THESIS FOR THE DEGREE OF DOCTOR OF PHILOSOPHY

Root cause analysis for resilient production systems

through Industry 4.0 technologies

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ABSTRACT

Creating and developing resilient production systems is critical if manufacturing companies are to thrive in a globally competitive market. Being flexible and agile, resilient systems can avoid, withstand, adapt to and recover from disturbances. A crucial ability is learning from experienced disturbances so they can be avoided in future. This is commonly done in manufacturing companies by performing a root cause analysis. However, the current practice of root cause analysis lacks efficiency and effectiveness, which contributes to the high reoccurrence of disturbances encountered daily by manufacturing companies. Fortunately, with the introduction of Industry 4.0 technologies, the process of root cause analysis is expected to change greatly. With the aim of supporting practitioners in improving their root cause analysis processes, this research focuses on: (1) describing the current challenges; (2) describing the requirements for new technological solutions; and (3) identifying and designing new technological solutions, given the context of Industry 4.0. To do so, a qualitative approach was adopted, inspired by design science research (DSR) and based on six studies involving manufacturing companies and technology providers.

Regarding the main challenges, the results of this research indicate that manufacturing companies are still performing unstructured root cause analysis, relying on experts to identify root causes and struggling to know how to analyse and integrate relevant data effectively. Furthermore, regarding requirements, the results of this research indicate that technological solutions for root cause analysis should be data-driven and easy to use. They should integrate different data sources, allow secure collaboration and support employee learning. Based on the requirements, the results of this research indicate that the leading technological solutions involve such things as data analytics, the development of thesauruses of disturbances and their causes, the design of specific data architectures and systems for root cause analysis and the design of platforms for stronger collaboration. Finally, in this research, specific high-level designs are proposed for an application to support root cause analysis of machine stops; and a collaborative platform for root cause analysis at the value-chain level. This research has practical and theoretical implications. Its results may be used directly by practitioners to gain insight into potential improvements to their practices and as input for developing specific root cause analysis applications. The results of this research also advance knowledge in the field of root cause analysis by providing empirical evidence of challenges, requirements and solutions.

Keywords: root cause analysis, production disturbances, resilient systems, Industry 4.0

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“É junto dos bão que a gente fica mió” – Guimarães Rosa

A few months before I moved to Sweden, I went to an astrologer. I was very curious to know what my future would look like as I was moving to a new country, a new job, new friends, a new life. Amongst many other things, he told me that my stars indicated I would meet many teachers in the coming years and that they’d have distinct roles in my life. I’m still not sure how much I believe in astrology; I’m fully aware that it isn’t exactly scientific. But one thing is for sure; the astrologer was absolutely right about this point. Five years have passed and it’s now time for me to thank all the teachers I’ve encountered along the way.

First of all, I’d like to thank my supervisor Prof. Anders. You’re a role model. I still can’t believe how lucky I was to have you as my supervisor. You inspire everyone around you with your kindness, generosity, intelligence and the way you deal with the challenges of research. You taught me to believe in myself as a researcher and I’m forever grateful for your support.

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Adriana Ito

Göteborg, 2023

APPENDED PAPERS

PAPER 1	Ito, A., Ylipää, T., Skoogh, A., & Gullander, P. Handling production disturbances: where are we and where are we heading? International Conference on Industrial Engineering and Operations Management, Sao Paulo, Brazil, 6th-8th April, 2021.
CONTRIBUTION	Principal author. With Torbjörn and Per, Adriana conducted the company interviews and data analysis. Adriana wrote the paper, bearing in mind the comments of her co-authors.
PAPER 2	Ito, A., Ylipää, T., Gullander, P., Bokrantz, J. and Skoogh, A. (2021), Prioritisation of root cause analysis in production disturbance management, International Journal of Quality & Reliability Management, Vol. 39 No. 5, pp. 1133-1150. https://doi.org/10.1108/IJQRM-12-2020-0402
CONTRIBUTION	Principal author. With Torbjörn and Per, Adriana conducted the interviews, focus groups and data analysis. Adriana wrote the paper, bearing in mind the comments of her co-authors.
PAPER 3	Ito, A., Hagström, M., Bokrantz, J., Skoogh, A., Nawcki, M., Gandhi, K., Bergsjö, D., & Bärring, M. (2022). Improved root cause analysis supporting resilient production systems. Journal of Manufacturing Systems, 64 (August), 468–478. https://doi.org/10.1016/j.jmsy.2022.07.015
CONTRIBUTION	Principal author. Adriana conducted the literature review, analysed the collected data and wrote the paper, bearing in mind the comments of her co-authors.
PAPER 4	Ito, A., Söderkvist Vermelin, W., Gullander, P., Ylipää, T., Hildenbrand, J., Bokrantz, J. & Skoogh, A. Challenges, requirements and a high-level design for a root cause analysis application. Submitted to Journal of Industrial Information Integration.
CONTRIBUTION	Principal author. With Torbjörn, Wilhelm, Per and Jutta, Adriana conducted the company interviews, focus groups and data analysis. With her co-authors, she also designed the proposed solution in the

article. Adriana wrote the paper, bearing in mind the comments of her co-authors.

PAPER 5	Ito, A., Hagström, M., Li, D., Bokrantz, J., Skoogh, A., Bärring, M., Stahre, J. A collaborative digital platform for root cause analysis in the value chain. 10th International Conference on Industrial Engineering and Applications (ICIEA 2023). April 2023.
CONTRIBUTION	Principal author. With Dan, Adriana conducted the company interviews, focus groups and data analysis. With Dan, she also designed the proposed solution in the article. Adriana wrote the paper, bearing in mind the comments of her co-authors.
PAPER 6	Ito, A., Ylipää, T., Gullander, P., Bokrantz, J., Centerholt, V. and Skoogh, A. (2021), "Dealing with resistance to the use of Industry 4.0 technologies in production disturbance management", Journal of Manufacturing Technology Management, Vol. 32 No. 9, pp. 285-303. https://doi.org/10.1108/JMTM-12-2020-0475
CONTRIBUTION	Principal author. With Torbjörn, Per and Victor, Adriana conducted the company interviews. Adriana conducted the literature review and with her co-authors, analysed the collected data. Adriana wrote the paper, bearing in mind the comments of her co-authors.

TABLE OF CONTENTS

1

“Viver - não é? - é muito perigoso. Porque ainda não se sabe. Porque aprender-a-viver é que é o viver mesmo.”

– Guimarães Rosa, from Grande Sertão: Veredas

INTRODUCTION

This chapter presents the background to the thesis, its research vision, purpose and aim. The research questions which guide this work are also provided alongside the thesis’ delimitations and structure.

1.1 BACKGROUND

Can you imagine how your life would be if there were no boots to wear in the wintertime? No washing machines? Computers? Smartphones? Undoubtedly, the invention of all sorts of products has made human life easier and more pleasant. And thanks to the development of production systems[1], most of us in the modern world have access to those products. For most people on this planet, production systems are actually one of the catalysts for better living conditions.

To compete in a global market, production systems need distinguishing features. One such critical feature is resilience (Bhamra et al., 2011). Despite the remarkable advances in production systems throughout the various industrial revolutions (Lu, 2017), there is still major room for improvement if they are to become highly resilient (Zhang & Van Luttervelt, 2011). Resilient production systems can avoid, withstand, adapt to and recover from disturbances (Madni & Jackson, 2011). They can adjust their functioning before, during or after changes and disturbances (Hollnagel et al., 2013). To do so requires the key ability of *learning*. Resilient production systems can *learn* from both successful and unsuccessful situations and then improve accordingly (Hollnagel et al., 2013).

To learn from production disturbances and avoid a reoccurrence, manufacturing companies commonly conduct root cause analysis (Ma et al., 2021; Mahto & Kumar, 2008). This is a systematic investigation, the main objective of which is to identify and eradicate the most basic (or root) causes of production disturbances (Dorsch et al., 1997; Mahto & Kumar, 2008). Typically, an investigation group is formed with employees from different departments, which will define the problem precisely, collect and analyse relevant data, identify the root causes and suggest suitable countermeasures (Andersen & Fagerhaug, 2006; Mahto & Kumar, 2008). An investigation group might use different tools to identify the root causes depending on the type of event being analysed. Such tools might include five whys, a fishbone diagram or a fault tree analysis (Andersen & Fagerhaug, 2006; Dorsch et al., 1997; Vo et al., 2020).

Previous research has recognised that root cause analysis tends not to be effective or efficient in manufacturing companies (Brundage et al., 2017; Lokrantz et al., 2018; Mourtzis et al., 2015). The investigation group might need a long time (sometimes months) to find the root causes of a specific disturbance, while a large number of disturbances occur and reoccur in the production system (Ma et al., 2021; Reis & Gins, 2017). A spiral is created, whereby companies focus most of their attention and efforts on mitigating the symptoms of production disturbances, rather than understanding and dealing with their causes. Few lessons are learned from actual production disturbances and the development of resilient production systems is prevented. This situation also contributes to the underperformance of production systems, resulting in the low overall equipment efficiency figures seen in manufacturing companies (Ylipää et al., 2017).

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[1] This thesis considers production systems to be socio-technical systems. According to Baxter & Sommerville (2011), socio-technical systems are systems that *"involve a complex interaction between humans, machines and the environmental aspects of the work system"*.

To improve the root cause analysis process, academic publications have concentrated primarily on two areas. The first one prescribes how root cause analysis should be conducted in general; the traditional steps that should be followed and the conventional tools and methods that can be applied. Publications include the books written by Andersen & Fagerhaug (2006), Vanden Heuvel et al. (2008) and Oakes (2019). These devote little attention to how technology can be used to facilitate a process. The second area covers studies in which technological solutions are proposed to establish cause-and-effect relationships for particular disturbances and consider specific datasets. In this type of study, the proposed solution is typically context-dependent, potentially making it hard for practitioners to understand how the results could apply to their cases. Examples are the studies by Sand et al. (2016) and Mehrabi & Weaver (2020), which present data-analytics-related solutions for root cause analysis of an electromagnetic actuator assembly line and vehicle assembly plant. There is a lack of publications describing the current situation regarding the practice of root cause analysis or any technological solutions aimed at improving overall processes that are not restricted to a specific context. This thesis aims to fill this gap.

To do so, it is important to consider the current context of Industry 4.0, in which different technologies provide the means for a major change in the way root cause analysis can be performed. The internet of things, cloud technologies, data analytics and other Industry 4.0-related technologies will enable connectivity, data sharing and new forms of analysis and visualisation; they will support practitioners in finding the root causes of their production disturbances (Vo et al., 2020). Some researchers envisage that a production system almost-free of disturbance can be achieved (J. Lee et al., 2017).

Considering the gap that has been presented and the Industry 4.0 context, this thesis focuses on understanding the current challenges among manufacturing companies when performing root cause analysis and their requirements for new technological solutions. Solutions are also identified and suggested based on this knowledge.

1.2 VISION AND PURPOSE

The vision of this thesis is to create a highly resilient production system with major learning capabilities. The purpose of this thesis is to support this creation by investigating the challenges/requirements related to root cause analysis and identifying/designing technological solutions that can lead to improvements considering Industry 4.0 technologies.

1.3 AIM AND RESEARCH QUESTIONS

This thesis aims to support practitioners working with root cause analysis by developing knowledge and proposing solutions. To this end, three research questions have been formulated:

RQ 1) What are the current industrial challenges regarding root cause analysis?

The first research question focuses on understanding the current situation regarding the management of production disturbances and root cause analysis among industrial companies. Current challenges must be understood if suitable solutions are to be provided. The challenges are explored from different perspectives: root cause analysis as part of disturbance management, prioritising root cause analysis, the phases of root cause analysis and resistance to the introduction of new technologies to assist the process.

RQ 2) What are the requirements for new root cause analysis solutions?

To support industrial practitioners in improving their practices, it is critical to understand their *needs and wishes* (the requirements) so that solutions can be designed accordingly. In the context of this research, a "requirement" is understood to be *"a condition or capability needed by a user to solve a problem or achieve an objective"* (Aurum & Wohlin, 2005). To identify the requirements, the focus is given to the different stakeholders affected by production disturbances and the companies' various needs and wishes for new applications for root cause analysis at the company and value chain levels.

RQ 3) Based on the requirements, how can root cause analysis be improved and lead to more resilient production systems?

Based on the identified requirements, the objective of the third research question is to explore and design conceptual solutions which may improve the practice of root cause analysis and bring about more resilient systems. The emphasis is on technological solutions, meaning applications/technologies that facilitate identifying and dealing with root causes in manufacturing companies, at the company and value-chain levels.

1.4 DELIMITATIONS

This thesis focuses on developing resilient production systems by improving root cause analysis in the light of Industry 4.0 technologies. This is the main scope of this work and, thus, some delimitations can be set.

In the creation of resilient systems, it is critical to develop the ability to learn. Learning should come from successful as well as unsuccessful events. This thesis concentrates on the ability of production systems to learn from unsuccessful events, or disturbances. This research does not cover the learning process for successful events.

In improving the root cause analysis process, the emphasis may be on *soft* aspects, such as those related to employee commitment or organisational culture. These are undoubtfully essential to the implementation of effective root cause analysis practices and should be investigated further. However, this thesis concentrates primarily on the technological aspects.

1.5 THESIS STRUCTURE

This thesis is structured as six distinct chapters, as outlined in Table 1.

Table 1: Overview of thesis structure.

1. INTRODUCTION	The background to this research is presented, alongside its vision, purpose, aim, research questions and delimitations.
2. FRAME OF REFERENCE	This chapter presents the theoretical foundation. It includes sections on resilient production systems, production disturbances, root cause analysis, and Industry 4.0 technologies.
3. RESEARCH APPROACH	This chapter presents the researcher's background and worldview, with an explanation of the research approach and chosen methods.
4. RESULTS	This chapter presents the results of the six studies conducted in this research (A, B, C, D, E, F), relating them to the research questions (RQ1, RQ2, RQ3).
5. DISCUSSION	This chapter presents a discussion of the results, provides answers to the research questions, explains the contributions of this work, presents the methodological reflections and offers suggestions for future work.
6. CONCLUSIONS	This chapter summarises the thesis and its conclusions.

2

"As coisas mudam no devagar depressa dos tempos."

– Guimarães Rosa, from *Grande Sertão: Veredas*

FRAME OF REFERENCE

This chapter presents the relevant frame of reference for this thesis. Firstly, the background to resilient production systems is outlined. The focus then moves to production disturbances, followed by root cause analysis. Finally, the background to Industry 4.0 and emerging technologies is presented.

This chapter presents four areas that have most influenced this thesis. They are: resilient production systems, production disturbances, root cause analysis and Industry 4.0 technologies. Figure 1[2] shows how the different areas relate to each other.

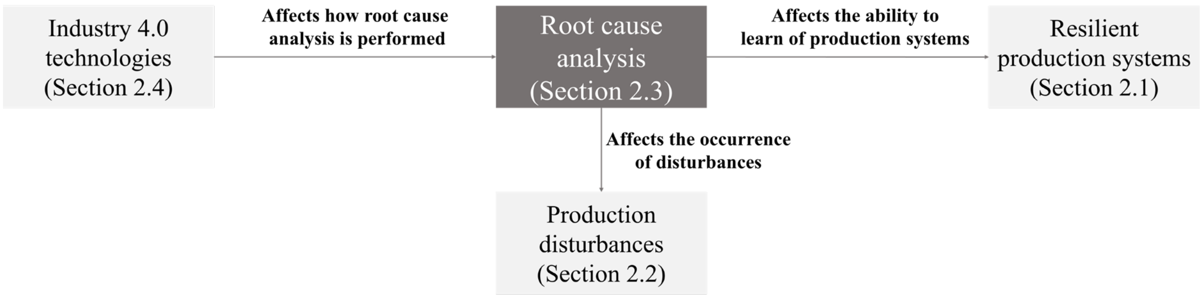

Figure 1: Connecting root cause analysis to different areas (own elaboration).

The vision of this research is to create and develop resilient production systems (background knowledge is presented in Section 2.1). To achieve this, it is essential to develop systems' ability to learn. This can be accomplished by performing root cause analysis (see Figure 1 – arrow between root cause analysis and resilient production systems). Root cause analysis is the main phenomenon investigated in this thesis, with the background to this topic presented in Section 2.3. An efficient, effective root cause analysis process can prevent the reoccurrence of production disturbances (see Figure 1 – arrow between root cause analysis and production disturbances). Section 2.2 covers the topic of production disturbances. Furthermore, in investigating different strategies to improve the root cause analysis process, it is also important to consider the current context of Industry 4.0 (presented in Section 2.4). Industry 4.0 technologies can also affect how root cause analysis is performed, facilitating the different phases of the process (see Figure 1 – arrow between industry 4.0 technologies and root cause analysis). In summary, by applying Industry 4.0 technologies, root cause analysis can be improved, thus reducing the occurrence of production disturbances and strengthening the learning capability of production systems. This may make them more resilient.

2.1 RESILIENT PRODUCTION SYSTEMS

As presented in Chapter 1. Introduction, this thesis envisages the creation of a highly resilient production system. Resilience is a concept used with different meanings and implications in different fields, such as ecology, psychology, economy and engineering (Cimellaro et al., 2016). This research emphasises resilience in the engineering context, more specifically the context of

[2] Other relationships could be established from Figure 1, such as how Industry 4.0 technologies might directly affect the creation of resilient production systems or how production disturbances are related to resilient production systems. Since the focus of this thesis regards root cause analysis, in Figure 1, only the relationships involving it are highlighted.

production systems. Resilient production systems are needed to ensure that companies can compete in the global market (Bhamra et al., 2011).

Among the various suggested definitions of resilience (such as those identified by Righi et al. (2015) and Sanchis et al. (2020)), two have influenced this thesis the most. The first one, by Hollnagel et al. (2013), states that resilience is *"the intrinsic ability of a system to adjust its functioning prior to, during, or following changes and disturbances, so that it can sustain required operations under both expected and unexpected conditions"*. The second one, by Zhang & Lin (2010) refers to resilience as *"the system's capability of leading to success from failure on the system's own - in particular its own infrastructure, substance"*. Combining these two definitions, it may be asserted that resilience is a multi-faceted feature that involves avoiding, withstanding, adapting to and recovering from disturbances (Madni & Jackson, 2011). Different strategies may be used to make production systems more resilient by improving such aspects as their robustness, reliability, agility, flexibility and adaptability (Stricker & Lanza, 2014; Zhang & Van Luttervelt, 2011).

Four main capabilities are necessary for a production system to be considered resilient (Hollnagel et al., 2013). The first concerns *responding* to disturbances; knowing the best way to react in the case of an unexpected event. In case of a disturbance, time may be critical and foreknowledge of the best countermeasures is needed so that the system can reconfigure and adapt, returning to normal conditions or adjusting to new ones as fast as possible (Hollnagel et al., 2013; Madni & Jackson, 2011).

The second capability concerns *monitoring* (Hollnagel et al., 2013). Being alert and detecting disturbances as soon as they emerge leads to greater agility. This is only achieved if the different critical variables are known and monitored. Monitoring encompasses not only the production system's own performance but also the external environment (Hollnagel et al., 2013; Madni & Jackson, 2011).

The third capability concerns *anticipating* disturbances (Hollnagel et al., 2013). Being aware of possible hazards and sensing changes in current conditions is critical in resilient production systems, especially when it concerns defining possible countermeasures (Hollnagel et al., 2013; Righi et al., 2015). Anticipation enables preparedness in production systems (Madni & Jackson, 2011).

The last capability in a resilient production system concerns *learning* (Hollnagel et al., 2013). In this case, learning refers to both successful and unsuccessful events. It is critical to understand those situations in which the system has behaved as desired and learn from them (Hollnagel et al., 2013; Madni & Jackson, 2011). However, situations involving disturbances and failures are inevitable (Zhang & Van Luttervelt, 2011). In such cases, a system should also learn from its negative experience, understand its own vulnerabilities and ensure that it adapts, so that it is no longer vulnerable to the same type of threat.

The primary focus of this thesis is on *learning* ability, specifically that relating to past negative experiences. Among the various negative experiences, one that is central to the case being made in this research concerns production disturbances. The next section gives more details about production disturbances.

2.2 PRODUCTION DISTURBANCES

Background knowledge of production disturbances is necessary to understand the challenges faced by manufacturing companies and their various requirements. Therefore, this subsection is closely related to RQ1 and RQ2.

Production disturbances are closely related to resilience. Indeed, a resilient production system is resilient to some type of failure or disruption, such as production disturbances. In a resilient production system, a critical goal is being able to avoid, withstand, adapt to and recover from disturbances (Madni & Jackson, 2011). This thesis has adopted the following definition of a production disturbance: *"an unexpected and undesired event that causes the production system not to perform as planned"*. There are different types of production disturbances and what is considered a disturbance may vary depending on the company. For example, some companies may not consider preventative maintenance or work meetings to be disturbances but others might (Bokrantz, Skoogh, Ylipää, et al., 2016). However, in most companies, certain types of issues are mostly considered disturbances. This is true for quality issues, material shortages, machine failures, reprogramming and incidents (Bokrantz, Skoogh, Ylipää, et al., 2016; Islam & Tedford, 2012).

Although there is no full consensus on all types of production disturbances, they undoubtedly do cause a lot of trouble in production systems. Disturbances are the primary reason for almost half of Sweden's production capacity being compromised (Ylipää et al., 2017). This means that Swedish production systems could be twice as productive as they currently are. Reducing the incidence of production disturbances can directly affect the competitiveness of manufacturing companies (Islam & Tedford, 2012).

Moreover, production disturbances correlate with safety issues. When operators have to deal with unfamiliar situations, as tends to happen with disturbances, the likelihood of a safety incident increases (Toulouse, 2002). Production disturbances also lead to greater resource utilisation (Ingemansson & Bolmsjö, 2004). For example, energy consumption is higher if machines must be restarted often. Furthermore, the service life of machines is minimised if they are constantly breaking down and raw material consumption is greater when scrap parts are produced.

Manufacturing companies struggle to manage production disturbances and a vicious cycle often results: the company primarily focuses its attention and resources on firefighting the consequences and symptoms of disturbances; being time and money to prevent disturbances quite restricted (Lokrantz et al., 2018). The same experienced disturbances reoccur, while new ones appear and yet more emphasis is placed on firefighting symptoms, with the spiral continuing. Reducing the occurrence and reoccurrence of production disturbances requires a learning strategy. In companies, this usually takes the form of root cause analysis, which is further examined below.

2.3 ROOT CAUSE ANALYSIS

Background knowledge of root cause analysis is fundamental to understanding the challenges faced by manufacturing companies, their requirements and possible improvements. Therefore, this subsection is closely related to all three research questions.

Learning from actual disturbances may increase the capabilities of production systems to avoid, withstand, adapt to and recover from such disturbances (Hollnagel et al., 2013; Madni & Jackson, 2011), thus making them more resilient. Given the aim of learning from and understanding past events, root cause analysis may be considered a suitable strategy. This is a problem-solving method that became popular with the introduction of the Toyota production system and lean manufacturing approach, which supported continuous improvement in manufacturing companies (Bhamu & Sangwan, 2014).

Root cause analysis is an investigation performed after a production disturbance has happened (Andersen & Fagerhaug, 2006; Mahto & Kumar, 2008). The central idea is to identify the primary causes of disturbances - the root causes - so that the appropriate countermeasures can be taken to prevent the same type of disturbance from reoccurring (Andersen & Fagerhaug, 2006; Vanden Heuvel et al., 2008). In analysing a specific disturbance, it should be more appropriate and cost-effective to manage its causes, rather than just firefighting and mitigating its effects or symptoms (Brundage et al., 2017; Lokrantz et al., 2018; Mourtzis et al., 2015).

Specifying exactly what a root cause is poses a challenge. Andersen & Fagerhaug (2006) consider root causes to be "*the evil at the bottom that sets in motion the entire cause- and-effect chain causing the problem(s)*". Rooney & Vanden Hauvel (2004) suggest that root causes are specific underlying causes which can be easily identified and that management can control and fix. Only when the root causes are identified and handled can we be sure that the same problem (or its symptoms) will not reappear (Vanden Heuvel et al., 2008).

Different phases are usually recommended in the literature on root cause analysis. For example, Vanden Heuvel et al. (2008) consider the steps of investigation initiation, data collection, data analysis and recommendation generation. Rooney & Vanden Hauvel (2004) suggest that the main stages of root cause analysis are data collection, causal factor charting, root cause identification and recommendation generation/implementation. Furthermore, Andersen & Fagerhaug (2006) propose the steps of problem understanding, problem cause brainstorming, data collection, data analysis, root cause identification, root cause elimination and solution implementation. In the case of this research, the stages considered for root cause analysis are: (1) problem identification, (2) data collection, (3) identification of root causes and (4) identification and implementation of countermeasures, combining the view of different authors (Andersen & Fagerhaug, 2006; Rooney & Vanden Hauvel, 2004).

When conducting root cause analysis, companies may use different tools or techniques such as five whys, fishbone diagrams and fault tree analysis (Bokrantz, Skoogh, & Ylipää, 2016; Ma et al., 2021). The choice of technique may depend on the type of disturbance being analysed. For example, in the case of simple disturbances, five whys can be used. But in the case of complex issues, fault tree analyses may be more suitable for establishing cause-and-effect relationships (Dorsch et al., 1997; Sarkar et al., 2013).

Although it is fairly easy to find recipes in the literature for performing root cause analysis and using different tools and methods, in practice, investigations can be quite challenging (Lokrantz et al., 2018; Ma et al., 2021). When performed in manufacturing companies, root cause analysis tends to be an investigation involving employees with different backgrounds, such as maintenance, production and quality (Mahto & Kumar, 2008; Vanden Heuvel et al., 2008). Most of the time, expert knowledge is necessary to establish cause-and-effect relationships and determine the root causes. This is because, in many cases, different causes may lead to the same symptom and the same cause may lead to different symptoms (Lokrantz et al., 2018). Relying on expert knowledge has many drawbacks; knowledge is not saved, stored, or easily transferred and in some instances, the expertise knowledge may not be completely accurate (Lokrantz et al., 2018). Furthermore, root cause analysis processes are still commonly based on brainstorming sessions, with limited use of digital technologies (Brundage et al., 2017). In this scenario, it is not surprising that finding the root causes of a specific disturbance may take months (Reis & Gins, 2017). In production systems that experience a lot of disturbances (perhaps up to 100 a day), it is highly unlikely that all the root causes will be found using current methods.

Specific solutions have been proposed to improve the root cause analysis process. For example, Lokrantz et al. (2018) suggest a machine learning framework using Bayesian networks to model the causal relationships between manufacturing stages using expert knowledge. Furthermore, Kozjek et al. (2017) recommend a data-analysis method integrating different heuristic algorithms (such as decision trees and clustering) and supporting the identification of root causes by trying to identify types of faulty operating conditions. Such publications are needed as inspiration for specific new applications. However, practitioners may find it challenging to implement such suggestions, as the solutions are often developed with certain disturbances, datasets and other case specifics in mind.

To help practitioners improve their root cause analysis processes, it is important to understand how technological solutions can be applied in a more generic and transferable way, given the current digitalisation context. Thus, the next section presents the context of Industry 4.0.

2.4 INDUSTRY 4.0 AND EMERGING TECHNOLOGIES

Understanding the emerging technologies and the context of Industry 4.0 provides the background for investigating how root cause analysis can be improved. Therefore, this subsection is closely related to RQ3.

Industry 4.0, or the Fourth Industrial Revolution, is an industrial breakthrough that creates new ways for manufacturing companies to produce, improve and distribute their products. Industry 4.0 was named after the three earlier industrial revolutions. In the first one (18th century), the use of water and steam enabled manufacturing to be mechanised (Liao et al., 2017). In the second industrial revolution (at the beginning of the 20th century), mass production was facilitated by the use of electricity. In the third industrial revolution (in the 1970s), electronics and information technology supported further automation of production systems (Lu, 2017). In recent years, Industry 4.0 has provided a completely new way of controlling a production environment, with devices, machines and humans interlinked but able to act autonomously. Industry 4.0 technologies might do for mental power what the steam engine and its successors (electricity and automation) did for muscle power (Snow et al., 2017).

Industry 4.0 is designed based on the principles of interconnection, decentralised decisions, information transparency and technical assistance (Hermann et al., 2016). The different actors of production systems (machines, devices, sensors and people) are interconnected through wireless communication technologies and able to interact rapidly. The possibility of information-sharing among the different actors creates the basis for collaboration in the network. The fusion of the physical and virtual worlds is enabled by the high level of connectivity between the various objects, which in turn allows an advanced form of information transparency.

Data can be analysed using the information provided by all the actors, thus allowing the creation of a virtual copy of the physical world. With actors' interconnection and information transparency, autonomous and decentralised decisions become possible. Tasks are conducted as autonomously as possible and only when interference or conflicting goals occur are they delegated to a higher monitoring level. Virtual and physical assistance is available as technological assistance for humans in their tasks. The systems can aggregate and visualise information to support decisions and robots can conduct a range of activities that are unpleasant, exhausting or unsafe for humans (Hermann et al., 2016).

Different technologies lay the foundation for Industry 4.0 and enable the transformation of production systems from isolated, optimised cells to fully integrated, automated and optimised production flows. These include cyber-physical systems, big data, data analytics, advanced robotics, the internet of things and people, smart sensors and smart devices, cloud computing, additive manufacturing and augmented and virtual reality (Blaszczyk & Wisniewski, 2019; Dalenogare et al., 2018). These technologies have also the potential to help improve the practice of root cause analysis in manufacturing companies.

3

"O senhor saiba: eu toda a minha vida pensei por mim, sou nascido diferente. Eu sou é eu mesmo. Diverjo de todo o mundo."

– Guimarães Rosa, from *Grande Sertão: Veredas*

RESEARCH APPROACH

This chapter presents the rationale for the research approach chosen in this work. The author explains her background and worldview and how she believes it has influenced her research approach. The design and methods used in this research are also detailed in context of the research questions and studies.

3.1 BACKGROUND AND WORLDVIEW

Before starting my PhD, I worked for Brazil's largest oil company for about ten years. Among other things, the department I worked for was responsible for the root cause analysis of most critical incidents and accidents at fourteen different refineries. We investigated the causes of disturbances that had led to: major financial losses; impacts on the supply chain of the whole country; environmental disasters; and severe injuries to employees. The main objective was to ensure the same problems would not reoccur in the future and to make the system more resilient and safe. With that company, I had a great opportunity to understand the practical consequences of production disturbances, the challenges in conducting effective and efficient root cause analysis and how important this process is in avoiding future issues.

I believe that, based on my previous experience, I had a *practical attitude* toward the topic I researched during my PhD. By "practical attitude", I mean that I'm driven to solve practitioners' problems by applying scientifical methods. To me, it's important that the scientific outcome is deemed useful and relevant by those working in root cause analysis. In this case, the scientific outcome might take different forms; among other things, it could be a new theory, a model, a framework or a tool.

3.2 RESEARCH APPROACH

3.2.1 Defining the research questions

The formulation of my research questions was greatly influenced by my practical attitude to root cause analysis (see RQ1, RQ2 and RQ3 in Section 1.3, Aim and research questions). My main objective from the outset was to suggest different solutions to the challenges experienced by practitioners. Doing this necessitated describing those challenges, which became the focus of my first research question. Once that had been done, the next step would be to understand what companies expected, wanted and needed from the various technological solutions that could support their root cause analysis processes. This defined my second research question. Based on the challenges and requirements, it would then be possible to design suitable conceptual technological solutions. This became the focus of my third research question.

Just after completing my Licentiate[3] in December 2020, I discovered design science research (DSR). This inspired me greatly as it resonates with my practical attitude. DSR isn't just about explaining how things; it also deals with indicating how things ought to be (Niiniluoto, 1993; Simon, 1988). In DSR, the question "will it work?" is more important than "is it valid or true?". This means that the underlying epistemological notion is pragmatism (Romme, 2003). DSR revolves around artefacts. Artefacts refer to everything that can be used to transform the current

[3] The Licentiate of Engineering is an intermediate postgraduate degree offered in a few countries, including Sweden. It can be seen as an academic step halfway between a Master's and a PhD.

situation into the desired one, including constructs, frameworks, methods, models, guidelines, materials, objects and tools (Gregor & Hevner, 2013; Hevner et al., 2004). When conducting DSR, the first step usually involves creating an understanding of the problem. Peffers et al. (2007) refer to this as “problem identification and motivation”, while Vaishnavi et al. (2015) call it “awareness of the problem”. The second step is to define the objectives and requirements of possible solutions and is called the “definition of the objectives for a solution” by Peffers et al. (2007). Subsequently, in the third step, solutions can be identified and designed (this phase is referred to as “design and development” or “suggestion and development” (Peffers et al., 2007; Vaishnavi et al., 2015)). In the final step of DSR, the designed solutions can be implemented and evaluated and their effectiveness tested (van Aken et al., 2016). This last phase is called “evaluation”, by Peffers et al. (2007) and Vaishnavi et al. (2015).

The first three steps prescribed in DSR are closely related to my research questions, which focused on identifying challenges and requirements and identifying/designing new solutions. Although I did not define a research question for the fourth step of evaluation, this was examined in this research (as further explained at the end of Section 3.3).

3.2.2 Strategy to answer the research questions – qualitative studies

To answer the research questions, I chose to conduct qualitative studies. A qualitative research strategy would allow me to understand the phenomenon in its natural context, by interviewing/collaborating with people working directly with root cause analysis. Indeed, Hammarberg et al. (2016) indicate that qualitative methods are suitable for answering questions related to experiences, meanings and perspectives from the standpoint of the participants, which was my primary intention. Furthermore, qualitative methods offer a suitable way of investigating phenomena in depth (Moser & Korstjens, 2017); something I also found helpful in understanding the challenges and requirements of root cause analysis and in designing solutions for it.

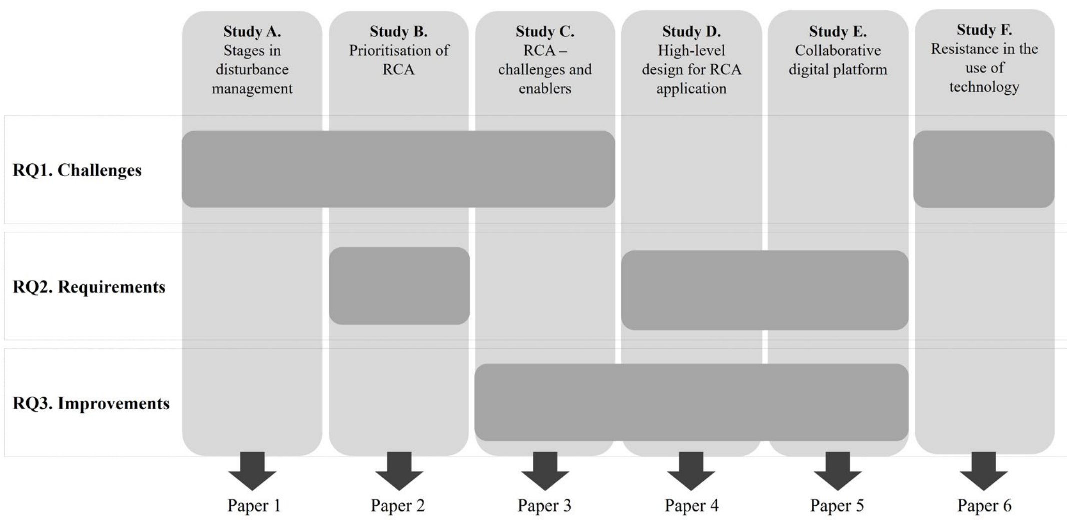

Figure 2: Research questions in relation to the studies conducted in this thesis and its appended papers.

To answer the research questions, six different qualitative studies (described in the six appended papers) were conducted over five years of research, as summarised in Figure 2. Those studies explored root cause analysis from different perspectives:

a. Study A studied root cause analysis as part of disturbance management;
b. Study B examined the prioritisation of root cause analysis;
c. Study C investigated the process of root cause analysis itself;
d. Study D focused on possible improvements to root cause analysis at manufacturing company level;
e. Study E explored root cause analysis at value-chain level;
f. Study F studied resistance to the use of new technologies.

A summary of the different methods applied in the studies appears in Section 3.4, at the end of this chapter.

3.2.3 The studies and their relationship to the research questions

The various perspectives used in the studies to investigate root cause analysis produced answers to each of the research questions. The next three paragraphs explain how the studies answer the research questions.

RQ1 – Challenges in root cause analysis – Studies A, B, C and F

As illustrated in Figure 2, studies A, B, C and F provide answers to RQ1, focusing on different challenges experienced by manufacturing companies in root cause analysis. Study A gives a general presentation of the current situation regarding production disturbance management. Study B identifies the challenges in prioritising root cause analysis of disturbances. Study C presents the challenges identified in the literature regarding the different phases of root cause analysis. And Study F identifies the various sources of resistance to using technology to support root cause analysis in disturbance management.

RQ2 – Requirements for new solutions for root cause analysis – Studies B, D and E

Studies B, D and E provide answers to RQ2 (regarding requirements for new root cause analysis solutions, see Figure 2). Study B identifies the different stakeholders and values that are impacted by production disturbances and should be considered when designing new technological solutions. Studies D and E identify and describe companies' needs and wishes (requirements) regarding root cause analysis on both the individual and value-chain levels.

RQ3 – Improvements (identifying and designing solutions for root cause analysis) – Studies C, D and E

As presented in Figure 2, answers to RQ3 (regarding possible solutions to root cause analysis) are provided in Studies C, D and E. Study C identifies individual enablers of/solutions to the different phases of root cause analysis. Studies D and E propose specific solutions for improving root cause analysis. These entail a high-level design for a root cause analysis application at company level and a digital platform to enable collaboration at value-chain level.

3.3 DATA COLLECTION, DATA ANALYSIS AND MEASURES TO ENHANCE RESEARCH QUALITY

Table 2 presents the different methods used in the studies for this research regarding data collection, data analysis and measures to ensure research quality.

Table 2: Studies conducted for this thesis; their research design, data collection, data analysis and quality enhancement methods.

	Data collection	**Data analysis**	**Measures to ensure research quality**
Study A. Stages in disturbance management	Interviews and literature review	Transcription of interviews, inductive coding (literature review) and deductive coding (interviews)	Triangulation of methods, triangulation of investigators, member checking
Study B. Prioritisation of RCA	Interviews and focus groups	Transcription of interviews, inductive coding	Triangulation of data, triangulation of investigators, member checking, prolonged engagement, transparency
Study C. RCA - challenges and enablers	Literature review	Deductive and inductive coding	Triangulation of investigators, transparency
Study D. High-level design for an RCA application	Interviews and focus groups	Transcription of interviews, inductive coding	Triangulation of data, triangulation of investigators, member checking, prolonged engagement, transparency
Study E. Collaborative digital platform	Interviews and focus groups	Transcription of interviews, inductive coding	Triangulation of data, triangulation of investigators, member checking, prolonged engagement, transparency
Study F. Resistance to the use of technology	Interviews and literature review	Transcription of interviews, inductive coding (literature review) and deductive coding (interviews)	Triangulation of methods, triangulation of investigators, member checking, transparency

This research adopted a qualitative strategy based on interviews, focus groups and literature reviews. Interviews and focus groups were essential to investigating the phenomena in their natural environment and for a deeper understanding of the challenges, requirements and possibilities for improvement from the perspective of practitioners. They were applied in all studies, except Study C. Companies and technology providers willing to improve the root cause analysis process were selected to take part in the studies. Employees working in areas relating to production disturbance management and root cause analysis (such as production, continuous improvement, quality, maintenance and the development of solutions) were selected to participate in the interviews and focus group discussions. All interviews and focus groups for this research were recorded and transcribed.

Literature reviews were fundamental to the compilation and organisation of existing knowledge on root cause analysis, as this knowledge tends to be dispersed across a wide range of journals. Specific screening strategies were designed for data collection in the studies for which a literature review was applied (Studies A, C and F).

For data analysis (all studies), continuous discussions with other researchers were held at weekly meetings when the data gathered from the different studies was examined. The NVivo software was used for data coding in all studies. Inductive and/or deductive coding was applied, depending on the individual research design and goal of the study.

A primary concern of this research was to ensure the results were considered trustworthy and that they were potentially transferable to other contexts. Therefore, different strategies were used to enhance research quality, as suggested by Korstjens & Moser (2018); Miles et al. (2014), Riege (2003) and Aguinis & Solarino (2019). The main measures applied in the different studies refer to triangulation (of methods, data and researchers), member checking, prolonged engagement and transparency (in both methods and results). Furthermore, in this thesis, I present some reflections on my personal biases (see Section 5.4 Methodological reflections).

Measures were also taken to validate/evaluate the results of the studies. The final results of all the studies were presented to practitioners for them to confirm that the results were coherent and relevant to their practices. In particular, for Studies D and E (in which DSR was applied throughout), the final versions of designed conceptual solutions were presented on different occasions to the study participants. Their feedback was collected as to whether they found the proposed solutions useful in their practices and how the solutions might improve the root cause analysis process.

3.4 SUMMARY OF GOALS AND METHODS APPLIED IN THE STUDIES

The next chapter (4. Results) presents the results of the studies. However, the goals and methods applied are not covered. Aiming to offer the reader a quick reference of what was done in each study, the goals and methods used are summarised in this subsection. Some of the information presented in the previous sections (3.2 and 3.3) might be repeated.

In **Study A**, a literature review and a series of interviews were conducted to answer RQ1. The aim was to identify the current situation of manufacturing companies regarding production disturbance management and describe how Industry 4.0 technologies might be helpful in improving the process. A screening strategy was developed for the literature review and inductive coding was applied in the analysis. The interviews were recorded and transcribed and deductive coding was then applied based on the literature review results. The quality of the research was enhanced by triangulating methods and researchers and by member checking. More details of the methods used in Study A are provided in appended Paper 1.

In **Study B**, a series of interviews and focus groups were conducted to answer RQ1 and RQ2. The study focused on describing the current practices for prioritising which production disturbances should undergo root cause analysis and identifying the impacted stakeholders and values. Data collected during the interviews and focus groups was transcribed and inductive coding was applied to the analysis. The quality of the research was enhanced by triangulating data, member checking, prolonged engagement with the participants and transparency. More details of the methods used in Study B are provided in appended Paper 2.

Study C aimed to identify and describe challenges and enablers within the process of root cause analysis in manufacturing companies, thus answering RQ1 and RQ3. In this case, a systematic literature review was conducted. A specific screening strategy for articles was created for data collection. This involved the use of inductive and deductive coding in analysing the articles. The quality of the research was enhanced by triangulating researchers and through transparency in the methods and results. More details of the methods used in Study C are provided in appended Paper 3.

Study D focused on designing a high-level system for an application to support root cause analysis, providing answers to RQ2 and RQ3. This was a qualitative study, involving a series of interviews and focus group discussions. Inductive coding was applied to the data analysis. The quality of the research was enhanced by triangulating researchers, member checking, prolonged engagement and transparency. More details of the methods used in Study D are provided in appended Paper 4.

Study E provides answers to RQ2 and RQ3. It aimed to design a collaborative platform for root cause analysis at the supply chain level. A qualitative study was conducted, with data collected through interviews and focus group discussions. After transcription of the interviews and discussions, inductive coding was used in the data analysis. The quality of the research was enhanced by triangulating data and researchers, member checking, prolonged engagement with the participants and transparency. More details of the methods used in Study E are provided in appended Paper 5.

Finally, **Study F** focused on identifying the sources of resistance to the use of technology in disturbance management and suitable managerial approaches to deal with them, thus answering RQ1. A literature review and a series of interviews were conducted, with the data analysed through inductive and deductive coding. The quality of the research was enhanced by triangulating researchers, member checking and transparency. More details of the methods used in Study F are provided in appended Paper 6.

4

"Eu quase que nada não sei. Mas desconfio de muita coisa."

– Guimarães Rosa, from Grande Sertão: Veredas

RESULTS

This chapter presents the results of the studies (described in the appended papers) and their contributions to answering the research questions.

Table 3 provides some reading guidelines for this chapter by presenting how the subsections relate to the different studies/papers and their main contributions to the research questions.

Table 3: Results sections in relation to RQs, papers and main contributions.

Section/subsection	Related study/paper	Main contribution
4.1 RQ1 – Challenges in root cause analysis		
4.1.1 Stages in managing production disturbances	Study A/Paper 1	Description of the current way of working of manufacturing companies in the different stages of production disturbance management.
4.1.2 Challenges in prioritising root cause analysis	Study B/Paper 2	Identification of the challenges manufacturing companies face when prioritising disturbances that should undergo root cause analysis.
4.1.3 Challenges in different phases of root cause analysis	Study C/Paper 3	Identification of the challenges in the different phases of root cause analysis.
4.1.4 Resistance to the use of technologies	Study F/Paper 6	Identification of the sources of resistance to the introduction of new technologies in disturbance management.
4.2 RQ2 – Requirements for new root cause analysis solutions		
4.2.1 Impacted stakeholders and factors	Study B/Paper 2	Mapping of different stakeholders and factors impacted by production disturbances that should be considered in prioritising root cause analysis.
4.2.2 Requirements at the company level	Study D/Paper 4	Identification of requirements for new root cause analysis solutions at individual company level.
4.2.3 Requirements at the value-chain level	Study E/Paper 5	Description of requirements for new root cause analysis solutions at value-chain level.
4.3 RQ3 – Identifying and designing improvements for root cause analysis		
4.3.1 Enablers in the phases of root cause analysis	Study C/Paper 3	Identification of enablers to improve the different phases of root cause analysis.
4.3.2 A high-level design for a root cause analysis application	Study D/Paper 4	Design of a high-level system for applying root cause analysis.
4.3.3 A collaborative digital platform for root cause analysis	Study E/Paper 5	Design of a collaborative platform for root cause analysis at the value-chain level.

4.1 RQ1 – CHALLENGES IN ROOT CAUSE ANALYSIS

This section presents the results of RQ1: "What are the current industrial challenges regarding root cause analysis?". The RQ is answered by Appended Papers 1, 2, 3 & 6 (which summarise Studies A, B, C and F).

4.1.1 Stages in managing production disturbances

Root cause analysis can be interpreted as one of the stages in the process of managing production disturbances. At the beginning of my research, I focused on understanding the current situation of those different stages, conducting a series of interviews with five companies (Study A, Paper 1). The results of this study appear below.

When handling production disturbances, companies usually do so in stages (see Figure 3). The stages are: detection, diagnosis, mitigation/correction, root cause analysis, prevention and prediction. Detection, diagnosis and mitigation/correction are reactive stages and are necessary to ensure that a disturbance and its impacts are controlled and that normal conditions are then re-established in the production system. Root cause analysis, prevention and prediction are proactive stages. These are crucial to a deeper understanding of disturbances, in terms of their causes and mechanisms and how they can be completely eradicated from a production system. Proactive stages usually take longer to implement than reactive ones.

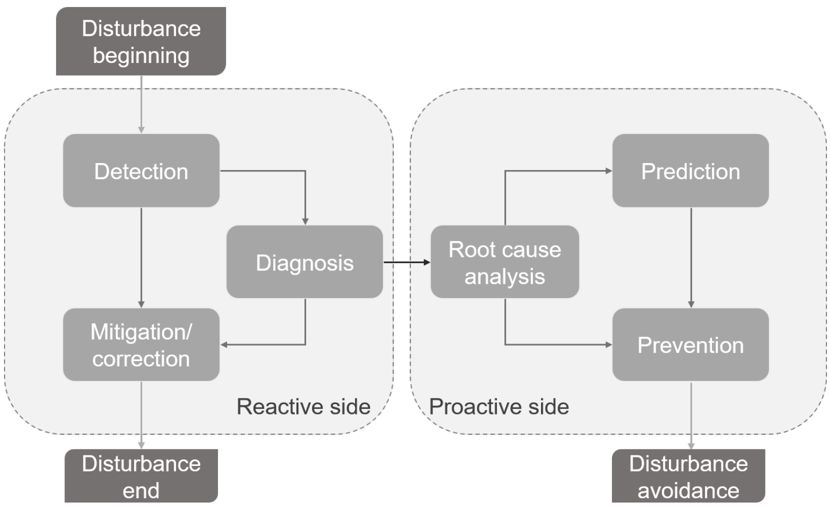

Figure 3: Stages in production disturbance management (adapted from Paper 1).

Once a disturbance starts, the first stage is its detection. This is when people involved in the production operations recognise that an unplanned and undesired event has begun. Among the companies interviewed in Study A, the main strategies used for detection involved the monitoring of the alarms in the various machines and the use of human senses. This means that most of the time, either the operators will perceive an indication coming from one of the machines (such as a red light), or they will see, hear, smell, or feel that a machine is not working properly. The companies interviewed in Study A perceived themselves as quite good at detecting disturbances in production systems.

After detection, the next stage in disturbance management tends to be diagnosis. Diagnosis refers to identifying the immediate cause of a disturbance. For example, an operator detects a quality disturbance in the parts being produced and considers that a specific machine is malfunctioning. In this case, the malfunctioning machine can be considered the immediate cause. Among the companies interviewed in Study A, diagnosis was mostly based on the judgment of operators and technicians, grounded in their knowledge and experience. Unlike detection, companies perceived themselves as less competent at diagnosis.

Another stage on the reactive side is mitigation/correction. In this stage, necessary measures are taken to stop/contain a disturbance, as are the countermeasures needed to minimise its effects. Mitigation/correction can happen immediately after detection, even if the immediate causes are unclear. This might happen when a machine is restarted after malfunctioning, to resume normal operation. However, the immediate cause is very often identified at the diagnostic stage before a disturbance is mitigated and corrected. For example, if a machine malfunction is known to be caused by a certain part, simply re-starting the machine might not lead to the resumption of normal conditions. In this case, diagnosis (knowing which part is causing the issue) is necessary to define the appropriate countermeasure (such as maintenance of the specific part). A mitigation/correction strategy used by some companies involves written procedures in which operators can find suggestions for dealing with different types of disturbances. In other cases, mitigation/correction may be based primarily on the tacit knowledge of operators and supervisors. The companies interviewed in Study A perceived themselves as fairly good at mitigation/correction compared to the other stages. This reflects the reactive mindset concerning production disturbance management in manufacturing companies.

The first stage on the proactive side (see Figure 3) refers to root cause analysis. Root cause analysis is an investigation performed after a disturbance to identify its root causes and the actions required to eliminate them. Root cause analysis is usually performed by a group of people with different backgrounds (depending on the type of disturbance these may include production, maintenance, quality and safety). The interviewed companies pointed out that they use simple root cause analysis techniques, such as five whys and fishbone diagrams. These methods primarily rely on pen and paper, meaning that digital solutions are seldom part of the process. Furthermore, the companies perceived their root cause analysis performance to be better than when it concerned prediction and prevention but not as satisfactory as was the case for detection and mitigation/correction.

Once the patterns, behaviours and causes of disturbances are understood, predictions can be made. Predicting disturbances refers to the foreknowledge that a disturbance is about to happen. For prediction to happen, the mechanisms leading to a disturbance must be known; in other words, the root causes should be known. Among the companies interviewed in Study A, prediction was almost non-existent.

The final stage in production disturbance management is prevention. Prevention concerns the actions needed to ensure a disturbance will not reoccur. The root causes also need to be known in this case. Thus, there is also a link between root cause analysis and prevention (see Figure 3). Apart from root cause analysis, companies also use risk analysis, such as FMEA (failure mode and effect analysis) or HAZOP (hazard and operability) studies to identify potential issues and possible solutions to avoid disturbances emerging in a production system. However, companies do not perceive themselves as having a satisfactory performance in this process, existing great room for improvement.

To summarise, it may be said that the companies interviewed in Study A perceived themselves as performing better in the reactive stages than in the proactive ones. In general, the way companies carry out detection, diagnosis and mitigation/correction was perceived to be more satisfactory than the way they carried out root cause analysis, prevention and prediction. The reactive mindset prevalent in manufacturing companies is reflected in the high number of reoccurring disturbances experienced in their production systems.

4.1.2 Challenges in prioritising root cause analysis

Once the current situation regarding stages in production disturbance management had been understood, my study companies advocated a focus on root cause analysis. Specifically, they considered that it would be valuable to detail the challenges in terms of prioritising which disturbances should undergo root cause analysis. This became one of the objectives of Study B. This subsection summarises the results of Study B (a study based on interviews and focus groups) relating to the challenges of prioritising disturbances. For more details, please refer to Paper 2.

Two different approaches are usually taken to prioritising root cause analysis among manufacturing companies. In some companies, a group of people may hold regular meetings to discuss and decide which production disturbances should be analysed further. Employees from production, maintenance, quality and continuous improvement are usually part of this type of group and a joint decision is often made regarding prioritisation, based on the perspectives of the different departments. In other companies, prioritisation might be centralised to one person, commonly the production manager.

A primary difference between prioritisation done by a group or by a central manager is the time spent on the decision. A group decision usually takes longer than a centralised process, as time is needed for the group to discuss and reach a consensus. Less time may be needed for centralised decisions by a single manager. However, this approach has drawbacks. Firstly, if the manager is not available, the process may be hindered. Furthermore, potentially only one perspective is considered in prioritising which disturbances should go through root cause analysis, often the production department's perspective.

One challenge that has been identified as common to both approaches concerns the prioritisation criteria. Companies in which a group makes the decision usually use pre-defined criteria. These include the duration, frequency and location of disturbances (in bottleneck machines, for example). Nevertheless, it is common for unrelated, non-predefined criteria also to be taken into consideration during the prioritisation process. In companies where the manager makes the decision, no pre-defined criteria tend to be used. In both situations, since pre-defined criteria are not systematically used, ambiguity may arise for those working with production disturbances.

A further challenge identified in both processes is the use of past data to support prioritisation decisions. In most manufacturing companies, such data is very limited. Generally, even if data is available, companies rely mainly on static analysis, such as Pareto or ABC analysis, rather than analysing production disturbance trends. Also, there is no formal practice for capturing reusable knowledge and data regarding the actual prioritisation process.

To summarise, the following challenges are highlighted (from Paper 2):

(1) When a group makes a decision, time is needed to reach a consensus;

(2) When prioritisation is centralised, the process becomes person-dependent;

(3) When the prioritisation centres on one person, the set priority usually considers only the production perspective;

(4) The prioritisation criteria can be vague;

(5) The use of data to support prioritisation of root cause analysis is limited.

4.1.3 Challenges in the different phases of root cause analysis

After prioritising which production disturbances should undergo root cause analysis, companies start the process. Many of the companies I collaborated with on the different projects said they found their root cause analysis processes to be inefficient and ineffective. To help the companies overcome the challenges in performing their root cause analyses, it was first necessary to document the challenges they had experienced. This became one of the goals of the literature review conducted in Study C (Paper 3). The results appear below.

Root cause analysis can be divided into the phases of problem identification, data collection, identification of root causes and identification and implementation of countermeasures. Table 4 presents the challenges identified in the different phases and supporting literature. This is part of the results of the literature review conducted in Study C. It should be noted that, in conducting this study, a new challenge area was derived inductively – knowledge management. This was included as one of the phases in root cause analysis (also presented in Table 4). The challenges identified in the different phases are detailed in the following subsections.

Table 4. Challenges in the root cause analysis process (Adapted from Paper 3).

RCA phase	Related articles	Identified challenge
1. Problem identification	(Kinghorst et al., 2018; Vodenčarević & Fett, 2015)	Large volume of alarms
	(Mehrabi & Weaver, 2020; Noursadeghi et al., 2012)	Need for expertise
	(M. C. Lee & Chang, 2012)	Employee bias
2. Data collection	(Ooi et al., 2019; Palasciano et al., 2016; Shukla et al., 2015)	Lack of data
	(Ong et al., 2015; Ooi et al., 2019; Stojanovic & Stojanovic, 2017; Wang et al., 2020)	Poor data quality
	(Kozjek et al., 2017; Liewald et al., 2018; Wang et al., 2020)	Lack of data integration
3. Identification of root causes	(Noursadeghi et al., 2012; Ong et al., 2015)	Large volume of data
	(Lokrantz et al., 2018; Palasciano et al., 2016; Stojanovic & Stojanovic, 2017)	Expertise need
	(M. C. Lee & Chang, 2012)	Employee bias
	(Brundage et al., 2017; Madsen et al., 2017)	Miscommunication
	(Baier et al., 2019; Brundage et al., 2017; Huertas-Quintero et al., 2011; Mehrabi & Weaver, 2020)	Ad hoc process
4. Identification and implementation of countermeasures	(Viveros et al., 2014)	Lack of structured countermeasure identification and validation
5. Knowledge management	(Lokrantz et al., 2018; Mourtzis et al., 2016; Qian et al., 2019)	Poor knowledge-sharing
	(Brundage et al., 2017)	Underuse of knowledge gained from past investigations

4.1.3.1 Challenges related to problem identification

The process of root cause analysis typically begins with identification of the problem. As the first row of Table 4 indicates, there are some challenges in determining precisely what the problem is. The literature review identified three primary challenges regarding the problem identification phase: a large volume of alarms (alarm flood), a need for expertise and employee bias.

Monitoring alarms in machines and operating systems is an approach frequently used by operators to detect when a problem has begun in a production system. The first challenge of problem identification is that, in some cases, operators may be flooded with too many alarms simultaneously (Kinghorst et al., 2018; Vodenčarević & Fett, 2015). An alarm flood can occur when a disturbance affects various production variables at the same time and the system is unable to isolate the most critical one. Multiple alarms, including irrelevant ones, are then activated, making it difficult for an operator to understand exactly what is going on and focus on the most critical aspect. Vodenčarević & Fett (2015) report having experienced alarm bursts with more than 200 alarms reported per second.

The need for expertise is another challenge to problem identification. A disturbance in one location may impact the earlier and later stages of a production system. This makes it difficult to pinpoint the precise origin of a disturbance (Mehrabi & Weaver, 2020; Noursadeghi et al., 2012). Furthermore, it may be difficult to establish a cause-and-effect link because the variation in different process parameters may result in identical outcomes. Establishing the connection between a symptom and the problem often requires knowledge and experience of the process (Noursadeghi et al., 2012). Companies may have to rely on individual expertise and knowledge to identify problems correctly; this can be troublesome in certain cases (such as if the employee is absent or no longer working for the organisation).

The final challenge in this stage relates to employee bias (M. C. Lee & Chang, 2012). Various factors may contribute to employee bias in problem identification. An individual or particular department may feel that highlighting a problem might be disadvantageous to them. For instance, an employee may believe that they started a given issue and that admitting it might negatively affect their career. Thus, the problem may remain "undiscovered" or be purposefully misidentified. Another type of bias is confirmation bias. Employees may assume a current disturbance is similar to those they have experienced previously, even though this is not the case. Instead of relying on evidence and facts, the problem identification in this situation may be negatively affected by personal views and beliefs.

4.1.3.2 Challenges related to data collection

Data must be gathered for analysis so that the root causes can be identified in the root cause analysis process. Kozjek et al. (2017) categorise three different sorts of data: process-specific, fault-specific, or "other types of data". Process-specific data refers to the production process-related data, 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 collected from other systems, such as maintenance, quality, logistics, inspection, suppliers and customers (Kozjek et al., 2017). The various sorts of data may be either structured or unstructured. The data collection phase has different challenges (as shown in the second row of Table 4). These are: limited availability of data, poor data quality and lack of integration.

In some companies, data availability may be limited, such as in production systems whose machines may not have an adequate number of sensors installed (Palasciano et al., 2016; Shukla et al., 2015). Furthermore, data may be unavailable when machines have sensors but the data they produce is not collected and stored in a database for further use (Ooi et al., 2019). Additionally, although process-specific data is often available, fault-specific data may not be (or not to the same extent); this type of data is crucial to understanding why disturbances happen

(Ooi et al., 2019). This can happen for a variety of reasons, including it not being part of a company's culture to report and gather data on disturbances, or that staff may not have the time to do so (particularly when they are busy trying to manage the consequences of disturbances). Moreover, companies often may not have access to "other types of data". This occurs, for example, when another player in the supply chain (such as suppliers or customers) owns the data or when there is no integration of internal systems such as maintenance, quality and logistics.

During the data collection phase, another issue that may arise is that there is data but its quality is low. Ooi et al. (2019) indicate that most manufacturing companies rely on manual data collection. This can be time-consuming and because the process is more prone to errors, the data quality is generally worse (compared to an automatic process). On other occasions, data may be incomplete (Ong et al., 2015). This is particularly problematic for fault-related data, which is usually much scarcer than process-related and "other types of data". Another quality issue may arise if the sensors used in the manufacturing system are not properly positioned. Poor sensor distribution may result in the collection of contradictory, inconsistent and ambiguous data, making it difficult to identify the sources of disturbances. (Shukla et al., 2015).

Data integration is the third and last challenge in data collection. Data in manufacturing companies is frequently spread across numerous systems (Kozjek et al., 2017) and in various formats. Examples of such systems include those used for production control, maintenance, quality, inspection, planning, logistics, inventory, customer orders and customer complaints. It can be difficult to combine and integrate information from several systems in order to understand the reasons that led to a disturbance (Liewald et al., 2018). For instance, data from diverse systems may be registered with different timestamps and identification numbers, making it a challenge to integrate and consolidate it for analysis. Different designations may be used to refer to a specific machine and its parts in the maintenance system, as compared to the production, planning or quality systems. Kozjek et al. (2017) claim that the creation of comprehensive databases combining the various types of operational data for decision support is lacking.

4.1.3.3 Challenges related to identification of root causes

Data should be analysed after collection, to allow the discovery of patterns and correlations which may indicate root causes. Five challenges were identified regarding this phase: large volumes of data, a need for expertise, employee bias*,* ad hoc process and miscommunication (third row of Table 4).

When identifying root causes, companies must often analyse a great deal of data. Making sense of this data to locate root causes can be challenging (Noursadeghi et al., 2012). Ong et al. (2015) refer to this issue as a "rich data but poor information" problem. At this point, expert participation is frequently needed so that root causes can be identified and to establish relationships between variables that are not obvious (Lokrantz et al., 2018). In manufacturing companies, knowledge of processes, possible disturbances and their causes tends to be tacit rather than explicit. Similar to the problem identification phase, a dependence on expert knowledge to identify root causes may become an issue if the expert is absent or is no longer employed by the company.

Moreover, as with the problem identification phase, employee bias may occur throughout the identification of root causes (M. C. Lee & Chang, 2012; Lokrantz et al., 2018; Stojanovic & Stojanovic, 2017). Bias in root cause assessment may arise for different reasons and may lead an investigation to make erroneous judgments (Huertas-Quintero et al., 2011; Lokrantz et al., 2018). This is especially the case in companies where there is a blame culture. Employee bias can cause underlying causes to be incorrectly identified in an effort to prevent any immediate negative effects for a particular employee or group.

Another challenge relates to miscommunication in the root cause identification process. Brundage et al. (2017) point out that, during this phase, a group of people with diverse backgrounds usually gets to work together. Meetings, exchanges of emails, phone calls and so on are frequently needed and miscommunication can arise. Time may be required for people to understand each other's perspectives and come to a consensus regarding the root causes (Brundage et al., 2017; Madsen et al., 2017).

Lastly, according to some authors, identifying root causes tends to be an ad hoc practice (Baier et al., 2019; Brundage et al., 2017; Huertas-Quintero et al., 2011; Mehrabi & Weaver, 2020). Manufacturing companies often lack a formal monitoring procedure when analysing root causes, making it challenging for employees to perform the task systematically. For every new disturbance, a different procedure may be conducted. This poses some challenges in comparing the performance and outcomes of investigations and reusing the knowledge acquired in the process.

4.1.3.4 Challenges related to identifying and implementing countermeasures

Identifying and implementing actions to correct and eliminate root causes is one critical phase in the root cause analysis process. This phase does not cover mitigating actions after a disturbance has occurred. Rather, it refers to the countermeasures needed to eliminate root causes. Only when suitable actions have been identified and employed and root causes eliminated can a company certify that a similar disturbance will not reoccur. Viveros et al. (2014) indicate that seldom any systematic way for identify countermeasures and validate their effectiveness is applied in the root cause analysis process. This could result in countermeasures being defined which do not have the desired outcome of eradicating root causes.

4.1.3.5 Challenges related to knowledge management in root cause analysis

A knowledge management phase is essential if the phases described in the previous subsections are to be improved (problem identification, data collection, identification of root causes, identification and implementation of countermeasures). Companies can ensure greater efficiency through knowledge management by disseminating the findings of the root cause analyses they perform. This phase identified two challenges: poor knowledge-sharing and underuse of knowledge gained from past investigations (last row of Table 4).

Qian et al. (2019) note that despite factories within the same company having had identical issues, knowledge of disturbances, their root causes and any countermeasures is not shared between the different locations. Information is usually captured and stored locally, making the knowledge transfer process between different plants very challenging (Brundage et al., 2017; Qian et al., 2019). Furthermore, a lack of collaboration might impose difficulties on the root cause analysis process, not only within a company but also at the supply chain level. Mourtzis et al. (2016) indicate that existing collaboration practices within and outside companies need modernisation.

Brundage et al. (2017) point out that the knowledge acquired in past root cause analysis investigations is also very limited. In manufacturing companies, root cause analysis is often conducted using “pen and paper” and no digital data storage of the results. Without using the knowledge gained from earlier investigations, the procedure is frequently repeated when a similar disturbance arises.

4.1.4 Resistance to the use of technologies in disturbance management

One great challenge experienced by manufacturing companies relates to ensuring that new technologies are smoothly adopted by employees so that the root cause analysis process can be improved. Study F focused on understanding the main sources of resistance to the use of technologies in production disturbance management, through a literature review and a series of interviews. Those results appear below (for more details, please refer to Paper 6).

The identified sources of resistance are (1) feelings of over-supervision, (2) unclear value, (3) feelings of inadequacy, (4) concerns about job and power loss and (5) work overload. Table 5, from Paper 6, presents the sources of resistance according to the literature review and conducted interviews in Study F. The sources of resistance are detailed in the following subsections.

Table 5: Sources of resistance, related literature and sample statements (from Paper 6).

Sources of resistance	**Selected articles**	**Sample statements (companies)**
Feelings of over-supervision	(Aromaa et al., 2019; Birkel et al., 2019; Horvath et al., 2018; Horváth & Szabó, 2019; Kaasinen et al., 2019; Klumpp et al., 2019; Merhar et al., 2019; Mora Sanchez, 2019; Pradhan & Agwa-Ejon, 2018; Zimmermann et al., 2019)	*"The breaks became shorter because people feel over-monitored."*
Unclear value	(Bag et al., 2018; Birkel et al., 2019; Bruno et al., 2019; Hahm, 2018; Le Grand & Deneckere, 2019; Merhar et al., 2019)	*"No 'why'. But if you don't understand why you're using the technology, you're not going to use it."*
Feelings of inadequacy	(Bag et al., 2018; Birkel et al., 2019; Bruno et al., 2019; Chei et al., 2019; Daling et al., 2020; Eimontaite et al., 2019; Greinke et al., 2016; Hahm, 2018; Horváth & Szabó, 2019; Klumpp et al., 2019; Loch et al., 2016; Merhar et al., 2019; Pejic-Bach et al., 2020; Whysall et al., 2019; Zimmermann et al., 2019)	*"Sometimes there's a dislike of doing something differently because people have always done things in a certain way. It can be troublesome with the new technology."*
Concerns about job and power loss	(Birkel et al., 2019; Eimontaite et al., 2019; Hahm, 2018; Horvath et al., 2018; Horváth & Szabó, 2019; Klumpp et al., 2019; Le Grand & Deneckere, 2019; Mora Sanchez, 2019; Pradhan & Agwa-Ejon, 2018; Xing et al., 2019)	_
Work overload	(Birkel et al., 2019)	*"People cannot be in two places at the same time. Sometimes there's a problem in one machine and the operator is trying to solve that problem… And then another problem comes. It's very difficult to find the actual root cause."*

4.1.4.1 Feelings of over-supervision

According to the literature review, a feeling of over-supervision is anticipated due to the extensive collection of data by sensors, machines, devices and people that might be brought about through the adoption of Industry 4.0 technologies (Birkel et al., 2019; Zimmermann et al., 2019). The status of machinery, as well as the statuses of employees and their actions, are all accessible in real time (Pradhan & Agwa-Ejon, 2018). If there is a disturbance, the worker running a particular machine can be easily identified by using Industry 4.0 technological advancements.

In manufacturing companies, resistance is experienced in managing production disturbances due to feelings of over-supervision. The companies investigated in Study F (Paper 6) use specific software to monitor their disturbances. Disturbances are logged automatically, with operators expected to report their causes. Ultimately, this means an operator must report their own absence due to breaks/pauses, or even their own errors. According to the interviewees, the use of the software impacted the length of breaks, due to the feelings of over-supervision it engendered among the operators.

Another issue is that the operators would occasionally present concerns that information on the causes of disturbances gathered by the software could be used against them. The interviewees believed that operators sometimes intentionally provided incorrect information to avoid being reprimanded for causing a production disturbance.

4.1.4.2 Unclear value

Another source of resistance identified in the literature is the unclear value of the technology. This may arise among employees when they do not understand why the technology is being used (Le Grand & Deneckere, 2019). Birkel et al. (2019) indicate that resistance is expected in cases where there is a lack of understanding of the reasons for using Industry 4.0 technologies. Analogous conclusions are reported by Hahm (2018), who indicates that acceptance is augmented when employees are conscious of the value of big data, the internet of things, artificial intelligence and cloud computing technologies.

Consistent with the literature, the companies examined in Study F (Paper 6) struggled with unclear value as a cause of resistance to the use of technology in production disturbance management. The empirical results show that an operator needs to know what is being done with shop floor data at the organisational level. If not, they may lose interest in using technology. It is crucial for operators to see how the technology they are using benefits the work being carried out.

4.1.4.3 Feelings of inadequacy

According to the literature, adopting and implementing new technologies usually requires employees to have new technical and soft abilities, such as IT-related knowledge and problem-solving capacity (Birkel et al., 2019; Pejic-Bach et al., 2020; Whysall et al., 2019). One problem that can arise is that workers feel they lack the necessary skills to use new technologies (Horváth & Szabó, 2019), which causes stress and anxiety. This situation is worsened if there is time pressure (Birkel et al., 2019). Feelings of inadequacy and frustration (Daling et al., 2020) are likely to emerge. To accept and use Industry 4.0 technologies, workers must feel confident in their skills (Eimontaite et al., 2019; Hahm, 2018; Klumpp et al., 2019).

The empirical findings of Study F (Paper 6) are consistent with the conclusions in the literature. During the interviews, it was indicated that certain employees may find using new technology to be challenging, thus making them less eager to apply it. Companies also recognise that technology should be as simple as possible, to generate involvement by the operators in managing production disturbances.

4.1.4.4 Concerns about loss of jobs and power

One of the most significant concerns raised in Industry 4.0 literature is that using technology might result in mass unemployment (Birkel et al., 2019). Automation is expected to replace most tasks currently performed by people (Birkel et al., 2019; Mora Sanchez, 2019), especially repetitive and unsafe tasks (Birkel et al., 2019; Mora Sanchez, 2019; Pradhan & Agwa-Ejon, 2018). Many articles point out employees' concerns that Industry 4.0 may eliminate their jobs and lower their prestige in their companies (Eimontaite et al., 2019; Hahm, 2018; Horváth & Szabó, 2019; Klumpp et al., 2019; Le Grand & Deneckere, 2019; Mora Sanchez, 2019; Pradhan & Agwa-Ejon, 2018).

By contrast with the literature review's findings, the interviews from Study F (Paper 6) showed no mention of the possibility that resistance to using technology might be caused by fear of job loss. This may be because the specific technology used for handling production disturbances was not seen as a threat to operators' jobs or power, as they remained essential to the task, especially when evaluating the causes of disturbances. Thus, in these circumstances, technology does not lead to a fear of losing one's job or power. This difference might also be due to the specific situation in Sweden, where the social security system is very comprehensive. Depending on the technology used and the location of the company, fear of losing jobs and power is very likely a source of resistance (even though the empirical findings did not confirm those of the literature review).

4.1.4.5 Work overload

Resistance may arise in the implementation and use of new technologies in production systems, if employees are overburdened with work or responsibility, leading to more stress (Birkel et al., 2019).

The adoption and use of technology in the companies investigated in Study F (Paper 6) led to changes in the operators' tasks. Their workload became heavier as all disturbances were now monitored and their causes assessed. Previously, only disturbances deemed critical were checked. The companies mentioned that many operators felt they had insufficient time for all their activities; a factor that may have caused the appropriate use of technology in managing production disturbances to be deprioritised. Interestingly, this issue goes virtually uninvestigated in the literature. Only one article in the literature review mentioned work overload as a possible source of resistance (see Table 5: Sources of resistance, related literature and sample statements (from Paper 6).

4.1.5 Summary – challenges in root cause analysis

This research identifies various challenges to root cause analysis experienced by manufacturing companies. Subsection 4.1.1 described the disturbance management process usually performed by companies as having root cause analysis at its centre. Subsection 4.1.2 identified the main challenges companies face in prioritising which production disturbances should undergo root cause analysis. Subsection 4.1.3 then described the challenges experienced in the different phases of root cause analysis. Finally, Subsection 4.1.4 focused on the sources of resistance when new technologies are adopted to improve processes.

Some highlights of the challenges to root cause analysis:

- Manufacturing companies still have a somewhat reactive attitude when dealing with production disturbances. They concentrate most of their effort on detection, diagnosis and mitigation/correction. There is a great deal of room for improvement in root cause analysis, prediction and prevention.
- Prioritising which disturbances should undergo root cause analysis is a critical step that companies struggle with. The use of past data is limited and vague criteria tend to be used in such a prioritisation. Furthermore, excessive time may be needed for a group to make the decision. On the other hand, when a centralised decision is made (by, say, a manager), only the production perspective tends to be considered.
- When the process of root cause analysis is started, companies also face challenges in finding the root causes efficiently. The main challenges include a need for expertise, bias, poor knowledge-sharing, no use of past investigations and data-related issues (such as lack of data and data quality).
- Finally, resistance usually emerges among employees when new technologies are introduced to improve the management of production disturbances. The main sources of resistance are feelings of over-supervision, unclear value, feelings of inadequacy, concerns about loss of jobs and power and work overload.

4.2 RQ2 – REQUIREMENTS FOR NEW ROOT CAUSE ANALYSIS SOLUTIONS

After detailing the different challenges regarding root cause analysis, the next step in the research was to investigate the various needs and wishes (or requirements) of manufacturing companies regarding improving the process. This was a necessary intermediate step in identifying and proposing new solutions. This section presents the results of RQ2: "What are the requirements for new root cause analysis solutions?" The RQ is answered by Appended Papers 2, 4 & 5 (which summarise Studies B, D and E).

4.2.1 Impacted stakeholders and factors

Study B focused on identifying the stakeholders affected by disturbances and who might have different root cause analysis requirements, plus the various factors that are impacted. The results presented in this subsection are from a series of workshops conducted with practitioners in Study B (Paper 2).

Various stakeholders may be impacted by production disturbances (see Figure 4). People who work closely with disturbances, like operators, managers and consultants, may feel their effects right away. At plant level, the effects may extend further than just the production and maintenance departments. In short, depending on the type of disturbance, almost all a company's employees may be affected.

STAKEHOLDRES	**Individual level**	**Plant level**	**Firm level**	**Outside**
	Operators	Production department	Owners	Customers
	Managers	Planning department	Shareholders	Suppliers
	Consultants	Quality department	CEO	Equipment manufacturers
		Maintenance department		Competitors
		Finance department		Employees' families
		Logistics department		Academics
		Human resources department		Authorities
		Tool department		Industrial organisations
		Safety department		Society
		Sales/marketing department		Environment
		Purchase department		

Figure 4: Stakeholders impacted by production disturbances (from Paper 2).

Disturbances can also have effects outside companies (see Figure 4), reaching customers, suppliers and equipment manufacturers. This is especially critical when catastrophic disturbances happen. These may involve government bodies and industrial organisations and lead to the creation of regulations, or changes to existing ones. Competitors are very likely the only stakeholders that might be positively affected by production disturbances. Even so, the long-term effects of disturbances on society as a whole are mostly negative.

Production disturbances have various impacts on the different levels of a company (see Figure 5). The factors deemed most important are in bold. From right to left in Figure 5, outside the company, customer interests that may be affected by disturbances are satisfaction, deliverability and trust. Not only is a company's reputation related to how its customers perceive it but also how its suppliers, equipment manufacturers, industry groups, official bodies and society as a whole see it. Production disturbances may affect the business relationships with all these stakeholders, as they can have consequences for a company's reputation. At company level, the results will be affected because disturbances increase production costs and lead to lower profits. The need for investment is also likely to be greater, specifically to deal with the consequences of disturbances.

At the plant level, production disturbances may affect the goals of different departments. Manufacturing performance is impacted, which may lead to problems regarding the quality of final products, longer production times and lower productivity. Also, operations become less predictable, increasing the complexity of the production system. Strategies such as increasing stock levels may be considered as a means of dealing with disturbances, rising production costs.

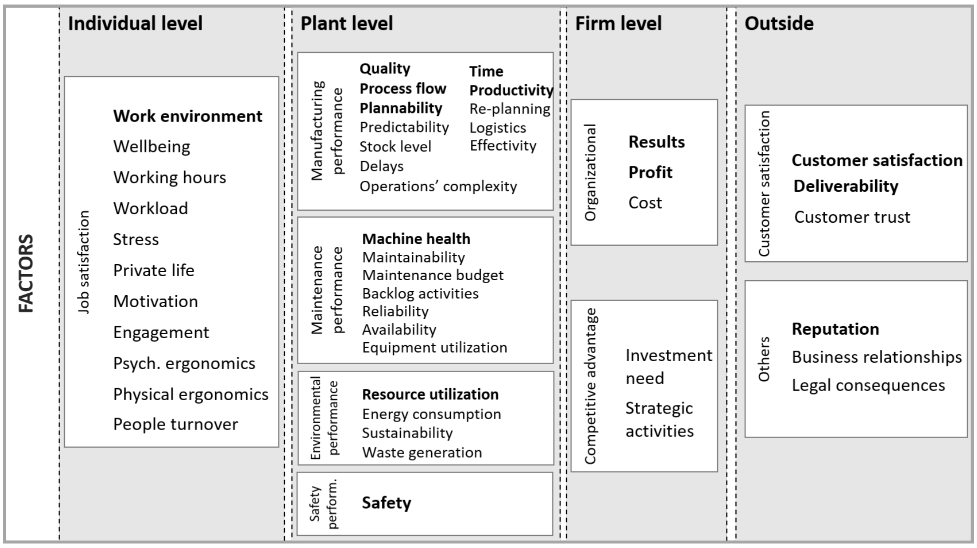

Figure 5. Impacted factors on different levels (from Paper 2).

Maintenance performance is also negatively affected. Without a steady flow of operations, a machine's health is reduced. Disturbances mean that machines are constantly subjected to variations in their setting parameters, making it impossible for them to operate under optimal conditions. A frequent incidence of production disturbances creates a situation in which availability and reliability levels are lowered and a great deal of maintenance is required.

The increased need for resources caused by production disturbances also affects environmental sustainability. The more disturbances a system has, the more scrap parts get produced and the more energy is needed to produce the same number of final products. Furthermore, when production systems become less predictable, employees may face more unusual situations. Thus, disturbances also have a negative effect on safety; working conditions become unstable, possibly resulting in more incidents and accidents.

Employees are also individually affected but not just in regard to their safety. Repeated unexpected problems occurring in production systems can create a greater workload for operators, supervisors and managers. This can make people feel more stressed, negatively affecting their motivation and engagement and even their personal lives.

The 14 factors identified as most relevant are: quality, work environment, safety, time, results, customer satisfaction, productivity, deliverability, resource utilisation, profit, process flow, plannability, machine health and reputation.

4.2.2 Requirements at company level

Study D investigated the requirements for new solutions to improve the root cause analysis process at company level. The following subsection presents the identified requirements. Study D was a qualitative study involving a series of focus groups and interviews with manufacturing companies and technology providers (for more details, see Paper 4).

Study D investigated the requirements for new solutions related to root cause analysis performed at company level. To summarise, the main business objective is for root cause analysis to become an efficient, effective process. Table 6 presents some of the statements illustrating the identified requirements that are further detailed in this subsection.

Table 6: Sample statements regarding requirements for root cause analysis (from Paper 4).

Statements	**Identified requirements**
"The root cause analysis should be more data-driven." *"We want to understand what we can do with the data from each system and how to visualise it."* *"We need to take advantage of digitalisation and use more data in root cause analysis."*	Data-driven root cause analysis
"We need to be able to link different data systems, formats and modalities." *"We need to cross different data and different information…"* *"The data at the system level and at the machine level need to be synchronised."*	Integration of data sources
"It would be interesting to have some type of simple model that could help the operator with problems and symptoms in the root cause analysis." *"New solutions should be simple and easy to use to increase engagement."*	Intuitive and easy-to-use solutions

The first requirement that was identified related to "data-driven root cause analysis" (see first row of Table 6). Participants stated that various relevant datasets may be used to search for root causes in manufacturing companies. It is essential to start by mapping those datasets so as to understand how they can be integrated, analysed and visualised and thus support investigation groups when performing root cause analysis. A process based on data may help make better, more systematic decisions in the root cause analysis process.

A second requirement refers to the integration of various data systems (see second row of Table 6). Commonly, manufacturing companies' data systems are not integrated. This means that when it is necessary to combine data from, say, maintenance, quality or production systems, it has to be done manually. This requires time and is a task prone to errors. When looking for root causes, integration is needed in order to establish how different activities from different departments (or how different variables) might have affected each other. In this case, integration enables the simultaneous analysis and visualisation of heterogeneous data sources.

The final requirement identified is the development of tools that are intuitive and simple.

Solutions that are complicated or that take too long to use may not be adopted by employees. In this case, employees may feel that the cost-benefit of using the tool is not good enough. New solutions should have simple, intuitive interfaces which provide insightful visualisation to support investigation teams in identifying root causes.

4.2.3 Requirements at value-chain level

Study E (Paper 5) focused on identifying the requirements for designing root cause analysis solutions at value-chain level. A series of workshops and interviews were conducted with three manufacturing companies in the same value chain and seven technology providers. The results of this study on the different requirements are summarised in this subsection (see Paper 5 for more details).

Table 7: Requirements for root cause analysis solutions in the value chain (statements from Paper 5).

Identified requirements	**Statements**
Agility	*"We need to increase our agility and reduce our inertia in the value chain."*
Knowledge-sharing	*"...maybe you can bring out different checks and can get information from another company that you didn't know they had. Learning from other companies is necessary to survive in a competitive environment."* *"We need to make the expert knowledge available to everyone."*
Visibility	*"I mean, we need some kind of place where you can make sure everybody has the latest information about the quality problem we're trying to solve together."*
Secure applications	*"I think we need information from the technology providers on how to use different protocols so the information can be shared safely."* *"Cyber-security is needed."*

The first requirement identified in Study E concerns agility (see Table 7). The participating companies highlighted the necessity of making the value chain more adaptable and efficient in handling disturbances so that they can be promptly resolved and action taken to prevent a reoccurrence.

A second requirement concerns knowledge-sharing (second row of Table 7). This was recognised by the participants as an essential feature in new solutions aimed at organisations seeking to compete in the global economy. Disturbances that might impact a specific company could be prevented at their origins, or even at an earlier point in the value chain. This may become possible when more knowledge about the manufacturing processes is shared. Some examples of knowledge-sharing in this context include understanding the upstream and downstream processes, their most common disturbances, the quality checks performed throughout the production steps and how the different production variables at a specific point affect the rest of the value chain. Knowledge should not be restricted to a small group of experts;

it should be available along the entire value chain.

The companies also highlighted the need for visibility regarding root cause analysis in the value chain (third row in Table 7). It is important for all actors to know the current analysis stage of a given investigation, how the work is conducted, those participating in the investigation and the results obtained.

Secure applications are the final requirement identified (last row in Table 7). The companies emphasised the importance of setting up security protocols to provide confidence that any data or information they share won't be misused by another actor in the value chain. Additionally, when sharing information, care should be taken to avoid placing crucial data anywhere it might be compromised.

4.2.4 Summary – requirements for new root cause analysis solutions

In this research, different requirements for new solutions to improve the process of root cause analysis were identified. In Subsection 4.2.1, the different stakeholders and values that are impacted by production disturbances were listed. Subsections 4.2.2 and 4.2.3 described the requirements for new solutions that can support practitioners at individual manufacturing company level and value-chain level.

Some highlights from the identified requirements for new solutions related to root cause analysis:

- Production disturbances impact a great number of stakeholders in different ways. This should be considered in the development of new solutions. Different roles might be affected at the individual (operators, managers), plant (different departments) and firm levels (shareholders, owners). Sometimes, the effects of disturbance are even felt outside companies. The main factors impacted by disturbances are quality, work environment, safety, time, results, customer satisfaction, productivity, deliverability, resource utilisation, profit, process flow, plannability, machine health and reputation.
- The main requirements of companies for new solutions to improve the root cause analysis process are that they should be data-driven, integrate different sources of data and be intuitive and easy to use.
- In case of disturbances at the value-chain level, a joint root cause analysis might be conducted. New solutions to improve this process should securely enable greater agility, knowledge-sharing between different actors and visibility in the process.

4.3 RQ3 – IDENTIFYING AND DESIGNING IMPROVEMENTS FOR ROOT CAUSE ANALYSIS

Based on the identified challenges and requirements, RQ3 identifies, suggests and designs solutions that can lead to the improvement of the process of root cause analysis. This section presents the results of Studies C, D and E (Papers 3,4 and 5) in relation to RQ3: "Based on the *requirements, how can root cause analysis be improved and lead to more resilient production systems?".*

4.3.1 Enablers in the different phases of root cause analysis

The focus of Study C (Paper 3) was to use a literature review to identify the current technologies and solutions being applied in improving root cause analysis. Table 8 presents the enablers related to root cause analysis and the related literature identified in Study C. The following subsections provide more details about the enablers identified in each phase of root cause analysis.

Table 8. Enablers in the root cause analysis process (from Paper 3).

RCA phase	Related articles	Identified enabler
1. Problem identification	(Kinghorst et al., 2018; Vodenčarević & Fett, 2015)	Alarm analysis algorithms
	(Sand et al., 2016)	Enhanced visualisation
	(Mourtzis et al., 2016)	Collaborative platforms
	(Brundage et al., 2017; Chakravorti et al., 2018)	Thesaurus of problems
2. Data collection	(Shukla et al., 2015)	Sensor location algorithms
	(Madsen et al., 2017; Ooi et al., 2019; Palasciano et al., 2016; Stojanovic & Stojanovic, 2017)	Interconnection technology
	(Chakravorti et al., 2018; Stojanovic & Stojanovic, 2017)	Data architecture development
	(Ong et al., 2015)	Data quality improvement
3. Identification of root causes	(Baier et al., 2019; Nonaka et al., 2008)	Enhanced visualisation
	(Chakravorti et al., 2018; Kozjek et al., 2017; Lokrantz et al., 2018; Madsen et al., 2017; Mehrabi & Weaver, 2020; Noursadeghi et al., 2012; Sand et al., 2016; Stojanovic & Stojanovic, 2017)	Machine learning techniques
	(Mourtzis et al., 2016)	Collaborative platforms
	(Brundage et al., 2017)	Thesaurus of causes
	(M. C. Lee & Chang, 2012)	Combination of methods
4. Identification and implementation of countermeasures	(Viveros et al., 2014)	Combination of methods
	(Mourtzis et al., 2016)	Collaborative platforms
	(Brundage et al., 2017)	Thesaurus of countermeasures
5. Knowledge management	(Brundage et al., 2017; Mourtzis et al., 2016)	Root cause analysis platforms

4.3.1.1 Enablers related to problem identification

Four enablers were identified for the problem identification phase (see first row of Table 8 for related literature). The first enabler focuses on alarm analysis. To address the issue of operators being inundated with multiple simultaneous alarms, Vodenarevi and Fett (Vodenarevi & Fett, 2015) state that the data-mining field has focused on developing various algorithms for isolating critical alarms. This is critical information for an operator during a production disturbance because it can indicate which machine (or parts thereof) should be dealt with. Kinghorst et al. (2018) propose a graph-based approach based on the conditional probability of an alarm, A, occurring in the presence of a second alarm, B. This can be used to split alarm data automatically, thus aiding operators in identifying statistically dependent and critical alarms. This is an important enabler for identifying the problem because it helps the operator focus on a specific machine, part of a machine, or process variable that requires immediate attention.

The second enabler is the use of tools to improve the visualisation of problematic process parameters. To achieve this, Sand et al. (2016) suggest a real-time, fast-reaction system that analyses process data, detects jumps, outliers and anomalous distributions and then tracks changes back in the process variables. Decision trees and cluster analysis are developed using data mining and operators can view the results as graphs. An effective visualisation strategy can help operators identify problems quickly and precisely.

The third identified enabler for problem identification is using collaborative platforms. By using a collaborative platform, employees can ask for feedback regarding problem statements (Mourtzis et al., 2016). In this case, once the employee seeking feedback has posted the proposed statement, other employees can vote on a social platform as to whether they agree with the proposed statement or they can suggest something else. By using advanced indexing techniques, it is also possible to access previous problem descriptions and aid the identification of current problems. To support operators in problem detection, the suggested platform enables the use of natural language, both in expressing new problems and retrieving ones that have already occurred (Mourtzis et al., 2016).

The fourth proposed tool for problem identification involves creating a thesaurus of all potential problems and alternative terms (different names that the same problem may go by) (Brundage et al., 2017; Chakravorti et al., 2018). To develop such a thesaurus, Chakravorti et al. (2018) suggest using a maintenance manual. However, Brundage et al. (2017) recommend using expert knowledge and machine learning. In this kind of solution, an operator enters a potential problem description which can then be compared in a thesaurus of terms that have already been used. A suggested problem description can then be made.

4.3.1.2 Enablers related to data collection

Different enablers for data collection were identified in the reviewed studies and the relevant literature appears in the second row of Table 8. The first enabler refers to installing suitable sensors in the manufacturing system to allow automatic data collection. According to Shukla et al. (2015), it is also crucial to place sensors in the proper locations. To optimise sensor placement, the same authors present a feature-based method for use in multi-station assembly processes for spotting product quality deviations. The method aims to maximise the number of measurements of crucial design features and gather crucial information for a more accurate root cause analysis.

Proper sensor location is necessary but not enough on its own. Data collected by sensors must be stored in a database for further analysis (Madsen et al., 2017; Ooi et al., 2019; Palasciano et al., 2016). Ooi et al. (2019) recommend an IoT gateway solution to handle the internetworking connections between the devices and subsystems, plus using a cloud connection to guarantee communication reliability. Furthermore, Palasciano et al. (2016) suggest a data acquisition platform based on a monitoring system (a data recorder) connected to the machines and an internet-accessible database that can be tailored to a specific production system. In the presented case, the data recorder keeps track of around two thousand variables, communicating with the machine's control unit and independent sensors to acquire the desired data (Palasciano et al., 2016).

Creating suitable data architectures to connect and integrate different data systems was also identified as an enabler (Chakravorti et al., 2018; Stojanovic & Stojanovic, 2017). Stojanovic & Stojanovic (2017) propose a data architecture combining data from machine sensors, the manufacturing execution system and human input (implicit knowledge from the workforce). Chakravorti et al. (2018) suggest a data architecture combining systems related to production, maintenance and planning. The integration of diverse data sources is critical to determining the root causes. This is because failures in production systems can be caused by a variety of different activities, with information typically scattered throughout the company and not always in the same format.

Finally, to address the issue of imbalanced disturbance data (when disturbance data is not as widely available as data on normal operating conditions), Ong et al. (2015) present a principal-component-analysis-based algorithm for weighing the data. This may be a required step in data processing so that interesting patterns can be detected, thus leading to insights into possible root causes.

4.3.1.3 Enablers relating to the identification of root causes

Various enablers were identified regarding the root cause identification phase (see third row of Table 8). Baier et al. (2019) and Nonaka et al. (2008) recommend the use of visualisation tools for identifying root causes more quickly. Baier et al. (2019) propose a method for graphically displaying data to determine the key influencing factors on end products which fail end-of-line tests. An analysis is performed, taking into account the relationship between the process variability of individual parameters and existing faults. The most significant process parameters are then used to generate a spectrogram (a graphical representation similar to those used for audio signals), to aid human interpretation. Nonaka et al. (2008) suggest a method of detecting productivity detractors in large-size production systems (bigger than 500 processes). The method is based on an examination of the coefficient of variation of the system's fluctuations. A visualisation matrix is created to help operators identify root causes in large and complex production systems.

Different researchers suggest the use of machine learning to identify relationships between variables and lead to the root causes of disturbances (Chakravorti et al., 2018; Kozjek et al., 2017; Sand et al., 2016; Stojanovic & Stojanovic, 2017). This can be achieved by categorising the data using expert knowledge and establishing correlations or by simply analysing unlabelled data to find patterns. Various machine-learning techniques are suggested, to help determine root causes. These include decision trees, clustering, Bayesian network and fuzzy set theory (Chakravorti et al., 2018; Kozjek et al., 2017; Sand et al., 2016; Stojanovic & Stojanovic, 2017). Stojanovic & Stojanovic (2017) suggest a model-driven root cause analysis in which an existing failure mode, effect and criticality analysis (FMECA) provides the machine learning algorithm with initial instructions on prominent failures. These are then further updated with real-time data. Kozjek et al. (2017) propose an approach based on two phases of data analysis. In the first phase, rules describing the production system are retrieved using a decision-tree heuristic algorithm and the domain expertise of the manufacturing process. In the second phase, the extracted rules and a machine learning clustering technique are used to indicate the faulty process conditions and their likely sources.

Mourtzis et al. (2016) recommend a collaborative platform for identifying root causes, similar to what was proposed in the problem identification phase. Once a problem has been found, employees from different areas can use the platform to suggest possible root causes. Other employees can then comment and vote on whether they agree that the suggested root causes are the real ones. Root causes are also suggested based on past investigations and using machine learning. The most likely root causes are then indicated, with their likelihood constantly recalculated based on user feedback. Analogous to what was suggested in the problem identification stage, Brundage et al. (2017) recommend creating a thesaurus. This is used to document all possible root causes of a disturbance alongside their likelihoods, with these also being constantly updated via machine learning. A list of all the different words used to describe the same causes is made using natural language. This makes it easier for users to recognise reoccurring root causes.

Finally, Lee & Chang (2012) propose combining the methods of root cause analysis, the theory of constraints and Six Sigma. The authors claim that this enables the strengths of the methodologies to be combined into a more assertive description of root causes. Accordingly, the theory of constraints can provide direction for crucial areas in which root cause analysis should be prioritised, while Six Sigma can provide a statistical technique for quantifying the main issues in the manufacturing system and their most likely causes.

4.3.1.4 Enablers related to identification and implementation of countermeasures

As shown in the fourth row of Table 8, the literature presents various enablers for identifying and implementing measures to ensure root cause eradication. The first of those concerns the use of specific methods combined with root cause analysis. Viveros et al. (2014) suggest combining root cause analysis with the TRIZ method. TRIZ stands for Theory of Inventive Problem Solving and is based on finding potential solutions to a problem. The authors recommend it should be applied when identifying countermeasures to the relevant root causes. In performing TRIZ, the group defines an “ideal final result”, which is followed by a contradiction analysis to identify potential adverse effects of the proposed countermeasures. The authors claim that introducing TRIZ into the identification of countermeasures may be a valuable way of brainstorming and verifying the most suitable actions for eradicating root causes.

As with the enablers identified in the problem and root cause identification phases, a collaborative platform may be used in which employees can share and discuss potential countermeasures for eradicating a root cause. In this case, employees may also vote and give feedback if they consider a specific countermeasure would eliminate a specific root cause (Mourtzis et al., 2016). Additionally, a thesaurus of all known countermeasures to a particular root cause can be built (Brundage et al., 2017). The most appropriate actions can be updated and recommended to employees through machine-learning algorithms. Furthermore, it is possible to develop a feedback mechanism by which implemented countermeasures can be validated. This allows companies to ensure they are taking the appropriate steps to reduce disturbances in their production systems.

4.3.1.5 Enablers related to knowledge management in root cause analysis

The outcomes of previous investigations should be used to enhance knowledge management in the root cause analysis process (see last row of Table 8 for related literature). So that employees avoid repeating the same or a similar investigation; this may lower the amount of redundant work. Less experienced workers may also benefit from studying older investigations carried out by more senior personnel. Both Mourtzis et al. (2016) and Brundage et al. (2017) propose solutions based on knowledge repositories that allow knowledge to be reused in all the various phases. This is based on the use of collaborative platforms and the development of a thesaurus of production disturbances, their causes and potential remedies.

4.3.2 A high-level design for root cause analysis application

Based on the identified requirements presented in Subsection 4.2, Study D proposed a high-level design for an application to support root cause analysis (Paper 4), for machine stop-related disturbances. This type of application can be used to help employees to identify potential areas relating to the root causes of disturbances.

The proposed high-level design can be broken down into three distinct components: (1) a data class diagram that presents pertinent information about machine stops and potential root causes, (2) a strategy for data integration, analysis and visualisation and (3) an activity diagram that presents the general actions of a possible application. Those are detailed in the following subsections.

4.3.2.1 Data class diagram - relevant data for root cause analysis (focus on machine stop)

Study D mapped different sources of data relating to machine stops. This mapping is presented below in a unified modelling language (UML) class diagram (Figure 6). UML is a general-purpose modelling language in the field of software engineering and is intended to provide a standard way to visualise the design of a system (Berardi et al., 2005).

Data concerning the current operating status of a machine is useful in determining the root causes when a stop takes place (see Figure 6, “machine stop” box). In this case, “status” relates to the order and product being manufactured, the shift, the start and end times of the stop and the operator running the machine. Information on the immediate causes (such as mechanical error or material defect) is also provided by the operator, plus any additional comments that may be judged important (such as unusual circumstances in the process).

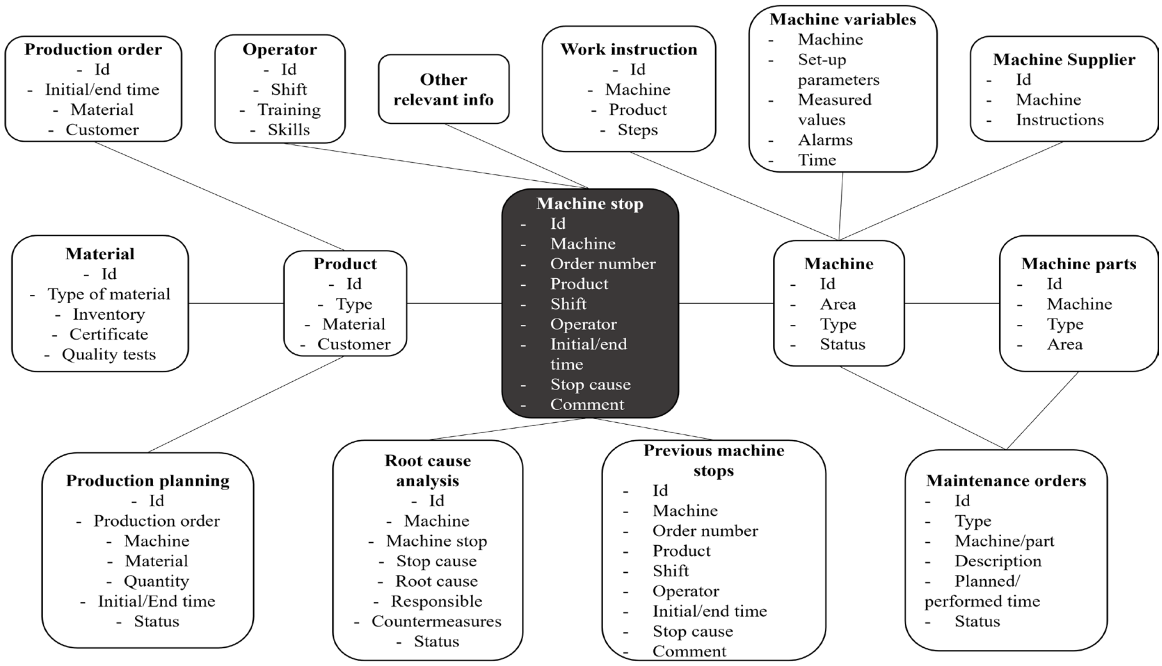

Figure 6: Class diagram of data related to machine stop (from Paper 4).

The machine stop is linked to a specific machine, which may comprise several parts (see Figure 6, “machine” and “machine parts” boxes). The maintenance records of the machine and its parts may be useful in determining the root causes of the machine’s stop. These records can be used to verify whether the various sorts of activities that were conducted, planned or delayed are somehow related to the root causes of the issue (can include preventative or corrective activities).

When investigating the root causes of machine stops, information about machine operating variables may also be examined (see Figure 6, “machine variables” box). In this situation, the machine’s setup parameters at the moment of the stop can be analysed, as well as the trends in the measured variables over a specified timeframe (such as temperature, vibration, speed or any other specific machine characteristics). The set-up parameters represent the anticipated operating conditions, while the measured variables are the values performed by the machine.

A specific product was being manufactured at the moment of the machine stop. This is linked to a production order (see Figure 6, “product” and “production order” boxes), which is part of a production plan specifying how various items should be produced, their quantities and their production schedule. This information is valuable in root cause investigation, as it indicates how earlier batches produced in the machine may have contributed to a stop. Furthermore, different raw materials can be associated with each product. Data from various quality tests/measurements and supplier certificates can also indicate what causes may have led to the stop (Figure 6, “material” box).

The information related to the operator handling the machine and instructions followed at the time of the stop may also help determine the main reasons why the machine stopped working (see Figure 6, “operator” and “work instruction” boxes). For example, it is possible to check whether a specific person was missing any type of training. It may also be appropriate to verify the suggested work instructions to check if they were clear and fulfilled their function.

There may also be a connection between the stop that is being investigated and earlier stops in the machine. Data on the immediately preceding stops, previously identified causes, the frequency and regularity of previous stops and the operators engaged can also be taken into account and examined in this case. Additionally, if a previous root cause analysis was performed for similar disturbances, the information gathered may also be relevant in identifying the root causes of the current machine stop being analysed (see Figure 6, “previous machine stops” and “root cause analysis” boxes).

4.3.2.2 Integration of data sources and analysis/visualisation strategies

Often, an investigation group must start by reviewing pertinent data when looking into potential root causes of a machine stop (mapped in Figure 6). This data is scattered across several systems and sources in companies, which makes data collection, analysis and visualisation challenging. Integrating the various systems and presenting appropriate data is essential to facilitating the root cause analysis process, so that the investigation group may select its focus areas.

Machine sensors and systems related to maintenance, quality, stops, prior investigations, planning and HR need to be integrated so that pertinent data on machine stops can be simultaneously gathered, analysed and visualised. Table 9 presents a set of suggestions for possible data analyses and visualisation strategies which (based on the mapped data presented in Figure 6) may be relevant to root cause analysis.

Table 9: Suggested data analysis and visualisation to support root cause analysis (from Paper 5).

Source	Data type	Relevant question	Data analysis/visualisation
Stop system	Previous machine stops	Are there any patterns for this type of stop?	Analysis of frequency and periodicity of a specific type of machine stop in a specific machine
		Are products or operators related to the stop?	Correlation of past stops and products, operators and immediate causes
Machine sensors	Machine variables	Are machine variables related to the stop?	Comparison of measured values and set-up parameters, analysis and detection of jumps and outliers in time
			Correlation of machine variables and machine stops
			Simultaneous visualisation of machine stops and machine variables
Maintenance	Maintenance orders	Is the last performed maintenance task related to the stop?	Visualisation of the last order & correlation of the last maintenance task and machine stops
		Is lack of maintenance related to the stop?	Visualisation of open orders & correlation of open maintenance tasks and machine stops
Root cause analysis	Past RCA	Are there any similarities between past identified root causes and the stop?	Visualisation of the last RCA conducted for a stop in the machine, visualisation of the last RCA of a similar stop (in any other similar machines)
			Correlation of root causes, types of stops and machines
HR system	Operator	Is competence related to the stop?	Visualisation of records of operator's training prior to the stop
			Comparison of operator's planned and performed training
Manufacturing system	Work instruction	Are the work instructions adequate?	Visualisation of work instructions for the machine/product for the time of the stop
Quality	Material	Is material quality related to the stop?	Visualisation of certificates from suppliers
			Analysis of trends in quality measurements of materials and any abnormal behaviours
Planning	Production planning	Are changeovers related to the stop?	Visualisation of the scheduled orders/changes in products prior to the stop
			Comparison of scheduled and performed orders

4.3.2.3 An activity diagram for a root cause analysis application

With the data mapped in Figure 6 and the suggested data analysis and visualisation (Table 9), an application can be further designed to support root cause analysis. Such an activity diagram is proposed in Figure 7 and considers how the user might handle the application.

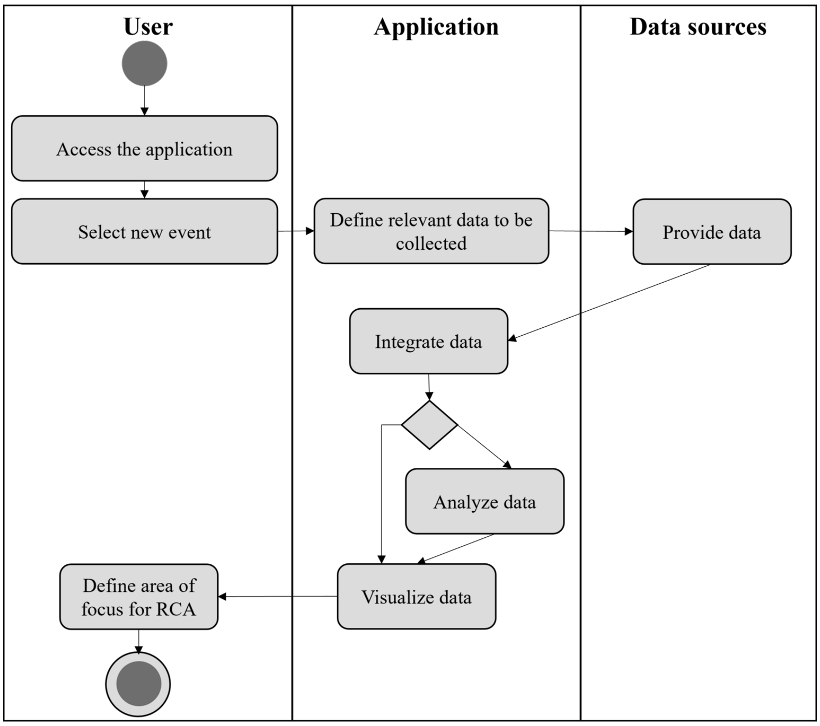

Figure 7: Activity diagram for an application to support root cause analysis (from Paper 5).

For a web-based application, a user can start by accessing it and selecting an event for further analysis (see Figure 7). The application will then define the relevant data sources from which data should be collected. The data sources are then accessed and pre-defined data is provided, as defined in the data class diagram (Figure 6). Data integration is based on the details of the event being analysed (information regarding the stop, the machine, the time, the operator and the product being produced).

With the data integration, information from different data sources (such as maintenance, quality, production and planning systems) can be simultaneously analysed and visualised, as suggested in Table 9. By visualising data, the investigation group (or an individual user) can determine the focus area of likely root causes.

4.3.3 A collaborative digital platform for root cause analysis

Based on some of the requirements presented in Subsection 4.2, Study E proposed a high-level design for a collaborative root cause analysis platform (summarised in Paper 5).

The proposed collaborative platform in Study E is intended to support collaborative investigations at the value-chain level (for disturbances involving more than one actor. The design of the platform is divided into two different parts: a use case diagram and a high-level architecture for the application. More details are provided in the following subsections.

4.3.3.1 Use case diagram - functionalities of the collaborative platform

Employees from all companies working with root cause analysis of quality issues are the platforms' intended users. They may work in areas such as quality, production, maintenance, continuous improvement, engineering and product development. Figure 8 shows the platform's high-level functionalities as a use-case diagram.

As presented in Figure 8, when a new disturbance is found that may relate to suppliers or customers, users should be able to launch a new joint investigation. They should also be able to gain insight into any underlying causes based on prior root cause analysis, then identify specialists in various areas of interest and exchange knowledge via a forum. This is further detailed in below.

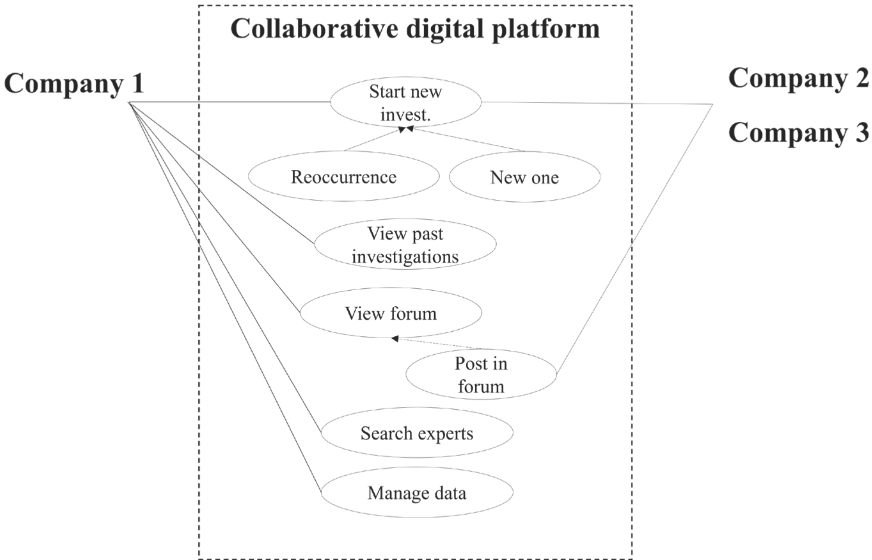

Figure 8: Use case diagram for the collaborative platform (from Paper 5).

a. New investigation

In the event of a new quality problem, an employee (user) at each of the plants has the option to start a new investigation. The quality disturbance may be brand-new (never before encountered) or a reoccurrence of a previous issue. The digital platform presents the findings of earlier root cause analyses, based on the description of the event being analysed. The contact information of employees involved in previous investigations is also presented. If no similar disturbances are found, the user can choose a related knowledge area and view the contact information of relevant employees from the various companies. A notification is sent to all employees from different companies (within parameters set by the user) to participate in the current root cause analysis.

b. View past and ongoing investigations

The user can also verify the findings of earlier investigations without starting a new investigation and enhance their learning from past incidents. The identified root causes are presented, plus any recommendations for eliminating them. Information about those involved in various companies' investigations is also presented. The user can then decide whether the identified root causes and recommendations apply to the issue they have encountered. The user will also have access to the details of relevant people who may be able to help with a specific issue.

The user can also verify the status of an ongoing root cause analysis. In this scenario, it is possible to confirm the various people involved and the stage of the analysis (such as whether data is being collected or the root causes have already been identified). All data and information shared between members of the investigation group is also visible.

c. Search experts

Sometimes, a user may just want to connect with other experts but without actually launching a new root cause analysis process. Thus, another feature of the platform is the option to search for specialists. The user can select an "area of knowledge" (such as maintenance or product development). The platform then gets pertinent information from different people in every company throughout the value chain related to the chosen area.

d. View forum

It is also possible to post on a forum when a user has a specific question but is unsure who to contact or wants a more comprehensive analysis of the situation, including experts from different fields. As soon as a question is submitted, all assigned employees from all companies will automatically receive a notification and be given the opportunity to respond. The platform records earlier questions that users have posted.

e. Manage data

Different types of data from the different companies may be exchanged between members of the investigation team during a root cause analysis process. All the exchanged information can be checked within the platform. Users can review the shared data/information and who has access to it throughout the value chain. They may also grant or revoke access as needed, increasing data security.

4.3.3.2 A high-level design for the collaborative platform

The designed platform allows greater collaboration in root cause analysis on issues involving multiple actors in the value chain. It connects experts from various manufacturing plants, presents regular updates on the progress of the root cause analysis, enables information and data-sharing between companies and encourages knowledge-sharing. Figure 9 displays the platform's high-level architecture. It connects various manufacturing companies and allows them to collaborate in a virtual setting. Figure 9 also illustrates how the platform may look as a web application.

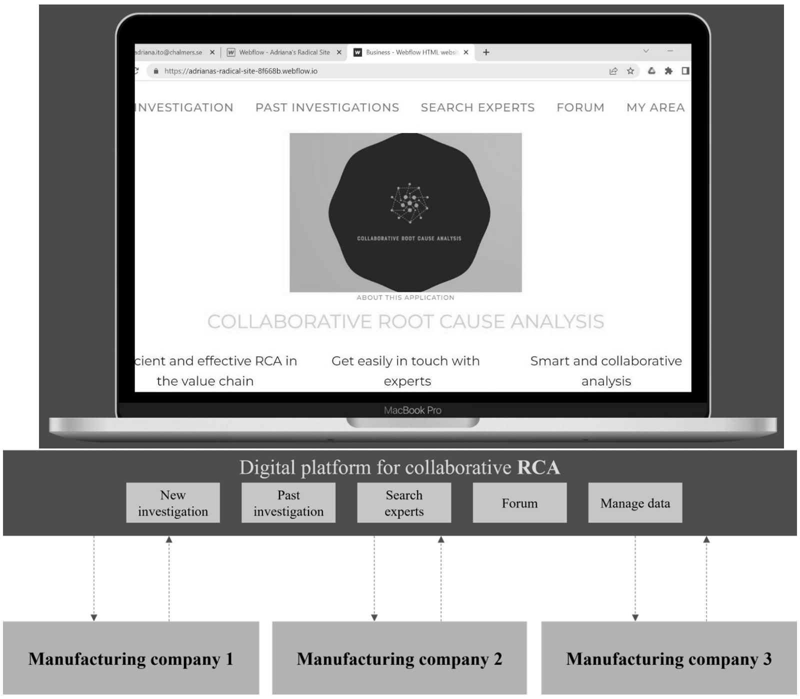

Figure 9: High-level design for a collaborative root cause analysis platform (from Paper 5).

4.3.4 Evaluation of the proposed solutions

Studies D and E proposed conceptual solutions to improve the root cause analysis process in context of a high-level design for a root cause analysis application and collaborative platform. To evaluate their relevance and usefulness, those solutions were presented to practitioners on different occasions. After the presentations, the practitioners' feedback was requested and how they believed the solutions could support their practices.

High-level design for a root cause analysis application

In the case of the high-level application design, an initial prototype was developed which allowed data related to past disturbances and machine variables to be combined. This enabled the visualisation of the trends in different types of disturbances and machine variables. Examples of disturbances include changeover, lack of operator and re-start of a machine. Examples of machine variables are temperature, pressure and speed.

This prototype was presented to practitioners working with root cause analysis and their comments regarding its potential to improve their practices were positive. The participants mentioned that this type of solution could aid the focus of root cause analysis investigations, as it allows different variables to be visualised simultaneously, thus facilitating the identification of cause-and-effect relationships. With this type of application, more disturbances could be analysed, as less time would be needed. The participants also mentioned that with the further integration of other types of data (such as those related to maintenance and quality), the application could become even more powerful. The prototype is in the initial stage of development (not yet published) and further development of it is considered to be future work.

Collaborative digital platform for root cause analysis

The collaborative digital platform was also presented to practitioners and they were asked whether they considered the conceptual solution useful. Their responses were positive and they mentioned that this type of solution is necessary, especially in connecting the right employees with specific knowledge which may be relevant to a specific root cause investigation. This makes the process more effective, as less time is spent finding the right people. The participants also mentioned that this type of solution would be useful, not only at the value-chain level but also between different plants in the same company. In this type of situation, knowledge-sharing can also be improved by using collaborative platforms.

4.3.5 Summary – identifying and designing solutions for root cause analysis

This research identified and proposed different solutions for root cause analysis. Subsection 4.3.1 described different enablers that allow improvements in the various phases of root cause analysis. Subsections 4.3.2 and 4.3.3 suggested a high-level design for a root cause analysis application and a collaborative digital platform, based on the identified challenges and requirements (described earlier).

Some highlights of the solutions relating to root cause analysis:

- Different technologies may be applied to improve the process of root cause analysis. Examples of enablers are “visualisation tools”, “collaborative platforms”, “thesaurus” and “machine learning techniques”. These may facilitate the performance of the various phases of root cause analysis.
- A high-level design is proposed for an application to help investigation groups conduct root cause analysis at company level. This design was based on a data-class diagram, the integration of different data sources and an activity diagram.
- A collaborative digital platform to facilitate root cause analysis conducted at the value-chain level was also proposed. This allows employees from different companies to start new (and check prior) investigations and connect with different experts in the value chain.

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5

"Vivendo, se aprende; mas o que se aprende, mais, é só fazer outras maiores perguntas."

– Guimarães Rosa, from *Grande Sertão: Veredas*

DISCUSSION

This chapter presents a discussion of this thesis. Its results are related to previous work, followed by the answers to the RQs. There is also a discussion of how the results of this work relate to the development of a resilient production system. Finally, the contributions of this research are highlighted.

5.1 POSITIONING THIS THESIS IN RELATION TO PREVIOUS RESEARCH

To create and develop resilient production systems, the ability to *learn* should be enhanced (Hollnagel et al., 2013). When conducting root cause analysis, companies gain insights into the reasons for the disturbances they experience, thus enabling learning. From this learning, the necessary changes to the design, operation and maintenance of production systems can be implemented to make them more adaptable, flexible, reliable and robust. These are necessary features in resilient production systems (Stricker & Lanza, 2014; Zhang & Van Luttervelt, 2011).

Resilient production systems are also associated with the *avoidance* of disturbances (Madni & Jackson, 2011). Avoidance can also be achieved by effective and efficient root cause analysis, whereby the primary reasons for disturbances are recognised and dealt with (Andersen & Fagerhaug, 2006; Mahto & Kumar, 2008). Improving root cause analysis can lead to more resilient production systems, by making it possible to learn from disturbances and avoid them in future.

The results of this thesis relate to previous research by identifying the challenges faced by practitioners and the requirements they have, all grounded in empirical evidence. Previous research has suggested that the current practice of root cause analysis lacks efficiency and effectiveness (Brundage et al., 2017; Lokrantz et al., 2018; Peerally et al., 2017). This has been empirically confirmed by the present research, which adds a detailed description of the challenges. Moreover, the findings of this research add to existing knowledge of root cause analysis by the explicit identification of requirements for new technological solutions.

This thesis has identified and proposed different technological solutions that can improve root cause analysis. Previous research has focused on prescribing how root cause analysis should be performed via traditional steps (such as in the cases of Andersen & Fagerhaug (2006) and Vanden Heuvel et al. (2008)) or on developing technological solutions for specific contexts (Huertas-Quintero et al., 2011; Kozjek et al., 2017). The results of this thesis also add to previous knowledge by identifying how different technological solutions can be used to improve the overall process of root cause analysis.

5.2 ANSWERING THE RESEARCH QUESTIONS

RQ1) What are the current challenges regarding root cause analysis among manufacturing companies?

Manufacturing companies still have a firefighting mindset when dealing with production disturbances. The results of Study A indicate that the emphasis is on the reactive steps of detection, diagnosis and mitigation/correction, rather than the proactive steps of root cause analysis, prevention and prediction. Disturbances reoccur in production systems and the cycle is not usually broken by proactive strategies.

Root cause analysis is the bridge between reactive and proactive strategies. A disturbance will stop reoccurring when the root causes are known and dealt with. In a production system that experiences a great number of disturbances on a daily basis, it is necessary to prioritise which ones should undergo root cause analysis. Study B identified the main challenges to prioritisation. In the case of companies that take a centralised approach to prioritisation (with the production manager making the decisions), root cause analysis prioritisation tends to become dependent on one person (the manager) and considers only one perspective (that of the production department). For companies in which a group sets priorities, a long time tends to be spent reaching a consensus. In all companies, the use of past data to make a decision is very limited and priorities are normally set based on vague criteria.

After prioritisation, the process of root cause analysis can start. When conducting root cause analysis, companies struggle with many challenges in the phases of problem identification, data collection, identification of root causes, identification and implementation of countermeasures and knowledge management. Study C identified the different challenges in each of these phases that hinder companies from effectively and efficiently finding the root causes of their disturbances. Typical challenges are a need for expertise, employee bias, lack of data, poor data quality, lack of data integration, ad hoc processes, poor knowledge-sharing and underuse of knowledge acquired in past investigations.

New technologies may be introduced in companies to improve the root cause analysis process. However, in this situation, employee resistance is very likely. The results of Study F indicate that five different sources of resistance are likely to emerge. These are: feelings of over-supervision, unclear value, feelings of inadequacy, concerns about job and power loss and work overload.

RQ2) What are the requirements for new root cause analysis solutions?

To support industrial practitioners in devising new technological solutions for root cause analysis, it is critical to understand their requirements. Study B identified the various stakeholders and values that should be considered, while Study D and E identified the requirements for solutions at the company and value-chain levels.

Different stakeholders and factors affected by disturbances have been identified in Study B and those should be considered when developing new root cause analysis solutions. Almost all company departments are impacted by disturbances and the effects of production disturbances may often be felt by outsiders (such as customers or suppliers). The most critical factors affected are quality, work environment, safety, time, results, customer satisfaction, productivity, deliverability, resource utilisation, profit, process flow, plannability, machine health and reputation.

Furthermore, the requirements on an individual company level have been identified, in terms of what should be improved in the root cause analysis process (Study D). The main requirements identified in this research are that solutions that can support root cause analysis should be data-driven, allow integration of data systems and be intuitive and easy-to-use.

Root cause analysis is also a process that happens at the value-chain level, especially when a disturbance impacts customers or/and suppliers. Therefore, Study E also focused on understanding the requirements for new solutions at this level. These involve making a new root cause analysis process more agile, considering a more robust knowledge-sharing, with greater visibility and using secure applications.

RQ3) Based on the requirements, how can root cause analysis be improved and lead to more resilient production systems?

The third research question concentrated on identifying and proposing solutions to improve root cause analysis. Study C identified enablers for the different root cause analysis phases. Studies D and E proposed a high-level design for an application to support root cause analysis in manufacturing companies and a collaborative root cause analysis platform in the value chain.

Current Industry 4.0 technologies offer new opportunities for different root cause analysis phases. Among the different enablers identified in Study C to improve root cause analysis were visualisation tools, collaborative platforms, thesauruses and machine learning techniques. These enablers may provide the means for root cause analysis to become a more effective and efficient process.

Study D focused on designing a high-level system for root cause analysis of machine stop-related disturbances. This system is composed of a data class diagram, a strategy for data integration, analysis and visualisation and an activity diagram. The class diagram shows information related to the disturbance (in this case, a machine stop) that may indicate the root causes of an issue. The suggestions for data integration, analysis and visualisation provide the necessary understanding of how data can be used, while the activity diagram illustrates how an application could be developed and used by employees performing root cause analysis.

Furthermore, root cause analysis is an important process that should be improved at the value-chain level. Collaboration on root cause analysis in the value chain could bring competitive advantages to all actors. Study E involved designing a digital root cause analysis platform with different modules to enable knowledge-sharing and better, stronger collaboration between companies. The design of the platform was divided into two different parts: an activity diagram and a high-level architecture. The activity diagram illustrates how the different actors could use the platform, while the high-level architecture presents how it might look.

The conceptual solutions proposed in Studies D and E were evaluated on different occasions. These solutions were presented to practitioners with a request for feedback. The positive comments indicate the conceptual solutions' potential for supporting practitioners in reducing the time to definitively identify root causes. This can help increase the learning ability and thus lead to more resilient production systems.

5.3 CONTRIBUTIONS OF THIS THESIS

This research makes theoretical contributions. Previous research about root cause analysis has focused on prescribing how root cause analysis should be conducted following traditional steps, in this case not considering the potential use of technologies to support the process (such as in the case of Andersen & Fagerhaug (2006) and Oakes (2019)). Furthermore, previous research has also focused on trying to establish cause-and-effect relationships for specific disturbances and situations, suggesting context-based solutions (examples are provided by Mehrabi & Weaver (2020) and Sand et al. (2016)). The prescription of how root cause analysis should performed and the establishment of cause-and-effect relationships are of great importance in the field of root cause analysis, and so is the understanding of challenges and requirements and the design of general solutions. Therefore, this thesis contributes theoretically to current knowledge by empirically identifying and explaining challenges, requirements and potential solutions for root cause analysis. From the knowledge that has been created and consolidated, hypotheses related to root cause analysis can be developed and tested.

This research also offers practical contributions. Conducting root cause analysis effectively and efficiently is a relevant, day-to-day challenge faced by manufacturing companies. By improving this process, companies can avoid the reoccurrence of disturbances in their production systems. Appropriate root cause analysis can enhance the ability of companies to learn from past events. Ultimately, improved root cause analysis can lead to the creation and development of more resilient production systems. The knowledge of what is challenging in the process, what needs to be improved (the requirements) and how the process can be improved is necessary for practitioners to gain insight into their root cause analysis processes. Moreover, the requirements and solutions identified in Studies D and E can also be used directly by technology providers as design input into the development of specific applications or systems for root cause analysis.

5.4 METHODOLOGICAL REFLECTIONS

This section presents some methodological reflections that I consider relevant to this thesis. These reflections cover (1) personal biases and credibility and (2) design science research.

Personal biases and credibility

When performing qualitative research, it is important to recognise potential personal biases which may have impacted the results (Miles et al., 2014). In my case, as mentioned in Chapter 2. Research Approach, before starting my PhD, I worked for many years in root cause analysis in the oil industry. This previous practical knowledge has influenced my choices regarding research questions, studies and methods. I consider this beneficial as, most of the time, I could relate to the experiences of the practitioners I worked with. Also, with particular reference to Studies D and E, in which design science research was more thoroughly applied, my previous experience was valuable in devising different propositions for the design of new solutions.

Conversely, my previous experience may also have influenced the conclusions I drew from the studies. In dealing with this, it was crucial to my research process to constantly work with other researchers on different research projects, as suggested by Miles et al. (2014) and Riege (2003). The weekly discussions with other researchers allowed me to consider other perspectives and regularly have my positions challenged. Another measure taken in the studies was to periodically present the results to the practitioners I was working with (member check), as recommended by Miles et al. (2014) and Riege (2003). The practitioners' feedback was considered in all studies and reflected in the papers I wrote and in this thesis. It was also important in my research process to have a prolonged engagement with the various participants in the studies (Miles et al., 2014; Riege, 2003). This allowed me to ensure that we had a common understanding of the different phenomena being investigated (like root cause analysis) and there were plenty of opportunities for clarification of concepts and discussion.

Design science research (DSR)

One final methodological reflection relates to applying DSR. This is a pragmatic research approach focusing on providing solutions to practical problems (Romme, 2003; van Aken et al., 2016). It was completely aligned with my research aspirations and inspired my research approach. In DSR, different steps are usually taken, as recommended by Peffers et al. (2007) and Vaishnavi et al. (2015), involving: (1) definition of the problem, (2) definition of objectives/requirements for the solution, (3) design of the solution and (4) evaluation of the solution.

The first three recommended steps are directly related to my research questions. However, this thesis did not include a research question for the fourth step (evaluation). Nevertheless, this step was also performed in this work. The results of the studies were presented to practitioners on several occasions and their feedback solicited as to whether the results were relevant to their practices. With particular reference to Studies D and E, the participants said they considered the suggested conceptual solutions might help reduce the time needed to find true root causes. This was because they provide focus to the investigation team (such as what data should be analysed, what types of analysis used and which employees should be involved).

The proposed conceptual solutions are still being developed into concrete artefacts in different projects, with their implementation and testing in a real setting planned over the coming months of this year. Once they are implemented, it will be possible to further evaluate their effectiveness and other effects on the practice of root cause analysis. I suggest further development and complete evaluation of the conceptual solutions as future work.

5.5 FUTURE WORK

With the development and introduction of Industry 4.0 technologies, the root cause analysis process is changing. This thesis focused on understanding the current challenges faced by manufacturing companies and their requirements for new solutions. Solutions that could facilitate the process of root cause analysis were also identified and designed. Although this thesis supports the advancement of the field of root cause analysis, various aspects were not covered. These should be considered in future research.

As an example, the importance levels of the different identified challenges, requirements and solutions were not compared in this thesis. Some challenges are very likely more critical than others (the same applies to requirements and solutions) and should therefore be investigated further. Quantitative studies involving a large number of companies might be suitable for such an investigation.

A further suggestion for future work is developing the proposed conceptual solutions into concrete artefacts. After such development, the artefacts might be then implemented and tested in a real setting, completing the evaluation loop suggested in design science research.

Root cause analysis is a process that is affected by *soft* aspects such as employees' engagement or organisational culture. These were not covered by this thesis, as mentioned in Section 1.4 Delimitations. However, during this research, it was quite clear that managerial aspects should also be considered in improving root cause analysis. This would, therefore, be another suggested area of future research.

6

“Fino, estranho, inacabado, é sempre o destino da gente.”
– Guimarães Rosa, from *Grande Sertão: Veredas*

CONCLUSIONS

This chapter presents the conclusions of this thesis.

Improving root cause analysis so that the learning ability of production systems can be enhanced and disturbances avoided is a cornerstone of the development of resilient systems. However, improvements in this process are only possible if the challenges faced by practitioners and their requirements for new solutions are understood. Based on this knowledge, solutions can then be identified or designed accordingly. This thesis investigated three areas relating to root cause analysis. These are: (1) the challenges faced by practitioners, (2) their requirements and (3) possible technological solutions. A qualitative approach to this work was taken, inspired by design science research.

The results of this thesis indicate that there are various challenges to overcome and requirements to be fulfilled if companies are to become highly effective and efficient in their root cause analysis processes. The main challenges include the reliance on experts, the struggle to integrate and analyse the data and the unstructured way of performing root cause analysis. The main requirements include new solutions to root cause analysis being data-driven, easy to use and allowing the integration of different data sources. There should also be collaboration and knowledge-sharing between different actors.

Furthermore, considering the identified challenges and requirements, the results of this thesis reveal that different technological solutions can be applied to improve the practice of root cause analysis. These include the use of machine learning techniques, the development of collaborative platforms and the development of specific data architectures for root cause analysis. Two specific conceptual designs for solutions were presented in this research; a high-level design for an application and a collaborative digital platform for root cause analysis at the value-chain level.

This research has theoretical as well as practical implications. Its results advance knowledge in the field of root cause analysis by providing empirical evidence about challenges, requirements and possible solutions. The results can also be used directly by practitioners to gain insights into potential improvements in their practices and as input to developing specific applications for root cause analysis. This will lead to a reduction in the time needed for root cause analysis and thus a more assertive process. The learning ability is thereby increased, leading to more resilient production systems.

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