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Review

Improved root cause analysis supporting resilient production systems

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ABSTRACT

Manufacturing companies struggle to be efficient and effective when conducting root cause analyses of production disturbances; a fact which hinders them from creating and developing resilient production systems. This article aims to describe the challenges and enablers identified in current research relating to the different phases of root cause analysis. A systematic literature review was conducted, in which a total of 14 challenges and 17 enablers are identified and described. These correlate to the different phases of root cause analysis. Examples of challenges are "need for expertise", "employee bias", "poor data quality" and "lack of data integration", among others. Examples of enablers are "visualisation tools", "collaborative platforms", "thesaurus" and "machine learning techniques". Based on these findings, the authors also propose potential areas for further research and then design inputs for new solutions to improve root cause analysis. This article provides a theoretical contribution in that it describes the challenges and enablers of root cause analysis and their correlation to the creation of resilient production systems. The article also provides practical contributions, with an overview of current research to support practitioners in gaining insights into potential solutions to be implemented and further developed, with the aim of improving root cause analysis in production systems.

1. Introduction

Within the context of manufacturing companies, the concept of resilience has received significant attention in recent years; especially after the outbreak of the COVID-19 pandemic. To survive and thrive in a competitive global market, manufacturing companies need to foster the creation and development of highly resilient production systems[1] [1]. Hollnagel et al. [2] point out four primary abilities that a production system needs if it is to become resilient to disturbances: (1) the ability to learn or *know what has happened*, (2) the ability to respond or *know what to do*, (3) the ability to monitor or *know what to look for*, and (4) the ability to anticipate or *know what to expect*. The focus of this study is on the first of these four abilities; the ability to learn from past experiences of production disturbances.

In manufacturing companies, a commonly applied strategy for learning from past disturbances is to conduct a root cause analysis. This is an investigative process to understand why a disturbance has happened by identifying its underlying causes, or "root causes" [3]. Once these root causes have been identified, countermeasures may be proposed and implemented to eliminate them [4]. The process ensures that the same disturbance will not happen again in a production system or, if it does reoccur, that its impacts will be minimised [4]. The process may also provide inputs into the design of more resilient production systems, targeting improved operational performance [5].

Nevertheless, manufacturing companies struggle to deal with production disturbances in their daily operations; as many as a hundred a day are not uncommon [6]. A significant proportion of such disturbances will most likely have been experienced before [7]. This points to a potential need to improve the root cause analysis process. Doing so might allow manufacturing companies to enhance their ability to learn from past disturbances and lead to the design and development of more resilient production systems [8]. The upcoming Industry 4.0

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[1] In this article, the terms *production system and manufacturing system* are used as synonyms. This reflects the fact that these terms are often used interchangeably in the context being studied, i.e. manufacturing companies. However, the authors acknowledge that this might not be the case for all research areas. In some contexts, clear distinctions may be made between these two terms.

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technologies is expected to afford new opportunities for root cause analysis. Lee et al. [9] predict that implementing cyber-physical systems will lead to worry-free manufacturing. The leading Industry 4.0 technologies include smart sensors and devices, data analytics, big data, Internet of Things, cloud computing and augmented and virtual reality [10].

While practitioners still struggle to be efficient and effective when conducting root cause analyses, the literature on this subject seems to be fragmented. There is a need for publications that condense current findings and make the knowledge more accessible to practitioners, whilst providing researchers with information on further academic developments. Hence, this article aims to describe the challenges and enablers identified in the literature regarding root cause analysis in the context of production systems. In this study, "challenges" refer to difficulties that practitioners encounter when performing root cause analysis, whereas "enablers" refer to activities or tools that practitioners can use to facilitate the same process. To achieve the defined aim, the authors conducted a literature review. To the best of the authors' knowledge, this is the first literature review regarding the subject.

The article is structured as follows. First, the frame of reference is presented, focusing on resilient systems, production disturbances, and the root cause analysis process. The methods used in the literature review are then detailed. Subsequently, the results are presented. These summarise the main challenges and enablers being researched in this area in terms of the different phases of root cause analysis. This is followed by a discussion, presenting a research agenda for the field, plus the main contributions of this study. Finally, the conclusions are presented.

2. Frame of reference

2.1. Resilient production systems and production disturbances

The concept of *resilience* has been used with different meanings and implications in various fields such as ecology, social science, psychology, economy and engineering [11]. This study focuses on resilience in the engineering field; more specifically the case of production systems in which the term has become more and more important [12,13]. The definition of resilience adopted here is that suggested by Zhang & Van Luttervelt [14] namely, "*the resilience of the production system means the system's capability of leading to success from failure on the system's own - in particular its own infrastructure, substance*". This definition considers a production system to be a sociotechnical system, including humans, machines, materials, energy, data, information and processes. When there is a disturbance, resilient production systems have the capacity to remain stable, respond fast, adapt and learn from the experience [14].

Zhang and Van Luttervelt [14] suggest some guidelines for developing resilient systems, such as increasing redundancy, total function management and ontology modelling to understand possible reconfiguration modes for disturbances. The same authors also emphasise a specific guideline whereby learning from past disturbances should be promoted in production systems. Dinh et al. [15] concur, suggesting that disturbances should be minimised and their effect limited. This, in turn, may be achieved by learning from past disturbance events. Hollnagel et al. [2] propose four abilities that characterise resilient systems: anticipating, monitoring, responding and learning. Once again, learning from the experience of production disturbances is listed as a necessary feature in developing resilient production systems. Moreover, learning from disturbances in existing production systems can provide the necessary knowledge for designing new, resilient production systems [5].

Production disturbances are all unwanted and unplanned events that make a system not perform as expected [16]. In a production system, hundreds of disturbances a day must often be managed [6]. These include quality issues, material shortages, machine failures, reprogramming, absenteeism, and incidents [17,18]. There are different ways to classify disturbances. For example, they may be internal or external to the production system; they may have minor or major impact; they may be completely new events or reoccurrences of past disturbances [19,20]. This study focuses on disturbances that reoccur, regardless of their source (internal or external) or their impacts (minor or major).

When managing disturbances, companies tend to follow six different stages: (1) detection, (2) diagnosis of the immediate cause, (3) mitigation to re-establish normal conditions, (4) root cause analysis, (5) prevention and (6) prediction [16]. The first three stages may be considered reactive and the last three proactive. The reactive stages focus on ensuring that normal operating conditions are re-established after a disturbance. By contrast, the proactive stages concentrate on ensuring that disturbances will not reoccur or, if they do, that their impacts are minimised [16]. Specifically, the root cause analysis stage concentrates on understanding why a disturbance happened. It identifies the causes so that these may be dealt with and inhibits similar disturbances from reoccurring in the production system. The following sub-section provides further details about this stage.

2.2. Root cause analysis

Root cause analysis is a problem-solving method that became widespread with the introduction of the Toyota production system and the lean manufacturing approach, which supports manufacturing companies in their continuous improvement processes of areas including production cost, productivity, quality, and maintenance [21,22]. Root cause analysis comes about as an investigative process conducted after the occurrence of a production disturbance. Its aim is to determine the root causes and implement corrective action [3,4,23]. Root causes are the most essential, underlying causes of a disturbance [23]. A disturbance is only eradicated (without reoccurring) if the root causes are corrected and eliminated, rather than merely addressing the immediate and obvious symptoms [4,24].

The root cause analysis process is often conducted by a group of people with diverse backgrounds [3,23]. When conducting root cause analysis, groups might use one or more different tools and methods to find the root causes [23]. Among the most commonly applied tools and methods are five whys, fishbone diagrams, cause and effect analysis, fault tree analysis and Six Sigma [24,25]. The process of root cause analysis can also be conducted in different ways, with different phases [4]. However, in manufacturing companies, the root cause analysis process tends to consider the phases of: (1) problem identification, (2) data collection, (3) identification of root causes and (4) identification and implementation of countermeasures [26,27].

Manufacturing companies still struggle to be effective and efficient when conducting root cause analysis of their production disturbances. Firstly, defining the root causes tends to be time-consuming, sometimes taking months [28]. Time is needed to collect all the information, analyse the data, draw conclusions and verify the root causes and countermeasures. Secondly, finding the real root causes can be a difficult task, commonly necessitating the participation of a multidisciplinary group of people. Since time and knowledge can be limited in manufacturing companies, a great number of disturbances end up not being investigated [6]. At other times, when disturbances are investigated, the conclusions as to the root causes may be inexact, leading to their reoccurrence in a production system [3,29,30].

Nevertheless, it is anticipated that the way manufacturing companies conduct root cause analyses of their production disturbances will change. With the rise Industry 4.0 technologies, different solutions will support root cause analysis [27]. Some researchers have even envisioned a production system nearly free of disturbances due to the implementation of Industry 4.0 technologies and new ways of working [9]. Various technologies support the realisation of the Industry 4.0 era. The most important are smart sensors, smart devices, data analytics, cloud technologies, big data, the Internet of things (IoT), augmented and virtual reality [10,31,32].

3. Methods

To achieve the aim of this study (as presented in the Introduction), the authors chose to conduct a literature review. This approach is considered appropriate when the research objective (as with the present study) is to provide an overview of an issue [33,34]. The proper steps were followed to enhance methodological quality, as presented in the following sub-sections. These were targeted to make this review clear and trustworthy, following the recommendations of Aguinis et al. [35], Moher et al. [36], and Snyder [33].

3.1. Goal and scope

The literature review process was started by defining the goal of the research and delimiting its scope, as suggested by Aguinis et al. [35]. This study's goal was defined as being "to identify and describe the challenges of, and enablers for, root cause analysis of production disturbances in the context of production systems". Once the goal was defined, the authors checked whether any previous publication had addressed the same or a similar issue. A search was carried out in Scopus and Web of Science. However, these searches did not reveal any relevant publications.

Regarding the scope of the literature review, the authors determined that it would focus solely on academic publications. This choice was made since the objective of the article was to describe current research in the field. Among the academic publications, qualitative and quantitative studies would be considered as well as empirical and theoretical ones. This literature review also focused on root cause analysis of production disturbances in the context of production systems. In this study, "production systems" (or "manufacturing systems") refer to manufacturing companies' industrial processes for transforming raw materials into finished goods.

3.2. Identification of articles

The identification of articles was the next step in the review process, consistent with the recommendations of Aguinis et al. [35] and Snyder [33]. The authors decided not to select any specific journals for the extraction of articles. This was because the topic being investigated (root cause analysis of production disturbances) has been published in a wide range of journals. Thus, any limitations on journals might lead to the exclusion of relevant publications. Instead, the authors chose to search for articles in databases, accessing a large number of journal sources. Scopus and Web of Science were the databases selected for the search, due to their extended coverage. The keywords for the database searches were then defined. This was an interactive process between the authors, with different searches being tested and the results analysed. Several discussion and feedback sessions between the authors took place until a consensus was reached on the keywords. The final agreed keywords were ("root cause analysis" AND ("production system*" OR "manufacturing system*")). The authors chose not to include the term "resilience" in the search, as this might have excluded many publications which did not explicitly establish a relationship between root cause analysis and resilience. The defined keywords were searched in the two databases limited to articles' titles, abstracts and keywords on the 12th of May 2021.

3.3. Inclusion and exclusion criteria

The next step was to define the inclusion and exclusion criteria, as advised by Aguinis et al. [35], Snyder [33] and Moher et al. [36]. Table 1 shows the agreed exclusion criteria. The first criterion for excluding articles related to the context of manufacturing companies. Root cause analysis is a process commonly applied in other fields such as medicine, software development, nuclear energy, construction and so on. However, articles unrelated to production system applications (specifically in manufacturing companies) were excluded. The second criterion concerned the relationship of the article to *production* disturbances. Articles related to disturbances in other contexts (project management, for example) were excluded. The third criterion related to the article's focus on root cause analysis. Articles mentioning "root cause analysis", but which were not closely related to the topic, were excluded. Examples were articles claiming that root cause analysis was needed for a specific issue but which did not develop the idea. Finally, the authors defined a criterion for excluding similar articles. In cases where two similar articles had the same authors (a conference paper and an extended journal paper, for example), the less complete article was excluded.

Table 1
Agreed exclusion criteria.

Criteria	Criteria explanation
Not related	Not-Man: the article is not related to manufacturing companies Not-Dis: the article is not related to production disturbances Not-RCA: the article is not related to root cause analysis SW: a similar article was identified

3.4. Selection of articles

After defining the inclusion and exclusion criteria, the authors selected the articles, as summarised in Fig. 1 (process adapted from [36]). This step started with the identification of 60 articles from Scopus and 36 articles from Web of Science; 96 in total. After removing the duplicates, 67 articles were selected. The abstracts of those 67 were read and screened based on the criteria presented in Table 1. Where doubt persisted, the authors decided to include the article for the next stage (full reading). In total, 39 articles were selected for full reading. After full reading, the articles were screened again, based on the exclusion criteria. Finally, 34 articles were selected for content extraction.

3.5. Data analysis

The data analysis process started with the organisation of papers according to their titles, authors, source titles, database where they were found and year of publication. The articles were then classified according to type of study (empirical/not empirical), proposition of an enabler (yes/no), related technologies (type of technology, or not technology-related). The objective of this step was to gain an overview

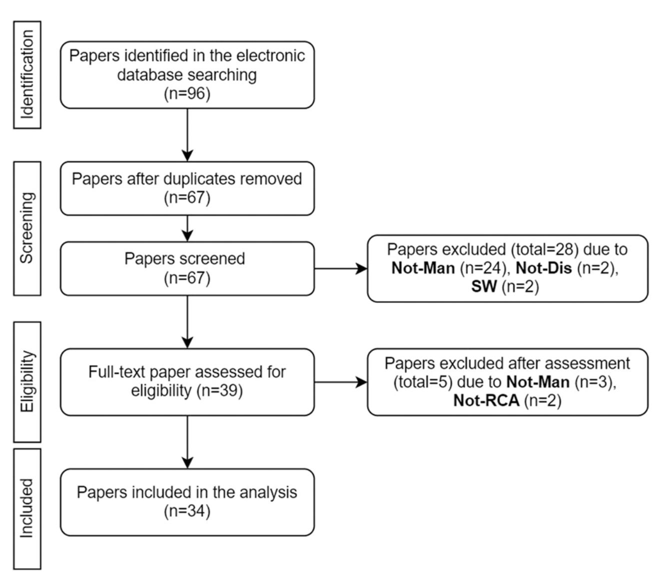

Fig. 1. Literature review process.
(adapted from [36] for this study)

of current research.

Fig. 2 shows the framework used as a basis for content extraction and analysis. The authors looked for data to populate the proposed framework in terms of challenges and enablers in the root cause analysis process, which might impact the ability to learn from past disturbances and develop resilient production systems. The selected articles were read and coded using the Nvivo software. New codes were extracted as they emerged in the reading/coding process and classified as "challenges" or "enablers". Once all the articles were coded, the codes in "challenges" and "enablers" were further classified into the different phases of the root cause analysis process: (1) problem identification; (2) data collection; (3) root cause identification; and (4) countermeasure identification and implementation. An additional phase ((5) knowledge management) was derived inductively from the codes. The codes were then labeled inductively, accordingly to what type of challenge or enabler they were tackling. Labels such as "employee bias" or "expertise need" are examples of labels under "challenges", while "data architecture development" and "collaborative platforms" are examples of labels under "enablers".

4. Results

4.1. Overview of included articles

Fig. 3 presents the publication years of the selected articles. It should be noted that the search was conducted in May 2021 and did not, therefore, cover the whole year. The 34 articles were collected from 30 different sources (journals and conference proceedings), showing that publication on this subject is quite widespread. The years of publication in Fig. 3 and the wide variety of publication sources indicate that there is no clear trend in the publication of relevant articles about root cause analysis. The selected articles were classified as "empirical" or "not empirical" and as "proposing a solution" or "not proposing a solution". The field is quite practice-orientated, as reflected by the fact that 94% of the articles present empirical results. Furthermore, the field has a pragmatic orientation, with 64% of the articles proposing practical solutions for improving the root cause analysis process. The authors identified 14 different challenges and 17 different enablers presented in

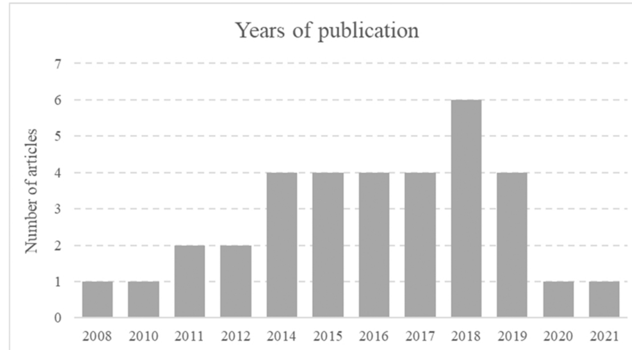

Fig. 3. Years of publication of selected articles.

Table 2
Challenges in the root cause analysis process.

Phase in RCA process	Challenge	Related literature
1. Problem identification	Large volume of alarms	[37.[38]
	Need for expertise	[39.40]
	Employee bias	[26]
2. Data collection	Lack of data	[41–43]
	Poor data quality	[41,44–46]
	Lack of data integration	[44,47,48]
3. Identification of root causes	Large volume of data	[39,46]
	Expertise need	[30,42,45]
	Employee bias	[26]
	Miscommunication	[49,50]
	Ad hoc process	[40,50–52]
4. Identification and implementation of countermeasures	Lack of structured countermeasure identification and validation	[29]
5. Knowledge management	Poor knowledge-sharing	[30,53,54]
	Underuse of knowledge gained from past investigations	[50]

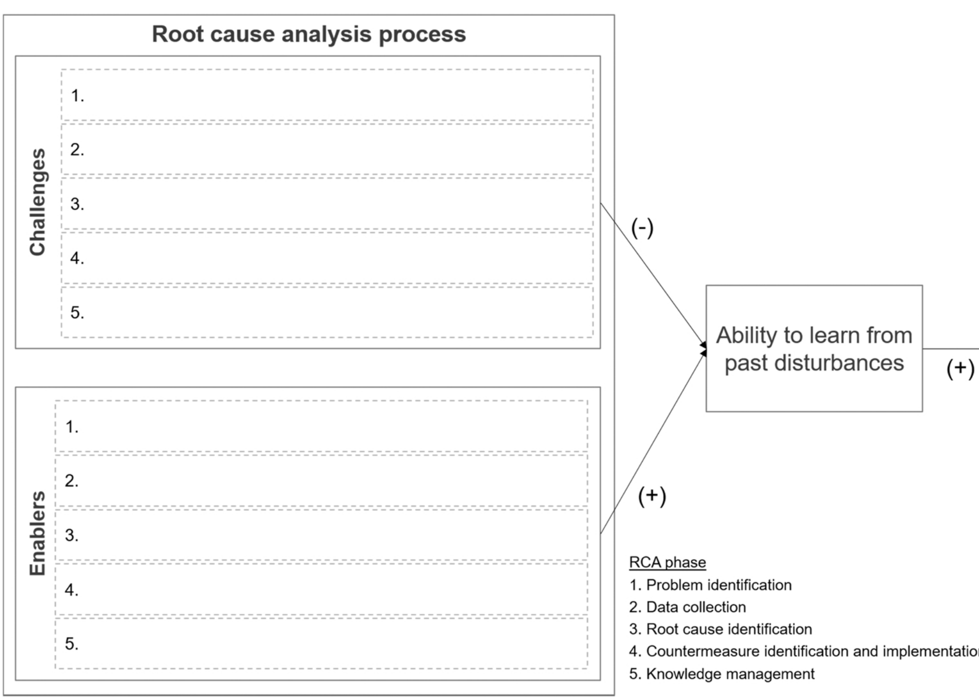

Fig. 2. Framework for content extraction.

the 34 reviewed articles. Those were classified in the different phases of the root cause analysis process and are detailed in the following subsections. The related publications are presented in Tables 2 and 3.

4.2. Challenges in root cause analysis

4.2.1. Challenges related to problem identification

The root cause analysis process usually starts with a recognition that there is a problem in a production system. However, there are some challenges in identifying precisely what the problem is, as shown in the first row of Table 2. According to the literature reviewed, three are the main problems: large volume of alarms happening simultaneously (alarm flood), the need for expertise to define the problem, and employee bias.

A common strategy used by operators to recognise that a problem has started in a production system is to monitor alarms in the machines and operating systems. The first challenge of problem identification is that, in some cases, operators may be flooded with too many alarms simultaneously [37,38]. One possible cause of an alarm flood is when a disturbance impacts many different production variables simultaneously, with the system unable to isolate the most critical one. Multiple alarms are then activated, including unimportant ones, making it hard for an operator to understand exactly what is going on and focus on the most critical aspect. Vodenčarević and Fett [37] report having experienced situations of alarm bursts with more than 200 reported alarms per second.

Another challenge relating to problem identification is the need for expertise. Disturbances propagate and, thus, a problem in one place can affect previous and subsequent points in a system. This makes it difficult to identify the exact source of a disturbance [39,40]. Additionally, the variation of different process parameters might lead to similar outcomes, making it challenging to define a cause-and-effect relationship. Establishing the relationship between a symptom and the problem often requires knowledge and experience of a process [39]. Companies may have to rely on specific employees to properly identify problems; this can be particularly problematic if the employee is unavailable or no longer works for the company.

The final challenge in this phase concerns employee bias [26]. Employee bias in problem identification may happen for different reasons. An employee or specific department may discern that pointing out a problem would have negative consequences for them. For example, an employee might believe that he or she initiated a specific problem, and indicating it might lead to drawbacks in the career. Thus, the problem may remain “undiscovered”, or be wrongly identified on purpose. Confirmation bias may also arise; in other words, employees may assume a current disturbance to be similar to those experienced previously, even if this is not the case. The problem identification, in this case, might be wrongly influenced by personal beliefs, instead of relying on data and facts.

Table 3
Enablers in the root cause analysis process.

Phase in RCA process	Enabler	Related literature
1. Problem identification	Alarm analysis algorithms	[37,38]
	Enhanced visualisation	[55]
	Collaborative platforms	[54]
	Thesaurus of problems	[50,56]
2. Data collection	Sensor location algorithms	[43]
	Interconnection technology	[41,42,45,49]
	Data architecture development	[45,56]
	Data quality improvement	[46]
3. Identification of root causes	Enhanced visualisation	[51,57]
	Machine learning techniques	[30,39,40,45,47,49,55,56]
	Collaborative platforms	[54]
	Thesaurus of causes	[50]
	Combination of methods	[26]
4. Identification and implementation of countermeasures	Combination of methods	[29]
	Collaborative platforms	[54]
	Thesaurus of countermeasures	[50]
5. Knowledge management	Root cause analysis platforms	[50,54]

4.2.2. Challenges related to data collection

The root cause analysis process requires the collection of data for further analysis, to identify the root causes. Kozjek et al. [47] classify three different types of data: process-specific, fault-specific, or “other types of data”. Process-specific data refers to data directly connected to the production process, such as process parameters and variables. Fault-specific data refers to alarms and disturbance data (such as the description, location, product impacted and type). “Other types of data” refers to data that can be collected from other systems, such as maintenance, quality, logistics, inspection, suppliers and customers [47]. The different types of data may be structured or unstructured. Different challenges may arise in the data collection phase (as shown in the second row of Table 2). The results of this literature review indicate the main challenges as being the limited availability of data, poor data quality and lack of integration.

In some manufacturing companies, the availability of data may be limited. This is the case in production systems whose machines may not have enough sensors installed [42,43]. Additionally, data may be unavailable when machines are equipped with sensors but the resulting data is not collected and stored in a database for further use [41]. Moreover, although process-specific data is often available, the same may not occur (or not to the same extent) for fault-specific data, even though this type of data is critical to understanding the causes of disturbances [41]. This can happen for several reasons, including that it may not be part of a company’s culture to report and collect data about disturbances or that employees may not have enough time to perform those activities (especially when they are focused on firefighting the disturbances). Furthermore, often “other types of data” may be inaccessible to manufacturing companies. This arises when data belongs to another actor in the supply chain (suppliers or customers, for example) or when internal systems (maintenance, quality, logistics, etc.) are not integrated.

Another issue that may arise in the data collection phase is data being available but not at the proper level of quality. Ooi et al. [41] point out that many manufacturing companies still rely on manual data collection. This can be time-consuming and, because the process is more error-prone, the data quality tends to be lower (compared to an automatic process). At other times, data may be incomplete [46]. This is especially an issue for fault-related data, which tends to be much scarcer than process-related and “other types of data”. A further quality issue may emerge if the sensors used in the production system are not correctly located. Poor sensor distribution may lead to the collection of conflicting, inconsistent and vague data, making it hard to find the sources of the disturbances [43].

The third and final challenge in data collection is data integration. In manufacturing companies, data is often dispersed across many different systems [47] and in various formats. Examples of systems include those used for production control, maintenance, quality, inspection, planning, logistics, inventory, customer orders and customer complaints. Integrating data from different systems to understand the events that led to a disturbance can be quite challenging [48]. For example, data from different systems might be logged with different timestamps and identification numbers, making it more difficult the consolidation for further analysis. A maintenance system might, for instance, use different denominations to refer to a specific machine and its parts compared to the production, planning or quality systems. Kozjek et al. [47] believe there is a lack of development of holistic databases integrating the various kinds of operational and decision-support data.

4.2.3. Challenges related to identification of root causes

Once collected, data should be analysed to identify different patterns and correlations that can lead to the root causes. This review identified five challenges regarding this phase: large volume of data, need for expertise, employee bias, ad hoc process and miscommunication. The related articles appear in the third row of Table 2.

During the process of identifying root causes, companies often need to analyse a large amount of data. Making sense of the data, identifying important patterns and locating the root causes can be challenging [39]. Ong et al. [46] refer to the issue as a "rich data but poor information" problem. At this point, expert participation is usually necessary to identify root causes [30]. Expertise is frequently needed to correlate variables that are not obvious in the data and establish the link between different datasets. Knowledge of processes and understanding of possible disturbances and their causes tend to be tacit rather than explicit in manufacturing companies. Like in the problem identification phase, a reliance on expert knowledge to identify root causes can become an issue if the expert is unavailable or no longer working for the company.

Furthermore, as in the problem identification phase, employee bias may exist during the identification of root causes [26,30,45]. Root-cause assessment bias may emerge for different reasons and may lead an investigation to draw the wrong conclusions [30,52]. Especially for companies with a blame culture, employee bias may lead to misidentification of root causes to avoid any direct negative consequences for a specific employee or group.

Another challenge concerns miscommunication during the root cause identification. Brundage et al. [50] point out that this phase usually involves a group of people with different backgrounds. Meetings, exchanges of emails, phone calls and so on are usually necessary and miscommunication often arises. Time may be required so that people can understand each other's perspectives; this impacts the time needed for identifying root causes [49,50].

Finally, some authors consider that identifying root causes tends to be an ad hoc practice [40,50–52]. Often, companies have no structured process to be followed when analysing root causes. This makes it more difficult for employees to perform this task systematically. A different process may be conducted for each new disturbance and this may impose some issues when comparing the performance and outcomes of investigations and reusing data from previous root cause analyses.

4.2.4. Challenges related to identifying and implementing countermeasures

One important phase in the root cause analysis process refers to identifying and implementing actions to correct and eliminate root causes. This phase does not refer to mitigating actions after a disturbance has occurred. Rather, it refers to the actions needed to eradicate root causes. Only when countermeasures have been identified and implemented and disturbances eliminated can a company ensure a similar disturbance will not reoccur. Viveros et al. [29] suggest that the root cause analysis process should be improved so it can become efficient and effective in defining and implementing actions to prevent the recurrence of disturbances (see the fourth row of Table 2). The same authors point out that often there is no systematic way in the root cause analysis process to define countermeasures and test whether they are effective. This may lead to countermeasures being defined that will not have the desired effect of eliminating root causes.

4.2.5. Challenges related to knowledge management in root cause analysis

To improve the four phases described in the previous sub-sections (problem identification, data collection, identification of root causes, identification and implementation of countermeasures), a knowledge management phase is necessary. Through knowledge management, companies can guarantee greater efficiency through the dissemination of the learnings of the conducted root cause analyses. In this phase, two challenges were identified in the reviewed literature: poor knowledge-sharing and underuse of knowledge gained from past investigations. The related literature appears in the last row of Table 2.

Qian et al. [53] identify that companies with different plants worldwide commonly do not share knowledge about disturbances among their plants, even though the individual plants may have experienced similar issues and come up with different solutions. Information tends to be locally captured and stored, making it difficult to transfer knowledge between different locations [50,53]. Moreover, a lack of collaboration imposes challenges to the root cause analysis process within both the company and the supply chain. Mourtzis et al. [54] point out that, even though modern companies should collaborate with different stakeholders across the supply chain, current collaboration practices within and outside companies need modernisation to improve the root cause analysis process.

Brundage et al. [50] indicate that the use of past root cause analysis investigations is also very limited in companies. In manufacturing companies, root cause analysis is often conducted using "pen and paper", with no proper digital data storage of the findings. When a similar disturbance occurs, the process is often repeated and a new investigation conducted, without utilising knowledge gained from previous occasions.

4.3. Enablers to more effective and more efficient root cause analysis

Similar to what was done with the challenges in the process, the 17 identified enablers for the root cause analysis process were divided according to which phase they impact mostly, as shown in Table 3. More details are provided in the following sub-sections.

4.3.1. Enablers related to problem identification

Four enablers were identified for the problem identification phase (see the first row of Table 3 for related literature). The first enabler is based on alarm analysis. To tackle the problem of operators being flooded with multiple simultaneous alarms, Vodenčarević and Fett [37] indicate that the data-mining field has focused on developing different algorithms for isolating critical alarms. This is essential information for an operator in the course of a disturbance in a production system, once it can give directions regarding the machine or the parts of the machine that should be dealt with. Kinghorst et al. [38] propose a graph-based approach based on the conditional probability of an alarm A in the occurrence of a second alarm B that can be used to automatically split alarm data, thus helping operators identify statistically dependent and critical alarms. This is an important enabler in the identification of the problem, since it supports the operator in the delimitation of a specific machine, part of a machine, or a process variable that demands immediate attention.

The second enabler concerns the use of tools to enhance the visualisation of problematic process parameters. To do so, Sand et al. [55] propose a real time fast reaction system that analyses process data, detecting jumps, outliers and anomalous distributions and tracks back the changes in the process variables. Based on data mining, cluster analysis and decision trees are created, and the results can be presented in graphs for the operators. An efficient visualisation strategy can support operators in fast and focused problem identification.

The third enabler involves collaborative platforms, as proposed by Mourtzis et al. [54]. Once a problem is detected, the employee who detected it can ask for feedback from other employees about their problem statement. After submitting a new problem, other employees can vote on a social platform as to whether or not they agree with the proposed statement. Past problem descriptions can also be retrieved through advanced indexing techniques supporting problem identification for newly experienced issues. The proposed platform allows the use of natural language in retrieving past problems and describing new ones, creating an intuitive tool to support operators in problem identification [54].

The fourth proposed enabler for problem identification is the development of a thesaurus of all possible problems stored with alternative terms; the different names by which the same problem may be known [50,56]. Chakravorti et al. [56] recommend using a maintenance manual to create such a thesaurus, while Brundage et al. [50] suggest basing the creation on expert knowledge combined with machine learning. In this type of solution, an operator inputs a possible description of the problem, which can be compared against a thesaurus of previously based terms. A suggestion can then be made to the operator regarding potential descriptions to the problem.

4.3.2. Enablers related to data collection

Among the reviewed articles, different enablers were identified regarding data collection, with the related literature presented in the second row of Table 3. The first of those involves having proper sensors in the production system to enable automatic data collection. Shukla et al. [43] suggest that not only is having the sensors important but also placing them correctly. To do so, the same authors present a feature-based approach for determining the optimal sensor distribution of multi-station assembly processes for identifying product quality deviations, with the objective of maximizing the number of measurement of critical design features, collecting essential data for better root cause analysis.

Correctly locating the sensors is necessary, but not enough. To connect the sensors to the IT infrastructure, it is also essential for data to be collected in a database for later data analysis [41,42,49]. Ooi et al. [41] propose a collaborative IoT gateway solution to manage the internetworking connections between the devices and subsystems, plus connection to the cloud to assure communication reliability. Furthermore, Palasciano et al. [42] propose a data acquisition platform comprising a monitoring system connected to the machines (data recorder), plus an Internet-accessible database that can be customised to a given production system. In the presented platform, the data recorder keeps track of two thousand different parameters, communicating with the control unit of the machines and independent sensors in order to retrieve the intended data.

To connect and integrate different data systems, Chakravorti et al. [56] and Stojanovic & Stojanovic [45] also recommend developing suitable data architectures. Stojanovic & Stojanovic [45] propose a data architecture that integrates data retrieved from machine sensors, the manufacturing execution system, and human input (implicit knowledge from the workforce). Chakravorti et al. [56] propose a data architecture combining systems related to production and machine data acquisition, maintenance management, and planning systems. The integration of different sources of data is essential to find the root causes, since the faults in production systems might be initiated by a great number of different activities, being the information usually spread in the company and commonly not in the same format.

Finally, to deal with the issue of imbalanced disturbance data, namely that disturbance data is not as available as data regarding normal operating behaviors, Ong & Choo [46] propose an algorithm for weighting the data based on principal component analysis. This might be a necessary step in data treatment, so that interesting patterns can be further extracted, leading to insights about likely root causes.

4.3.3. Enablers relating to identification of root causes

The reviewed articles propose different enablers regarding the root cause identification phase (see third row of Table 3). Baier et al. [51] and Nonaka et al. [57] suggest using visualisation tools for faster identification of root causes. Baier et al. [51] propose a solution for displaying data graphically for determining the main influencing factors on end products failing end-of-line tests. In this case, an analysis is done considering the correlation between the process variability of individual parameters and existing errors. A spectrogram (a graphical representation similar to audio signals) is then generated with the most important process parameters, facilitating human interpretation. Nonaka et al. [57] present an approach to identify productivity detractors in large-size production systems (more than 500 processes). The approach is based on the analysis of the coeficient of variation of the fluctations in the system. As a result, a visualisation matrix is built to support operators in finding root causes in large and complex production systems.

The use of machine learning to establish correlations between variables and find the root causes of disturbances is suggested by Chakravorti et al. [56], Kozjek et al. [47], Sand et al. [55] and Stojanovic & Stojanovic [45]. This can be done by using expert knowledge to categorise the data and establish correlations, or by analysing unlabelled data directly to identify patterns. Different machine learning techniques are suggested to help in identifying root causes. These include decision trees, clustering, Bayesian network and fuzzy set theory [45,47,55,56]. Stojanovic & Stojanovic [45] propose a model-driven root cause analysis in which an existing failure mode, effect and criticality analysis (FMECA) provides the initial instructions regarding prominent failures for the machine learning algorithm, being this further updated with real-time data. Kozjek et al. [47] suggest a method based on two data analysis phases. In the first one, rules describing the production system are extracted through a decision tree heuristic algorithm and expert knowledge about the manufacturing process. In the second phase, based on the extracted rules and by applying a machine learning clustering technique, the faulty conditions of the process are revealed together with their likely sources, guiding the search for root causes.

Mourtzis et al. [54] suggest the use of a collaborative platform for root cause identification, similar to what was proposed in the problem identification phase. Once an issue is identified, employees from different areas can suggest potential root causes in the collaborative platform. Other employees can then comment and vote on whether they agree that the suggested root causes are the true ones. Root causes are also suggested based on past investigations and by applying machine learning. The most likely root causes are then presented, with their probability being constantly recalculated based on users' feedback. Moreover, similar to what was proposed in the problem identification stage, Brundage et al. [50] suggest the development of a thesaurus, cataloging all possible root causes of a disturbance alongside their probabilities, with these also being constantly updated via machine learning. Different terms used to describe all possible denominations of the same causes are compiled using natural language, facilitating the recognition of reoccurring root causes for users.

Finally, Lee & Chang [26] propose combining root cause analysis with the methods of the theory of constraints and Six Sigma. According to the authors, this allows the methods' strengths to be united in a more assertive definition of root causes. On that account, theory of constraints can provide guidance for critical areas in which root cause analysis should be prioritised, whereas Six Sigma offers a statistical strategy to quantify the main issues in the production system and their most likely causes.

4.3.4. Enablers related to identification and implementation of countermeasures

To identify and implement actions assuring the root causes will be eradicated, different enablers are presented in the literature (see fourth row of Table 3). The first of those involves using specific methods alongside root cause analysis. Viveros et al. [29] propose combining root cause analysis with the TRIZ method. TRIZ stands for Theory of Inventive Problem Solving and is based on brainstorming possible solutions for an issue, and the same authors suggest it to be applied for the identification of countermeasures for the identified root causes. When conducting TRIZ, an "ideal final result" is defined by the group, being a contradiction analysis carried out afterward for the identification of possible side-effects of the proposed countermeasures. The authors suggest that introducing TRIZ in the identification of countermeasures might be a valuable manner of coming up and verifing the most suitable actions to be implemented to correct the root causes.

As with the enablers identified in the problem and root cause identification phases, a collaborative platform can also be used so that employees can share potential actions for solving a root cause. Employees may also vote and comment if they believe a specific countermeasure would eradicate a particular root cause [54]. Furthermore, a thesaurus may also be created with all known countermeasures for a specific root cause [50]. By applying machine learning, the most appropriate actions can be updated and suggested to employees. Additionally, it is also possible to create a feedback strategy in which the implemented countermeasures can be validated regarding their efficacy in eradicating the root causes, allowing manufacturing companies to make sure they are taking the right measures to minimize disturbances in their production systems.

4.3.5. Enablers related to knowledge management in root cause analysis

To improve knowledge management in the root cause analysis process, it is important to use the results of past investigations (see last row of Table 3 for related literature). This might reduce the level of duplicated work so that employees can avoid repeating the same or a similar investigation. It can also help less experienced employees to learn from past investigations conducted by more senior employees. Both Brundage et al. [50] and Mourtzis et al. [54] suggest solutions based on knowledge repositories that enable knowledge to be reused in all the different phases. This is based on the use of collaborative platforms and the creation of a knowledge encyclopedia for production disturbances, their causes and any countermeasures.

5. Discussion

In this study, a literature review was conducted to identify and describe challenges and enablers related to the process of root cause analysis. The result was a total of 14 challenges and 17 enablers. Previous research indicates that manufacturing companies face challenges in being effective and efficient in root cause analysis [3,6,28,30]. Moreover, previous research suggests that Industry 4.0 technology is expected to change how manufacturing companies deal with production disturbances [9], [28]. However, precisely what the challenges and enablers are and how they relate to the different phases of root cause analysis has not been systematically clarified by previous research. This study adds to current research by filling this gap. The results presented are consistent with previous research but offer a higher level of detail on the challenges and enablers. Fig. 4 summarises how the main findings of this study relate to the goal of developing resilient production systems, as further detailed in sub-Section 5.1. Based on their results, the authors propose a research agenda and possible design inputs for new solutions in sub-Section 5.2. The limitations of the present study are presented in sub-Section 5.3.

5.1. Challenges and enablers and their relationship to resilient production systems

By following the root cause analysis process, companies gain insights leading to changes in the design and operation of their production systems. They can also avoid the reoccurrence of disturbances or minimise their impact. Ultimately, proper root cause analysis enhances the ability of companies to learn from past events, leading to more resilient production systems (see Fig. 4). This study has identified challenges and enablers in the different phases of root cause analysis (see Tables 2 and 3 for related articles). As shown in Fig. 4, the challenges are expected to negatively affect the performance of root cause analysis. This reduces the likelihood of companies learning from past disturbances. The challenges increase the time needed to find and deal with root causes, thus decreasing the efficiency of a process. Moreover, the challenges also make it hard to find the true root causes, thus reducing the effectiveness of a process. Furthermore, as presented in Fig. 4, the identified enablers to improve the root cause analysis phases have the opposite effect. In other words, they have a positive impact on a company's ability to learn from past disturbances, leading to more resilient production systems. The enablers are expected to make the root cause analysis process more efficient and effective, allowing companies to find and deal with the true root causes more quickly.

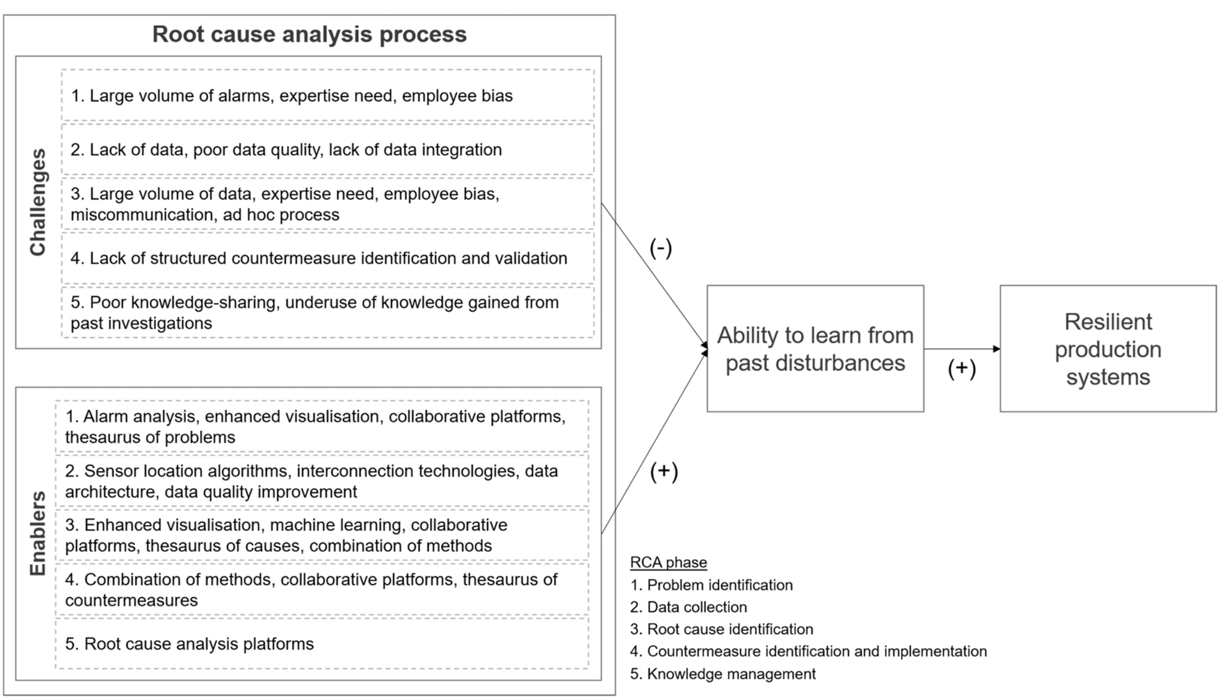

Fig. 4. Root cause analysis process (challenges and enablers) and relationship to resilient production systems.

5.2. Improved root cause analysis of production disturbances for the development of resilient production systems – research agenda and design inputs for new solutions

Although different solutions for improving root cause analysis in manufacturing companies have already been proposed, the results of this literature review indicate further areas of potential research by the academic community to help practitioners deal with their challenges. The same areas may also comprise potential design inputs to new solutions. The following sub-sections elucidate these areas.

a. Use of diverse datasets in the root cause analysis process.

Data analytics is likely one of the most promising areas for helping practitioners find and deal with root causes. Some researchers have focused on it, as shown in Table 3. However, there are limitations to the currently presented enablers, chief among them being the use of limited types of data. The enablers identified in this study focus primarily on structured data, either as process-related, fault-related or "other" types of data, such as maintenance or quality data. There is much unexplored potential for using unstructured data in all phases of the root cause analysis process. Examples of unstructured data are video, image, sound and free text. Video, image and sound data might be acquired by, say, recording a production system's operations, video calls, or visual inspections. Free text might be acquired from such things as reports, handbooks, emails, free descriptions of disturbances and their causes. These types of data can help in analysing previous events and decisions which may have caused a specific disturbance. Further research should focus on: (1) understanding what types of unstructured data are potentially available in production systems related to disturbances; (2) identifying the challenges of integrating them into current datasets; and (3) proposing solutions to overcome the challenges of integration and draw insights to aid the root cause analysis process. New datasets may then be used in designing new solutions for improved root cause analysis.

b. Collaboration outside manufacturing companies – development of collaborative platforms.

As shown in Table 3, one of the reviewed articles proposes collaborative platforms as an enabler for improving the performance of the root cause analysis process. However, this platform focuses primarily on collaboration within companies. There is also a potential unexplored collaboration outside manufacturing companies. This may be further investigated from the supply chain perspective and from that of other companies working in the same type of field. From the supply chain perspective, greater integration, information-sharing and collaboration between manufacturing companies, logistics operators, suppliers, technology providers and customers can be promoted, thus improving the root cause analysis process. Often, a disturbance within a company is reflected across the whole supply chain. Also often, a disturbance in a production system may originate from outside a company. Furthermore, the effects of production disturbances can commonly be recognised among customers, especially if they are quality-related. Researchers can help practitioners develop strategies and technical solutions to improve outside collaboration practices in their root cause analysis process, thus leading to higher effectiveness and efficiency.

Moreover, collaboration may also be achieved among companies with similar production systems. Collaborating to disseminate knowledge gained and identify problems, causes and countermeasures can put companies in a win-win situation, help them become more assertive and speed up the process of finding and dealing with root causes. Although various competitive issues may minimise the opportunities for collaboration in this scenario, collaboration can play a critical role in avoiding future instances of specific types of disturbances, such as safety-related ones.

There are different ways in which researchers may help companies achieve greater collaboration in the supply chain and among companies in the same area. One possible way is the further development of collaborative platforms, including additional stakeholders (outside the company). In such platforms, companies can share data and information related to disturbances within their supply chain, thus enhancing agility and disseminating the findings of specific investigations. The same idea can also be used as a design input for new solutions.

c. Creation of holistic data architectures.

As the basis for the development of data analytics-related solutions and collaborative platforms, it is critical to properly integrate the different types of data flowing from different systems into various levels within companies and outside them. This can only be achieved if the different data sources in the production systems/companies such as sensors, machines, systems (maintenance, production, quality, etc.) are interconnected and integrated. It can be particularly challenging for a root cause analysis process to match different data types if the data architecture was not conceived for that purpose.

Although some publications propose different data architecture solutions (as shown in Table 3), given the limitations regarding the data types and collaboration aspects, further research is necessary. In developing data architectures, new types should also be considered (such as unstructured data), as well as integrating systems outside manufacturing companies (from other actors in the supply chain, for example). With holistic data architecture, it is possible to combine different data sources and integrate different systems outside a company, thus leading to a more insightful root cause analysis process. Researchers can help practitioners in proposing data architecture solutions that consider all potential data types and which are simple and easy to implement in their current production systems, being this also a potential feature for new solutions.

d. Support to employees in the root cause analysis process.

Although the reviewed literature emphasizes the need for expertise as a challenge in the root cause analysis process (see Table 2), employee training, education and support as potential enablers to the issue are not mentioned. Rather, the focus tends to fall primarily on technological solutions. However, humans will continue to be part of the root cause analysis process and their role is expected to become more and more refined. Finding the root causes of less complex problems is expected to become automated but, in complex disturbances, the participation of humans in the root cause analysis process will continue to be critical. Therefore, it is essential to provide employees with the necessary education and also to ensure they have enough time to understand and perform the necessary tasks related to the root cause analysis process.

The authors also recommend future research to focus on strategies to develop effective training in implementing root cause analysis. One suggestion is the development of intuitive applications that can guide employees in the different phases of root cause analysis. This would be adapted to their production system contexts, using the various existing datasets to gain insights. Furthermore, the authors suggest new management strategies to be further researched to certify employees get the necessary support and time they need to perform the tasks in the different phases of root cause analysis. One possible focus area regards the development of shop floor management strategies, focusing on developing specific organizational frameworks to be applied in the root cause analysis process.

5.3. Limitations

When performing a literature review, relevant articles might not be included depending primarily on the definition of the scope and the search process. In the case of this study, the authors defined the scope as being academic publications available in the databases Scopus and Web of Science, meaning that relevant publications not found in those databases were not included. The choice of keywords for the search in the databases (see sub-Section 3.2 for details) also has a similar effect. In this study, the authors defined the search string as ("root cause analysis" AND ("production system*" OR "manufacturing system*"), being potential relevant articles that might have used different denominations not included in the review.

One emerging area that should be highlighted concerns *automatic root cause analysis*. Automatic root cause analysis can be applicable to address the identified challenges, but relevant publications might not have been captured in the defined search strategy if they have focused on contexts other than production/manufacturing systems. As further research, the authors suggest a specific review of literature regarding general applications of automatic root cause analysis, pointing out the differences in relation to non-automatic solutions.

6. Conclusion

Through a systematic literature review, this study identifies and explains the challenges and enablers proposed in current research for the root cause analysis process. A total of 14 challenges and 17 enablers in the different phases of the process were identified. Challenges include e. g., “need for expertise”, “employee bias”, “poor data quality”, and “lack of data integration”, and enablers include e.g., “visualisation tools”, “collaborative platforms”, “thesaurus”, and “machine learning techniques”. Based on the findings, a research agenda and potential design inputs for new solutions have been proposed, hoping to support the development of more resilient production systems.

Specifically, four main focus areas are suggested in the research agenda: (1) use of diverse datasets in the root cause analysis process, (2) collaboration outside manufacturing companies – development of collaborative platforms, (3) creation of holistic data architectures, and (4) support to employees in the root cause analysis process. This study also explains the relationship between the root cause analysis process and the ability to learn from past disturbances. The challenges and enablers can help practitioners better understand their current issues regarding root cause analysis and assist them in selecting potential solutions that are ready to test and implement. The proposed design inputs can also guide how current processes might be further improved, thus leading to more resilient production systems.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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