data from the end-of-line optical inspection or time-series data with a very high noise ratio, the time to find a root cause or build a fitting IM can extend. Also, quality data is very important for new technology like, with its deep neural network model architecture, to be used [75]. This means that there is a pressing need for established benchmarks or objective evaluation values that could more concretely measure the impact of new RCA, IM, and ML technologies in production settings. This would facilitate a more empirical assessment of innovations in this area and support the development of implementation guidelines. New measurement methods need to be introduced which are extending the current practice of solely involving data science typical metrics like accuracy, precision or recall.

In conclusion, while our study has illuminated various advancements and challenges, it also highlights the critical need for more rigorous empirical evaluations and the development of standards in the application of ML and IM in RCA. We recommend focusing future research on creating and leveraging open-source, high-quality datasets to build and test models that are both effective and adaptable to the unique conditions of production environments. Additionally, exploring quantifiable benefits and articulating clear metrics for success in RCA practices are essential for advancing the field and ensuring robust and reliable decision-making in production quality management.

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